

Article

An Operational Split-Window Algorithm for Retrieving Land Surface Temperature from Geostationary Satellite Data: A Case Study on Himawari-8 AHI Data

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Abstract: An operational split-window (SW) algorithm was developed to retrieve high-temporal-resolution land surface temperature (LST) from global geostationary (GEO) satellite data. First, the MODTRAN 5.2 and SeeBor V5.0 atmospheric profiles were used to establish a simulation database to derive the SW algorithm coefficients for GEO satellites. Then, the dynamic land surface emissivities (LSEs) in the two SW bands were estimated using the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Emissivity Dataset (GED), fractional vegetation cover (FVC), and snow cover products. Here, the proposed SW algorithm was applied to Himawari-8 Advanced Himawari Imager (AHI) observations. LST estimates were retrieved in January, April, July, and October 2016, and three validation methods were used to evaluate the LST retrievals, including the temperature-based (T-based) method, radiance-based (R-based) method, and intercomparison method. The in situ night-time observations from two Heihe Watershed Allied Telemetry Experimental Research (HiWATER) sites and four Terrestrial Ecosystem Research Network (TERN) OzFlux sites were used in the T-based validation, where a mean bias of -0.70 K and a mean root-mean-square error (RMSE) of 2.29 K were achieved. In the R-based validation, the biases were 0.14 and -0.13 K and RMSEs were 0.83 and 0.86 K for the daytime and nighttime, respectively, over four forest sites, four desert sites, and two inland water sites. Additionally, the AHI LST estimates were compared with the Collection 6 MYD11_L2 and MYD21_L2 LST products over southeastern China and the Australian continent, and the results indicated that the AHI LST was more consistent with the MYD21 LST and was generally higher than the MYD11 LST. The pronounced discrepancy between the AHI and MYD11 LST could be mainly caused by the differences in the emissivities used. We conclude that the developed SW algorithm is of high accuracy and shows promise in producing LST data with global coverage using observations from a constellation of GEO satellites.

Keywords: Himawari-8 AHI; operational split-window algorithm; land surface temperature; emissivity; validation

1. Introduction

During the surface energy balance processes, land surface temperature (LST) is one of the most critical parameters, governing the energy exchange in the surface-atmosphere continuum [1,2]. LST has been widely used in the study of the urban heat-island effect [3,4], global warming, and drought monitoring [5,6]. Therefore, LST retrievals with demonstrated accuracy are required in these subsequent applications. In recent decades, researchers have made significant developments in LST retrieval using thermal infrared (TIR) remote sensing technology [7] and have proposed the single-channel algorithm [8], multi-channel algorithms [9–11], such as the split-window (SW) algorithm [12], and the temperature and emissivity separation (TES) algorithm [13].

The different LST estimation algorithms were initially applied to polar-orbiting satellite data to retrieve LST, and several operational LST products have been made accessible to the public, e.g. the Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and Visible Infrared Imaging Radiometer Suite (VIIRS) LST products [14–17]. High spatial resolution is the main feature of polar-orbit satellites, but the temporal resolution is relatively low. In contrast, geostationary (GEO) satellites observe the land surface with a high frequency (10 minutes to 1 hour for a full disk scan), which has merits in studying the LST diurnal cycle [18–20]. Several series of GEO satellites have been currently launched globally, including the Geostationary Operational Environmental Satellite (GOES), Meteosat Second Generation (MSG), Multifunction Transport SATellite (MTSAT), and Feng Yun (FY) meteorological satellites. However, due to the observation mode of GEO sensors, one GEO satellite can only observe a fixed part of the Earth. The high-temporal-resolution global LST products are composed of several GEO satellites and cover the globe. For example, the Globtemperature project (<http://data.globtemperature.info/>) produced a fused LST product (2011–2013) at the global scale with high temporal resolution based on three GEO satellites, i.e., GOES, MSG, and MTSAT-2/Himawari. The Copernicus Global Land service plan (<http://land.copernicus.eu/global/>) is similar to the Globtemperature project, which intends to merge the Satellite Application Facility on Land Surface Analysis (LSA SAF) LST product retrieved from MSG SEVIRI with the LST retrieved from other GEO satellites to generate global LST products [21]. However, this project mainly covers the United States, Europe, Africa, and Australia, and lacks coverage in Asia (especially China and India).

The SW algorithm is efficient and accurate for producing LST products from remote sensing data [14,18,19], and can be applied to almost all GEO sensors, except for GOES 13/15 imagers, which only have one thermal band. Many studies have shown that the emissivities of the two TIR bands are critical inputs and greatly impact the LST retrieval accuracy in the SW algorithm [19,22–26]. Different methods for estimating emissivity from satellite data have been developed, such as the classification-based method, the normalized difference vegetation index (NDVI) threshold method, the physics day/night algorithm method, and the high spectral resolution (HSR) emissivity algorithm [15,27–30]. MODIS MOD11 LSE products are estimated using the classification-based method. However, many studies have pointed out that classification-based method could cause large uncertainties in the emissivity estimation over barren surfaces and further introduce large errors into LST retrievals [25,31–33]. The National Aeronautics and Space Administration (NASA) released a new emissivity dataset called the ASTER Global Emissivity Dataset (ASTER GED) in 2014, which is a global mean emissivity database produced using all clear-sky ASTER images from 2000 to 2008 [34]. Validations have shown that this emissivity product has high accuracy over barren surfaces [35,36]. Therefore, with the aim of LST retrieval accuracy over barren surfaces, this product has been used in emissivity estimation for many polar-orbiting satellites, such as Landsat, Feng Yun 3 (FY-3) VIRR, MODIS, VIIRS, and SLTSR [25,35–39]. Similarly, the ASTER GED can be utilized to estimate the emissivity for global GEO sensors.

To support the generation of global GEO LST products with high temporal resolution, an operational SW algorithm was developed to retrieve LST using global GEO satellite data in this study. In particular, the ASTER GED and fractional vegetation cover (FVC) data were used together

to produce an accurate and dynamic emissivity product to enhance the accuracy of LST estimate. A comprehensive evaluation of the accuracy of the LST retrieval algorithm is of great importance for the generation of LST products [40–42]. Three methods are generally used for validating the LST product, i.e., temperature-based (T-based) [17,43], radiance-based (R-based) [26,44–46] and intercomparison methods [47–49]. In this study, Himawari-8 Advanced Himawari Imager (AHI) data from 2016 were used to evaluate the proposed SW algorithm, and all three validation methods were investigated. The flowchart of the LST retrieval and validation strategy is shown in Figure 1, and the LST retrieval algorithm and the LSE estimation are described in Section 2. In Section 3, the experimental data and validation strategy are described. The validation results are given in Section 4. Finally, the discussion is presented in Section 5, and the conclusion is presented in Section 6.

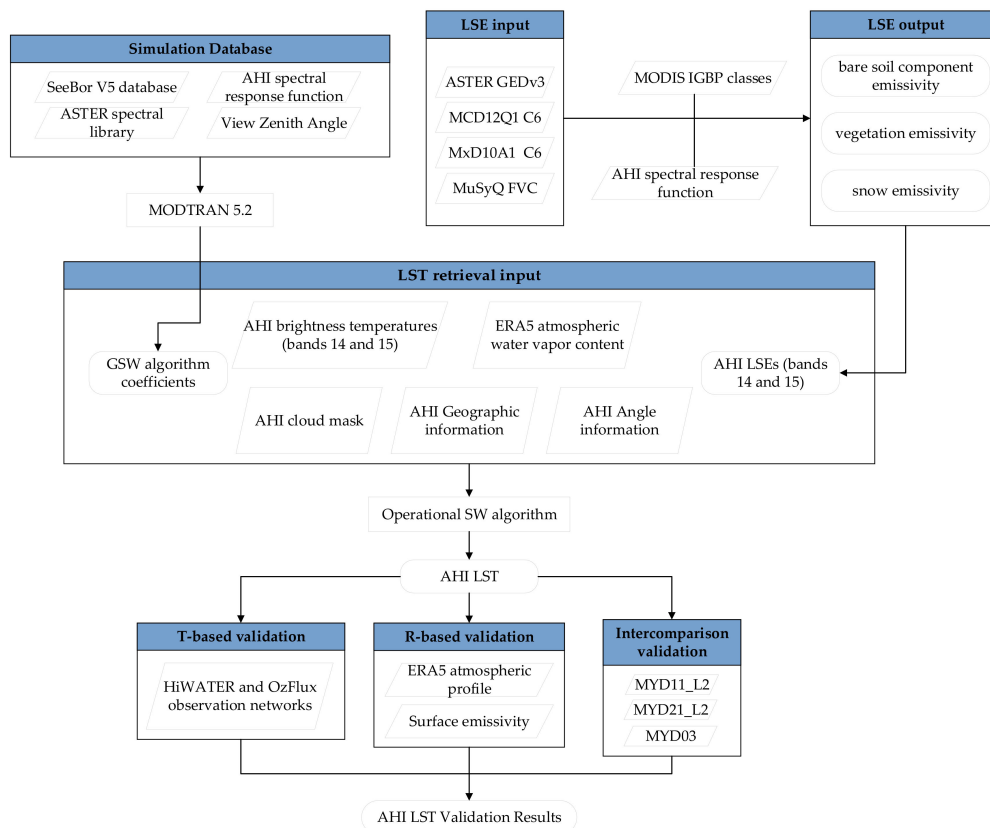


Figure 1. Flowchart of land surface temperature (LST) retrieval and validation from Himawari-8 Advanced Himawari Imager (AHI).

2. Methodology

2.1. LST Retrieval Algorithm

The SW algorithm has a simple form and high calculation efficiency, so it is widely adopted in LST retrieval, and one of the most representative SW algorithms is the generalized split-window (GSW) algorithm, which was successfully adopted for producing several satellite LST products [14,50]. Thus, we chose the GSW algorithm to retrieve LST in this study. The GSW algorithm was originally developed for LST retrieval from the Advanced Very High Resolution Radiometer (AVHRR) and MODIS [14,22,51,52], and later adapted to other polar-orbiting and GEO satellites [19,47,50,53]. Wan [52] proposed a refined GSW algorithm for producing the MODIS Collection 6 (C6) LST product, and we used this algorithm for LST retrieval from GEO satellites, which is given by the following equations:

$$LST = C + \left(A_1 + A_2 \frac{1 - \varepsilon}{\varepsilon} + A_3 \frac{\Delta \varepsilon}{\varepsilon^2} \right) \frac{T_i + T_j}{2} + \left(B_1 + B_2 \frac{1 - \varepsilon}{\varepsilon} + B_3 \frac{\Delta \varepsilon}{\varepsilon^2} \right) \frac{T_i - T_j}{2} + D(T_i - T_j)^2 \quad (1)$$

$$\varepsilon = (\varepsilon_i + \varepsilon_j)/2 \quad (2)$$

$$\Delta\varepsilon = \varepsilon_i - \varepsilon_j \quad (3)$$

where T_i and T_j are brightness temperatures (BTs) of two thermal bands. ε_i and ε_j are the emissivities of the corresponding bands, and A_i , B_i , ($i = 1,2,3$), C , and D are the algorithm coefficients.

The first step of LST retrieval is to obtain accurate GSW algorithm coefficients. Therefore, it is necessary to establish a database by using the radiative transfer model (RTM) and atmospheric profile database, and we chose MODTRAN 5.2 and the Seebor V5.0 atmospheric profiles in this study. First, 9136 cloud-free atmospheric profiles over the land surface were selected from the Seebor V5.0 database, from which the temperature, humidity, and ozone content at different atmospheric pressure levels were acquired, and these profiles were divided into day and night profiles, according to the local sunrise and sunset times to represent the global atmospheric and surface situations [54]. The air temperature at the bottom layer of the atmospheric profile (T_0) changed from 200.2 K to 318.5 K, and the water vapor content (WVC) changed from 0.1 to 7.8 g/cm². Then, the atmospheric transmittance, upwelling radiance, and downwelling radiance of these profiles were estimated using MODTRAN 5.2. For the atmospheric transmittance and upwelling radiance, ten view zenith angles (VZAs) were considered: 3°, 14.9°, 38.6°, 44.5°, 51.2°, 58°, 65°, 70°, 75°, and 80°, and they characterized the angular variation in the atmospheric parameters (atmospheric transmittance, and upwelling radiance) [55]. For the downwelling radiance, 53° was selected to take the place of the hemispherical value [56]. The LST in the simulation for each profile was changed to represent broad atmospheric conditions, i.e., changed between $T_0 - 20$ K and $T_0 + 4$ K at intervals of 3 K for cold atmospheric profiles ($T_0 \leq 280$ K) and changed between $T_0 - 5$ K and $T_0 + 29$ K at intervals of 5 K for warm atmospheric profiles ($T_0 > 280$ K). In addition, 81 emissivity spectra of typical land surfaces in the ASTER spectral library were used, including 4 vegetation, 2 water, 1 ice, 3 snow, 15 rock, 4 sand, and 52 soil spectra. Subsequently, with atmospheric parameters (atmospheric transmittance, upwelling radiance, and downwelling radiance), LSTs, and emissivities as inputs, the BTs of the top-of-atmosphere (TOA) in the two TIR bands were obtained. Finally, the algorithm coefficients in Equation (1) were obtained using multiple linear regressions [57]. Considering that the discontinuity of water vapor easily causes a step effect, WVC was divided into six subranges with an overlapping range of 0.5 g/cm²: [0–1.5], [1–2.5], [2–3.5], [3–4.5], [4–5.5], [5–7.8]. Finally, a lookup table of GSW algorithm coefficients for different VZAs and WVCs was established.

The process of LST retrieval included two steps. First, the coefficients of two neighboring subranges were selected according to the WVC and VZA, and we used bilinear interpolation to obtain the accurate algorithm coefficients. VZA was derived from the AHI L1 gridded data, and WVC was extracted from the ERA5 data. In this study, the WVC was extracted from the hourly ERA5 reanalysis in a $0.25^\circ \times 0.25^\circ$ grid. Second, the LSEs and BTs of the two SW bands were used to calculate the LST.

2.2. LSE Estimation

The ASTER GED [58] was utilized to calculate the LSE. The LSE was calculated using the vegetation cover method, which is given by the following equation [28]:

$$\varepsilon = \varepsilon_v f_v + \varepsilon_s (1 - f_v) + 4\langle d\varepsilon \rangle f_v (1 - f_v) \quad (4)$$

where f_v is FVC, which can be calculated using the NDVI, ε represents emissivity; its subscripts v and s represent vegetation and soil part, respectively, and $\langle d\varepsilon \rangle$ is the cavity term, which is given by:

$$\langle d\varepsilon \rangle = (1 - \varepsilon_s) \varepsilon_v F (1 - f) \quad (5)$$

where F is the shape factor depending on the vegetation height and separation between the surface elements [59].

Wang et al. [39] and Li et al. [35] developed a method to estimate the VIIRS and MODIS LSE, and we utilized this method to derive the AHI LSE. This method divided the land surface into three categories, namely, the surface covered by snow and ice, the surface covered by soil and vegetation, and the inland water. For the surface covered by snow and ice, the MODIS emissivity product was utilized to estimate the average emissivity, which was obtained from the University Wisconsin Global Infrared Land Surface Emissivity (UWIREMIS). Inland water accounts for a small proportion of the global land area, and the emissivity is stable and high, and was thus treated as a constant, and calculated using the water spectra in the ASTER spectral library. The surface covered by soil and vegetation accounts for the largest part of the land surface, and the soil emissivity was calculated using the following equation:

$$\varepsilon_{A,bare} = \frac{\varepsilon_A - \varepsilon_v f_{v,A}}{1 - f_{v,A}} \quad (6)$$

where ε_A is the ASTER GEDv3 emissivity, $\varepsilon_{A,bare}$ is the bare soil component emissivity, ε_v is the vegetation emissivity, and $f_{v,A}$ is the FVC calculated from ASTER GEDv3 mean NDVI.

Once the bare soil emissivity in the ASTER five bands was obtained, then the emissivities in the two SW bands were calculated using a linear conversion, which is given by the following equation:

$$\varepsilon_i = c_0 + c_1 \varepsilon_{10} + c_2 \varepsilon_{11} + c_3 \varepsilon_{12} + c_4 \varepsilon_{13} + c_5 \varepsilon_{14} \quad (7)$$

where ε_i is the emissivity of AHI bands 14 or 15, $\varepsilon_{10}-\varepsilon_{14}$ are the ASTER soil emissivities for bands 10–14, respectively, and c_0-c_5 are the regression coefficients. The regression coefficients and the RMSE of the regressions are listed in Table 1. A detailed description of how to calculate the soil component emissivity can be found in Wang et al. [39].

Table 1. Coefficients of the spectral conversion equation.

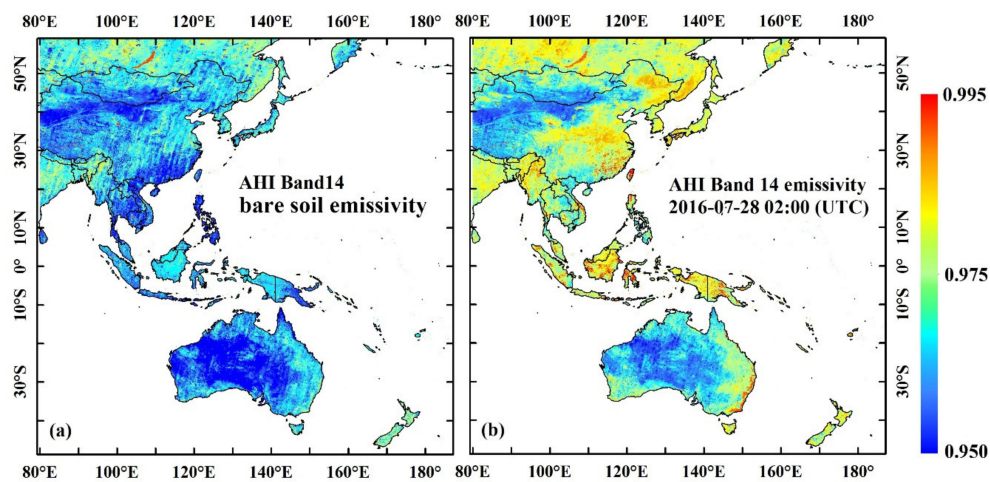
Band	c_0	c_1	c_2	c_3	c_4	c_5	R^2	RMSE
AHI band 14	0.0129	-	-	-	0.1644	0.8228	0.9991	0.0003
AHI band 15	0.5125	0.0145	0.0042	0.0291	-0.0176	0.4520	0.9080	0.0022

The vegetation emissivity in Equation (4) depends on different land surface types, and was calculated using the vegetation spectra in the ASTER spectral library, including the Johns Hopkins University (JHU) and Jet Propulsion Laboratory (JPL) spectral libraries. Further details can be found in [59], and the vegetation emissivities of MODIS International Geosphere-Biosphere Programme (IGBP) classes [60] are given in Table 2 [61].

The FVC was used for calculating the LSE using Equation (4), the AHI TOA NDVI was used to calculate the FVC for the daytime [62], and the FVC product produced by the MULTi-source data SYnergized Quantitative (MuSyQ) remote sensing production system [63] was used for the nighttime. The MuSyQ FVC product was generated using the FY-3 Medium Resolution Spectral Imager (MERSI) and MODIS data with a temporal resolution of 5 days and a spatial resolution of 1 km [64]. The snow/ice cover areas are mainly concentrated in high latitude and high-altitude areas, some are permanent snow/ice areas, while others are covered with fine or fresh snow only in winter, therefore, its dynamic changes need to be considered. Therefore, we used the MODIS snow fraction product (MxD10A1) [65,66] to calculate the snow emissivity and the methodology is similar to the method of vegetation emissivity. Figure 2 shows the soil emissivity of AHI band 14 and the AHI LSE (band 14) for July 28, 2016, 02:00 UTC.

Table 2. Vegetation emissivities and cavity terms of different land cover types in AHI bands 14 and 15 [35].

IGBP Class	Class Name	AHI Band 14	AHI Band 15	F
1	Evergreen Needleleaf Forest	0.989	0.991	0.25
2	Evergreen Broadleaf Forest	0.973	0.974	0.25
3	Deciduous Needleleaf Forest	0.989	0.991	0.25
4	Deciduous Broadleaf Forest	0.973	0.974	0.25
5	Mixed Forests	0.981	0.983	0.25
6	Closed Shrublands	0.981	0.983	0.15
7	Open Shrublands	0.981	0.983	0.07
8	Woody Savannas	0.967	0.970	0.14
9	Savannas	0.965	0.969	0.11
10	Grasslands	0.986	0.989	0.03
12	Croplands	0.986	0.989	0
13	Urban Areas	0.984	0.986	0.13
14	Cropland - Natural Vegetation Mosaic	0.977	0.980	0
16	Barren or Sparsely Vegetated	0.965	0.969	0.03

**Figure 2.** (a) The emissivity of the ground (bare soil emissivity) and (b) the emissivity of the land surface on 28 July, 2016, 02:00 UTC for AHI band 14.

3. Experimental Data and Validation Strategy

3.1. Himawari-8/AHI Data

Himawari-8 is the new generation GEO satellite of Japan, launched in October 2014. Compared with MTSAT-2 (launched in February 2006), it has significant improvements in the temporal and spatial resolutions, which can provide diurnal observations every 10 min, and it is located at approximately 140°E and covers East Asia and Australia. The AHI onboard Himawari-8 has 16 bands, including three visible bands, three near-infrared bands, and ten infrared bands, and we used data from two adjacent TIR bands: band 14 (11.2 μm) and band 15 (12.3 μm).

The AHI L1 gridded data (NetCDF4 format) provided full disk mode, the observation area was between 60°S–60°N and 80°E–160°W, the spatial resolution was 0.02°, and the projection mode was equal longitude and latitude projection [67]. We used the AHI full disk data in January, April, July, and October 2016 (representing four seasons of the year) to retrieve the LST, and the corresponding cloud mask products were used to perform cloud detection. The cloud mask product was applied with a new Himawari-8 Cloud and Haze Mask (HCHM) algorithm, which uses auxiliary digital elevation model data, combined with traditional indicators to identify clear, cloudy, or hazy conditions [68].

3.2. ERA5 Atmospheric Reanalysis Data

Atmospheric profiles are usually obtained from remote sensing retrievals or from the output of reanalysis products. Several studies have shown that different atmospheric profiles have a similar accuracy for LST retrieval [69–71]. Nevertheless, compared with satellite-retrieved atmospheric profile products, reanalysis data can provide globally continuous atmospheric information at a high temporal resolution, which may be more suitable for LST product generation and validation. Therefore, we selected the ERA5 reanalysis product to perform the R-based validation. ERA5 is the latest version of the European Center for Medium-range Weather Forecasts (ECMWF) global climate atmospheric reanalysis data, and the spatial resolution is improved with respect to ERA-Interim [72]. This dataset provides long-term historical data (from 1979 to the present) and offers global, $0.25^\circ \times 0.25^\circ$ resolution atmospheric profiles per hour, which can provide more detailed atmospheric information. These high-temporal-resolution reanalysis data are more suitable for studying the diurnal variation in temperature, and are also closer to the temporal resolution of GEO satellites. ERA5 has pressure level data and single-level data. The total column water vapor recorded in single-level data was used for LST retrieval. Pressure level data are composed of geopotential height, temperature, relative humidity, etc., and these parameters were provided at 37 pressure levels from 1000 hPa to 1 hPa, which were used for the R-based validation in this study.

3.3. MODIS Product

MODIS LST products are one of the most mature LST products and have been evaluated in many previous studies [17,51,52,73,74]. Therefore, satellite-derived LST products such as MYD11_L2 [75] and MYD21_L2 [76] were adopted for intercomparison. The MYD11_L2 product was generated using the GSW algorithm with a 1 km spatial resolution, and LSE was fixed based on 17 land cover types in MCD12Q1 C6 (the Terra and Aqua combined MODIS Land Cover Type) [77]. The latest version C6 MODIS LST products (MYD11_L2 and MYD21_L2) were used in this paper. The MYD21_L2 product is a new generation of LST&E products in C6, produced using the TES algorithm, and provides dynamic emissivities in three TIR bands, namely bands 29, 31, and 32 [78]. An improved water vapor scaling (WVS) method was adopted to perform the atmospheric correction, and a fast RTM, Radiative Transfer for (A)TOVS (RTTOV) [79,80], was adopted to promote the retrieval efficiency. The input atmospheric profiles were obtained from the MERRA-2 product [81]. Compared with the MYD11_L2 product, the MYD21_L2 product is more accurate over semiarid and arid areas and provides dynamic three-band emissivities, which can support the study of land cover changes [82]. To obtain a more accurate geographical position of each pixel, the MYD03 geolocation product was used, which has the same spatial resolution as the LST&E dataset. Table 3 summarizes the data used in the operational SW algorithm and the corresponding information.

Table 3. Summary of the inputs used in LST retrieval by the operational split-window (SW) algorithm.

Product	Temporal Resolution	Spatial Resolution	Purpose
Himawari-8/AHI	10 min	0.02°	brightness temperature, angle information, geolocation.
ERA5 atmospheric reanalysis	1 h	0.25°	water vapor content
ASTER GEDv3	multi-year average (2000 to 2008)	1 km	bare soil component emissivity
MCD12Q1 C6	yearly	500 m	land cover types
MxD10_L2	daily	500 m	snow fraction
MuSyQ FVC	5 days	1 km	fractional vegetation cover

3.4. Validation Strategy

Three validation methods were utilized to evaluate the AHI LST, including T-based validation, R-based validation, and intercomparison validation. Two sites in the HiWATER network and four sites in the OzFlux network were selected for the T-based validation. Four desert sites, four forest sites,

and two inland water sites were chosen for the R-based validation. Figure 3 shows the locations of the validation sites.

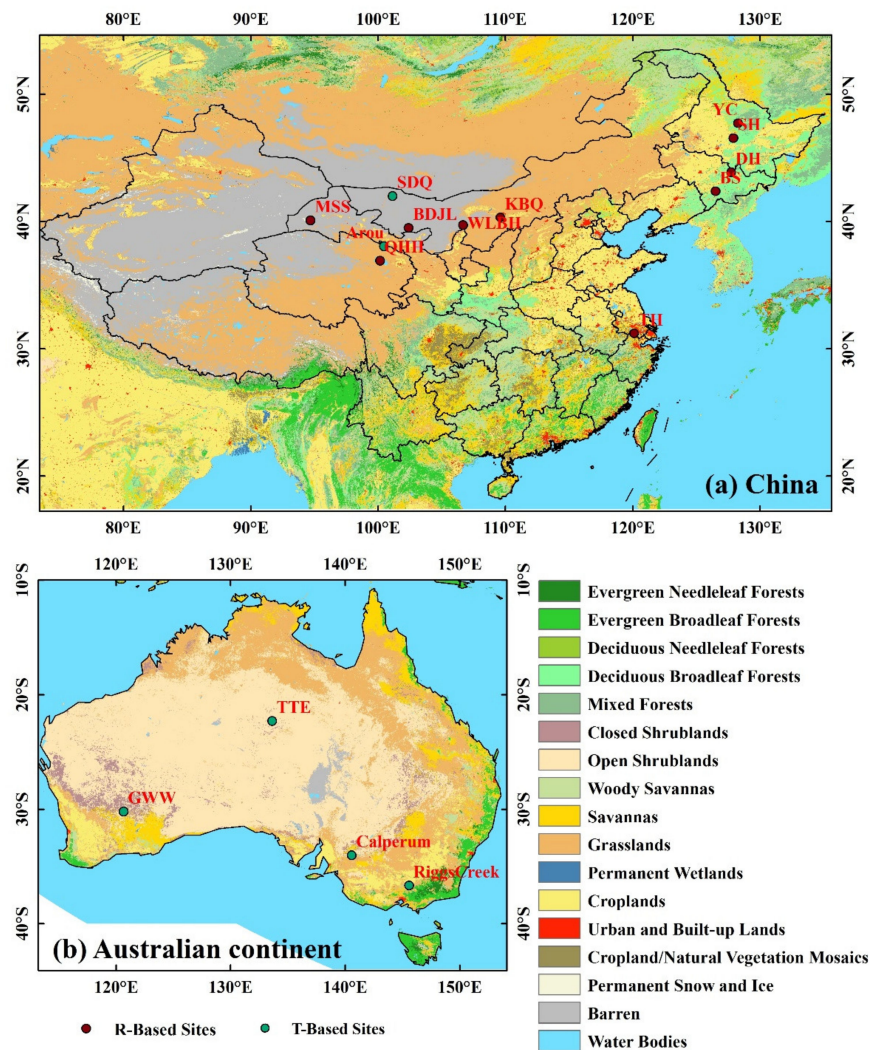


Figure 3. The geographic locations of the sites used in T-based and R-based validation (R-based sites: YC, SH, DH, MSS, WLBH, BDJL, KBO, QHH, TH. T-Based Sites: Arou, SDQ, GWW, Riggs Creek, Calperum, TTE), the background map is the Moderate Resolution Imaging Spectroradiometer (MODIS) MCD12Q1 product.

3.4.1. T-Based Validation

The ground LST measurements collected from the two observation networks were utilized for the T-based validation, which includes the HiWATER and OzFlux networks. The HiWATER project is a remote sensing experiment for ecological hydrology in the Heihe River Basin (HRB), which is located in the arid area of northwestern China, and this project has been ongoing since 2012 [83,84]. The TERN OzFlux is an Australian ecosystem research network [85,86] that can provide continuous, long-term meteorological measurement data. Two sites from the HiWATER project and four sites in the OzFlux network were selected for LST validation, given that these sites are relatively homogeneous at the satellite pixel scale, and the information of the sites is given in Table 4 [46,87].

Table 4. Information on the T-based sites.

Network.	Site Name	Location	Altitude	Land Cover Type	Instrument	Instrument Height
HiWATER	Arou	100.4643°E 38.0473°N	3033 m	Alpine meadows	CNR1	5 m
	Si Dao Qiao (SDQ)	101.1374°E 42.0012°N	935 m	Mixed forest	CNR1	10 m
OzFlux	Great Western Woodlands (GWW)	120.6541°E 30.1913°S	449 m	Woodland	CNR1	35 m
	Riggs Creek	145.5760°E 36.6499°S	151 m	Pasture	CNR4	4 m
	Calperum	140.5877°E 34.0027°S	64 m	Barren/sparsely vegetated	CNR4	20 m
	Ti Tree East (TTE)	133.6400°E 22.2870°S	553 m	Savanna	CNR1	9.9 m

The stations deployed in HiWATER and OzFlux have two main observation instruments: the SI-111 radiometer and the CNR1/CNR4 net radiometer. The six sites selected in this study all used CNR1/CNR4 net radiometers. The CNR1/4 net radiometers were compared with an Eppley Precision Infrared Radiometer (PIR) during the HiWATER experiment, and the estimated difference was approximately $3 \text{ W}\cdot\text{m}^{-2}$ at night, equivalent to an error of 0.5 K in the LST [17,88]. The in situ LST was obtained using Equation (8):

$$LST = \left[\frac{F^\uparrow - (1 - \varepsilon_b) \times F^\downarrow}{\varepsilon_b \times \sigma} \right]^{\frac{1}{4}} \quad (8)$$

where $F^\uparrow$ and $F^\downarrow$ are the surface upwelling and atmospheric downwelling longwave radiations ($\text{W}\cdot\text{m}^{-2}$); ε_b is the surface broadband emissivity (BBE), which was estimated using the VIIRS broadband emissivity product [39]; and σ is the Stefan Boltzmann constant ($5.67 \times 10^{-8} \text{ W}\cdot\text{m}^{-2}\cdot\text{K}^{-4}$).

Using site measurements to evaluate remote sensing products is difficult. The ground sites only represent a small area within 10 m of the flux tower, so it is difficult to represent the actual conditions within a footprint of the sensor. In addition, ground measurements are vulnerable to direct sunlight and shadows during the daytime; thus, nighttime ground measurements are usually used to evaluate satellite LST products [32,89]. The AHI has a coarse spatial resolution, so we only used nighttime measurements to perform the T-based validation in this study. The ASTER LST product (AST08) is often used to assess the spatial heterogeneity of T-based validation sites, due to its high spatial resolution (90 m). According to the spatial resolution of the AHI (2 km), we extracted the ASTER LST pixels in a subset of $2 \times 2 \text{ km}^2$ for each site and calculated the mean values of standard deviation (stdev) for the LST for a seven-year period (2013–2019), and the uncertainty (mean stdev) of each site during the nighttime was obtained. Table 5 shows the LST uncertainties of the six sites, which were lower than 1 K for all sites. Therefore, all sites were treated as homogeneous during the nighttime.

Table 5. The mean values of LST standard deviations within $2 \times 2 \text{ km}^2$ Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) pixels from 2013–2019 during the nighttime for the T-based sites.

Network	Site Name	Mean STDEV (K)	Images Number
HiWATER	Arou	0.99 ± 0.31	7
	SDQ	0.79 ± 0.32	6
OzFlux	GWW	0.38 ± 0.09	5
	Riggs Creek	0.98 ± 0.46	4
	Calperum	0.38 ± 0.09	6
	TTE	0.70 ± 0.48	6

3.4.2. R-Based Validation

Three land cover types (forest, desert, and inland water) were selected to perform the R-based validation (Table 6). The four forest sites (BS, DH, SH, YC) are located in the forest area of Northeast China, near BaiShan city, DunHua city, SuiHua city, and YiChun city. The four desert sites are located in northwestern China. The WLBH site is situated in the Ulan Buh Desert, the MSS site is close to Dunhuang city, Gansu Province, the BDJL site is situated in the Badain Jaran Desert, and the KBQ site is situated in the Hobq Desert. The inland water sites are situated in Qinghai Lake and Taihu Lake. The QHH site is situated in the center of Qinghai Lake, which is situated in the northeast of the Qinghai-Tibet Plateau, and belongs to the high-altitude area, and the altitude is 3198 m. The TH site is situated in the center of Taihu Lake, which lies across Jiangsu Province and Zhejiang Province, and is located in an open area less than 10 m above sea level.

Table 6. Information on the R-based sites.

Land Cover Type	Site Name	Latitude (°N)	Longitude (°E)	Elevation (m)
Forest	YC	47.7221	128.2909	468
	SH	46.5485	127.9156	291
	BS	42.3612	126.5107	965
	DH	43.8643	127.7383	610
Desert	MSS	40.0831	94.6791	1248
	WLBH	39.7192	106.6719	1104
	BDJL	39.4989	102.3813	1400
	KBQ	39.7558	109.6161	1096
Inland Water	QHH	36.9186	100.1407	3198
	TH	31.1953	120.1086	0

The emissivities of MODIS band 31 of MYD21 products were first utilized to assess the spatial uncertainty of the R-based validation sites. Table 7 shows the average stdev values of emissivity in MODIS band 31 within 3×3 pixels of the 10 sites in 2016. These sites were characterized by relatively small differences in emissivity, and the mean values of LSE stdev were less than 0.01 during the daytime, and less than 0.008 during the nighttime. The forest sites appeared to be more homogeneous than other sites, and the stdev values were relatively small during the nighttime over a wider spatial scale. Therefore, these sites are situated over homogeneous and flat areas and can be used for R-based validation.

In the process of R-based validation, the in situ LST was simulated using the satellite-retrieved LST, surface emissivity, and atmospheric profiles. The ERA5 atmospheric reanalysis data were selected as the profile source, which were closer to the temporal and spatial resolutions of the Himawari-8 AHI. The atmospheric profile of the AHI overpass time was obtained using the linear interpolation of two neighboring ERA5 profiles. The surface emissivity was calculated using measurements in the laboratory and the ASTER spectral library. The emissivity measurements of the desert sites were carried out in the laboratory. We collected sand samples around the desert site in the field experiment. To ensure that enough samples can represent one pixel of the satellite, we collected 10 samples around each site. The specific method was to collect samples every 100 m within 1 km. Finally, a dedicated FT-IR spectrometer was used in the laboratory to measure the emissivities of the desert sites; the band value was obtained using the AHI spectral response function (SRF), and the average value of 10 samples was used [74]. According to the MODIS classification product, the four forest sites belong to deciduous broadleaf forests. Thus, the deciduous forest and water spectral samples in the ASTER spectral library were directly used for the four forest sites and two inland water sites, because the emissivities of these two surface types were relatively high and stable in the two SW bands.

Table 7. The emissivity statistics for the R-based sites within 3×3 MYD21 (band 31) pixels in 2016.

Land Cover Type	Site Name	Daytime			Nighttime		
		ϵ_{31} mean	ϵ_{31} stdev	N	ϵ_{31} mean	ϵ_{31} stdev	N
Forest	YC	0.972	0.010	1172	0.975	0.006	1182
	SH	0.973	0.009	971	0.973	0.007	1140
	BS	0.972	0.011	785	0.977	0.006	1095
	DH	0.974	0.008	854	0.977	0.005	1091
	Mean	0.973	0.009	-	0.976	0.006	-
Desert	MSS	0.950	0.009	1807	0.949	0.008	2125
	WLBH	0.947	0.010	1861	0.945	0.007	2262
	BDJL	0.947	0.008	1895	0.946	0.007	2206
	KBQ	0.951	0.009	186	0.947	0.007	245
	Mean	0.948	0.009	-	0.947	0.007	-
Inland Water	QHH	0.978	0.004	1529	0.978	0.004	795
	TH	0.973	0.012	1081	0.972	0.010	779
	Mean	0.976	0.007	-	0.975	0.007	-

MODTRAN 5.2 was used to simulate the TOA BT of the AHI, and considering the influence of atmospheric absorption, band 14 (centered at $11.2 \mu\text{m}$) was selected to simulate the TOA BT. According to the retrieved AHI LST, we adjusted each AHI LST in the range of $\pm 10 \text{ K}$, with a step of 5 K , and obtained five LST values. Then, we simulated the corresponding BT until two calculated BTs (band 14) were within the BTs measured by the satellite. Finally, the R-based LST was obtained by interpolation between the two calculated TOA BTs and BTs measured by the satellite [44,74]. The results were screened by using the difference ($\delta(BT_{11} - BT_{12})$) between the calculated BT difference ($BT_{11}^{\text{calc}} - BT_{12}^{\text{calc}}$) and the observed BT difference ($BT_{11}^{\text{obs}} - BT_{12}^{\text{obs}}$), and a threshold value of 0.5 K was used to select the qualified atmospheric profiles [90,91]. The total uncertainty in the R-based validation method when considering the maximum errors of the input emissivity, atmospheric profiles, and the radiative transfer code was $\pm 0.47 \text{ K}$ [90].

3.4.3. Intercomparison Validation

To further validate the AHI LST, the LST&E products of C6 MYD11_L2 and MYD21_L2 were utilized to perform the intercomparison. Southeastern China and the Australian continent were chosen as the study area due to the smaller VZAs of these two areas. The area selected in southeastern China is located at 102°E – 124°E , 17°N – 40°N , and the VZA of the AHI is approximately 30° – 60° in this region and 20° – 45° on the Australian continent.

However, there were great differences in temporal-spatial resolution and VZA between the MODIS and AHI products. To select as many pixels as possible with similar conditions in the study area, four factors were considered: the spatial collocation of pixels, the temporal concurrence, the alignment of viewing geometry, and the BT difference of the two sensors [48,92]. The selection criteria are outlined as follows below.

First, because the spatial resolution of MODIS (1 km) is higher than that of AHI (2 km), the MYD11_L2 and MYD21_L2 products were resampled to the spatial resolution of the AHI. The pixels within the selected area were identified by the geolocations of the MODIS and AHI LST products. When the corresponding pixels of the two sensors were clear-sky data, they were selected.

Second, based on the time-screening of the pixels in the study area, the time resolution of AHI was 10 min , and MODIS sampled the same area twice each day (Daily 5-Min L2 Swath 1 km). Therefore, we used the observation time of MODIS to match the AHI data at the same time. The time difference corresponding to each of the collocated pixels was calculated, and the threshold of the time difference was 5 min [93,94].

Third, to reduce the impacts of the angle effect on the LST validation, the maximum VZAs corresponding to the two study areas were 45° (Australian continent) and 60° (southeastern China). To ensure that the VZA of the collocated pixel was similar, we used Equation (9) to control the observation angle, and the angle threshold was 0.02 [92].

$$\left| \frac{\cos(VZA_{AHI})}{\cos(VZA_{MODIS})} - 1 \right| < 0.02 \quad (9)$$

Finally, we used MODTRAN 5.2 and Seebor V5.0 profiles to simulate the TOA BTs in two SW bands of MODIS and AHI. The results showed that the BT biases of the two sensors were very small at 11 µm (biases were less than 0.2 K) under the same conditions [95]. Therefore, we selected pixels with the absolute value of the BT difference at 11 µm within 2 K for validation.

4. Results

4.1. T-Based Validation Results

The AHI LSTs were directly evaluated using the ground LSTs (AHI LST—in situ LST), and the results are presented in Table 8. Notably, the four months (January, April, July, and October) in China correspond to winter, spring, summer, and autumn, respectively. Conversely, the four months represent summer, autumn, winter, and spring over the Australian continent. During the nighttime, the biases of the AHI LSTs at the six sites were mostly negative, ranging from −1.14 K to 0.12 K, and the mean value was −0.70 K. The result demonstrates that the AHI LSTs were marginally lower than the ground LSTs, and the maximum bias occurred at the SDQ site (−1.41 K). The mean RMSE of the six sites was 2.29 K, with values ranging from 1.81 K to 3.03 K. To analyze the seasonal variation in the validation results, the biases and RMSEs of the four months are shown in Figure 4. Larger variations in the LST discrepancies can be found for the two HiWATER sites, especially for the SDQ sites. Larger biases and RMSEs were obtained in April and July, and smaller biases and RMSEs were obtained in January and October, with the largest bias (−2.44 K) and RMSE (3.45 K) values obtained in July for the SDQ site. The reason for this result was likely an increased WVC during summer, and the SW algorithm has large errors under humid atmospheric conditions [18,48]. In addition, Figure 4a,b have many negative LST biases. Larger negative biases mostly appeared in the vegetation growing season, such as April and July in the HiWATER Network and January and April in the OzFlux Network. During the vegetation growing season, green vegetation emissivity is generally higher than dead/leaf-off vegetation or bare soil emissivity, and the AHI emissivity estimation is related to FVC. The areas with high FVC also have high emissivity. Therefore, the overestimation of FVC may lead to negative LST biases. [35,89]. The variations in the LST discrepancies were less dependent on the season for the four OzFlux sites. Larger RMSEs were observed in January, with the TTE site showing the largest RMSE (3.75 K). The TTE site is located in the semiarid area of the central Australian continent, and the land cover type is savanna, which has a large LST directionality [96,97]. Thus, this site had the largest RMSE.

Table 8. Nighttime T-based validation results for the AHI LSTs at Heihe Watershed Allied Telemetry Experimental Research (HiWATER) and OzFlux over four months.

Network	Site Name	Bias	RMSE	N
HiWATER	Arou	−0.76	1.97	2065
	SDQ	−1.41	2.48	4181
OzFlux	GWW	−0.99	1.81	1196
	Riggs Creek	0.12	2.39	861
	TTE	−0.56	3.03	1392
	Calperum	−0.60	2.03	1150
Mean		−0.70	2.29	-

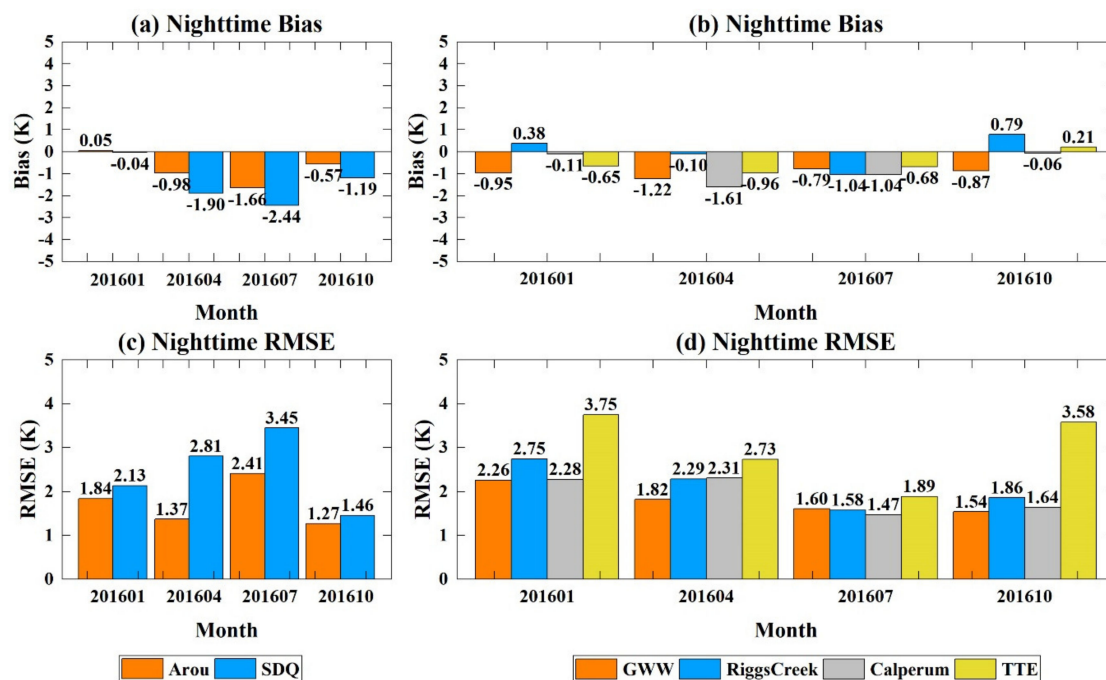


Figure 4. The biases and root-mean-square errors (RMSEs) of the LST differences between AHI LSTs and in situ LSTs in different months during the nighttime for the T-based sites.

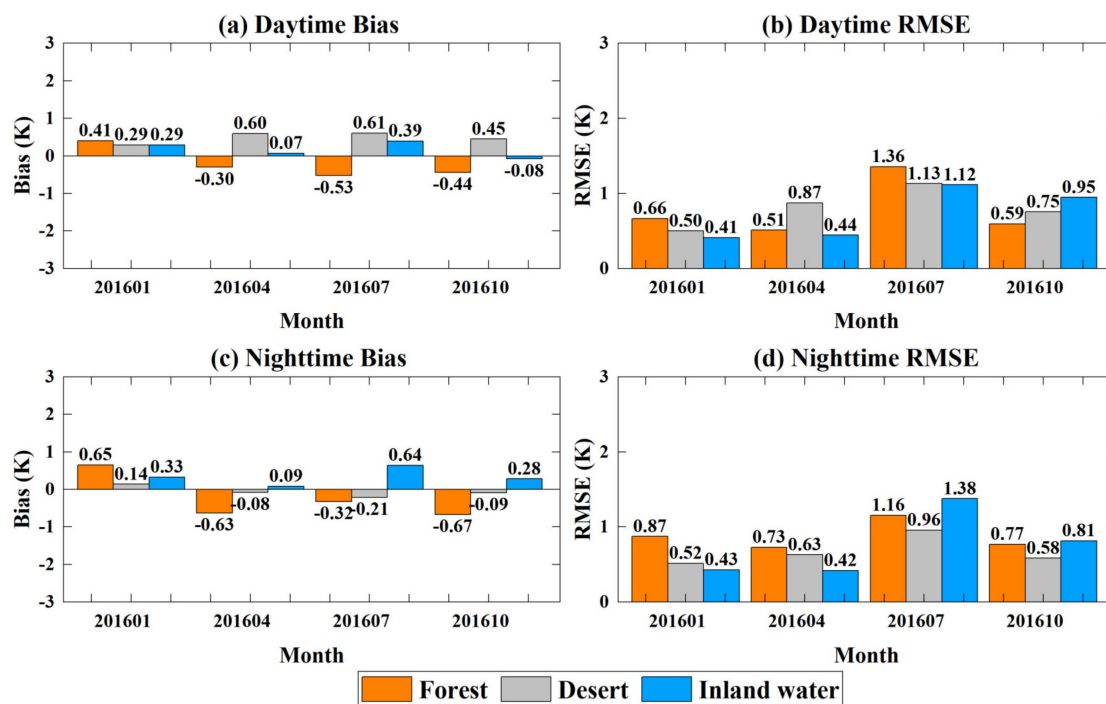
4.2. R-Based Validation Results

Table 9 shows the R-based validation results of the three land types. The AHI LST was slightly underestimated at the four forest sites during both the daytime and nighttime. The average bias was -0.15 K for the daytime, and the biases ranged from -0.37 K to -0.05 K. The nighttime biases ranged from -0.44 K to 0.02 K, and the average value was -0.23 K. The RMSEs were lower than 1 K for all four forest sites. The AHI LST was slightly overestimated at the four desert sites during the daytime, and was underestimated during the nighttime. The biases ranged from -0.03 K to 0.82 K for the daytime, with an average value of 0.48 K; and the biases ranged from -0.46 K to 0.15 K for the nighttime, with an average value of -0.14 K. Except for the BDJL site, the RMSEs were lower than 1 K for all four desert sites. The AHI LST was slightly overestimated at the two inland water sites during both daytime and nighttime. The bias ranged from 0.15 K to 0.28 K for the daytime, with an average value of 0.23 K; and the bias ranged from 0.28 K to 0.50 K for the nighttime, with an average value of 0.41 K. The RMSE was smaller than 0.7 K and 1.4 K for the QHH and TH sites, respectively. The R-based validation results demonstrated that the proposed SW algorithm was accurate over multiple land surface types.

Figure 5 shows the histograms of biases and RMSEs in four months of 2016 for the three land surface types during the daytime and nighttime. The absolute biases in the four months were smaller than 0.7 K for all three land surface types during both the daytime and nighttime, and there was no significant discrepancy between the four months. However, the RMSEs had a larger difference between the four months. The RMSEs in January, April, and October were smaller than 1 K, while the RMSEs in July were larger than 1 K. The reason for the larger RMSEs in July was due to the larger WVC in summer. Taking the TH site as an example, we analyzed the daily average WVC changes in the four months and the influence of the daily average WVC on the LST error in July (Figure 6). The TH site is located in southern China, so the WVC of this site was very high in July, ranging from 4 to 6.5 g/cm², as shown in Figure 6a, and Figure 6b shows the scatterplots between the LST absolute error and daily average WVC in July for the TH site. There was an obvious correlation between the LST absolute error and WVC. The LST absolute error increased with increasing WVC, which indicates that there were larger errors in the SW algorithm under humid atmospheric conditions [18,48].

Table 9. AHI LST R-based validation results at each site during the daytime and nighttime.

Land Cover Type	Site Name	Daytime			Nighttime		
		Bias	RMSE	N	Bias	RMSE	N
Forest	YC	−0.13	0.82	3204	−0.30	0.85	2927
	SH	−0.05	0.81	3272	−0.19	0.94	2980
	BS	−0.06	0.73	3853	0.02	0.96	3017
	DH	−0.37	0.85	3617	−0.44	0.79	2968
	Mean	−0.15	0.80	-	−0.23	0.89	-
Desert	MSS	−0.03	0.74	1777	−0.46	0.82	2225
	WLBH	0.51	0.80	3425	−0.03	0.74	1980
	KBQ	0.43	0.73	3490	−0.13	0.73	1683
	BDJL	0.82	1.05	2894	0.15	0.80	1762
	Mean	0.48	0.83	-	−0.14	0.77	-
Inland water	QHH	0.15	0.40	996	0.28	0.68	617
	TH	0.28	1.23	1829	0.50	1.31	1441
	Mean	0.23	0.94	-	0.41	1.07	-
Mean		0.14	0.83	-	−0.13	0.86	-

**Figure 5.** The biases and RMSEs of the differences between AHI LSTs and R-based LSTs in different months during the daytime and nighttime for the forest, desert, and inland water validation sites.

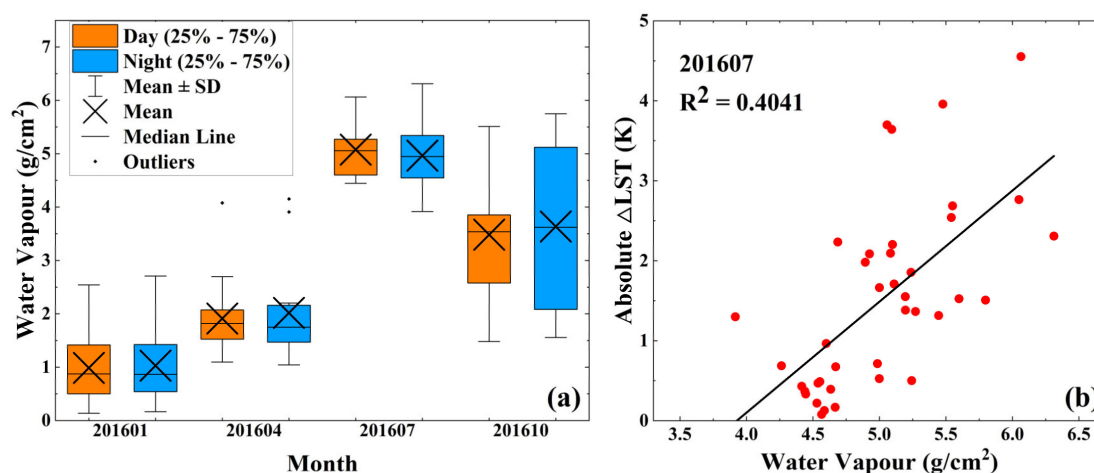


Figure 6. (a) The daily average water vapor content (WVC) of the ERA5 atmospheric reanalysis product (used for AHI LST retrieval) in four months at the TH site and (b) the AHI LST absolute error versus the daily average WVC at the TH site in July 2016.

4.3. Intercomparison Validation of Results

The comparison of results for the AHI LSTs versus the two MODIS LST products over southeastern China and the Australian continent in the four months of 2016 during the daytime and nighttime is shown in Table 10. The mean biases were 1.94 K and −0.54 K based on a comparison with the respective MYD11 and MYD21 LST products in southeastern China during the daytime. This finding indicated that the AHI LSTs were higher than the MYD11 LSTs, and lower than the MYD21 LSTs during the daytime. The maximum biases of these two products occurred in July, with values of 2.48 K and −1.66 K for MYD11 and MYD21, respectively. The mean RMSEs were 2.68 K and 2.04 K compared with the respective MYD11 and MYD21 LST products during the daytime, with maximum and minimum RMSEs appearing in July and January, respectively. With respect to the nighttime, the mean biases were 0.46 K and −0.78 K compared with the respective MYD11 and MYD21 LST products in southeastern China. The maximum biases of these two products also occurred in July, with values of 0.84 K and −1.08 K for MYD11 and MYD21, respectively. The mean RMSEs were 1.40 K and 1.51 K, in comparison with the MYD11 and MYD21 LST products, respectively. The RMSEs during the daytime were larger than those at night. This difference was mainly caused by the spatial variability and directionality of LST, which was more pronounced during the daytime than the nighttime, due to the effects of structural shading, evaporative cooling, and surface-air temperature differences [98,99].

Across the Australian continent, the mean biases showed significant differences, especially during the daytime. The biases ranged from 2.75 K to 4.63 K, in comparison with the MYD11 LST product during the daytime, with a mean value of 3.35 K. The biases ranged from −0.06 K to 0.98 K in comparison with the MYD21 LST product during the daytime, with an average value of 0.74 K. This finding indicated that AHI LSTs were higher than MYD11 LSTs, and were more consistent with MYD21 LSTs. The mean RMSEs were 3.35 K and 2.12 K in comparison with the respective MYD11 and MYD21 LST products during the daytime. The maximum RMSEs of these two products occurred in January (summer) during the daytime, with values of 5.45 K and 3.18 K for MYD11 and MYD21, respectively. In the nighttime, the AHI LSTs were slightly higher than the MYD11 LSTs, and lower than those of MYD21, with mean biases of 1.12 K and −0.61 K for MYD11 and MYD21, respectively. The mean RMSEs were 1.66 K and 1.29 K in comparison with the respective MYD11 and MYD21 LST products during the nighttime. The largest bias and RMSEs also occurred in January during the nighttime.

Table 10. Comparison of the AHI LSTs versus two MODIS LST products during the daytime and nighttime in four months of 2016 across the two study areas.

MODIS LST Products			Daytime				N	Nighttime				N
			MYD11_L2		MYD21_L2			MYD11_L2		MYD21_L2		
Study Area	Season	Month	Bias	RMSE	Bias	RMSE		Bias	RMSE	Bias	RMSE	
Southeastern China	Winter	201601	1.43	2.00	0.49	1.55	75,805	0.18	1.11	−0.34	1.21	45,963
	Spring	201604	1.98	2.62	−0.16	1.68	80,997	0.41	1.26	−0.57	1.32	124,586
	Summer	201607	2.48	3.46	−1.66	2.81	90,589	0.84	1.77	−1.08	1.76	141,554
	Autumn	201610	1.75	2.51	−0.62	1.98	77,096	0.21	1.25	−0.80	1.54	134,296
	Mean		1.94	2.68	−0.54	2.04	-	0.46	1.40	−0.78	1.51	-
Australian continent	Summer	201601	4.63	5.45	−0.06	3.18	432,751	1.32	1.91	−1.11	1.66	654,108
	Autumn	201604	3.68	4.13	0.98	2.33	748,572	1.08	1.61	−0.74	1.38	1,052,311
	Winter	201607	2.75	3.08	0.78	1.61	969,707	0.90	1.47	−0.41	1.12	818,831
	Spring	201610	3.10	3.57	0.87	1.99	921,616	1.21	1.69	−0.37	1.13	1,176,677
	Mean		3.35	3.82	0.74	2.12	-	1.12	1.66	−0.61	1.29	-

Table 11. Statistics of emissivity in AHI band 14 and MODIS band 31 of the MYD11 and MYD21 products over the two study areas during the daytime and nighttime.

LSE Products			Daytime						N	Nighttime						N
			AHI		MYD11_L2		MYD21_L2			AHI		MYD11_L2		MYD21_L2		
Study Area	Season	Month	e14 mean	e14 stdev	e31 mean	e31 stdev	e31 mean	e31 stdev		e14 mean	e14 stdev	e31 mean	e31 stdev	e31 mean	e31 stdev	
Southeastern China	Winter	201601	0.973	0.006	0.982	0.004	0.975	0.006	75,805	0.975	0.005	0.982	0.002	0.976	0.005	45,963
	Spring	201604	0.973	0.006	0.982	0.003	0.972	0.006	80,997	0.973	0.007	0.982	0.004	0.972	0.007	124,586
	Summer	201607	0.974	0.006	0.982	0.004	0.971	0.006	90,589	0.973	0.006	0.982	0.004	0.971	0.007	141,554
	Autumn	201610	0.971	0.007	0.981	0.006	0.972	0.008	77,096	0.974	0.006	0.982	0.003	0.974	0.006	134,296
		Mean		0.973	0.006	0.982	0.004	0.972	0.007	-	0.973	0.006	0.982	0.003	0.972	0.006
Australian continent	Summer	201601	0.964	0.007	0.975	0.005	0.965	0.008	432,751	0.967	0.006	0.976	0.005	0.964	0.008	654,108
	Autumn	201604	0.964	0.007	0.975	0.005	0.967	0.007	748,572	0.967	0.006	0.975	0.005	0.965	0.008	1,052,311
	Winter	201607	0.964	0.007	0.975	0.005	0.966	0.008	969,707	0.968	0.006	0.976	0.005	0.967	0.009	818,831
	Spring	201610	0.964	0.007	0.974	0.004	0.967	0.008	921,616	0.967	0.006	0.975	0.005	0.967	0.008	1,176,677
		Mean		0.964	0.007	0.975	0.005	0.966	0.008	-	0.967	0.006	0.976	0.005	0.966	0.008

To further analyze the difference between the AHI LSTs and two MODIS LST products, the average biases and the standard deviations (stdev) of the emissivity in AHI band 14 (AHI e14) and MODIS band 31 of the MYD11 (MYD11 e31) and MYD21 (MYD21 e31) products are shown in Table 11. The boxplots of the emissivity in AHI bands 14 and 15 and MODIS bands 31 and 32 of the MYD11 and MYD21 products are also shown in Figures 7 and 8. The AHI emissivities of the two SW bands were more consistent with those of MYD21 in the two study areas, and the AHI and MYD21 emissivities were both smaller than those of MYD11.

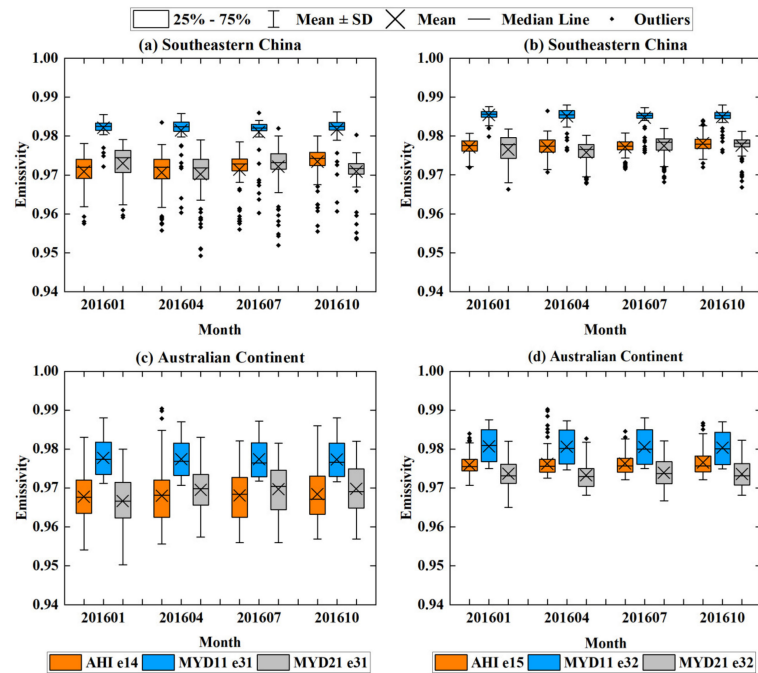


Figure 7. Daytime emissivity values of AHI in bands 14 and 15 and of MYD11 and MYD21 in bands 31 and 32 over the two study areas. (a,b) Southeastern China results and (c,d) Australian continent results.

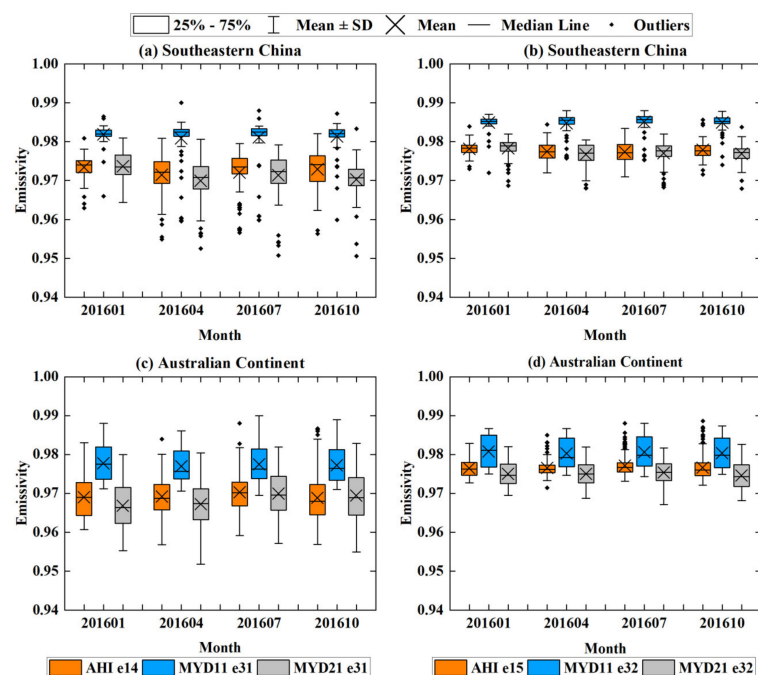


Figure 8. Nighttime emissivity values of AHI in bands 14 and 15 and of MYD11 and MYD21 in bands 31 and 32 over the two study areas. (a,b) Southeastern China results and (c,d) Australian continent results.

The mean emissivities of AHI e14, MYD11 e31, and MYD21 e31 in southeastern China were 0.973, 0.982, and 0.974, respectively. MYD11 e31 was overestimated by 0.009 compared with AHI e14. Emissivity errors have a significant impact on the accuracy of the GSW algorithm, and an emissivity error of 0.005 would result in LST errors of at least 1 K [18,50,100]. Therefore, the LST underestimation of MYD11 was mainly due to the overestimation of emissivity. In addition, the coefficients of the GSW algorithm for retrieving AHI LST and MYD11 were different, which may also cause the difference between these two LST results.

The mean emissivities of AHI e14, MYD11 e31, and MYD21 e31 for the Australian continent during the daytime were 0.964, 0.975, and 0.966, respectively, which were lower than those for southeastern China. This difference occurred because the Australian continent has a large area of open shrublands and barren surfaces, which have lower emissivity values. In addition, the emissivities of the Australian continent had larger fluctuations than those of southeastern China.

5. Discussion

Considering that the classification-based emissivity method may cause large uncertainties in LST retrieval, particularly over barren surfaces [17,31,52], the ASTER GED product was introduced into the operational SW algorithm in this paper, and the accuracies of LST estimates were improved. The intercomparison results indicated that the estimated LSEs were consistent with the MYD21 LSEs. The ASTER GED and MYD21 emissivity products were retrieved using the TES algorithm, which demonstrates that the emissivity retrieved using the TES algorithm has high accuracy [35,74,78]. Thus, the LSE of the MYD21 LST product may be used to support LST retrieval from different satellite data using the operational SW algorithm.

At present, the global GEO satellite LST product provided by the GlobTemperature project uses three GEO satellites (GOES, MSG, and MTSAT/Himawari), which lack coverage in western and southern Asian countries, such as western China and India. In addition, the effective spatial coverage of the GEO satellites is mainly located between 60°S–60°N, due to the larger VZA in the high-altitude area. The purpose of this study was to develop an operational SW algorithm applicable to global GEO satellites and to use this algorithm to produce global GEO LST products for the future. We plan to apply this algorithm to nine GEO satellites, which include Feng Yun 2E (FY-2E), Feng Yun 4A (FY-4A), MTSAT-2, Himawari-8, GOES 13/15, GOES 16/17, and MSG-2, to produce 5 km hourly global GEO LST products from 2009 to 2020. In addition, the dual-window algorithm will be applied to GOES 13/15 data, because these two satellites do not have SW bands [39,101]. The satellites and algorithms used in the generation of the global GEO LST products are summarized in Table 12. Generation of the global GEO LST products is a challenging task, and we also need to consider the effects of spectral mismatch and resolution inconsistency among multiple sensors, so intercalibration, pixel resampling, and correction of the time difference between different sensors are required [92]. In addition, we plan to use the gap-filling method [102,103] to recover the LSTs under cloudy conditions and to produce an all-sky LST product in the future, which will be more useful for different applications. In addition, the influence of topography on LST retrieval [104,105] was not considered in this study, and needs to be studied in the future.

The GEO satellite has relatively low spatial resolution, so the T-based validation is suitable for land surfaces with greater homogeneity, such as inland water and cropland areas [56,106]. It is challenging to evaluate the global GEO LST product using in situ measurements [107]. An upscaling model must be used to scale the ground site measurements to the satellite pixel scale when employing the T-based validation [108]. Thus, the R-based validation method is more suitable for implementation at the global scale over multiple land surface types. The input emissivity of the R-based validation can be acquired from the MYD21 LSE product. In addition, the efficiency can be improved using RTTOV instead of MODTRAN.

Table 12. Summary of satellites and algorithms used in generation of the global geostationary (GEO) LST products.

Sensor	Time Range	Temporal/Spatial Resolution	Algorithm
GOES 13/15 IMAGER	2009–2018	1 h/4 km	operational SW algorithm
GOES 16/17 ABI	2018–2020	15 min/2 km	
MTSAT-2 IMAGER	2009–2015	1 h/4 km	
Himawari-8 AHI	2016–2020	10 min/2 km	
MSG-2 SEVIRI	2009–2020	15 min/3 km	
FY-2E S-VISSR	2009–2018	1 h/5 km	
FY-4 AGRI	2018–2020	15 min/4 km	

6. Conclusions

An operational SW algorithm for generating high-temporal-resolution LST products was proposed in this paper. The ASTER GED product was introduced to estimate the emissivity for the SW algorithm, and the accuracy of the proposed SW algorithm was evaluated using the AHI as a case study. The AHI LSTs were validated using three methods, and the different validation methods complement each other so that the comprehensive validation of the LST products can be realized.

The in situ LSTs used for T-based validation were obtained from the HiWATER and OzFlux networks, and we selected nighttime measurements for validation. The T-based validation result shows that the mean bias was -0.70 K, and the mean RMSE was 2.29 K. Three land surface types, i.e., forest, desert and inland water, were used for R-based validation. The overall accuracies were 0.14 K (bias) and 0.83 K (RMSE) during the daytime and -0.13 K (bias) and 0.86 K (RMSE) at night. The results show that the operational SW algorithm was sensitive to WVC under warm and humid conditions. Additionally, two MODIS LST products (MYD11_L2 and MYD21_L2) were used for intercomparison validation with AHI LSTs over Southeastern China and the Australian continent. The results show that the emissivities of the two SW bands of the AHI were closer to those of MYD21, and the AHI LST was more consistent with the MYD21 LST, and was generally higher than the MYD11 LST. In the two study areas, the changes in emissivity were small between different seasons, but the changes in emissivity over Southeastern China were smaller than those over the Australian continent. The LST differences between the three products over Southeastern China were also smaller than those over the Australian continent. The validation results of the two study areas in spring, autumn and winter were obviously better than those in summer, especially in the daytime, and the best results were obtained in winter. The validation results of the operational SW algorithm show that the algorithm is accurate and can be used to generate hourly LST products from global GEO satellite data.

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References

- Li, Z.; Tang, B.; Wu, H.; Ren, H.; Yan, G.; Wan, Z.; Trigo, I.F.; Sobrino, J.A. Satellite-derived land surface temperature: Current status and perspectives. *Remote Sens. Environ.* **2013**, *131*, 14–37. [\[CrossRef\]](#)
- Cao, B.; Liu, Q.; Du, Y.; Roujean, J.-L.; Gastellu-Etchegorry, J.-P.; Trigo, I.F.; Zhan, W.; Yu, Y.; Cheng, J.; Jacob, F.; et al. A review of earth surface thermal radiation directionality observing and modeling: Historical development, current status and perspectives. *Remote Sens. Environ.* **2019**, *232*, 111304. [\[CrossRef\]](#)
- Yamamoto, Y.; Ishikawa, H. Influence of urban spatial configuration and sea breeze on land surface temperature on summer clear-sky days. *Urban Clim.* **2020**, *31*, 100578. [\[CrossRef\]](#)
- Yamamoto, Y.; Ishikawa, H. Spatiotemporal Variability Characteristics of Clear-Sky Land Surface Temperature in Urban Areas of Japan Observed by Himawari-8. *SOLA* **2018**, *14*, 179–184. [\[CrossRef\]](#)
- Hu, T.; Renzullo, L.J.; Dijk, A.I.; He, J.; Tian, S.; Xu, Z.; Zhou, J.; Liu, T.; Liu, Q. Monitoring agricultural drought in Australia using MTSAT-2 land surface temperature retrievals. *Remote Sens. Environ.* **2020**, *236*, 1–13. [\[CrossRef\]](#)
- Hu, T.; Dijk, A.I.; Renzullo, L.J.; Xu, Z.; He, J.; Tian, S.; Zhou, J.; Li, H. On agricultural drought monitoring in Australia using Himawari-8 geostationary thermal infrared observations. *Int. J. Appl. Earth Obs. Geoinf.* **2020**, *91*, 1–13. [\[CrossRef\]](#)
- McMillin, L.M. Estimation of Sea Surface Temperatures from Two Infrared Window Measurements with Different Absorption. *J. Geophys. Res.* **1975**, *80*, 5113–5117. [\[CrossRef\]](#)
- Qin, Z.; Karnieli, A.; Berliner, P. A mono-window algorithm for retrieving land surface temperature from Landsat TM data and its application to the Israel-Egypt border region. *Int. J. Remote Sens.* **2001**, *22*, 3719–3746. [\[CrossRef\]](#)
- Sun, D.; Pinker, R.T. Estimation of land surface temperature from a Geostationary Operational Environmental Satellite (GOES-8). *J. Geophys. Res. Atmos.* **2003**, *108*. [\[CrossRef\]](#)
- Sun, D.; Pinker, R.T. Retrieval of surface temperature from the MSG-SEVIRI observations: Part I. Methodology. *Int. J. Remote Sens.* **2007**, *28*, 5255–5272. [\[CrossRef\]](#)
- Yamamoto, Y.; Ishikawa, H.; Oku, Y.; Hu, Z. An Algorithm for Land Surface Temperature Retrieval Using Three Thermal Infrared Bands of Himawari-8. *J. Meteorol. Soc. Jpn. Ser. II* **2018**, *96*, 59–76. [\[CrossRef\]](#)
- Sobrino, J.A.; Caselles, V.; Coll, C. Theoretical split-window algorithms for determining the actual surface temperature. *II Nuovo Cim. C* **1993**, *16*, 219–236. [\[CrossRef\]](#)
- Gillespie, A.; Rokugawa, S.; Matsunaga, T.; Cothorn, J.S.; Hook, S.; Kahle, A.B. A temperature and emissivity separation algorithm for Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) images. *IEEE Trans. Geosci. Remote Sens.* **1998**, *36*, 1113–1126. [\[CrossRef\]](#)
- Wan, Z.; Dozier, J. A generalized split-window algorithm for retrieving land-surface temperature from space. *IEEE Trans. Geosci. Remote Sens.* **1996**, *34*, 892–905. [\[CrossRef\]](#)
- Wan, Z.; Li, Z. A physics-based algorithm for retrieving land-surface emissivity and temperature from EOS/MODIS data. *IEEE Trans. Geosci. Remote Sens.* **1997**, *35*, 980–996. [\[CrossRef\]](#)
- Islam, T.; Hulley, G.C.; Malakar, N.K.; Radocinski, R.G.; Guillevic, P.C.; Hook, S.J. A Physics-Based Algorithm for the Simultaneous Retrieval of Land Surface Temperature and Emissivity from VIIRS Thermal Infrared Data. *IEEE Trans. Geosci. Remote Sens.* **2016**, *55*, 563–576. [\[CrossRef\]](#)
- Li, H.; Sun, D.; Yu, Y.; Wang, H.; Liu, Y.; Liu, Q.; Du, Y.; Wang, H.; Cao, B. Evaluation of the VIIRS and MODIS LST products in an arid area of Northwest China. *Remote Sens. Environ.* **2014**, *142*, 111–121. [\[CrossRef\]](#)
- Yu, Y.; Privette, J.L.; Pinheiro, A.C.T. Evaluation of Split-Window Land Surface Temperature Algorithms for Generating Climate Data Records. *IEEE Trans. Geosci. Remote Sens.* **2008**, *46*, 179–192. [\[CrossRef\]](#)
- Tang, B.; Bi, Y.; Li, Z.; Xia, J. Generalized Split-Window Algorithm for Estimate of Land Surface Temperature from Chinese Geostationary FengYun Meteorological Satellite (FY-2C) Data. *Sensors* **2008**, *8*, 933–951. [\[CrossRef\]](#)
- Gao, C.; Tang, B.; Wu, H.; Jiang, X.; Li, Z. A generalized split-window algorithm for land surface temperature estimation from MSG-2/SEVIRI data. *Int. J. Remote Sens.* **2013**, *34*, 4182–4199. [\[CrossRef\]](#)
- Trigo, I.F. Land surface temperature from multiple geostationary satellites. *Int. J. Remote Sens.* **2013**, *34*, 3051–3068. [\[CrossRef\]](#)
- Liu, Y.; Yu, Y.; Yu, P.; Wang, H.; Rao, Y. Enterprise LST Algorithm Development and Its Evaluation with NOAA 20 Data. *Remote Sens.* **2019**, *11*, 2003. [\[CrossRef\]](#)
- Tang, B.; Shao, K.; Li, Z.; Wu, H.; Nerry, F.; Zhou, G. Estimation and Validation of Land Surface Temperatures from Chinese Second-Generation Polar-Orbit FY-3A VIRR Data. *Remote Sens.* **2015**, *7*, 3250–3273. [\[CrossRef\]](#)

24. Qin, Z.; Dall’Olmo, G.; Karnieli, A.; Berliner, P. Derivation of split window algorithm and its sensitivity analysis for retrieving land surface temperature from NOAA-advanced very high resolution radiometer data. *J. Geophys. Res. Atmos.* **2001**, *106*, 22655–22670. [[CrossRef](#)]
25. Jiang, J.; Li, H.; Liu, Q.; Wang, H.; Du, Y.; Cao, B.; Zhong, B.; Wu, S. Evaluation of land surface temperature retrieval from FY-3B/VIRR data in an arid area of northwestern China. *Remote Sens.* **2015**, *7*, 7080–7104. [[CrossRef](#)]
26. Wang, M.; He, G.; Zhang, Z.; Wang, G.; Wang, Z.; Yin, R.; Cui, S.; Wu, Z.; Cao, X. A radiance-based split-window algorithm for land surface temperature retrieval: Theory and application to MODIS data. *Int. J. Appl. Earth Obs. Geoinf.* **2019**, *76*, 204–217. [[CrossRef](#)]
27. Snyder, W.C.; Wan, Z.; Zhang, Y.; Feng, Y. Classification-based emissivity for land surface temperature measurement from space. *Int. J. Remote Sens.* **1998**, *19*, 2753–2774. [[CrossRef](#)]
28. Valor, E.; Caselles, V. Mapping land surface emissivity from NDVI: Application to European, African, and South American areas. *Remote Sens. Environ.* **1996**, *57*, 167–184. [[CrossRef](#)]
29. Yamamoto, Y.; Ishikawa, H. Thermal Land Surface Emissivity for Retrieving Land Surface Temperature from Himawari-8. *J. Meteorol. Soc. Jpn. Ser. II* **2018**, *96B*, 43–58. [[CrossRef](#)]
30. Seemann, S.W.; Borbas, E.E.; Knuteson, R.O.; Stephenson, G.R.; Huang, H.-L. Development of a global infrared land surface emissivity database for application to clear sky sounding retrievals from multispectral satellite radiance measurements. *J. Appl. Meteorol. Climatol.* **2008**, *47*, 108–123. [[CrossRef](#)]
31. Duan, S.; Li, Z.; Cheng, J.; Leng, P. Cross-satellite comparison of operational land surface temperature products derived from MODIS and ASTER data over bare soil surfaces. *ISPRS J. Photogramm. Remote Sens.* **2017**, *126*, 1–10. [[CrossRef](#)]
32. Duan, S.; Li, Z.; Li, H.; Götsche, F.-M.; Wu, H.; Zhao, W.; Leng, P.; Zhang, X.; Coll, C. Validation of Collection 6 MODIS land surface temperature product using in situ measurements. *Remote Sens. Environ.* **2019**, *225*, 16–29. [[CrossRef](#)]
33. Olioso, A. Simulating the relationship between thermal emissivity and the normalized difference vegetation index. *Int. J. Remote Sens.* **1995**, *16*, 3211–3216. [[CrossRef](#)]
34. Hulley, G.C.; Hook, S.J.; Abbott, E.; Malakar, N.; Islam, T.; Abrams, M. The ASTER Global Emissivity Dataset (ASTER GED): Mapping Earth’s emissivity at 100 meter spatial scale. *Geophys. Res. Lett.* **2015**, *42*, 7966–7976. [[CrossRef](#)]
35. Li, H.; Yang, Y.; Li, R.; Wang, H.; Cao, B.; Bian, Z.; Hu, T.; Du, Y.; Sun, L.; Liu, Q. Comparison of the MuSyQ and MODIS Collection 6 land surface temperature products over barren surfaces in the Heihe River basin, China. *IEEE Trans. Geosci. Remote Sens.* **2019**, *57*, 8081–8094. [[CrossRef](#)]
36. Meng, X.; Li, H.; Du, Y.; Liu, Q.; Zhu, J.; Sun, L. Retrieving land surface temperature from landsat 8 TIRS data using RTTOV and ASTER GED. In Proceedings of the 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Beijing, China, 10–15 July 2016; pp. 4302–4305.
37. Duan, S.; Li, Z.; Wang, C.; Zhang, S.; Tang, B.; Leng, P.; Gao, M. Land-surface temperature retrieval from Landsat 8 single-channel thermal infrared data in combination with NCEP reanalysis data and ASTER GED product. *Int. J. Remote Sens.* **2019**, *40*, 1763–1778. [[CrossRef](#)]
38. Zhang, S.; Duan, S.; Li, Z.; Huang, C.; Wu, H.; Han, X.; Leng, P.; Gao, M. Improvement of Split-Window Algorithm for Land Surface Temperature Retrieval from Sentinel-3A SLSTR Data Over Barren Surfaces Using ASTER GED Product. *Remote Sens.* **2019**, *11*, 3025. [[CrossRef](#)]
39. Wang, H.; Yu, Y.; Yu, P.; Liu, Y. Land Surface Emissivity Product for NOAA JPSS and GOES-R Missions: Methodology and Evaluation. *IEEE Trans. Geosci. Remote Sens.* **2020**, *58*, 307–318. [[CrossRef](#)]
40. Li, H.; Wang, H.; Yang, Y.; Du, Y.; Cao, B.; Bian, Z.; Liu, Q. Evaluation of Atmospheric Correction Methods for the ASTER Temperature and Emissivity Separation Algorithm Using Ground Observation Networks in the HiWATER Experiment. *IEEE Trans. Geosci. Remote Sens.* **2019**, *57*, 3001–3014. [[CrossRef](#)]
41. Sekertekin, A.; Bonafoni, S. Land Surface Temperature Retrieval from Landsat 5, 7, and 8 over Rural Areas: Assessment of Different Retrieval Algorithms and Emissivity Models and Toolbox Implementation. *Remote Sens.* **2020**, *12*, 294. [[CrossRef](#)]
42. Wang, L.; Lu, Y.; Yao, Y. Comparison of Three Algorithms for the Retrieval of Land Surface Temperature from Landsat 8 Images. *Sensors* **2019**, *19*, 5049. [[CrossRef](#)] [[PubMed](#)]
43. Yu, W.; Ma, M.; Li, Z.; Tan, J.; Wu, A. New Scheme for validating remote-sensing land surface temperature products with station observations. *Remote Sens.* **2017**, *9*, 1210. [[CrossRef](#)]

44. Duan, S.; Li, Z.; Wu, H.; Leng, P.; Gao, M.; Wang, C. Radiance-based validation of land surface temperature products derived from Collection 6 MODIS thermal infrared data. *Int. J. Appl. Earth Obs. Geoinf.* **2018**, *70*, 84–92. [[CrossRef](#)]
45. Hulley, G.C.; Hughes, C.G.; Hook, S.J. Quantifying uncertainties in land surface temperature and emissivity retrievals from ASTER and MODIS thermal infrared data. *J. Geophys. Res. Atmos.* **2012**, *117*, 1–18. [[CrossRef](#)]
46. Yu, W.; Ma, M.; Yang, H.; Tan, J.; Li, X. Supplement of the radiance-based method to validate satellite-derived land surface temperature products over heterogeneous land surfaces. *Remote Sens. Environ.* **2019**, *230*, 111188. [[CrossRef](#)]
47. Choi, Y.-Y.; Suh, M.-S. Development of Himawari-8/Advanced Himawari Imager (AHI) Land Surface Temperature Retrieval Algorithm. *Remote Sens.* **2018**, *10*, 2013. [[CrossRef](#)]
48. Duan, S.; Li, Z. Intercomparison of operational land surface temperature products derived from MSG-SEVIRI and Terra/Aqua-MODIS data. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2015**, *8*, 4163–4170. [[CrossRef](#)]
49. Hulley, G.C.; Malakar, N.K.; Islam, T.; Freepartner, R. NASA's MODIS and VIIRS Land Surface Temperature and Emissivity Products: A Long-Term and Consistent Earth System Data Record. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2017**, *11*, 522–535. [[CrossRef](#)]
50. Freitas, S.C.; Trigo, I.F.; Bioucas-Dias, J.M.; Göttsche, F.-M. Quantifying the Uncertainty of Land Surface Temperature Retrievals from SEVIRI/Meteosat. *IEEE Trans. Geosci. Remote Sens.* **2010**, *48*, 523–534. [[CrossRef](#)]
51. Wan, Z. New refinements and validation of the MODIS land-surface temperature/emissivity products. *Remote Sens. Environ.* **2008**, *112*, 59–74. [[CrossRef](#)]
52. Wan, Z. New refinements and validation of the collection-6 MODIS land-surface temperature/emissivity product. *Remote Sens. Environ.* **2014**, *140*, 36–45. [[CrossRef](#)]
53. Göttsche, F.-M.; Olesen, F.-S.; Trigo, I.; Bork-Unkelbach, A.; Martin, M. Long term validation of land surface temperature retrieved from MSG/SEVIRI with continuous in-situ measurements in Africa. *Remote Sens.* **2016**, *8*, 410. [[CrossRef](#)]
54. Borbas, E.; Seemann, S.W.; Huang, H.-L.; Li, J.; Menzel, W.P. Global profile training database for satellite regression retrievals with estimates of skin temperature and emissivity. In Proceedings of the 14th International TOVS Study Conference, Beijing, China, 25–31 May 2005; pp. 763–770.
55. Wan, Z.; Dozier, J. Land-surface temperature measurement from space: Physical principles and inverse modeling. *IEEE Trans. Geosci. Remote Sens.* **1989**, *27*, 268–278. [[CrossRef](#)]
56. Coll, C.; Caselles, V.; Galve, J.M.; Valor, E.; Niclos, R.; Sánchez, J.M.; Rivas, R. Ground measurements for the validation of land surface temperatures derived from AATSR and MODIS data. *Remote Sens. Environ.* **2005**, *97*, 288–300. [[CrossRef](#)]
57. Andrews, D.F. A robust method for multiple linear regression. *Technometrics* **1974**, *16*, 523–531. [[CrossRef](#)]
58. NASA. ASTER Global Emissivity Dataset, 1-kilometer, HDF5. Available online: <https://e4ftl01.cr.usgs.gov/ASTT/AG1km.003/> (accessed on 20 July 2020).
59. Peres, L.F.; DaCamara, C.C. Emissivity maps to retrieve land-surface temperature from MSG/SEVIRI. *IEEE Trans. Geosci. Remote Sens.* **2005**, *43*, 1834–1844. [[CrossRef](#)]
60. Loveland, T.; Zhu, Z.; Ohlen, D.; Brown, J.; Redd, B.; Yang, L. An Analysis of IGBP Global Land-Cover Characterization Process. *Photogramm. Eng. Remote Sens.* **1999**, *65*, 1069–1074.
61. Trigo, I.F.; Peres, L.F.; Da Camara, C.C.; Freitas, S.C. Thermal land surface emissivity retrieved from SEVIRI/Meteosat. *IEEE Trans. Geosci. Remote Sens.* **2008**, *46*, 307–315. [[CrossRef](#)]
62. Carlson, T.N.; Ripley, D.A. On the relation between NDVI, fractional vegetation cover, and leaf area index. *Remote Sens. Environ.* **1997**, *62*, 241–252. [[CrossRef](#)]
63. Li, H.; Tang, P. Dps-MuSyQ: A Distributed Parallel Processing System for Multi-Source Data Synergized Quantitative Remote Sensing Products Producing. *IEEE Access* **2020**, *8*, 79510–79520. [[CrossRef](#)]
64. Mu, X.; Liu, Q.; Ruan, G.; Zhao, J.; Zhong, B.; Wu, S.; Peng, J. A 1 km/5 day Fractional Vegetation Cover Dataset over China-ASEAN (2013). *J. Glob. Change Data Discov.* **2017**, *1*, 45–51. [[CrossRef](#)]
65. Hall, D.K.; Riggs, G.A. MODIS/Terra Snow Cover Daily L3 Global 500m SIN Grid, Version 6. Available online: <https://n5eil01u.ecs.nsidc.org/MOST/MOD10A1.006/> (accessed on 20 July 2020).
66. Hall, D.K.; Riggs, G.A. MODIS/Aqua Snow Cover Daily L3 Global 500m SIN Grid, Version 6. Available online: <https://n5eil01u.ecs.nsidc.org/MOSA/MYD10A1.006/> (accessed on 20 July 2020).

67. Bessho, K.; Date, K.; Hayashi, M.; Ikeda, A.; Imai, T.; Inoue, H.; Kumagai, Y.; Miyakawa, T.; Murata, H.; Ohno, T. An introduction to Himawari-8/9—Japan's new-generation geostationary meteorological satellites. *J. Meteorol. Soc. Jpn. Ser. II* **2016**, *94*, 151–183. [\[CrossRef\]](#)
68. Shang, H.; Chen, L.; Letu, H.; Zhao, M.; Li, S.; Bao, S. Development of a daytime cloud and haze detection algorithm for Himawari-8 satellite measurements over central and eastern China. *J. Geophys. Res. Atmos.* **2017**, *122*, 3528–3543. [\[CrossRef\]](#)
69. Li, H.; Liu, Q.; Du, Y.; Jiang, J.; Wang, H. Evaluation of the NCEP and MODIS Atmospheric Products for Single Channel Land Surface Temperature Retrieval With Ground Measurements: A Case Study of HJ-1B IRS Data. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2013**, *6*, 1399–1408. [\[CrossRef\]](#)
70. Yang, J.; Duan, S.; Zhang, X.; Wu, P.; Huang, C.; Leng, P.; Gao, M. Evaluation of Seven Atmospheric Profiles from Reanalysis and Satellite-Derived Products: Implication for Single-Channel Land Surface Temperature Retrieval. *Remote Sens.* **2020**, *12*, 791. [\[CrossRef\]](#)
71. Meng, X.; Cheng, J. Evaluating Eight Global Reanalysis Products for Atmospheric Correction of Thermal Infrared Sensor—Application to Landsat 8 TIRS10 Data. *Remote Sens.* **2018**, *10*, 474. [\[CrossRef\]](#)
72. Hersbach, H.; Dee, D. ERA5 reanalysis is in production. *ECMWF Newsl.* **2016**, *147*, 5–6.
73. Li, S.; Yu, Y.; Sun, D.; Tarpley, D.; Zhan, X.; Chiu, L. Evaluation of 10 year AQUA/MODIS land surface temperature with SURFRAD observations. *Int. J. Remote Sens.* **2014**, *35*, 830–856. [\[CrossRef\]](#)
74. Li, H.; Li, R.; Yang, Y.; Cao, B.; Bian, Z.; Hu, T.; Du, Y.; Sun, L.; Liu, Q. Temperature-based and Radiance-based Validation of the Collection 6 MYD11 and MYD21 Land Surface Temperature Products Over Barren Surfaces in Northwestern China. *IEEE Trans. Geosci. Remote Sens.* **2020**, 1–14, in press. [\[CrossRef\]](#)
75. Wan, Z.; Hook, S.; Hulley, G. MYD11_L2 MODIS/Aqua Land Surface Temperature/Emissivity 5-Min L2 Swath 1km V006. Available online: https://e4ftl01.cr.usgs.gov/MOLA/MYD11_L2.006/ (accessed on 20 July 2020).
76. Hulley, G. MYD21 MODIS/Aqua Land Surface Temperature/3-Band Emissivity 5-Min L2 1km V006. Available online: <https://e4ftl01.cr.usgs.gov/MOLA/MYD21.006/> (accessed on 20 July 2020).
77. Friedl, M.; Sulla-Menasse, D. MCD12Q1 MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V006. Available online: <https://e4ftl01.cr.usgs.gov/MOTA/MCD12Q1.006/> (accessed on 20 July 2020).
78. Hulley, G.C.; Malakar, N.K.; Hughes, T.; Islam, T.; Hook, S.J. *Moderate Resolution Imaging Spectroradiometer (MODIS) MOD21 Land Surface Temperature and Emissivity Algorithm Theoretical Basis Document*; Jet Propulsion Laboratory, National Aeronautics and Space Administration: Pasadena, CA, USA, 5 January 2016.
79. Matricardi, M.; Chevallier, F.; Kelly, G.; Thépaut, J. An improved general fast radiative transfer model for the assimilation of radiance observations. *Q. J. R. Meteorol. Soc.* **2004**, *130*, 153–173. [\[CrossRef\]](#)
80. Saunders, R.; Matricardi, M.; Brunel, P. An improved fast radiative transfer model for assimilation of satellite radiance observations. *Q. J. R. Meteorol. Soc.* **1999**, *125*, 1407–1425. [\[CrossRef\]](#)
81. Gelaro, R.; McCarty, W.; Suárez, M.J.; Todling, R.; Molod, A.; Takacs, L.; Randles, C.A.; Darmenov, A.; Bosilovich, M.G.; Reichle, R.J. The modern-era retrospective analysis for research and applications, version 2 (MERRA-2). *J. Clim.* **2017**, *30*, 5419–5454. [\[CrossRef\]](#) [\[PubMed\]](#)
82. Hulley, G.C.; Veraverbeke, S.; Hook, S.J. Thermal-based techniques for land cover change detection using a new dynamic MODIS multispectral emissivity product (MOD21). *Remote Sens. Environ.* **2014**, *140*, 755–765. [\[CrossRef\]](#)
83. Li, X.; Cheng, G.; Liu, S.; Xiao, Q.; Ma, M.; Jin, R.; Che, T.; Liu, Q.; Wang, W.; Qi, Y. Heihe watershed allied telemetry experimental research (HiWATER): Scientific objectives and experimental design. *Bull. Am. Meteorol. Soc.* **2013**, *94*, 1145–1160. [\[CrossRef\]](#)
84. Liu, S.; Li, X.; Xu, Z.; Che, T.; Xiao, Q.; Ma, M.; Liu, Q.; Jin, R.; Guo, J.; Wang, L.; et al. The Heihe Integrated Observatory Network: A Basin-Scale Land Surface Processes Observatory in China. *Vadose Zone J.* **2018**, *17*, 180072. [\[CrossRef\]](#)
85. Beringer, J.; Hutley, L.B.; McHugh, I.; Arndt, S.K.; Campbell, D.; Cleugh, H.A.; Cleverly, J.; De Dios, V.R.; Eamus, D.; Evans, B. An introduction to the Australian and New Zealand flux tower network-OzFlux. *Biogeosciences* **2016**, *13*, 5895–5916. [\[CrossRef\]](#)
86. Karan, M.; Liddell, M.; Prober, S.M.; Arndt, S.; Beringer, J.; Boer, M.; Cleverly, J.; Eamus, D.; Grace, P.; Van Gorsel, E. The Australian SuperSite Network: A continental, long-term terrestrial ecosystem observatory. *Sci. Total Environ.* **2016**, *568*, 1263–1274. [\[CrossRef\]](#)
87. Yu, Y.; Liu, Y.; Yu, P.; Wang, H. *Enterprise Algorithm Theoretical Basis Document for VIIRS Land Surface Temperature Production*; NOAA: Silver Spring, MD, USA, 2017.

88. Xu, Z.; Liu, S.; Li, X.; Shi, S.; Wang, J.; Zhu, Z.; Xu, T.; Wang, W.; Ma, M. Intercomparison of surface energy flux measurement systems used during the HiWATER-MUSOEXE. *J. Geophys. Res. Atmos.* **2013**, *118*, 13140–13157. [\[CrossRef\]](#)
89. Wang, W.; Liang, S.; Meyers, T. Validating MODIS land surface temperature products using long-term nighttime ground measurements. *Remote Sens. Environ.* **2008**, *112*, 623–635. [\[CrossRef\]](#)
90. Hulley, G.C.; Hook, S.J. A radiance-based method for estimating uncertainties in the Atmospheric Infrared Sounder (AIRS) land surface temperature product. *J. Geophys. Res. Atmos.* **2012**, *117*, 1–10. [\[CrossRef\]](#)
91. Wan, Z.; Li, Z. Radiance-based validation of the V5 MODIS land-surface temperature product. *Int. J. Remote Sens.* **2008**, *29*, 5373–5395. [\[CrossRef\]](#)
92. Hewison, T.J.; Wu, X.; Yu, F.; Tahara, Y.; Hu, X.; Kim, D.; Koenig, M. GSICS Inter-Calibration of Infrared Channels of Geostationary Imagers Using Metop/IASI. *IEEE Trans. Geosci. Remote Sens.* **2013**, *51*, 1160–1170. [\[CrossRef\]](#)
93. Frey, C.M.; Kuenzer, C.; Dech, S. Quantitative comparison of the operational NOAA-AVHRR LST product of DLR and the MODIS LST product V005. *Int. J. Remote Sens.* **2012**, *33*, 7165–7183. [\[CrossRef\]](#)
94. Qian, Y.; Li, Z.; Nerry, F. Evaluation of land surface temperature and emissivities retrieved from MSG/SEVIRI data with MODIS land surface temperature and emissivity products. *Int. J. Remote Sens.* **2013**, *34*, 3140–3152. [\[CrossRef\]](#)
95. Chang, T.; Xiong, X.; Angal, A. Terra and Aqua MODIS TEB intercomparison using Himawari-8/AHI as reference. *J. Appl. Remote Sens.* **2019**, *13*, 1–19. [\[CrossRef\]](#)
96. Pinheiro, A.C.T.; Privette, J.L.; Guillevic, P.C. Modeling the observed angular anisotropy of land surface temperature in a Savanna. *IEEE Trans. Geosci. Remote Sens.* **2006**, *44*, 1036–1047. [\[CrossRef\]](#)
97. Bian, Z.; Roujean, J.L.; Lagouarde, J.P.; Cao, B.; Li, H.; Du, Y.; Liu, Q.; Xiao, Q.; Liu, Q. A semi-empirical approach for modeling the vegetation thermal infrared directional anisotropy of canopies based on using vegetation indices. *ISPRS J. Photogramm. Remote Sens.* **2020**, *160*, 136–148. [\[CrossRef\]](#)
98. Coll, C.; Galve, J.M.; Niclòs, R.; Valor, E.; Barberà, M.J. Angular variations of brightness surface temperatures derived from dual-view measurements of the Advanced Along-Track Scanning Radiometer using a new single band atmospheric correction method. *Remote Sens. Environ.* **2019**, *223*, 274–290. [\[CrossRef\]](#)
99. Guillevic, P.C.; Biard, J.C.; Hulley, G.C.; Privette, J.L.; Hook, S.J.; Olioso, A.; Götsche, F.M.; Radocinski, R.; Román, M.O.; Yu, Y.; et al. Validation of Land Surface Temperature products derived from the Visible Infrared Imaging Radiometer Suite (VIIRS) using ground-based and heritage satellite measurements. *Remote Sens. Environ.* **2014**, *154*, 19–37. [\[CrossRef\]](#)
100. Galve, J.M.; Coll, C.; Caselles, V.; Valor, E. An Atmospheric Radiosounding Database for Generating Land Surface Temperature Algorithms. *IEEE Trans. Geosci. Remote Sens.* **2008**, *46*, 1547–1557. [\[CrossRef\]](#)
101. Pinker, R.T.; Ma, Y.; Chen, W.; Hulley, G.; Basara, J. Towards a Unified and Coherent Land Surface Temperature Earth System Data Record from Geostationary Satellites. *Remote Sens.* **2019**, *11*, 1399. [\[CrossRef\]](#)
102. Zou, Z.; Zhan, W.; Liu, Z.; Bechtel, B.; Gao, L.; Hong, F.; Huang, F.; Lai, J. Enhanced Modeling of Annual Temperature Cycles with Temporally Discrete Remotely Sensed Thermal Observations. *Remote Sens.* **2018**, *10*, 650. [\[CrossRef\]](#)
103. Li, X.; Long, D. An improvement in accuracy and spatiotemporal continuity of the MODIS precipitable water vapor product based on a data fusion approach. *Remote Sens. Environ.* **2020**, *248*, 111966. [\[CrossRef\]](#)
104. Olson, M.; Rupper, S.; Shean, D. Terrain induced biases in clear-sky shortwave radiation due to digital elevation model resolution for glaciers in complex terrain. *Front. Earth Sci.* **2019**, *7*, 216. [\[CrossRef\]](#)
105. Zhao, W.; Duan, S.; Li, A.; Yin, G. A practical method for reducing terrain effect on land surface temperature using random forest regression. *Remote Sens. Environ.* **2019**, *221*, 635–649. [\[CrossRef\]](#)
106. Wan, Z.; Zhang, Y.; Zhang, Q.; Li, Z. Validation of the land-surface temperature products retrieved from Terra Moderate Resolution Imaging Spectroradiometer data. *Remote Sens. Environ.* **2002**, *83*, 163–180. [\[CrossRef\]](#)
107. Guillevic, P.C.; Götsche, F.-M.; Nickeson, J.; Hulley, G.C.; Ghent, D.; Yu, Y.; Trigo, I.; Hook, S.J.; Sobrino, J.A.; Remedios, J.; et al. Land surface temperature product validation best practice protocol. *Best Pract. Satell. Deriv. Land Prod. Valid.* **2018**, *60*, 58. [\[CrossRef\]](#)
108. Guillevic, P.C.; Privette, J.L.; Coudert, B.; Palecki, M.A.; Demarty, J.; Ottele, C.; Augustine, J.A. Land Surface Temperature product validation using NOAA's surface climate observation networks—Scaling methodology for the Visible Infrared Imager Radiometer Suite (VIIRS). *Remote Sens. Environ.* **2012**, *124*, 282–298. [\[CrossRef\]](#)

