Journal of
Applied Remote Sensing

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Thanh Noi Phan, Martin Kappas, "Application of MODIS land surface temperature data: a systematic literature review and analysis," *J. Appl. Remote Sens.* **12**(4), 041501 (2018), doi: 10.1117/1.JRS.12.041501.

REVIEW

Application of MODIS land surface temperature data: a systematic literature review and analysis

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Abstract. The Moderate Resolution Imaging Spectroradiometer (MODIS) aboard the Terra and Aqua satellites, which provides a very high temporal (four times per day) and spatial (1 km) resolution, has become one of the most important and widely used sensors for a broad range of applications. We analyze 529 articles from 159 journals in the Scopus database from 2009 to 2018 to understand the global and longitudinal trends of MODIS land surface temperature (LST) data applications. The results show that the publications of papers related to MODIS LST data have been steadily rising annually. They spanned 19 subject areas from environmental, agricultural, and biological science to social science and medicine, indicating a wide range of MODIS LST data applications. Among the 159 journals, *Remote Sensing of Environment*, *Remote Sensing*, and the *International Journal of Remote Sensing* published the most articles. The study also showed that urban heat island (UHI), air temperature estimation/mapping (Ta estimation), soil moisture, evapotranspiration estimation, and drought monitoring/estimation were the most popular applications of MODIS LST data. Furthermore, we discuss the strengths, limitations, and future direction of research using MODIS LST data. © *2018 Society of Photo-Optical Instrumentation Engineers (SPIE)* [DOI: 10.1117/1.JRS.12.041501]

Keywords: land surface temperature; moderate resolution imaging spectroradiometer land surface temperature products; moderate resolution imaging spectroradiometer land surface temperature applications.

Paper 180278V received Apr. 4, 2018; accepted for publication Sep. 28, 2018; published online Oct. 25, 2018.

1 Introduction

Land surface temperature (LST) is the "skin" temperature of the earth surface, a key parameter for land-surface processing studies at both a regional and global scale.[1–5] It plays an important role in a wide range of fields, such as environmental monitoring,[6] hydrology,[7] urban climate, urban heat island (UHI),[8–10] and agriculture.[11–13] Due to rapid changes of LST on spatial and temporal scales, ground-based station observations cannot represent the LST of a region. In the other words, the observations from stations become insufficient for large areas.[3] Remotely sensed image data is one of the most suitable sources of LST data at high spatial and/or temporal resolution.[3,14] However, it is worth noting that, due to the trade-off between spatial and temporal resolution when designing satellite sensors, most of the single satellites cannot provide images with both spatial and temporal high resolution.[15] In general, if a satellite provides high spatial resolution images, then its temporal resolution is medium/low or vice versa.[16] For example, Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS) can provide daily LST data, but their spatial resolution is about 1000 m; meanwhile, Landsat can provide LST at 100-m resolution, but the temporal resolution is 16 days. Regarding the single satellite sensors, among various remote sensing sensors that provide LST data, the most popular sensors are the MODIS, AVHRR, Landsat (ETM+, OLI), and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER).

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To produce an overview of LST data applications, we searched {"sensor-name" AND ("land surface temperature" OR "LST")} within titles, abstracts, and keywords in the Scopus database (accessed on July 19, 2018). Articles published in book series were removed from the results so that only articles published in journals and conference proceedings in the English language were chosen. The results show that the number of publications with MODIS was highest when compared with AVHRR, Landsat, and ASTER (Fig. 1). The number of publications relating to MODIS LST has been steadily increasing from 2009 to 2018.

The results in Fig. 1 confirm that MODIS LST data are the most commonly used, which was stated in many previous studies.[17–19] Similar to MODIS LST data, AVHRR can provide very high temporal resolution (twice daily) and spatial resolution (~1.1 km) data; however, some studies have compared LST from MODIS and AVHRR with *in situ* LST and found that the difference between the *in situ* data and AVHRR was larger than those of MODIS.[20,21] As shown in Fig. 1, the number of publications using ASTER images has generally remained steady and low. One explanation could be that, although ASTER can provide very high spatial resolution (90 m) and a temporal resolution of 16 days, it is not free of charge and the data are only provided upon request.[22] Regarding the Landsat data, similar to MODIS, the number of publications has been on the rise between 2009 and 2018. From 2009 to 2015, the number Landsat publications was much lower than of MODIS; however, over the last 3 years (2016, 2017, and 2018) the number of publications using Landsat data has significantly risen, approaching the number of MODIS data publications (Fig. 1). This rising can be explained that because there has been a significant increase in applications of downscaling techniques, which mainly downscale MODIS LST data to the higher resolution (i.e., Landsat), or use MODIS LST and Landsat LST for downscaling and applied for specific applications.[23–29]

In this study, MODIS LST data indicate all MODIS LST data available and free for download from NASA Land Data Products and Services (Table 1).

The daily MODIS LST data products, MOD/MYD11A1 at 1 km and MOD/MYD11B1 at 6 km, are retrieved using the generalized split-window[30] and day/night algorithms,[31] respectively. MOD/MYD11C1 data products are derived from the MOD/MYD11B1 product, and stored in a 0.05 deg geographic climate modeling grid (CMG). The 8-day MODIS LST data

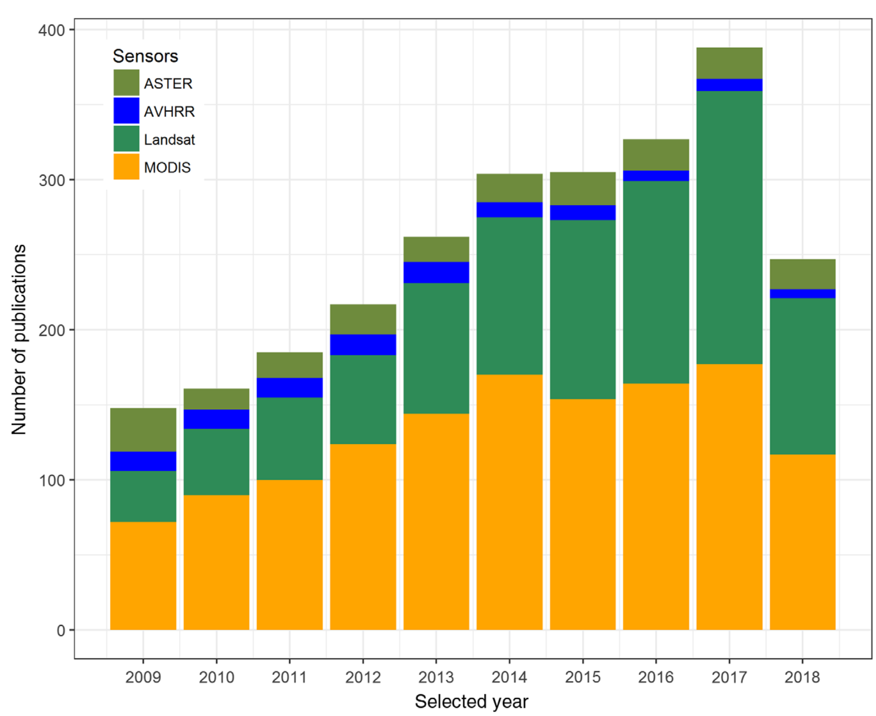

Fig. 1 The total number of articles for each related keyword searched in the Scopus database until July 19, 2018.

Table 1 Different types of MODIS LST data used for this review.

Products	Terra	Aqua
Land surface temperature/emissivity daily L3 global 1 km	MOD11A1	MYD11A1
Land surface temperature/emissivity 8-day L3 global 1 km	MOD11A2	MYD11A2
Land surface temperature/emissivity daily L3 global 6 km	MOD11B1	MYD11B1
Land surface temperature/emissivity 8-day L3 global 6 km	MOD11B2	MYD11B2
Land surface temperature/emissivity monthly L3 global 6 km	MOD11B3	MYD11B3
Land surface temperature/emissivity daily global 0.05 deg CMG	MOD11C1	MYD11C1
Land surface temperature/emissivity 8-day global 0.05 deg CMG	MOD11C2	MYD11C2
Land surface temperature/emissivity monthly global 0.05 deg CMG	MOD11C3	MYD11C3
Land surface temperature/emissivity 5-min L2 Swath 1 km	MOD11_L2	MYD11_L2

products, MODIS 11A2, 11B2, and 11C2, are retrieved by averaging from 2 to 8 days of the corresponding daily products. The monthly products, MOD/MYD 11B3, 11C3, are a monthly composite of LST at the same resolutions as 8-day MOD/MYD 11B2, and 11C2 products. MOD/MYD11_L2 products are the LST products at 1-km spatial resolution for a swath, which are produced daily at 5-min increments, using the generalized split-window algorithm.[17]

In addition, it is worth mentioning that, together with MOD/MYD11 data products, which were produced over nearly the last two decades, a new product, MOD/MYD21 LST and emissivity product, was planned to be released early in 2017 with MODIS collection 6 (C6) data. However, these products are currently unavailable due to science data quality issues.[32] Although MOD/MYD11 use generalized split-window and day/night algorithms, MOD/MYD21 is generated based on the ASTER temperature emissivity separation (TES) algorithm.[33] According to Coll et al.,[34] MODIS 21 TES algorithm is highly complementary to the MODIS 11 algorithms as it provides more accurate LST over semiarid and arid areas, but less accurate LST over heavily vegetated areas and water bodies, whereas MODIS 11 has its largest uncertainties in semiarid and arid areas, but optimum performance over heavily vegetated areas and water bodies.

To the best our knowledge, no previous review article has studied the applications of MODIS LST data in the literature. Therefore, it is practical to review the application of MODIS LST data over the last 10 years. The first objective is to provide a general overview and guidance about the popular applications of MODIS LST for prospective users. We believe this information will support and encourage novice researchers, particularly in developing countries, to study, evaluate, and apply MODIS LST data. The second objective is to analyze the trends and popular topics of MODIS LST related studies and the potential applications of this data.

2 Materials and Methods

2.1 *Bibliographic Database*

For many years, Web of Science (WoS) from the Thomson Reuters Institute for Scientific Information (ISI) was the only citation and publication database covering all domains of science. However, in 2004, Elsevier Science introduced the Scopus database, which is an effective alternative to WoS according to Vieira and Gomes.[35] Studies comparing WoS and Scopus have concluded that, when comparing different subject areas, an advantage in one of these databases is shown in Ref. 36. Studies comparing WoS and Scopus which focused on a specific field of study; however, concluded that it is difficult to determine the better database.[37,38] In addition, Vieira and Gomes[35] stated that Scopus contains a broader range of journals and provides 20% more coverage than WoS. This finding is consistent with studies by Jacso[39] and Falagas et al.,[40] which confirmed that Scopus covers more journals and analyzes citations faster than WoS. Moreover, Boyle and Sherman[41] recommended that Scopus should be chosen because of its outcome quality, time-saving features, ease of use, and larger amount of search results.

Currently, with almost 23,000 titles and 150,000 books from ∼5000 publishers, Scopus is considered one of the largest abstract and citation databases of peer-reviewed research literature.[42] We used the Scopus database to select publications for this study (accessed on July 12, 2018).

2.2 *Methods*

We followed four crucial steps for a systematic review outlined by Stewart:[43] (1) obtain all publications in the interested topic by using broad search keywords, (2) use strict and clear criteria to limit the universal results to targeted/eligible publications, (3) extract and code essential information from the eligible publications for the statistical outcome measures, and (4) report and discuss the methods, results based on the selected publications (Fig. 2).

As stated in Sec. 2.1, in this study, we used the Scopus database to search for publications. It should be noted that using the same search keywords, there are 1101 publications within the timespan 1999 to 2018; however, most of the studies (991 publications or ∼90%) were published in the period from 2009 to 2018. Therefore, we analyzed publications within this timespan.

First, we performed an advanced search in the Scopus database on July 12, 2018 using the keywords {"MODIS" AND ("land surface temperature" OR "LST")} in titles, abstracts, and keywords (including author keywords and index keywords) from 2009 to 2018. This search resulted in 1451 records. Next, we excluded conference papers, book chapters, review articles, letters, notes, and non-English articles, which resulted in 991 peer-reviewed articles (including published articles and articles in press) published in 159 journals. We further filtered this list by removing 136 articles that did not use MODIS LST data. Next, based on the titles, abstracts, and full texts (if necessary), we removed articles that focused more on theories and methods, or only analyzed the spatial and temporal variations of LST. As a result, 529 articles were selected for the final list (Fig. 2).

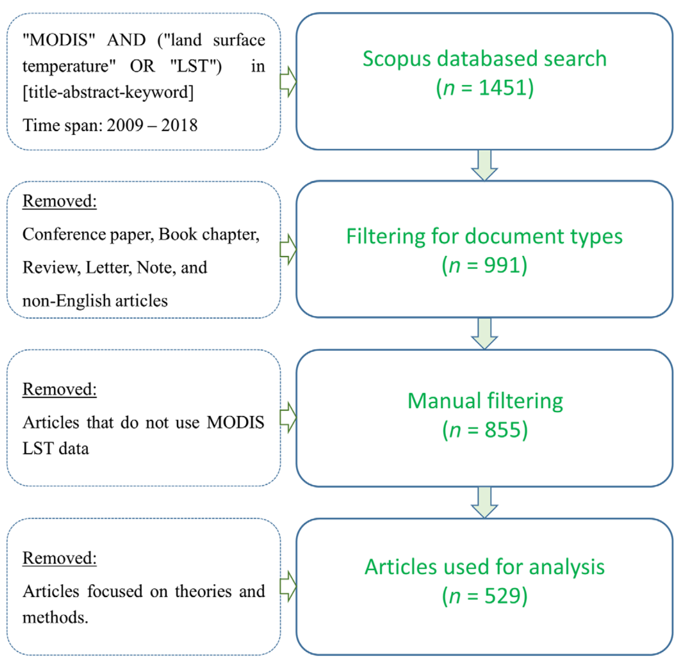

Fig. 2 The procedure for selecting articles from Scopus database.

3 Results

3.1 *General Research Output Based on Selected Publications*

In this section, we present an overview of research application trends using MODIS LST data based on the identified 529 articles published in 159 journals from January 2009 to July 2018.

Generally, the number of publications that used MODIS LST data increased from 2009 to 2017. It should be noted that the publications focusing on theories, methodologies, or validation purposes have been removed from this review study. In 2018, by the date of the Scopus search (July 12), there were 55 articles already published (or in press). It is reasonable to predict that this increasing trend will continue through 2018 (Fig. 3).

Regarding the subject classification of the publications, 529 articles were published within 19 subject areas in 159 journals. The top three subject areas were Earth and Planetary Sciences (397 articles—75%), Environmental Science (172 articles—32.5%), and Agricultural and Biological Sciences (164 articles—31%). The total number of articles was not equal to 529 because many belong to multiple subject areas. In addition, the studies of MODIS LST data were published in both general research area journals (e.g., J-STARS, *Hydrology*, and *Journal of Earth System Science*) and specific journals (e.g., *Remote Sensing of Environment* and *International Journal of Climatology*), indicating a wide range applications of MODIS LST data.

Table 2 shows the 11 most active journals that have published MODIS LST data-based research. Among the 529 articles, 255 articles (48.2%) were published in these 11 journals, whereas the remaining 274 (51.8%) were published in the other 148 journals. In addition, 65.8% of total citations (TC) were received for these 11 journals, whereas only 34.2% were received for the other 148 journals. The three major publication outlets for MODIS LST data-based research were *Remote Sensing of Environment*, *Remote Sensing*, and *International Journal of Remote Sensing*, with a total number of articles (% articles) of 62 (11.7%), 56 (10.6%), and 30 (5.7%), respectively. Table 2 shows that the journals with the highest TC values were *Remote Sensing of Environment* with 2808 citations (33.5%),

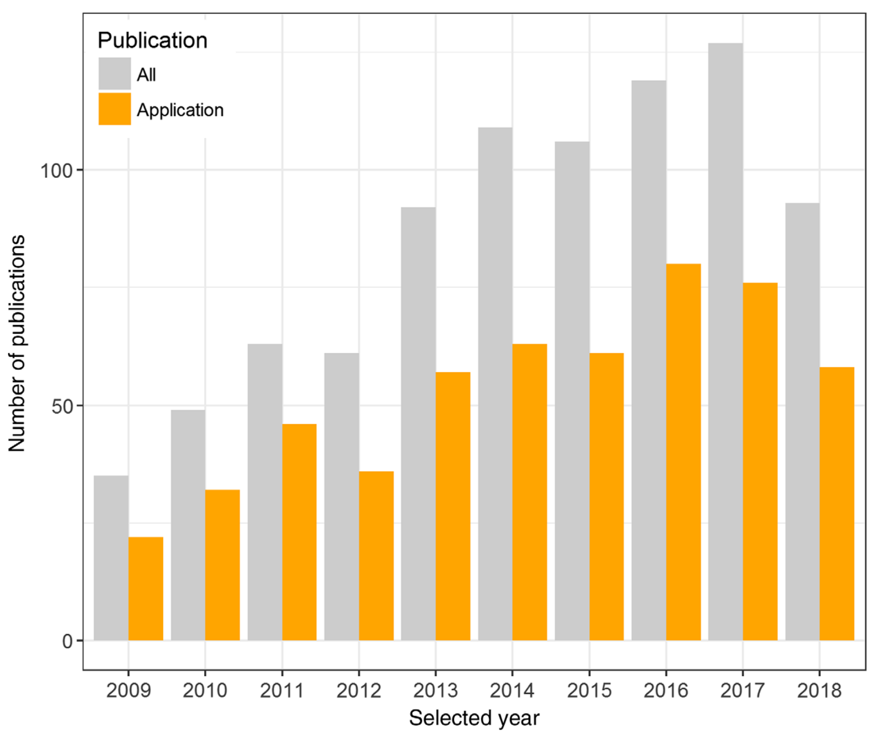

Fig. 3 The total publications (gray—855 articles) and applied for a specific field (orange—529 articles) in Scopus database from 2009 to 2018.

Table 2 The top most active journals publishing research based on MODIS LST data.

Ranking	Journal	Total articles (%)	Total citations (%)	Citations per articles
1	Remote Sensing Of Environment	62 (11.7)	2808 (33.5)	45.3
2	Remote Sensing	56 (10.6)	397 (4.7)	7.1
3	International Journal Of Remote Sensing	30 (5.7)	273 (3.3)	9.1
4	Journal Of Geophysical Research Atmospheres	20 (3.8)	293 (3.5)	14.7
5	ISPRS Journal Of Photogrammetry And Remote Sensing	17 (3.2)	344 (4.1)	20.2
6	International Journal Of Applied Earth Observation And Geoinformation	15 (2.8)	353 (4.2)	23.5
7	IEEE Journal Of Selected Topics In Applied Earth Observations And Remote Sensing (J-STARS)	13 (2.5)	73 (0.9)	5.6
8	Theoretical and Applied Climatology	12 (2.3)	353 (4.2)	29.4
9	Journal of Hydrology	10 (1.9)	215 (2.6)	21.5
9	Agricultural and Forest Meteorology	10 (1.9)	289 (3.4)	28.9
9	Hydrology and Earth System Sciences	10 (1.9)	126 (1.5)	12.6

Table 3 Top 10 most cited articles.

	Articles	Cited by	References
1	Remote sensing of the UHI effect across biomes in the continental USA	344	Imhoff et al.[44]
2	Evaluation of MODIS land surface temperature data to estimate air temperature in different ecosystems over Africa	199	Vancutsem et al.[45]
3	Monitoring agricultural drought for arid and humid regions using multisensor remote sensing data	141	Rhee et al.[46]
4	Downscaling SMOS-derived soil moisture using MODIS visible/infrared data	139	Piles et al.[47]
5	Estimating air surface temperature in Portugal using MODIS LST data	127	Benali et al.[48]
6	Estimating volumetric surface moisture content for cropped soils using a soil wetness index based on surface temperature and NDVI	109	Mallick et al.[49]
7	Exploring indicators for quantifying surface UHIs of European cities with MODIS land surface temperatures	103	Schwarz et al.[50]
8	Estimation of daily maximum and minimum air temperature using MODIS land surface temperature products	86	Zhu et al.[51]
9	Comparison of multiple models for estimating gross primary production using MODIS and eddy covariance data in Harvard Forest	85	Wu et al.[52]
10	Estimation of net radiation from the MODIS data under all sky conditions: Southern Great Plains case study	84	Bisht and Bras[53]

Remote Sensing with 397 citations (4.7%), and the *International Journal Of Applied Earth Observation and Geoinformation* with 353 citations (4.2%).

Table 3 shows the 10 most cited articles, which cover five application topics: UHI effect, Ta estimation, drought monitoring, soil moisture, estimating gross primary production, and net radiation estimation. Among the 10 most cited articles, three articles focus on Ta estimation, two articles focus on UHI effect, and two articles focus on soil moisture applications. Again, it is should be noted that the citation count in this review only used the Scopus database (other databases, e.g., Googlescholar, could show a higher number of citations). As shown in Table 3, the most cited article was written by Imhoff et al.[44] with 344 citations, followed by Vancutsem et al.[45] with 199 citations, and Rhee et al.[46] with 141 citations. These articles studied UHI, Ta estimation, and drought monitoring. An interesting finding is that these top three articles were published in the same year (2010), suggesting that these three topic applications could be the most applications of MODIS LST data.

3.2 *Main Applications of MODIS LST Data*

In order to get an overview of MODIS LST applications, we generated a word cloud using the titles of the 529 selected articles. As shown in Fig. 4, the most commonly used words were urban, heat, estimation, air, soil, island, and moisture. Based on this result and further investigating the titles, abstracts, and full text (if required) of the 529 selected articles, we found that the top five applications were UHI (63 articles—11.9%), air temperature (Ta) estimation (52 articles—9.8%), soil moisture estimation (50 articles—9.5%), evapotranspiration (48 articles—9.1%), and drought (33 articles—6.2%). This is consistent with the hypothesis we have made based on the citations trend shown in Table 3. The remaining (~50%) were applied for various application fields, such as risk mapping (e.g., earthquakes, forest fires, mosquitoes, and floods); agriculture (rice yields, paddy rice mapping, and rice quality); water (surface water temperature, lake temperature, and water pollution); hydrological models; urban expansion; snow melt; snow cover; and many others.[54–62]

Among these top five applications of MODIS LST, three applications could be considered significantly more popular because more than 50% of publications for these applications were published in the last 3 years. These applications are drought monitoring/assessment (21 articles—63.6%), UHI effect (35 articles—55.6%), and Ta estimation (27 articles—52%). However, in comparison with UHI or Ta estimation studies, drought studies used additional data from MODIS sensors (and other sensors). In the other words, MODIS LST is considered a key input for UHI and Ta studies; however, in drought studies, MODIS LST is just one input among many other important inputs (i.e., NDVI from MODIS, precipitation from TRMM).[46,63–66] Therefore, in the next section, we will discuss the UHI effects and Ta estimation/mapping studies.

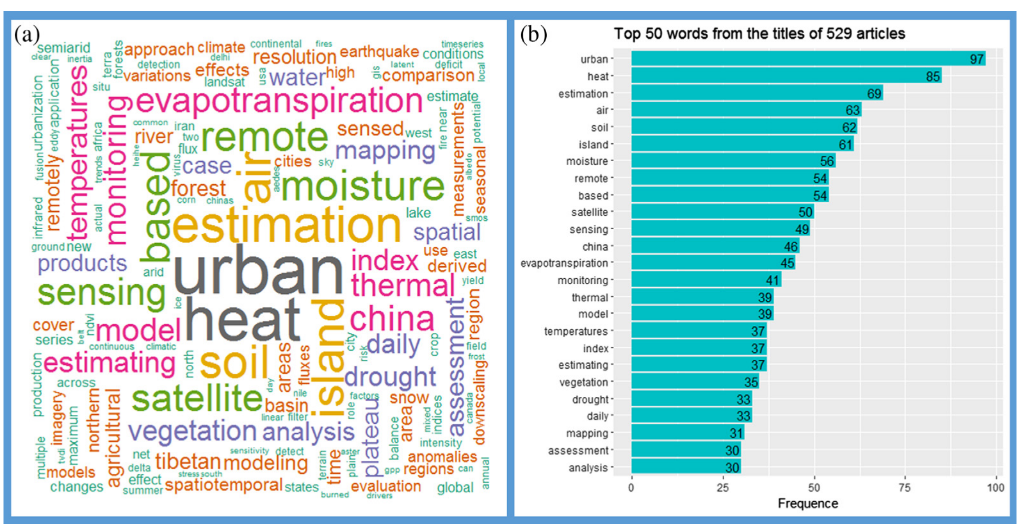

Fig. 4 (a) The cloud of the words contained in the titles of 529 selected articles. The size of each word is indicative of its relative frequency of occurrence and (b) the top 25 most frequently used words.

3.3 *UHI Using MODIS LST Data*

The UHI, a well-known effect of urbanization, is a common phenomenon, where surface temperatures are higher in urban areas than in the surrounding rural areas.[67] This effect is considered one of the most significant impacts of human activity on the Earth's surface climate.[68,69] Although UHI are localized hotspots in the landscape, they have a profound impact on the lives of the urban residents, who currently account for more than half of the total population; urban population is expected to rise about 66% by 2050.[70,71] In 2014, the number of people living in urban areas in developed regions such as Northern America, Latin America and the Caribbean, and Europe was estimated to be ~82%, 80%, and 73%, respectively. Meanwhile, the urban population of developing regions was around 48% and 40% for Asia and Africa, respectively. The UN[70] further predicted that the fastest urbanization will take place in Asia and Africa, with urban population predictions of about 64% and 54% by 2050, respectively.[70] This indicates that in these two regions, the urban landscape will change significantly, and therefore resources should be focused there to implement well-planned and sustainable development.

Traditionally, UHI studies were based on the data retrieved from ground weather stations.[72,73] Some limitations of UHI studies using weather station data have been reported in the literature because: (1) the distribution of weather stations, particularly in developing countries or remote regions, is usually sparse; therefore, it cannot represent the UHI for a whole city,[74] (2) most weather stations are located in urban areas, so rural station data for UHI analysis is lacking,[75] and (3) quality data from stations are usually not available to all users.[73] In contrast, remote sensing satellites provide easy to access LST data with global coverage at no cost and can therefore be considered the most suitable way to investigate the surface UHI (SUHI).

Rao[76] first reported the perspective of using remote sensing techniques for SUHI studies. In the subsequent years, many scholars stated that, in UHI studies, satellite temperature measurement produced better results than interpolating weather station observations.[77,78] Since the 1990s, the AVHRR sensor has been widely used for LST analysis[79,80] and the SUHI effect at the regional scale.[81,82] Later, ASTER, which provides both LST daytime and nighttime data at high spatial resolution (90 m), has been applied for SUHI studies in many cities.[83–85] Deilami et al.[86] produced a systematic review of spatiotemporal factors, data, methods, and mitigation measures of the UHI effect, investigating all English peer-reviewed articles published from January 1965 to July 2017. The results showed that the most widely used LST data for Ta were Landsat TM (54.6%), followed by Landsat ETM (34.6%) and MODIS (28.0%). The other satellite images used for UHI studies were Landsat 8,[87–90] SPOT,[91] and QuickBird.[92] However, as noticed by the USGS in August 2013, surface water temperatures derived from Landsat 8 TIRS data may be inaccurate, potentially impacting the results of research.[93] Obviously, this calibration problem has restricted the application of Landsat 8 TIRS for UHI studies.[94]

Although Landsat is considered one of the most popular satellite data sources for UHI studies, according to Deilami et al.,[86] there are two main shortcomings of Landsat data: (1) the low temporal resolution (16 days) is not suitable for diurnal or weekly UHI monitoring or assessment and (2) due to the small size of Landsat images, multiple images must be mosaiced when applied to regional and national areas. According to Irons et al.[95] and Wulder et al.,[96] the mosaic processing takes a significant amount of time. Currently, it is worth noting that the Landsat surface reflectance level-2 products can be retrieved from the NASA website at no cost, but the preprocessing time can be large when requesting multiple images for a large area.

To overcome the limitations of Landsat satellite data over the last decade, MODIS data have been widely applied to SUHI studies, particularly to those focusing on temporal variation, i.e., diurnal, seasonal, annual, decadal, and coarser scales.[50,97–99] In addition, it is worth noting that when investigating the SUHI using remote sensing LST data, not only the surface characteristics should be taken into consideration but also the climatic and meteorological conditions.[100,101] The potential applications and the rising trend of using MODIS data have been reported by Zhang et al.,[102] who conducted a bibliometric analysis of global remote sensing research from 2010 until 2015. To trace the temporal trend of the main applications using remote sensing techniques, they investigated the top keyword from each year (from 2010 to 2015), and the results showed that MODIS emerged as the core theme. The "MODIS" keyword ranked in the top six keywords (among "model," "classification," "algorithm," "SAR," and "remote sensing").

As mentioned in Sec. 3.2, one of the most popular applications of MODIS LST data is for UHI/SUHI studies, 12.3% (65 articles). It is worth noting that in UHI/SUHI studies, LST data from Landsat have been widely applied.[86] However, in recent years, the UHI studies are transitioning from single date to time series (multiple day), from local and regional to global. In addition, the variation of UHI/SUHI due to the changing seasons, daytime and nighttime, has been receiving the attention from scholars. Therefore, remote sensing image data that provide high temporal resolution (i.e., daily, hourly) and coverage of large areas (i.e., city) is becoming indispensable. MODIS satellite data, which provide four LST datasets each day at 1-km spatial resolution with global coverage, are among the most suitable sources for UHI studies at the regional and global scales. Another advantage of MODIS satellite data is that it provides readily available products for UHI applications (e.g., LST and land cover data), which significantly reduces the processing time. Among the 65 articles using MODIS LST data for SUHI studies, 13 articles were focused on analyzing diurnal SUHI, 19 articles analyzed the effects of season on SUHI intensity, and 37 articles investigated the effects of daytime and nighttime on SUHI intensity. Among these 37 articles, two studies (Haashemi et al.[8] and Bahi et al.[103]) used nighttime LST data of MODIS and daytime LST from Landsat images. It should be noted that among the 65 articles, the numbers of studies that were conducted in China, India, and the United States were 21, 9, and 7, respectively. The remaining articles were mostly implemented in EU cities. However, based on the prediction of UN,[70] urbanization will take place in developing countries regions, Africa, and Asia; this suggests that MODIS LST will be one of the most valuable data sources for the hot topic, UHI studies, in developing countries in the near future.

Another important point is that there are four MODIS LST data images at four times each day. Between the two satellites (Terra and Aqua) collecting these data, the overpass time of the Aqua satellite (1:30 a.m. and 1:30 a.m.) is closer to the occurrence of the highest and lowest temperatures in the diurnal cycle than the Terra satellite (10:30 a.m. and 10:30 p.m.). However, most studies choose to utilize either Terra data[9,103–107] or Aqua data[44,73,108–110] without explanation. According to Clinton and Gong,[111] the daytime SUHI monitored by Aqua LST (1:30 p.m.) was higher than that of Terra (10:30 a.m.). Therefore, a topic, for example, the effects of different time observations on UHI, should be taken into consideration for future studies.

3.4 *Air Surface Temperature Estimation Using MODIS LST Data*

Air surface temperature (Ta), which is usually measured at weather stations 2 m above the ground, is a key parameter for a wide range of applications.[48,112–114] Although it provides accurate Ta, it has limitations in spatial coverage. Traditionally, to obtain Ta for a large area, interpolation methods were used;[115,116] however, the accuracy of interpolation methods strongly depends on the distribution of weather stations.[45,117] Therefore, it is difficult to apply this method for regions with sparse weather stations, such as in developing countries and remote areas.

According to Li et al.[24] and Chen et al.,[118] remotely sensed LST data are considered one of the most suitable ways to retrieve Ta data at local, regional, or global scales. Among the remote sensing satellites, the Advanced Very High Resolution Radiometer (AVHRR), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and Landsat can provide LST data, though LST data from MODIS are the most widely used.[19] To confirm this, we used the same search terms for ASTER, AVHRR, and Landsat (which resulted in 52 publication using MODIS LST). The result showed that from 2009 to 2018 there were only four records total; three for Landsat and one for ASTER.[119–122] This result indicates that MODIS LST is the most popular and widely used source for Ta estimation studies. Among these four articles, Zhu et al.[122] used both Landsat 8 and MODIS LST for Ta estimation, showing that Ta could be estimated at the 30-m (using Landsat 8) and 1000-m scales (using MODIS) with a root mean square error (RMSE) of 1.7°C and 2.6°C, respectively. Among the 52 Ta estimation publications collected for this study, the number of studies that applied MODIS LST for daily, weekly, and monthly Ta estimation were 45, 2, and 7, respectively. The total number is not equal to 52 because two studies were applied for both daily and weekly Ta,[48,123] and one study was applied to estimate both daily and monthly Ta.[124] In addition, the difference between daily, weekly, and monthly articles also suggests that the high temporal resolution of MODIS LST data (four times daily) is one of the largest advantages of MODIS data and is, therefore, widely applied for Ta estimation.

Three common method types were used: statistical methods (78.8%—41 articles), machine learning methods (13.5%—7 articles), and temperature vegetation index methods (7.7%—4 articles). It is worth noting that in most of the articles using statistical or machine learning methods, MODIS LST data were combined with auxiliary variables. The most widely used auxiliary variables were elevation, NDVI, Julian day, latitude, longitude, and day length.[123,125–127] Although statistical methods were the most widely used, by 2013 the researchers started focusing on machine learning approaches.[127–133] Some studies compared the performance of advanced statistical methods and machine learning methods but with inconclusive results. Xu et al.[129] compared two methods, linear regression, and random forest (RF) for Ta estimation in British Columbia, Canada, concluding that the RF model achieved better accuracy [mean absolute error (MAE) = 2.02°C, $R^2 = 074$, compared with MAE = 2.41°C, $R^2 = 064$]. Meyer et al.[130] compared a simple linear regression model with three machine learning algorithms [RF, generalized boosted regression models (GBM), and Cubist (CB)] for Ta estimation in Antarctica. Their results showed that machine learning algorithms only slightly outperformed the simple linear estimation model. Among the three machine learning methods, GBM showed the best results for Ta estimation. Zhang et al.[131] compared six statistical models (i.e., multiple linear regression, the partial least squares regression, back propagation neural network, support vector regression, RF, and CB) with two types of MODIS LST data qualities (all clear sky data and only good data). They concluded that the performance of each algorithm depended on the different combinations of MODIS LST and the quality of data. Overall, however, RF and CB showed the best results of Ta estimation with both conditions of data quality. Noi et al.[132] compared the performance of a linear regression model (LM) with RF and CB algorithms, for two types of data input, MODIS LST data solely and MODIS LST with auxiliary variables (elevation and Julian day). Their results showed that both CB and LM performed well with MODIS LST solely, but when MODIS LST is used with auxiliary variables, CB and RF are recommended. Consistent with Zhang et al.[131] and Noi et al.,[132] Xu et al.[133] compared 10 machine learning algorithms for Ta monthly mapping in the Tibetan Plateau and reported that CB outperformed the other methods.

Regarding the MODIS LST data for Ta estimation, four MODIS LST data are available each day (Terra day, Terra night, Aqua day, and Aqua night), with overpass at local times 10:30 a.m., 10:30 p.m., 1:30 p.m., and 1:30 a.m., respectively. However, most of the studies have chosen only one or two MODIS LST data (among the four available) for Ta estimation. Generally, the selection was based on the overpass time of MODIS LST data. For example, Xu et al.[129] chose LST of Aqua daytime for Ta-max estimation in British Columbia, Canada; Zhang et al.[131] chose LST of Aqua daytime and Terra nighttime, for Ta-max and Ta-min estimation, respectively; and Yang et al.[134] chose LST of Aqua daytime and nighttime, for Ta-max and Ta-min estimation, respectively. Recently, some studies have chosen all four MODIS LST data for Ta estimation.[131,132,135,136]

Most recently, Yoo et al.[127] proposed a new method for Ta estimation by considering the lag time of heat transport from ground level to 2 m. Therefore, they also used the four LST data taken from the day before, so that they used eight MODIS LST datasets total for daily Ta estimation. They implemented this new method in two megacities, Los Angeles, USA, and Seoul, South Korea, and concluded that LST of the day before were crucial for estimating daily Ta in urban climates.

4 Discussions

It is known that remote sensing is the most suitable data for Earth surface-related studies due to its usefulness for monitoring the Earth surface, analyzing trends and patterns, and forecasting. Among various applications of remotely sensed data, land surface temperature (e.g., MODIS LST) is one of the most important variables for climate research and global change.[24] Zhang et al.[102] conducted a bibliometric analysis of global remote sensing research during the period 2010 through 2015, showing that MODIS is the most prevalent data source among all the other remotely sensed data (e.g., Landsat, AVHRR, ASTER, SPOT, and IKNOS).

As mentioned in the methods section (Sec. 2.2), although MODIS LST data have been available since 2000, most studies (~90%) using MODIS LST were implemented in the last 10 years

(2009 to 2018). This indicates that MODIS LST data are receiving a large amount of attention from scholars. In addition, in 2017, all MODIS LST data have been reprocessed by NASA and made available for download at no cost, in a collection called MODIS LST Collection 6 (C6).[19] Fixes and improvements have been made in C6, which were reported in detail in Wan.[17] Of these, removing the cloud-contaminated LST pixels is one of the best advantages of C6 compared with the previous collections (C4.1 and C5). Again, the availability of C6 cannot be understated, as the number of publications using MODIS LST data (all publications, including theories and methods publications) in 2017 was higher than in any previous year (Fig. 3) perhaps as a result. However, in addition to the advantages, MODIS LST data have some shortcomings that should be noted. First, similar to other optical (thermal) remotely sensed images, the most concerning problem of MODIS LST data is the lack of cloud-free images. If clouds are present, MODIS LST products are not available.[137] In addition, pixels that are partially covered or contaminated by clouds, which were not removed from the MODIS LST data may be present, because they could not be detected by the cloud removing mask algorithms.[138,139] Obviously, in practice, these pixels may affect study results. Second, the spatial resolution of MODIS LST data is too coarse for some applications, such as agriculture, drought, water management, vegetation phenology,[140,141] or detailed UHI.[86] Therefore, developing techniques to retrieve high spatial and high temporal resolution from currently available remotely sensed data is a current area of interest.[16,142] Third, most of the studies in the literature are using MODIS LST without concern for the quality of MODIS LST. Researchers should play more attention to this issue.

4.1 *Reconstruction of MODIS LST Data*

Regarding the reconstruction techniques, among the 855 articles (included articles focused on theories or methods developments/assessments), there were only 15 articles that considered missing MODIS LST data. Meanwhile, according to Zeng et al.,[143] completed cloud free MODIS LST data are rare, particularly during rainy seasons and in humid regions. Furthermore, according to Jin and Dickinson,[144] each day, the cloudy-sky condition is present over more than half the globe. This means that MODIS LST data, which have excluded all the cloudy-sky pixels from $M * D11$ products, lose more than half of LST data time series.[145] In addition, Østby et al.[146] compared 8 years of MODIS LST data with *in situ* observations in Austfonna (an Arctic ice cap located on Svalbard), showing that only 26% of the MODIS LST data are retrieved under actual clear sky conditions, of which the percentages of MODIS LST data under clear sky conditions for winter and summer are about 40% and 20%, respectively. As a result, the subsequent applications that use MODIS LST data will be greatly affected.[127]

Furthermore, many previous studies applied MODIS LST data without any consideration for cloud cover, just simply selecting the measurements under clear sky conditions (using the QC data file) for analysis.[48,125,131,147]

Among the 15 studies that implemented the reconstruction of MODIS LST data, most only focused on the method development and assessment.[125,148,149] Only a few studies used this technique for specific applications, e.g., Neteler[150] reconstructed MODIS LST for Ta estimation in a mountainous area. In future research, more studies should investigate the effects, and solutions to solve this problem.

4.2 *Downscaling Using MODIS LST Data*

Among the 855 articles (including articles focusing on theories and methods), there were 60 articles that applied downscaled methods. Among these, there were three studies on UHI effect,[151–153] 11 articles for monitoring/estimation evapotranspiration, and 12 articles for soil moisture applications, whereas the remaining articles mainly focused on theories or method developments/assessments.

Three types of downscaling studies used MODIS LST data: (1) downscaling MODIS LST data to higher spatial resolution (e.g., 250 and 30 m), (2) downscaling MODIS LST data to higher temporal resolution data (e.g., using hourly GOES—LST data), and (3) downscaling other lower spatial resolution products (e.g., SMOS: Soil Moisture and Ocean Salinity, AMSR-E: Advanced Microwave Scanning Radiometer–Earth Observing System).

As LST is considered one of the most crucial parameters for a wide range of applications, at various scales, high spatiotemporal resolution LST data are required. Currently, a number of sensors can provide high spatial resolution (i.e., Landsat, ASTER) or high temporal resolution (e.g., MODIS, GEOS), yet no sensor can provide LST data at both high spatial and temporal resolution. Therefore, downscaling (or fusion) techniques play a crucial role in retrieving high spatial and temporal resolution for many applications. Although Landsat images provide very high spatial resolutions (up to 60 m), the temporal resolution is too coarse (16 days); therefore, MODIS LST are normally downscaled to Landsat resolution.[16,24–26,154]

Another important point is that in developing countries, the agricultural field size and other land uses are small, and indeed much smaller than the spatial resolution of MODIS LST data. Therefore, one pixel contains many land cover types, receiving a mixed signal. To reduce the effect of this issue, downscaling to finer resolutions is necessary.

4.3 *Quality of MODIS LST Data*

According to Colditz et al.,[155] for a long-term time series, data quality is considered a critical issue. MODIS LST data are not available for locations (pixels) that are covered by cloud.[137] In addition, Wan[137] also noted that in MODIS LST products, pixels are still present which are covered by thin clouds that cloud-detecting algorithms cannot identify and remove. Therefore, the results of all applications using MODIS LST data are affected. Ackerman et al.[138] reported that there are ∼15% of contamination pixels existent in MODIS LST products. In addition, Williamson et al.[139] used ground-based meteorological station observations to evaluate the cloud contamination in clear sky MODIS Terra daytime LST in the southwest Yukon area, showing that 13% to 17% of MODIS LST data were unidentified clouds. This will obviously affect the results of subsequent MODIS LST data applications. However, to date, most studies have not considered this problem. Therefore, further studies should investigate the effect on MODIS LST quality and which cloud detection methods are needed.

5 Conclusions

This review gives an overview as well as some specific applications of MODIS LST data from Terra and Aqua satellites over the last 10 years. In general, the number of publications in peer-reviewed journals using MODIS LST data increases annually, indicating that this source of data is becoming more popular and widely used. Among 19 subject areas with several topics of application, the top five applications over the last 10 years were: UHI, air temperature estimation, soil moisture estimation, evapotranspiration estimation, and drought studies. In addition, in the last 3 years, a high number of publications were focused on three topics: drought monitoring/assessment, UHI, and Ta estimation. This reveals the wide range of applications of MODIS LST data. In spite of the advantages of MODIS LST data, some limitations remain, such as the cloud cover effect (included missing pixels, as well as the pixels covered by thin cloud) and the use of the MODIS data quality file (QC file). Some techniques like downscaling (fusion) and reconstruction will bring opportunities for recent and future applications. This study not only clarifies the global overview of MODIS LST data applications to novice researchers but also provides current research hotspots and future potential applications related to MODIS LST data.

Disclosures

No conflicts of interest, financial or otherwise, are declared by the authors.

Acknowledgments

We would like to acknowledge the Vietnamese government for its financial support. We would like to thank Michael Schlund (Institute of Geography, University of Göttingen) for constructive criticism of the initial version of this paper. We also thank the anonymous reviewers for their valuable comments, which improved our paper.

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