The impact of temporal aggregation of land surface temperature data for surface urban heat island (SUHI) monitoring

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ABSTRACT

The remotely sensed land surface temperature (LST) is widely used in studying the surface urban heat island (SUHI). Due to the influence of clouds, composite products usually are preferred; however, exactly what the impact of temporal aggregation is on LST and SUHI is still unknown. In this paper, we quantify this impact focusing on Houston, Texas and its surroundings using MODIS LST products from 2000 to 2010. The results show that 1) the SUHI values are more notably enhanced in the daytime than nighttime with an increasing trend with larger composite periods. 2) The influences of aggregation in the spring and summer are larger than autumn and winter for the daytime. 3) The temporal aggregation impacts the spatial pattern of the SUHI implying that the higher SUHI regions are more likely to have a larger gap between two composite scales and this is related to the amount and distribution of clouds.

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1. Introduction

More than 50% of the world population live in urban areas, and that proportion will likely grow in the future (WHO, 2010). One impact of the urban population is the urban heat island (UHI) (Gallo et al., 1993; Sen Roy & Yuan, 2009; Streutker, 2002). The urban environment with higher temperature not only affects the habitability caused by air pollution (Taha, 1997), and increases human health problems related to high temperature (Kalkstein & Greene, 1997; Patz et al., 2005), but also starts a vicious circle to encourage consumption energy to cool buildings, resulting in generating more anthropogenic heat. As a result, long term monitoring of UHI becomes necessary and it is essential to understand UHI features and the urban climatology behind it.

Remote sensing techniques introduce a new viewpoint to understand UHI, using land surface temperature (LST) to define the surface UHI (SUHI) (Voogt & Oke, 2003). Traditionally, air temperature differences between urban and rural areas using pairs of in-situ climatology data define UHI, and were conducted by many studies (Chow & Svoma, 2011; Gaffin et al., 2008; Gallo & Owen, 1999; Henry et al., 1989; Morris et al., 2001; Shao et al., 2011). However, the representativeness is questionable due to heterogeneous urban surface properties and comparatively insufficient data sources. After the advent of thermal remote sensing, LST data become available, and a variety of LST related SUHI studies used multiple sensors carried by satellites (Gallo et al., 1993; Streutker, 2003) and aircrafts (BenDor & Saaroni, 1997; Lo et al., 1997; Quattrochi et al., 2000). Satellite remote sensing overcomes some problems of in-situ measurements generally with wider sources, broader coverage, and steadier periodicity. Taking these features into consideration, using remote sensing to study SUHI can improve conductive to understand the spatial–temporal variability of physical processes, which influence the long-term urban climate.

The satellite remote sensing approach, however, has its own limitations. One of the primary issues affecting the data accuracy is that clouds can easily contaminate the data due to the indirectly detecting way of remote sensing. Hence, the accuracy of LST products is highly contingent upon the cloud-screening algorithm (Wan, 2008). Even though LST can be accurately derived, it is hard to avoid missing data due to clouds. Researchers commonly adopted two possible solutions to decrease the impact of clouds: choosing cloud-free images or constructing temporally composited data (Gallo & Owen, 1999; Holben, 1986; Los et al., 1994). For example, several SUHI studies only examined the nighttime thermal images (Matson et al., 1978; Streutker, 2003; Tiegong et al., 2008; Tomlinson et al., 2012; Zhou et al., 2011), because the solar radiation increases the instability of boundary layer during the daytime, which is more likely to form clouds. Meanwhile, the cooling differences due to energy budgets between the urban and surrounding rural areas are maximized (Voogt & Oke, 2003). As a result, nights are usually under the calm and clear conditions. Some research (Chen et al., 2006; Kato & Yamaguchi, 2005; Tan et al., 2006) was based on case studies in a short time period by selecting representative cloud-free LST images. However, this way is not suitable for a continuous monitoring or a large area investigation. On the other hand, temporal composite products can minimize the number of gaps created by clouds or any other undesirable conditions in the long time series (Gallo & Owen, 1999; Pinty et
al., 2002). Sometimes, it is preferred to use a coarser temporal resolution of remote sensing data over a long observational period, so that the SUHI analyses can be based on high clear-sky-coverage and consistent-repeat-period data.

SUHI studies, particularly for long-term or global analyses, commonly adopt temporally composited remote sensing. Composite data directly increase the clear sky coverage across urban and rural regions, which are beneficial to do spatial comparison for SUHI studies. For example, Gallo and Owen (1999) used monthly and seasonal Advanced Very High Resolution Radiometer (AVHRR) composites to analyze the SUHI effect, recommending monthly composites for summer and fall and biweekly composites for winter. Schwarz et al. (2011) used monthly composite LST generated from Moderate Resolution Imaging Spectroradiometer (MODIS) 8-day LST to explore indicators for quantifying SUHI of European cities. Unfortunately, these SUHI studies did not consider the possible errors caused by composite processes.

Normalized Difference Vegetation Index (NDVI) is one of a few biophysical variables that has been discussed for temporal compositing methods and associated biases. Compositing NDVI from AVHRR by the Maximum NDVI (MaN) compositing method results in a positive bias (Moody & Strahler, 1994). Moreover, the magnitude of biases depends on the composite methods. The composite maximum NDVI of AVHRR suggests significantly higher and generally less variable values when using MaN method rather than using Maximum Temperature (MaT) (Roy, 1997). Also, Tan et al. (2006) pointed out that MODIS 8-day composites of NDVI are overestimated by MaN and minimum blue method due to gridding artifacts. However, the processing methods and properties of LST are dissimilar with NDVI. The results may be not applicable to LST.

LST properties are a result of surface–atmosphere interactions and energy budget considerations, closely related to surface conditions (such as emissivity, land cover and structure, and moisture), subsurface properties (such as conductivity and specific heat density), and atmospheric properties (such as solar radiation, wind speed, and clouds) (Norman et al., 1995; Roy, 1997). Meanwhile, the characteristics of AVHRR and MODIS sensors are different in many ways, such as spectral range and instantaneous field of view. As a result, the bias magnitudes may vary from different sensors. The product of composite MODIS LST released from NASA utilizes another aggregation method, simply by averaging the daily MOD11A1 product (Wan, 2007). The main bias is expected to be introduced by clouds, because the distinct urban climate system exerts influences on cloud occurrence frequency (Romanov, 1999; Talha, 1997), leading to the urban/rural data availability difference. However, what is the impact of temporal aggregation on MODIS LST is still unknown. In this paper, we examine this issue by focusing on Houston, Texas and its rural surroundings estimating the magnitudes of the influence of temporal aggregation on MODIS LST products for long term SUHI studies.

2. Study area

Houston, Texas is chosen as the study area in the domain ranging from 31.0° N, 97.0° W (northwest) to 28.5° N, 94.0° W (southeast) (Fig. 1). Houston is a coastal city on the Gulf of Mexico with a population of 2.1 million within about 1600 km² urban area (United State Census Bureau, 2010). The climate is classified as humid subtropical, which is characterized by hot, humid summers and generally mild to cool winters. The land cover types in the study area according to MODIS land cover data from 2001 to 2009, except sea and land water (21.6%), primarily include cropland/natural vegetation mosaic (28.3 % ± 6.8 %), woody savannas (13.5 % ± 4.6 %), croplands (11.7 % ± 2.5 %), grasslands (9.1 % ± 2.6 %), mixed forest (7.2 % ± 2.8 %) and urban and built-up (3.9 % ± 0.03 %). Fig. 1 illustrates the land cover in 2009 with the super neighborhood boundary (SNBR, from COHGIS 2010 (http://cohgis.houstontx.gov/cohgis2010/index.html)). SNBR portrays the main Houston urban area without extra roads and small pieces of land outside main urban region, so we use it as the boundary of the Houston urban area instead of the administrative boundary in the later analyses.

3. Data and methods

3.1. Data and data processing

We used the daily (MOD11A1/MYD11A1) and 8-day composite (MOD11A2/MYD11A2) MODIS LST products from Mar. 5th, 2000 (MOD11A1; Jul. 8th, 2002 for MYD11A1) to Dec. 31st, 2010 at 1 km spatial resolution. MODIS is a 36-band instrument aboard the Terra (EOS AM) and Aqua (EOS PM) satellites, which covers the earth surface 4 times each day at the daytime (around 10:30 and 13:30 local time) and nighttime (around 22:30 and 1:30 local time). The MOD11A1/MYD11A1 products are produced daily using the generalized split-window LST algorithm (Wan & Dozier, 1996). The emissivities in bands 31 and 32 in the products are estimated by the classification-based emissivity method according to the land cover types (Wan, 2009).

All sea pixels were excluded after reprojection and extracted the subset of the study area. Considering both the location and the climate in Houston, we also masked the unreasonable LST values before analyses. According to the low air temperature record from NOAA Online Weather Data (www.nws.noaa.gov/climate/xmaccis.php?wfo=ghx) and considering the relationship between surface and air temperature (Jin & Dickinson, 2010; Sun & Mahrt, 1995), we set the low threshold of 280 K for May to September, and 258 K for other months. There are two images available for each daytime and nighttime. In order to simplify the comparison, we used the average of daytime or the average of nighttime values, although each pair was obtained approximately 3 h apart. This process is done after the separately aggregating Terra and Aqua images. In addition, only the first 360 days were accounted for statistics, so that 8-day composite LST dataset can match the daily dataset better in a one year period.

The MODIS land cover type product (MCD12Q1, 500 m, yearly) was introduced to explore the impact of temporal aggregation in a spatial perspective. We chose International Geosphere Biosphere Programme (IGBP) classification out of five schemes in MCD12Q1, which includes 17 classes with natural vegetation, developed and mosaicked land, and non-vegetated land classes. After being projected to the same coordinate system as the LST data, the land-cover maps were resampled to 1 km using the majority resampling method. Unfortunately, there are only 9 annual land cover maps available from 2001 to 2009 online, while LST datasets have a wider time series span (2000–2010), so the 2000 and 2010 LST data were assessed using the nearest year 2001 and 2009, respectively.

3.2. Analysis methods

UHI is defined by the temperature differences between urban and non-urban areas. However, the differentiation between “urban” and “rural” remains diverse (Schwarz et al., 2011). In this study, we defined the urban temperature using mean urban LST in SNBR boundary of Houston. Then, the temperature differences (also called SUHI maps) were calculated from

$$\Delta T(i,j) = T_{\text{urban}} - T(i,j)$$

where $T_{\text{urban}}$ is the mean of LST in SNBR boundary with the land cover type of urban and built-up, and $T(i,j)$ is a pixel in the LST image at the position of $(i,j)$. Generally, the non-urban areas reflect positive values in SUHI maps, which indicate the LST difference magnitudes between the Houston urban and the non-urban areas.

Daily and 8-day composite LST values of Houston and non-Houston areas were calculated and compared to show the seasonal, annual, and
interannual dynamics of urban–rural climate. Then, the impact of temporal aggregation on SUHI was evaluated from two points of view: time and space. The analyses of the temporal aggregation were aimed to test whether the impact of aggregation varies with time of year, while the spatial analyses were attempting to ascertain what the impact of the aggregation has on the spatial variance. The major statistics were calculated using MODIS daily and 8-day composite data, because 8-day composites are a primary MODIS LST product, and the cloud contamination in the Houston urban area in this study. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

To assess the influence of temporal aggregation, we estimated 2-, 4-, 8-, 16-, and 32-day composite SUHI maps based on daily LST using a moving window algorithm. This resulted in a composite LST image from each fixed composite period (window size: from 2 to 32 days) and moves the window forward day by day, then estimated the SUHI from these composited LST images. The mean SUHI magnitudes in study area at each composite scale were calculated before estimating the mean SUHI from Terra and Aqua. Then the mean SUHI were compared with daily mean SUHI in the same period. Moreover, to evaluate the cost and gain, the clear sky coverage ratio \( R_{cc} \) was calculated based on each composite LST image:

\[
R_{cc} = \frac{N_{cc}}{N_{total} - N_{nod}}
\]

(2)

where \( N_{cc} \) is the total number of land surface pixels under clear sky conditions, \( N_{total} \) is the total number of pixels in an image, and \( N_{nod} \) is the number of masked sea pixels.

Regression analyses for day and night were performed on 8-day averages of daily SUHI versus the SUHI derived from the 8-day composite data, respectively. Such analyses were also undertaken for seasonal relationships. To evaluate the 8-day composite data performance, coefficient of determination \( (R^2) \), root mean square error (RMSE), and slope and intercept of the regression were calculated. Moreover, the differential SUHI maps between 8-day composite images and the corresponding daily images were calculated and the seasonal statistics were calculated.

In order to explore the spatial variability caused by temporal aggregation, summer composite SUHI maps during 11 years were generated from daily and 8-day composite LST as well as their differential maps for day and night, respectively. Land cover is a critical forcing for development of the UHI (Jin & Shepherd, 2005), and the relationship between UHI and land cover has been reported widely in the literature (Voogt & Oke, 2003). We statistically analyzed the mean SUHI magnitudes of each main land cover type at summer-season and annual periods to assess the responses of different land cover types to the temporal aggregation.

To quantify the potential influence of cloud contamination on the aggregation product, the linear aggregations were tested between \( R_{cc} \) and aggregation biases at the 2-, 4-, 8-, 16- and 32-day composite scales. The aggregation biases are generated from the differences between the mean composite SUHI in the study area and the daily mean SUHI in the composite period. Moreover, the spatially heterogeneous distribution of clouds was also assessed seasonally by calculation of the available pixel ratio (APR) maps (Spring MAM, Summer JJA, Autumn SON, and Winter DJF). APR is defined as follows:

\[
APR(i,j) = \frac{\sum_{i=1}^{N} n(i,j,z)}{N}
\]

(3)

where \( n = 1 \) when the value of the pixel at \( (i,j) \) is meaningful (non-NaN), otherwise \( n \) equals 0; \( N \) is the total number of images in each season. APR maps are directly derived from the daily dataset, because this originally reflects the cloud contamination frequency. A higher APR value means less cloud contamination during this season at this pixel.

4. Results

4.1. Temporal aggregation influence on LST in the urban and rural areas

We began by focusing on the temporal LST patterns of Houston and the surrounding areas. The mean daily average LSTs of 11 years are 301.1 ± 6.5 K (daily), 302.7 ± 6.8 K (8-day) in the Houston urban area, and 297.8 ± 6.5 K (daily), 299.2 ± 6.3 K (8-day) in the non-Houston area during the daytime. For the nighttime, the mean LSTs are lower than those during the daytime, which are 289.8 ± 7.2 K (daily), 289.7 ± 7.0 K (8-day) in the Houston urban, and 287.9 ± 7.1 K (daily) and 287.8 ± 6.9 K (8-day) in the non-Houston area. The 8-day composite LST shows higher temperature in the daytime and lower one at night, which increases the diurnal LST by 1.7 K (the Houston urban) and 1.5 K (the non-Houston area), respectively.

The mean daily, seasonal, annual and interannual LST patterns assessed by daily LST in the Houston urban and the non-Houston urban area are shown in Fig. 2. There is a marked seasonal trend of the mean LST. Compared with the mean LST in 45 8-day periods
between the two datasets, the annual trend doesn’t agree well in quantitative features (Paired t-test, \(p < 0.01\)) in the daytime with mean differences (8-day minus daily) about 1.9 K (Fig. 2a) and 1.5 K (Fig. 2b). However, these differences are not statistically significant during nighttime (Fig. 2c and d). Moreover, the composited data are generally less varied due to the aggregation reducing the LST range. The standard deviation (STD) shows a different diurnal and seasonal pattern for the urban and non-urban areas. There is a relatively higher STD in summer during the daytime in the Houston urban area, and in contrast, the STD is notably lower in summer during nighttime in both Houston and non-Houston areas.

The interannual comparison was also conducted from 2000 to 2010 (Fig. 2). The statistics show that the mean 8-day LST is always higher than that of daily dataset during the daytime, while the nighttime mean LST is opposite. The t-test indicates that the annual differences between the two datasets are not significant.

4.2. Temporal aggregation influence on temporal dynamics of SUHI

4.2.1. Multi-scale composite SUHI comparisons

In order to examine the impact of the time scale of temporal aggregation on SUHI as well as on the clear sky coverage, the 2-, 4-, 8-, 16-, and 32-day temporal composites were calculated by the moving window algorithm. The 11-year mean of statistics were plotted in Fig. 3, showing the annual trend of daily and multi-scale composite SUHI magnitudes. The interannual variation of the SUHI (not shown figure) in summer day is relatively larger than other seasons with the standard deviation of 2.4 K at the daily scale and 2.2 K at the 8-day scale, resulting in slightly higher variation of biases. However, the variations of the biases at 6 temporal scales are less than 1.6 K in the summer day. Conversely, the summer nights are with smaller variations of SUHI and the aggregation biases during the 11 years than other seasons, which are also much smaller than daytime. The seasonal pattern of SUHI

Fig. 2. The daily average LSTs of Houston urban and non-Houston urban areas during 11 years. The daily average LSTs are arranged as 8-day period by 45 8-day periods in a year by 11 years. The missing values are in black. The bottom plot shows the mean and standard deviation (STD) in every 8-day period using daily (red, downward error bar) and 8-day composite data (green, upward error bar). The right box-plots illustrate the distributions of daily (red) and 8-day composite data (green) LST in each year. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
in each scale is clear, indicating higher SUHI values in spring and autumn. With the increasing composite scale, the SUHI values are more notably enhanced in the daytime than nighttime. We compared the composite SUHI with the daily scale and found that the summer shows the largest variation (Fig. 3(b)) with about 3.5 K at 32-day composite scale for the day, while the temporal scaling exerts less influence in winter. The impact is also less at the nighttime than the daytime, with relatively similar values in Fig. 3(d).

The advantages of utilizing composite data include the high efficiency for long term monitoring, as well as the great improvement of clear sky coverage which is essential for spatial analyses. The 11-year-averaged annual clear sky coverages at six scales are shown in Fig. 4. Since the compositing process decreases the cloud coverage by adding more information, the clear sky coverage increases as an increase of composite time period, which is greatly affected in a short composite period, compared with 0.44 for daily LST, 0.61, 0.80 and 0.93 at 2-, 4- and 8-day levels during the daytime, respectively. Based on daily data, the clear sky coverage differs substantially in summer for day (0.36) and night (0.54) due to diurnal energy balance patterns in urban environments. Generally, when the composite scales are greater than the 8-day period, the SUHI maps in a year-long period reach a high quality of clear sky coverage for both day and night, and with a seasonal analysis, a shorter compositing period can result in the similarly high quality.

One of the primary issues associated with temporal scaling of SUHI from remote sensing is that cloud contamination determines the availability of SUHI maps and the magnitudes of SUHI related to the mean urban LST. We will discuss this issue in further details in Section 4.4.

### 4.2.2. Linear regression analysis between daily and 8-day composite SUHI

The trend in the improvement of the clear sky coverage resulting in an increased error of SUHI is clear. Next, we scrutinized daily and 8-day composite LST product available online to quantify the errors. A scatter plot of the mean daily SUHI during 8-day period versus the 8-day composite SUHI from early 2000 to 2010 for day and night, respectively (Fig. 5), examines the influence of temporal aggregation on SUHI. At first glance, the aggregation process directly results in a higher SUHI magnitude than that using daily SUHI, especially in the daytime. Similar regression analyses were also implemented at a seasonal scale, and the results are shown in Table 1. The 8-day composite SUHI seasonally differed from the daily SUHI. The stronger $R^2$ in summer during the daytime explains the variation of 8-day composite SUHI caused by the variation of daily data. Spring has the largest absolute bias, as high as 2.5 K in the daytime. For the nighttime, the spring shows the highest $R^2$ and a slope of near 1. Generally, the SUHI estimated from the two datasets indicates a smaller difference during the nighttime.
4.2.3. Statistics of SUHI dynamics from daily and 8-day composite data

The annual SUHI trends using daily and 8-day composite datasets were calculated and plotted in Fig. 6. Agreeing with the regression result, the 8-day aggregation of LST generally enhances the SUHI during the daytime, and the effects become greater in the warm seasons rather than the cold seasons. The influence on the nighttime SUHI is comparatively less notable. The aggregation increases 1.4 K of pseudo median in the daytime and 0.4 K for the nighttime in Wilcoxon Signed-Rank test, which are significantly different ($p < 0.01$). Additional statistics of the seasonal mean SUHI with its STD was listed in Table 2. We observed a strong seasonal pattern of SUHI in the daytime, illustrating about 1–2 K higher mean SUHI in spring and autumn than summer. The nighttime mean SUHI is quite stable, which differs less than 0.5 K among seasons. The seasonal mean SUHI differences between 8-day composite and daily datasets varied with a remarkable diurnal pattern. Generally, the aggregation causes few differences at night, especially in winter; the effects are greater with seasonal variations in the daytime. The largest mean gap is as high as 1.8 K during 11 years, and occurs in the summer.

4.3. Temporal aggregation influence on the spatial pattern of SUHI

The primary purpose of comparing the spatial differences is to characterize how much spatial variation is introduced as a result of temporal aggregation. As shown above, the largest SUHI differences during the day occur in summer, so we chose this season to assess the spatial variability. The summer mean SUHI maps during 11 years, as well as their differences for both day and night are shown in Fig. 7. Some negative values in the Houston urban are due to the definition of SUHI in Eq. (1), where they have higher LST than the mean Houston urban LST. The SUHI shows a higher magnitude in the daytime composite dataset, and especially in the northeastern corner of the domain. Linking SUHI with the land cover map shown in Fig. 1 turns out to be a similar pattern. Nighttime SUHI maps and their differential map, which are more homogeneous, indicate that there is no remarkable spatial variation caused by the temporal composite process at night, which just consolidates the results in Section 4.2.

The major land cover types cluster regionally with relative homogeneity, the northeastern corner of which is primarily covered by mixed forest and woody savannas. To further assess the possible reason causing the spatial difference during the day time as well as the magnitude of the response, we introduced the land cover maps (MCD12Q1) to build a relationship between SUHI and the main land cover types (Fig. 8) for both summer and annual scales.

Since the SUHI accounts for smaller urbanized areas outside of Houston, the urban SUHI has a value slightly higher than zero due to comparing with the mean Houston LST, which agrees with the findings that the smaller cities are with the less SUHI intensity (Oke, 1973). SUHI magnitudes of mixed forest and woody savannas are apparently higher than grassland, cropland and cropland/natural vegetation mosaic in the daytime, which can be explained by the lower albedo and the higher evapotranspiration ability of trees enhancing the available net radiation and losing more energy through latent heat flux. In the summer day, the LST of grass is even higher than the urban LST, which shows a negative mean SUHI in Fig. 8(c).

The distinct diurnal pattern results from the change of energy budgets between day and night, and this difference also can be found between daily and 8-day composite data. With the exception of grass, the distributions of 8-day composite SUHI are generally more concentrated than daily, due to decreasing the variation by averaging daily values. The statistical test results show that the differences of the two datasets in each land cover types are significant (Welch’s $t$ test, $p < 0.01$), with a mean difference of about 1.3 K (annual) and 1.7 K (summer) for the day, and about 0.4 K (annual) and 0.3 K (summer) at the night. Further details are shown in Table 3. These results imply that the higher SUHI regions are more likely to have a larger gap between two composite scales in the daytime.

4.4. Influence of clouds

The SUHI is composed of the differences between urban and rural LST, and missing either LST cannot generate a SUHI map. Fig. 2 illustrates the influence of clouds showing missing LST with black pixels, suggesting that this influence becomes larger in urban than rural and in the daytime than nighttime. Statistically, about 76% (day) and 81% (night) of total daily LST images were valid (cloud free) for Houston urban area LST to generate SUHI maps. 8-day composite product shares a higher proportion (above 98%), due to increasing the LST availability through a series of images. The similar results can be found in Fig. 4.

Table 1

The statistical results from the regression between daily and 8-day composite SUHI from 2000 to 2010.

<table>
<thead>
<tr>
<th>Season</th>
<th>Daytime</th>
<th>Nighttime</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Slope</td>
<td>Intercept</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spring</td>
<td>0.57*</td>
<td>2.49</td>
</tr>
<tr>
<td>Summer</td>
<td>1.14</td>
<td>1.56</td>
</tr>
<tr>
<td>Autumn</td>
<td>0.95</td>
<td>0.95</td>
</tr>
<tr>
<td>Winter</td>
<td>0.88</td>
<td>0.55</td>
</tr>
<tr>
<td>Annual</td>
<td>0.86</td>
<td>1.35</td>
</tr>
</tbody>
</table>

* The t-test results are not significant ($p$-value > 0.05) at 95% confidence level.

Fig. 5. Scatter plot showing the average of daily SUHI images in 8-day period against its corresponding 8-day composite SUHI value across the study area.
The benefit of temporal composite is significant; however, it may result in the bias of SUHI using an aggregated dataset. Fig. 9 shows the linear relationship between the $R_{csc}$ and the aggregation biases at the 8-day composite scale. Due to the large variation of aggregation effect in summer, the 2-, 4-, 8-, 16-, and 32-day composite aggregation biases in summer were analyzed for day and night, respectively (Table 4). As the length of the composite period increases, the $R_{csc}$ grows quickly resulting in a more concentrated distribution without a significant linear relationship. Hence, Fig. 9 only shows the regression lines with statistically significant level ($p < 0.05$). The slope of regression lines is positive, showing an increase in bias with a growing $R_{csc}$ in the daytime. Also, the composite scale matters, which matches the results from Fig. 3, showing a larger slope with a longer composite period. In contrast, the increase in cloud ratio results in a decrease in error, which is close to 0 at high $R_{csc}$ end. Moreover, the composite scale does not greatly affect the biases from the aggregation process. It is postulated that the large cloud coverage decreases LSTs, and although the cloud and cloud-contaminated pixels have been removed (Wan, 2008), a residual cloud impact possibly exists on the adjacent pixels. For example, clouds cause the changes of energy and water balances, which affect the surrounding non-cloud pixels. The increase of $R_{csc}$ by aggregation actually does not physically compensate for the cloud effects, especially for the daytime due to the relatively low clear sky coverage (Fig. 4). The diurnal distinction of the bias-$R_{csc}$ relationships may be caused by the distributions of clouds exerting spatially variable impacts, leading to the variation of SUHI.

The enhanced SUHI is highly related to the characteristics of urban climate. The unstable boundary layer in the afternoon accelerates the generation of clouds above the urban area, which increases the cloud-contamination possibility at the time of the satellite overpass. The cloud contamination results in an absence of urban LST pixels, and thus it is difficult to calculate daily SUHI maps. While the composite values comparatively enhance the LST of areas around the city. Fig. 10 shows the daytime mean APR maps in the four seasons. A noticeable heterogeneity occurs in summer APR map (with STD of about 0.10), showing a lower ratio in Houston urban area and a higher one in northeastern corner. This trend matches the differential SUHI map in summer shown in Fig. 7. On the contrary, the more homogeneous winter APR map, with STD of about 0.04, explains well the smaller influence of temporal aggregation in winter (Table 2). Similarly, there is not a remarkable spatial bias of APR maps at night in each season (not shown), with the STD less than 0.05, although the mean APR value in summer is about 0.14 higher than that in winter.

A linear relationship was examined between APR and the SUHI difference map between 8-day and daily composite images in the summer during 11 years (Fig. 11). It turns out to be a strong positive correlation with $R^2$ of about 0.76, implying higher APR values with higher SUHI differences due to temporal aggregation. Also, a bias of land cover is exhibited in the APR maps, suggesting a relatively low APR with larger variance (such as urban and built-up areas, 0.15 ± 0.08 of APR with bias STD of 0.65 K) and high APR with a smaller variance (such as forest, 0.46 ± 0.04 of APR with bias STD of 0.19 K).

### Table 2

The seasonal statistical results of 8-day period mean SUHI and the STD.

<table>
<thead>
<tr>
<th>Seasons</th>
<th>8-day period of year</th>
<th>Day (K)</th>
<th>Night (K)</th>
<th>Day (K)</th>
<th>Night (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Daily 8-day</td>
<td>Daily 8-day</td>
<td>8-day – daily</td>
<td>8-day – daily</td>
</tr>
<tr>
<td>Spring</td>
<td>8–18</td>
<td>3.0 ± 2.3</td>
<td>4.6 ± 1.1</td>
<td>1.3 ± 1.8</td>
<td>1.9 ± 1.1</td>
</tr>
<tr>
<td>Summer</td>
<td>19–30</td>
<td>1.0 ± 2.6</td>
<td>2.8 ± 2.2</td>
<td>1.3 ± 1.1</td>
<td>1.7 ± 0.5</td>
</tr>
<tr>
<td>Autumn</td>
<td>31–41</td>
<td>2.0 ± 2.1</td>
<td>3.2 ± 1.2</td>
<td>1.7 ± 1.3</td>
<td>2.1 ± 0.7</td>
</tr>
<tr>
<td>Winter</td>
<td>1–7, 42–45</td>
<td>1.9 ± 2.1</td>
<td>2.8 ± 1.2</td>
<td>1.2 ± 1.9</td>
<td>1.6 ± 1.0</td>
</tr>
</tbody>
</table>

* This is the statistics from the differential maps generated from the 8-day composite SUHI minus the corresponding daily SUHI.
5. Discussion

The results suggest that the temporal aggregation of MODIS LST products leads to a more intensive SUHI effect with diurnal and seasonal patterns. We showed that the SUHI have a 1.29 K bias in the daytime and 0.36 K at night using 8-day composite dataset instead of daily dataset during 11 years across the study area. The seasonal variation suggests that it produces the highest potential difference at summer
Fig. 8. SUHI of daily and 8-day composite data with major land cover types in the study area. (a) and (b) are the daytime and nighttime SUHI for annual scale. (c) and (d) are daytime and nighttime SUHI only for the summer period.
day due to 8-day scale aggregation, which is about 2.8 K. In addition, the composite also has some impacts on the spatial distribution of the SUHI during the daytime, which is likely related to the land cover types.

The nighttime SUHI magnitude calculated from daily MODIS LST products is about 2.0 K during 11 years. Streutker (2003) pointed out that there was about 2–3 K SUHI magnitude in Houston by nighttime AVHRR data between 1985 and 1987, and between 1999 and 2001. The mean LST surrounding the Houston City, which was about 290 K, was higher than the result we estimated. These differences may be attributable to the accuracy of AVHRR (±1.5 K) (Prata, 1994) being lower, compared with MODIS (±1 K) (Wan & Dozier, 1996). The heterogeneous surface, unavailable atmospheric conditions for correction, and sensor view angle more or less limit the quality of LST achieved from satellites (Jin & Dickinson, 2010). The differences are also caused by the designation of urban, rural, and the whole region of study area defined. As there are many indicators used to define the SUHI in the literature, Schwarz et al. (2011) found that different indicators have weak correlations, and emphasized the importance of choosing methods to quantify SUHI effects. Hence, it is unclear how the choice of indicator will impact the aggregation results.

The diurnal SUHI shows that the midday SUHI magnitude of Houston is generally larger than that in midnight. The seasonal patterns indicated that the highest SUHI magnitude occurs in the spring, and the lowest magnitude happens at summer in the midday. Nighttime SUHI variation of four seasons is not notable. Compared with global analyses from Zhang et al. (2010) and European cities from Schwarz et al. (2011), the Houston summer SUHI is generally about 1 K lower, and about 3 K lower than the settlements larger than 500 km² globally, however, it is not necessary indicating that Houston is not hot during summer. The absolute LST in the study areas is as high as 305.0 K in summer. It is probably because of the humid coastal climate, dominated biomes (Imhoff et al., 2010; Zhang et al., 2010), and the city structure which is sprawling (Streutker, 2003). However, it is hard to exclude the possible influence by this distinct seasonal pattern of SUHI in Houston, which may lead to decreasing universality of our results to other areas. Consequently, additional studies of other cities need to be done in the future.

A significant negative relationship between land surface temperature and NDVI is found in many studies (Dousset & Gourmelon, 2003; Gallo et al., 1993), which is associated with a decrease in surface resistance to evapotranspiration, a large portion of energy for latent heat flux, as well as a reducing Bowen ratio (Mildrexler et al., 2011; Mu et al., 2007). In this study, we used land cover maps instead of vegetation index for a more specified spatial pattern analysis. However, if linking the SUHI magnitude with NDVI, the trends will be similar, indicating that forest has the largest cooling effect (Mildrexler et al., 2011), particularly in daytime (Lo et al., 1997). The SUHI analysis based on land cover types may exhibit some errors due to the coarse temporal resolution of land cover data, which may not perfectly match the actually situation during the year.

The bias of cloud contamination is a possible reason for increasing the SUHI magnitude using composited data. According to the research conducted by Romanov (1999) on the urban influence of the cloud cover, the results show that there is a considerable increase of cloud fraction in spring and summer while winter’s urban effect is slight in the daytime, which matches our findings: 1) the seasonal trends (Fig. 10), and 2) the differences of SUHI caused by aggregation increase in spring and summer, and decrease in winter (Table 2). As the results shown in Section 4.4, cloud formation is closely associated with land–atmosphere interactions. Urban areas are likely to be affected by clouds, due to their surface properties. The boundary layer heights over urban areas are generally higher than that over rural areas due to a warmer surface, as a consequence, the low-level convergence over the urban surface contributes to the formation or location of clouds (Angevine et al., 2003). Also, the urban climate increases the source of cloud condensation nuclei (Diem & Brown, 2003; Jin et al., 2005). Crops have a lower stomatal resistance,
er, the day and night, which may not correspond to the largest SUHI. Howev-
LST cannot represent the highest and lowest temperatures of the 
about 1.0 K higher than 2:30 am LST. The mean Terra and Aqua 
about 2.6 K higher than the late morning, and before midnight LST 
temperatures in a day. The statistics shows that the afternoon LST is 
overpass times of Terra and Aqua are before and after the highest 
the LST but also the clear sky coverage distribution and ratio. The 
ration between Terra and Aqua exists (Morris et al., 2001). However, remote sensing only works well under 
clear sky conditions. As a result, biases from the technique itself may in-
fluence will be integrated in the composite LST 
product online and decrease the LST value of that pixel over the 8-day 
period, which should be considered in applications. Also, cloudy urban 
environment effectively restrict the development of pronounced SUHI 
(Schwarz et al., 2011). However, remote sensing only works well under 
clear sky conditions. As a result, biases from the technique itself may in-
crease the SUHI magnitude for long time monitoring.

We illustrated the mean effects of Terra and Aqua. However, vari-
bation between Terra and Aqua exists (Schwarz et al., 2011), not only 
the LST but also the clear sky coverage distribution and ratio. The 
overpass times of Terra and Aqua are before and after the highest 
temperatures in a day. The statistics shows that the afternoon LST is 
about 2.6 K higher than the late morning, and before midnight LST 
is about 1.0 K higher than 2:30 am LST. The mean Terra and Aqua 
LST cannot represent the highest and lowest temperatures of the day and night, which may not correspond to the largest SUHI. How-
er, the $R_{uc}$ values of Terra and Aqua are statistically equal ($t$-test, 
$p < 0.05$). Due to the fact that the aggregation processing and analysis 
were conducted for Terra and Aqua separately, these results indicate 
the mean effect of temporal aggregation.

6. Conclusions

In order to investigate a long term urban heat island dynamics with maximum decreased influences of clouds, this paper discussed 
the impact of using the 2-, 4-, 8-, 16- and 32-day composite LST in-
stead of daily LST in Houston area to study SUHI. Especially, due to 
the availability and high clear sky coverage of 8-day composite LST, 
MODIS daily LST and 8-day composite LST products have been statisti-
cally compared for SUHI in both spatial and temporal respects.
Three main conclusions can be made from the results of this study. First, the temporal aggregation impact has seasonality and is also a function of composite scale. The seasonal pattern shows that the summer daytime SUHI has the largest magnitude and variation, while the nighttime SUHI magnitudes are much smaller and less variable. The composite scale is particularly important during the summer daytime. The higher the aggregation scale is, the higher SUHI biases are generated. However, the impact from the two factors for nighttime is comparably small. Consequently, we recommend using shorter composite period in summer daytime. Second, the temporal aggregation varies spatially, which is related to the land cover types. The mean bias caused by land cover types were calculated to be about 1.6–2.0 K during the daytime, and less than 0.4 K at night. Third, the potential cause of the errors from temporal aggregation is heterogeneously distributed clouds. The analysis shows that the land–atmosphere interactions, which result in higher frequency of clouds over the urban areas, are the primary reason.

However, additional research is required to conclude a rather common conclusion. As discussed above, it is preferable to know that the impact on temporal aggregation is independent from SUHI indicators. Also, it is worthwhile to test the aggregation impact on the cities in various climate regions. For example, although the impact is outstanding for summer daytime, cities in the dry regions may be less influenced by clouds. The seasonality and bias magnitude may vary. Also, the size and structure of city are also factors that impact SUHI, which may have more or less UHI effects due to the aggregation bias. In addition, other sensors have variable observation time, spatial extent of information; however, it will lose some accuracy, the extent of which differs diurnally and seasonally, particularly for the spatial coverage of information. For long term or global SUHI studies, it is beneficial to use 8-day composite LST if we can balance the gains and losses.

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