A first satellite-based observational assessment of urban thermal anisotropy

Leiqiu Hu^{a,*}, Andrew Monaghan^a, James A. Voogt^b, Michael Barlage^a

^a*National Center for Atmospheric Research, Boulder, CO, USA 80307*

^b*Department of Geography, University of Western Ontario, London, ON, Canada N6A 5C2*

Abstract

Complex urban environments with diverse urban canyon structures and building materials mixed with human-modified green space substantially influence the directional variation in upwelling thermal radiance. The thermal anisotropy at a satellite pixel scale (e.g. 1 km) is hard to quantify with current techniques through airborne observations and modeling. The various anisotropic features over urban and rural surfaces lead to an uncertainty regarding how this anisotropy of land surface temperature (LST) influences estimates of the surface urban heat island (SUHI). We quantify LST anisotropy over Chicago and New York using MODIS LST products during the warm months (May-September) for a 10-year period. The impacts of atmospheric attenuation and daily weather variability on LST are removed in order to isolate the anisotropic signal. We then calculate the anisotropy for different levels of urban land use intensity. The daytime maximum anisotropic effects can be up to 9 K for the most urbanized areas, while the nighttime

*leiqiu@ucar.edu

anisotropic effects are weaker but still discernible. Two anisotropic “hot spot” features are observed during daytime: one corresponds to the sensor-sun geometric effect with a higher proportion of sunlit surface components been seen a given view configuration, and the other occurs when sensor zenith angles are near nadir in the afternoon. Similar anisotropic features between the two cities confirm the broader applicability of our approach, while some unique features specific to each city emphasize that diverse urban surface properties and geographic settings can affect anisotropy. This study is the first of its kind to directly evaluate the influence of directional anisotropy on satellite-retrieved SUHI measurements, demonstrating that anisotropic effects can possibly modify the SUHI as measured with MODIS LST by 2.3 K, which is about 25 ~ 50% of the total magnitude of the SUHI over Chicago and New York. Our findings provide a statistical basis for the quantification of satellite-retrieved LST anisotropy over heterogeneous urban environments globally.

Keywords: Satellite thermal remote sensing, thermal anisotropy, land surface temperature, MODIS, surface urban heat island

1. Introduction

Land surface temperature (LST) is an important indicator of surface energy and moisture conditions (Li et al., 2013). LSTs retrieved from satellite data provide a means to understand land surface processes efficiently via consistent periodicity, high-spatial resolution, and global coverage. Satellite-

6 retrieved LST has been widely applied to investigate soil moisture, sur-
7 face energy fluxes, surface hydrology, vegetation dynamics, and environ-
8 mental and ecological changes (Zhang et al., 2015; Voogt and Grimmond,
9 2000; Voogt and Oke, 2003; Weng et al., 2004, 2014; Rigo and Parlow, 2007).
10 For urban climate research, satellite-based LST has the ability to compre-
11 hensively depict the complex temperature distribution spatially in highly
12 heterogeneous urban environments. Satellite-based LST measurements can
13 compensate for or complement traditional intra-urban measurements from
14 ground-based observations, which often have limited footprints and relatively
15 sparse coverage across urban regions, or are only installed for a short period
16 during intensive urban field campaigns. Consequently, satellite-based LST
17 fields have been widely used for surface urban heat island (SUHI) studies
18 (Voogt and Oke, 2003; Hung et al., 2006; Schwarz and Manceur, 2014), and
19 also have been assimilated into urban land/atmosphere model simulations or
20 used to validate them (Li and Bou-Zeid, 2013; Monaghan et al., 2014).

21 However, the anisotropy of satellite-based LST measurements is widely
22 found over a variety of surfaces including vegetated (Kimes, 1980; Pinheiro et al.,
23 2004), bare soil (Sobrino and Cuenca, 1999; Cuenca and Sobrino, 2004), and
24 urban areas (Lagouarde et al., 2004; Lagouarde and Irvine, 2008; Lagouarde et al.,
25 2012), which means the LST varies depending on the sensor view direction.
26 The anisotropy of LST primarily results from the angular variation of non-
27 isothermal components and emissivity detected from an instantaneous field
28 of view (IFOV) (Li et al., 2013). The three-dimensional (3D) structure of

the surface creates temperature variability due in part to different local solar zenith and azimuth angles on facets that create anisotropy (Lagouarde et al., 2000; Voogt, 2008; Duffour et al., 2015). The anisotropy is generated from the biased view of the facets that make up the urban surface from a particular view direction (Kimes, 1980; Lagouarde et al., 2004; Lagouarde and Irvine, 2008; Lagouarde et al., 2014; Duffour et al., 2015; Krayenhoff and Voogt, 2016). There are also other influences on anisotropy such as biases in material properties with orientations that may contribute to surface temperature differences. Thus, in complex urban environments with diverse urban canyon structures and building materials, mixed with human-modified green space, there is a particularly strong influence on the anisotropy of satellite-based LST (Voogt, 2008).

Previous studies have demonstrated a substantial contrast between daytime and nighttime anisotropic patterns. The anisotropic LST can exceed 10 K during the daytime over highly urbanized districts (Lagouarde et al., 2004; Lagouarde and Irvine, 2008; Voogt, 2008). The daytime anisotropic pattern reveals a significant “hot-spot” effect (a local maximum in the near-full hemispheric distribution of radiative temperature), where the sensor views the maximum proportions of sunlit components (the Sun is behind the sensor as it views the surface object). Anisotropy decreases rapidly following sunset so that it becomes small and nearly azimuthally independent later in the evening (Lagouarde et al., 2012).

Currently, direct observations from airborne sensors complimented with

52 in-situ measurements, and sensor-viewing modeling, are two primary ap-
 53 proaches to assess the effects of anisotropy on LST (or brightness tempera-
 54 ture) measurement in urban environments (Lagouarde et al., 2004; Lagouarde and Irvine,
 55 2008; Voogt, 2008). Integrated observations and modeling can help to estab-
 56 lish a relatively comprehensive quasi-simultaneous LST anisotropy distribu-
 57 tion, which may help minimize anisotropic effects on satellite-based LST
 58 measurements. However, there are a number of issues associated with apply-
 59 ing airborne and modeling approaches to adjust for the anisotropy of urban
 60 LST measurements from satellites. First, the validity of upscaling the fine
 61 scale experiments to comparatively coarse resolution satellite-based LST is
 62 uncertain (e.g. Moderate Resolution Imaging Spectroradiometer (MODIS)
 63 has 1 km resolution). For example, it isn't clear how much impact of sur-
 64 face topography variation and spatial variations of urban surface structures
 65 (e.g. built and vegetated structure and arrangements) at a fine scale affect
 66 the anisotropy at satellite observational scale. Moreover, we have limited in-
 67 formation on facet-scale variations of emissivity, and almost no information
 68 on whether individual material has emissivity that is non-isotropic. Second,
 69 airborne observations are quite expensive to obtain, which make it impossi-
 70 ble to conduct experiments over various types of cities globally. Third, the
 71 impact of anisotropic LST on SUHI quantifications is unknown due to the
 72 possible dissimilar anisotropic features of LST over urban and rural areas.

73 Anisotropy can be a particularly acute problem for sensors aboard polar-
 74 orbiting satellites designed to take repeat images with high temporal fre-

quency, because they have wide fields of view and a broad range of sensor zenith angles (ZA) in the cross track direction (Li et al., 2013). MODIS and Advanced Very High Resolution Radiometer (AVHRR) are infrared sensors that fall into this category. For instance, the sensor ZA of MODIS can be up to 65° in the cross-track direction. Due to anisotropy, LST detected from different sensor positions can confound the quantification of SUHI intensity, leading to unreliable estimates of SUHI over short timescales, such as daily. Moreover, additional biases can be introduced in studies that empirically correlate satellite-based LST and in-situ or gridded air temperature records regionally or globally.

Currently, substantial efforts are required to fully characterize and adjust for the anisotropic LST from satellites for urban applications. The challenges arise for a number of reasons. First, many factors that control anisotropic features of LST vary at multiple temporal and spatial scales: e.g., the annual solar angle change, vegetation phenology, weather variability, the urban built form as well as its relation to vegetation. Additionally, spatial variations in material properties may impact anisotropy, either due to differences in construction of different types of buildings in a particular city or due to differences in construction practices globally. Second, atmospheric effects are partially determined by the distance between the target and sensor, which is a function of the highly-variable sensor viewing angle. Unfortunately, completely eliminating the atmospheric impact on LST retrievals remains challenging for the foreseeable future (Li et al., 2013). Third, little

is known about the influence on LST of vegetation anisotropy within urban areas (Dyce, 2014), though most city environments have abundant vegetation that is difficult to distinguish from built-up components at the satellite observational scale. Vegetation types and coverage vary extensively across urban areas and thus are difficult and expensive to measure. In summary, it is demanding to measure and account for these fine scale effects at the satellite pixel scale over urban regions.

This study uses a novel method to assess the anisotropy of MODIS LST measurements over long-time scales (multi-year seasonal averages). The approach includes strategies to separate the influence of the atmosphere (after the atmospheric correction) and the influence of variable weather conditions from LST products. Our primary objectives are to quantify LST anisotropic features over various urban environments, estimate the SUHI variations due to the anisotropic LST, and demonstrate the applicability of our methodology for broader applications.

2. Data and Methodology

2.1. Study Areas and Data

Two large U.S. cities and their surrounding metropolitan areas are chosen for the experiment. Chicago is located on the southwestern shore of Lake Michigan with a population of about 2 million residents in the city and about 9.5 million in the metropolitan area (U.S. Census Bureau Population Division, 2014). This city has a humid continental climate with warm-to-hot and hu-

Figure 1: The urban land use fraction at 1 km resolution for Chicago (181 km by 181 km) and New York City (85 km by 145 km). The black contours separate the urban land use fraction at 20%, 40%, 60% and 80%. The regions in white and blue in the domains represent non-urban area and pure water surfaces, respectively. The grey area in New York City indicates where MODIS LST data are unavailable. The cross symbols show the locations of meteorological weather stations over the land and water surfaces; the weather station over the water surface for New York (not shown) is outside the domain.

120 mid summers. New York City has a population of about 8.5 million in the city
 121 and about 19.5 million in the metropolitan area (U.S. Census Bureau Population Division,
 122 2014), which is located in the northeastern U.S. coastal area under the in-
 123 fluence of the Atlantic Ocean. The city experiences a humid subtropical
 124 climate based on Koppen-Geiger climate classification (Kottek et al., 2006)
 125 with warm-to-hot and humid summers. The study domains used for the
 126 statistical analyses for each city are shown in Fig. 1. In order to produce
 127 representative and robust results, a large sample size of both urban areas and
 128 pure water surfaces is required. Therefore, extended regions were used for
 129 the initial data processing. Additional details are discussed in Section 2.2.

130 MODIS is onboard NASA's Terra and Aqua polar-orbiting satellites,
 131 which pass over the same location on Earth once or twice per day. Compared
 132 to the temporal flexibility of aircraft measurements, satellite orbits are pre-
 133 designed and shifted slightly for each revolution of the Earth. Consequently,
 134 the sun-surface-sensor geometry and overpass time for a given location vary
 135 daily. The sensor and solar zenith angles (ZA) (and azimuthal angles (AA))
 136 used in this study take the surface targets as references, which are defined
 137 as the angles from the nadir of a given grid cell to the sensor or Sun line
 138 of sight (see Fig.2 (a)). The sensor ZA is defined as the angle between the
 139 satellite sensor and nadir, shown as the shaded blue angle in Fig.2 (a). The
 140 sensor AAs (i.e. the surface object to the sensor with respect to north in
 141 a clockwise direction, indicated by the blue arrow in Fig.2 (a)) of satellite
 142 observations are nearly perpendicular to the axes of the track direction, and
 143 are approximately easterly or westerly depending on which side of the city
 144 the track for a given overpass occurs (see Fig. 2 (b) and (c) for Chicago). To
 145 simplify the notation in the later analysis, we use the positive and negative
 146 ZA to indicate whether the sensor/solar azimuthal angle is smaller than 180°
 147 (close to easterly) or larger than 180° (close to westerly). The observations
 148 from MODIS have a large range of sensor ZAs up to $\pm 65^\circ$ due to a scan
 149 angle of up to 55° and a wide swath of coverage for each satellite overpass.
 150 The sensor zenith and azimuth angle distributions of LST in Chicago for day
 151 and night are shown in Fig. 2 (b) and (c), respectively.

152 In contrast to airborne measurements or model simulations of quasi-

Figure 2: (a) The definition of the sensor/Sun zenith angle (ZA) and sensor azimuth angles (AA) in this study, where the surface object is the reference and the angles are measured from surface objects to the sensor/Sun indicated as blue and red arrows in the figure, respectively. (b) and (c) are polar plots of the sensor angle distributions and corresponding solar positions of cloud-free LST measurements in the Chicago area during daytime and nighttime, respectively. The polar plots show the surface to the sensor/Sun AA for the radii (0-360°) and ZA for the circles (0-65°). The green color represents data from the Terra satellite, where the distribution range of corresponding solar positions for Terra observations are defined by the polygon in green (The yellow-to-red colors within the polygon indicate the frequency (high-to-low) of solar positions). Aqua is similarly illustrated in blue. A higher frequency of surface-sensor geometric positions has a darker color. The distribution for New York is similar (not shown). The positive and negative ZAs described in (c), a notation that is used for simplification in the later analysis, represent the surface-sensor azimuth angles that are smaller (positive) and larger (negative) than 180°.

simultaneous anisotropy, it is difficult to obtain multi-angular satellite observations simultaneously of the same ground object (Ren et al., 2015). The angular LST analyses in this study thus represents a long-term, metropolitan-scale statistical viewpoint. Moreover, here we use LST rather than brightness temperature (which is widely used in airborne observations for anisotropy studies), and thus the emissivity for the LST retrieval is estimated based on the land cover types (Snyder et al., 1998), so it does not account for the uncertainty of emissivity due to the view angle, “cavity” effects from the urban canyon, or the heterogeneous surface components within a pixel.

The MODIS Land Surface Temperature and Emissivity 5-minute Level 2 version 5 product (MOD11_L2 from Terra and MYD11_L2 from Aqua) is the primary data used for the anisotropic LST assessment. This LST product is produced daily at 5-minute increments using the generalized split-window algorithm with a spatial resolution of approximately 1 km at nadir (Wan and Dozier, 1996; Wan, 2007). The corresponding sensor and solar ZA and AA for each LST pixel is extracted from the MODIS geolocation product (MOD03 from Terra and MYD03 from Aqua) at 1 km resolution. The median local solar time of four satellite overpasses is about 11:00 (Terra-Day), 13:00 (Aqua-Day), 22:00 (Terra-Night), and 2:00 (Aqua-Night) for Chicago and New York City. We collected the daily MODIS LST/geolocation products from May to September during 2003-2012. Additionally, to reduce impacts from cloud contaminated pixels (e.g. cloud edges), the lowest LST threshold was set to 270 K, and low-temperature outliers were removed (defined as a

176 pixel with a temperature < 1.5 times the interquartile range of the 25% LST
177 distribution of pixels in each image). Finally, LST images with more than
178 75% of clear-sky coverage over land surfaces and at least 20% (Chicago) or
179 80% (New York) clear-sky pixels over pure water surfaces were selected for
180 analysis.

181 We only assessed the five warmest months (May-September) of the year.
182 The selected months provide a range of variations in the solar position (e.g.
183 solar angle distributions for Chicago for Terra-Day and Aqua-Day in Fig.
184 2(b)), yet have relatively stable vegetation conditions over urban areas. Also,
185 the warmer seasons avoid the effects of winter snow or frozen water surfaces,
186 which may modulate the LST anisotropy in a manner that we cannot account
187 for. It is also important to quantify the impact of anisotropy on SUHI when
188 the negative effects of the UHI are most influential. Our approach is thus
189 simple and reasonably representative.

190 In order to identify urban areas, water surfaces and vegetation cover with
191 the highest fidelity possible, we employed the 30 m spatial resolution 2006 Na-
192 tional Land Cover Database (Homer et al., 2012)(http://www.mrlc.gov/nlcd06_data.php).
193 To match the scale of MODIS LST, the original land cover data were spatially
194 aggregated to 1 km by calculating land use type ratios in each 1 km grid cell.
195 Ancillary data of building footprints with building height information were
196 collected for Chicago (<https://data.cityofchicago.org/>) and New York
197 City (<https://data.cityofnewyork.us/>). The spatial coverage of datasets
198 is limited to the administrative boundary. We aggregated and characterized

199 the urban morphology at the 1 km scale from building information to match
200 the LST spatial resolution.

201 In each city, one pair of air temperatures from meteorological weather sta-
202 tions over land and water surfaces are used to decrease the impact of daily
203 weather variation on anisotropy quantification (see locations of weather sta-
204 tions in Fig. 1, cross symbol). The hourly near-surface observations over land
205 are from National Oceanographic and Atmospheric Administration (NOAA)
206 National Centers for Environmental Information (NCEI), including sites from
207 the John F. Kennedy International Airport (USAF-725053, New York) and
208 Chicago O'Hare International Airport (USAF-725300, Chicago). Over water,
209 a buoy 61 km south of Long Island (USAF-996420, near New York) is also
210 from NOAA NCEI, and a site over Lake Michigan near Chicago is from the
211 NOAA Great Lakes Environmental Research Laboratory (<http://www.glerl.noaa.gov/metdata/>)
212 The observations are selected within 1 hr of each satellite overpass during the
213 study period and are quality-controlled.

214 *2.2. Methods*

215 Each LST pixel has an unique solar/sensor angle configuration in a satel-
216 lite swath; meanwhile, the sensor ZA and AA variation at a city scale is
217 relatively small in each swath. Consequently, in order to quantify angular
218 variations of MODIS LST from sensor ZA -65° to $+65^\circ$ over heterogeneous
219 urban surfaces, we have to minimize other possible anisotropic contributors,
220 such as atmospheric attenuation, to decrease other impacts on quantifying

221 the anisotropy, such as daily weather variation, and to carefully identify
 222 anisotropy from spatiotemporally integrated information. In this section, we
 223 introduce practical methods to isolate the anisotropic effects from MODIS
 224 LST products by subtracting different terms that could represent the bi-
 225 ases from atmospheric effects and weather variability. The resultant dataset
 226 ($\Delta LST_{\Delta T_{air}}$) derived from LST is only a function of anisotropy (without
 227 a physical meaning). By quantifying the relative $\Delta LST_{\Delta T_{air}}$ variation, we
 228 therefore are able to assess the anisotropy of LST due to different surface
 229 structure and properties in cities for each satellite overpass.

230 *2.2.1. Reducing the impact of angular atmospheric attenuation*

231 The anisotropic effect of LST products can directly come from both var-
 232 ious surface properties as well as residual atmospheric effects in a certain
 233 view configuration. The calculation of MODIS LST at 1km is based on a
 234 generalized split-window algorithm by Wan and Dozier (1996), which cor-
 235 rects for atmospheric effects based on the differential absorption in two ther-
 236 mal bands from MODIS, rather than directly relying on radiative transfer
 237 models and atmospheric profiles. Consequently, it is difficult to physically
 238 identify the sources of uncorrected atmospheric attenuation from the LST
 239 products. Therefore, we propose an indirect way to decrease the impact of
 240 possible angular atmospheric effects in LST products. First, we assume that
 241 atmospheric conditions are similar over adjacent land and water areas, so
 242 the impact of angular atmospheric attenuation over land pixels can then be

approximately canceled by subtracting water surface temperature from land surface temperature for pixels with similar sensor ZAs, sensor azimuth angles, and observation times (within the same satellite image). We define the LST difference between land surfaces and pure-water surfaces by Eq. 1.

$$\Delta LST(t) = LST(t) - \overline{LST_{water}(t)} \quad (1)$$

where t is the satellite overpass time when the LSTs are observed within 5 min, and $\overline{LST_{water}(t)}$ is the averaged LST of all water pixels in the domain. In reality, this equation would also be a function of the sensor AAs and ZAs. However, the differences among sensor AAs in a given image are very small (about 2°), and can be neglected. While the sensor ZA spans a larger range of angles (up to 14° for Chicago and 9° in New York but often less), the geographic clustering of pure water pixels in each domain makes it impossible to calculate spatial-averaged $\overline{LST_{water}}$ for the full range of sensor ZAs over land for most overpasses. Thus, we also neglect sensor ZA differences when solving Eq. 1.

The surface of deep and relatively calm water bodies has a near-isotropic surface temperature distribution due to its homogenous surface properties (Nicolòs et al., 2004, 2005). Hence, ΔLST does change the anisotropic information caused by land surface properties. In order to show the existence of atmospheric impact and the effectiveness of our proposed method, the LST_{water} and ΔLST_{water} (LST and ΔLST over pure water surfaces) distri-

263 butions as a function of sensor ZA for Chicago and New York are shown
 264 in Fig. 3. Any directionality of the observed temperature over water is
 265 due to atmospheric attenuation, therefore the impacts of atmospheric at-
 266 tenuation are particularly pronounced during nighttime in New York, where
 267 increasing sensor ZAs are associated with decreasing LST (red lines, left
 268 y-axis). The relatively even distributions of ΔLST_{water} (blue lines, right
 269 y-axis) demonstrate that we can effectively minimize the possible angular
 270 effects from atmospheric attenuation on the MODIS LST product. The dis-
 271 tribution of ΔLST_{water} is consistent with our assumption that the water sur-
 272 face is near-Lambertian. The residual atmospheric impact might be surface
 273 temperature-dependent (e.g. the attenuation by the atmosphere from sur-
 274 face emission), or surface temperature-independent (e.g. the upwelling path
 275 radiance from atmosphere), so the simple subtraction of LST over land and
 276 adjacent water surfaces may not necessarily completely remove the residual
 277 impact from atmosphere over urban areas. Since the split-window algorithm
 278 does physically-consider atmospheric effects for LST retrievals, the residual
 279 atmospheric impact is relatively small and not necessarily constant across
 280 space and time (e.g. Fig. 3 for Chicago). The ΔLST term will thus reduce
 281 the residual atmospheric effect if it exists in the product (e.g., Fig. 3 for New
 282 York at nighttime).

Figure 3: The distributions of LST (LST_{water} , left y-axis, red) and ΔLST (ΔLST_{water} , right y-axis, blue) of pure water pixels with respect to sensor ZA in Chicago (top) and New York City (bottom). The solid lines indicate the mean values of LST (red) and ΔLST (blue) in each 5° interval of sensor ZA (the x-axis labels the center values of each ZA interval). The color-shaded bands depict the mean $\pm$ one standard deviation of the distributions.

283 *2.2.2. Reducing the bias from sampling due to weather variability*

284 The ZA variation in each image is relatively small (less than 15°) com-
285 pared to the total possible ZA range of sensor observations (from -65° to
286 $+65^\circ$). The ZA distribution as a whole is not even, and there are more clear-
287 sky data available with the high ZA range (Fig. 2(b) and (c)). Consequently,
288 the ΔLST with ZA in each interval sample a range of different hot and cold
289 days. For example, the sampling issue could explain the two strong dips
290 in ΔLST_{water} distribution for Terra-Night satellite overpass of New York in
291 Fig. 3. The daily water temperature variation is relatively small compared
292 to the land surface. Therefore, the impact from daily weather variation on
293 ΔLST over land areas is even larger. In order to reduce the potential bias on
294 our quantification of anisotropy from the uneven distribution of hot and cool
295 days across different sensor ZA groups, the ancillary air temperature from a
296 pair of weather stations over the land and adjacent water surface in each city
297 is introduced (see Fig. 1, cross symbols).

298 Daily weather variation influences LST, as well as the land-water temper-
299 ature difference (ΔLST). Therefore, the value of ΔLST described above is
300 not exclusively a function of the sensor angle. High positive correlations have
301 been found between LST and near-surface air temperature (T_{air}) under clear
302 skies, but absolute differences exist (Prihodko, 1997; Kawashima et al., 2000;
303 Benali et al., 2012), which are determined by different physical mechanisms
304 that control the two terms. Fortunately (and unlike LST), T_{air} is indepen-
305 dent of the sensor ZA (i.e, there is no anisotropic impact). This makes it

possible to estimate the effect of weather variability using T_{air} , and then we could minimize this effect on LST. Since we use the ΔLST (land-water difference), accordingly, the air temperature difference (ΔT_{air}) between the land ($T_{air,land}$) and water surface ($T_{air,water}$) is used to subtract this daily weather variation effect from ΔLST (Eq. 2), which helps more accurately isolate the impact of anisotropy on LST.

Considering the differences in absolute magnitudes of radiative temperature (measured by the satellites) and air temperature (measured by the weather stations) due to physical mechanisms, as well as in the locations of land and water surface measurements for the two cities, the daily ΔT_{air} variation may just account for a proportion of the daily variation of ΔLST in these cities. Accordingly, we introduce a term, α , to adapt the impact of local weather variation from ΔT_{air} on ΔLST . The new term, $\Delta LST_{\Delta T_{air}}$ in Eq. 3, is defined by subtracting the anomaly of ΔT_{air} from ΔLST with a magnitude adjustment α in a time series. The anomaly of ΔT_{air} is estimated from $\Delta T_{air} - \overline{\Delta T_{air}}$, where $\overline{\Delta T_{air}}$ is the temporal average of ΔT_{air} for the whole time series for each of the four satellite overpasses.

$$\Delta T_{air}(t) = T_{air,land}(t) - T_{air,water}(t) \quad (2)$$

$$\Delta LST_{\Delta T_{air}}(t) = \Delta LST(t) - \alpha \times (\Delta T_{air}(t) - \overline{\Delta T_{air}}) \quad (3)$$

where t is the satellite overpass time.

ΔLST and ΔT_{air} show a strong positive correlation in the 10-year time

series for each satellite overpass (when α equals 0 in Eq. 3, as shown in Fig.
 4). The correlation between $\Delta LST_{\Delta T_{air}}$ (Eq. 3) and ΔT_{air} (or $\Delta T_{air} - \overline{\Delta T_{air}}$,
 where $\overline{\Delta T_{air}}$ is a constant for each satellite overpass) are tested with different
 values of α as shown in Fig. 4. α is determined when $\Delta LST_{\Delta T_{air}}$ (Eq. 3)
 and ΔT_{air} have no significant correlation in a time series. In other words, the
 variation of air temperature is removed from LST, so the variation of weather
 conditions will be reduced in $\Delta LST_{\Delta T_{air}}$. Even though the daily variation
 may be not completely removed, e.g. surface moisture and wind may induce
 different levels of variation for ΔT_{air} and ΔLST , the later analyses based
 on $\Delta LST_{\Delta T_{air}}$ are highly aggregated temporally and spatially leading to less
 impact from daily variation on our results. Accordingly, we set α from 0.8 $\sim$
 1.2 for Chicago, and 0.6 $\sim$ 0.8 for New York City for four satellite overpasses,
 determined when correlation coefficients are close to 0 (shown in Fig 4). The
 resulting $\Delta LST_{\Delta T_{air}}$ allows us to identify the anisotropy attributed to the
 surface properties with minimal influence due to atmospheric effects and
 uneven sampling of weather conditions at different ZAs.

2.2.3. Accounting for the effect of urban surface properties

The angular LST strongly depends on the 3D structures in urban (Voogt,
 2008; Lagouarde et al., 2010) and non-urban areas (Lagouarde et al., 2000;
 Duffour et al., 2015). Particularly in urban areas, radiative transfers, tur-
 bulence intensity, and energy exchanges are governed largely by the spa-
 tial distribution of buildings, their sizes and orientations (Lagouarde et al.,

Figure 4: The Pearson product-moment correlation coefficients between spatially averaged $\Delta LST_{\Delta T_{air}}$ and ΔT_{air} at different α values. The solid dots indicate where there is no significant correlation at a confidence level of 0.95. The vertical lines highlight the α value chosen for the temperature correction in Eq. 3. α is set as 1.2, 0.9, 0.8, and 1.1 for Terra-Day, Aqua-Day, Terra-Night, and Aqua-Night in Chicago, respectively; New York has α values of 0.6 for Terra satellite observations and 0.8 for Aqua satellite observations.

2004; Voogt and Oke, 2003). For example, the Urban Sensor View Model
(Voogt, 2008; Krayenhoff and Voogt, 2016) suggests the surface structure
is one of most substantial contributors to the anisotropy. The aspect ra-
tio (height-to-width ratio, λ_s), complete aspect ratio (complete-to-plan area
ratio, λ_c), and roof-to-plan area ratio (λ_p) are some of the most widely
used urban morphologic parameters in urban atmosphere/climate modeling
(Grimmond and Oke, 1999; Hamdi and Schayes, 2008; Voogt, 2008). These
are also critical for understanding how shaded and sunlit surfaces affect the
anisotropic LST. We calculate these parameters as follows using gridded
building footprint and height data for Chicago and New York:

$$\lambda_c = \frac{A_{roof} + A_{wall} + A_{ground}}{A_{plan}} \quad (4)$$

$$\lambda_p = \frac{A_{roof}}{A_{plan}} \quad (5)$$

$$\lambda_s = \frac{1}{2} \left(\frac{\lambda_c - 1}{1 - \lambda_p} \right) \quad (6)$$

where A_{roof} , A_{wall} , and A_{ground} represent the areas of building roof, wall
and exposed ground; A_{plan} is the total plan area, which is the area of the
grid cell. Eq. 6 for the aspect ratio (λ_s) is from the estimation algo-
rithm used in the Temperatures of Urban Facets in 3-D (TUF-3D) model by
Krayenhoff and Voogt (2007). The buildings are considered to be regularly
shaped with flat roofs.

However, we quantified the anisotropic effects of satellite LST within dif-
ferent groups of urban land use fractions of each pixel rather than the building

365 morphological indicators directly. The primary reason is that detailed build-
 366 ing properties information is not widely available globally or outside of the
 367 administrative boundary (such as the building footprint and height informa-
 368 tion for Chicago and New York), whereas high-resolution land use data are
 369 comparably easier to obtain to estimate the urban land use fraction at the
 370 MODIS LST resolution. Fig. 5 suggests significantly strong positive rela-
 371 tionships between the three urban morphologic indicators and the urban land
 372 use fraction, showing the correlation coefficients higher than 0.95. Although
 373 the variation tends to be larger when the urban land use fraction increases,
 374 and the correlation is nonlinear and varies between the two cities, the general
 375 positive correlation is the same for both cities. For this study, which focuses
 376 on 10-year averages and aggregates results over space, the use of urban land
 377 use fraction to categorize the anisotropic effects on LST into classes is an
 378 appropriate proxy of building properties associated with anthropogenic land
 379 use intensity.

380 2.2.4. Anisotropy indicators and urban heat island curves (UHIC)

In order to quantify how land use intensity will affect the amplitude
 of angular LST anisotropy, the effective thermal anisotropy is introduced
 ($\delta LST_{dir,max-min}$, Eq. 7, Krayenhoff and Voogt (2007)).

$$\delta LST_{dir,max-min} = \max(\Delta LST_{\Delta T_{air}}(\theta)) - \min(\Delta LST_{\Delta T_{air}}(\theta)) \quad (7)$$

381 $\delta LST_{dir,max-min}$ captures the maximum temperature difference among

Figure 5: The aspect ratio (height-to-width ratio, λ_s), the complete aspect ratio (complete-to-plan area ratio, λ_c), and the roof-to-plan area ratio (λ_p) versus the urban land use fraction for Chicago and New York. The solid lines represent the mean of each morphologic parameter in every 10% interval of urban land use fraction (the x-axis indicates the center values of each interval), and the shaded area is one standard deviation from the mean.

various view angles. In this study, the sensor AA is only available for a predefined direction, so we only consider the anisotropy due to sensor ZA (θ) variations. LST anisotropic features can be easily compared among cities through this anisotropy indicator, otherwise the absolute $\Delta LST_{\Delta T_{air}}$ values may vary substantially among different cities depending on the selection of water surfaces, e.g. inland reservoirs, large lakes, or rivers.

Furthermore, we employ the urban heat island curve (UHIC) method (Hu and Brunsell, 2015) to assess the impact of anisotropy LST on SUHI intensity quantification. The UHIC utilizes the comprehensive temperature coverage provided by satellite observations, and can depict the temperature variation for different spatial aggregations of gridded land use data. In this study, we chose the urban land use fraction for each 1 km grid cell as our indicator of anthropogenic land use intensity. The temperatures in different groups of sensor ZAs associated with the urban land use percentages are then categorized within every 5% interval of urban land use. The maximum SUHI within different SZA groups is calculated for quantifying the impact of anisotropy. More details on the UHIC method can be found in Hu and Brunsell (2015).

3. Results

3.1. Angular effects of LST from MODIS

After independently processing each LST image by subtracting the mean water LST and adjusting weather variation from T_{air} accordingly, the entire

dataset of $\Delta LST_{\Delta T_{air}}$ during 10-year May-September is integrated tempo-
rally and categorized into nine urbanization-intensity groups according to
urban land use fractions (shown in Fig. 1). Then, the mean value of each
group in every 5° ZA interval is calculated and the results are shown in Fig.
6. Similar to the findings from Lagouarde et al. (2004, 2012), we observed
a strong anisotropy during the daytime, while the nighttime anisotropy is
smaller. In order to avoid unrepresentative values due to small sample sizes,
Fig. 6 only illustrates the mean temperatures that are statistically meaning-
ful with more than 100 samples. The sensor ZA groups with absolute angles
greater than 62.5° are not included for this reason.

Solar radiation and urban canyon structures are the primary reasons to
explain the day/night contrast of anisotropy over urban areas (Lagouarde et al.,
2010). The azimuthal angular difference between the solar and sensor posi-
tions is typically $45^\circ \pm 15^\circ$ or $135^\circ \mp 15^\circ$ (shown in Fig. 2a). Consequently,
the daytime anisotropy distributions are more likely asymmetric in Fig. 6.
Two "hot spots" (local maximums) can be clearly observed on the curves
for most daytime cases. One occurs likely due to geometric effects when
the sensor and solar ZAs are approximately the same (the grey-shaded areas
in Fig. 6), especially in the groups with higher urban land use intensities.
Although the azimuth viewing directions of sensor and the Sun are not the
same in this case, this hot spot likely results from a higher proportion of
sunlit surfaces being detected by the sensor. The secondary hot spot occurs
mainly during the early afternoon satellite overpass when the sensor ZA is

427 near nadir. The sensor detects the largest proportion of streets and roofs
428 when near nadir; these surfaces have higher surface temperatures compared
429 to walls (Voogt and Oke, 1997; Lagouarde et al., 2004; Hamdi and Schayes,
430 2005; Krayenhoff and Voogt, 2007; Christen et al., 2011). This secondary hot
431 spot has been found in the near-full hemispherical distribution from modeling
432 (Krayenhoff and Voogt, 2016).

433 Moreover, the daytime anisotropy shares a similar pattern among the
434 nine groups of land use intensity (Fig. 6), governed by solar radiation but
435 with a noticeable difference in amplitude (Fig. 7). It is evident that urban
436 canopy structures exert a strong effect on the LST. The maximum effective
437 directional anisotropy reaches approximately 8.8 K (Chicago) and 6.5 K (New
438 York) during afternoon. LST in Chicago has a much higher anisotropy in
439 the most urbanized land use category compared to New York during the
440 afternoon, which is partially due to different urban surface structures and
441 meteorological conditions in the two cities. In the most urbanized group,
442 the more dispersed arrangement of tall buildings in Chicago exhibits larger
443 anisotropy compared to that of the more closely spaced tall building clusters
444 of New York City, in agreement to model results using simple geometries by
445 Krayenhoff and Voogt (2016). Moreover, smaller air temperature differences
446 among different urban land use types due to New York’s ocean-influenced
447 climate also help decrease the anisotropy (Voogt, 2008). The role of angular
448 LST over non-urban areas is also important and dependent on land use and
449 associated vegetation canopy structure (Paw U et al., 1989; Li et al., 2004;

450 Lagouarde et al., 2000, 2014). For example, there are differences in the am-
451 plitude of daytime anisotropy in crop-dominated Chicago rural areas versus
452 forest-dominated New York rural areas.

453 The nighttime anisotropy is controlled by the heat loss differences due to
454 sky view factors that allow a surface to cool radiatively, as well as the various
455 thermal inertia of urban surface materials, and anthropogenic heat contri-
456 butions from in-building heating or cooling activities. The nighttime tem-
457 perature is comparatively symmetric with respect to the sensor ZA. Slightly
458 higher temperatures occur for the largest sensor ZAs, related to the higher
459 proportion of walls that are detected at large view angles. Walls are generally
460 warmer than roofs and streets at night due to differential thermal proper-
461 ties and exposure (Oke et al., 1991; Monaghan et al., 2014; Lagouarde et al.,
462 2012). However, the difference between LSTs for eastward versus westward
463 facing overpasses (due to west-facing walls receiving more afternoon sunlight;
464 e.g., Lagouarde et al. (2012)) is negligible in our results, perhaps because this
465 effect diminishes rapidly after sunset and the evening overpass does not oc-
466 cur until approximately 22:00 local solar time. Comparing the two cities, at
467 nighttime the differences of effective anisotropy among land use intensities
468 largely disappear for Chicago, whereas the anisotropic effects are distinctly
469 higher for urban versus rural land use intensities in New York. This may be
470 related to the higher building density and aspect ratio in New York, which
471 decreases energy loss rates in the urban canyon (Oke, 1982; Svensson, 2004).

Figure 6: The mean $\Delta LST_{\Delta T_{air}}$ distribution (left-y-axis) versus sensor ZA (θ , x-axis with a 5° interval) at four satellite overpass times for Chicago (a) and New York City (b). The colored solid lines represent the mean $\Delta LST_{\Delta T_{air}}(\theta)$ grouped into nine urban land use fraction intervals. The corresponding colored bars (right-y-axis) indicate the number of pixels in each urban land use fraction group. The shaded-grey vertical strips show the frequency of solar ZAs from high (darker-grey) to low (lighter-grey). The dashed vertical lines highlight the position of the groups with the smallest sensor ZAs (near the nadir).

Figure 7: The effective directional anisotropy ($\delta LST_{dir,max-min}$, see Eq. 7) at four satellite overpass times for Chicago and New York, estimated from Fig. 6. The colored solid lines represent $\delta LST_{dir,max-min}$ grouped by urban land use percentages.

3.2. Impact of anisotropic LST on SUHI quantification

The anisotropy of LST becomes critical and potentially problematic when applying satellite-retrieved LST for SUHI studies and other related urban surface process research. In order to assess the influence of anisotropy on the SUHI quantification, the UHIC based on $\Delta LST_{\Delta T_{air}}$ is illustrated in Fig. 8. The temperatures are grouped into six sensor ZA groups ranging from -65° to $+65^\circ$. An additional group with the sensor ZAs near nadir ($[-10,10]$) is also shown. It is noteworthy that the daytime temperatures in Chicago are slightly lower for the 95 ~ 100% urban category compared to the 90 ~ 95% category because the most urbanized areas are situated along the coast of Lake Michigan, where there is a moderating influence from the

Figure 8: The urban heat island curves (UHICs) estimated from $\Delta LST_{\Delta T_{air}}$ for the four satellite overpass times, categorized by 6+1 sensor ZA (SZA) groups. The green-colored lines indicate negative ZAs from which the sensor primarily views west-facing objects, whereas the red-colored lines indicate positive ZAs from which the sensor primarily views east-facing objects. The additional group distinguished by dark-grey dashed lines illustrates the temperature distribution observed from near nadir.

483 water. However, the contrast is not as obvious in New York, possibly because
 484 water bodies influence a broader spectrum of land use intensity categories.
 485 There are substantial differences among UHICs with various sensor ZAs. The
 486 daytime UHICs have higher temperatures for smaller view angles (i.e., nearer
 487 to nadir). The objects being viewed during daytime from similar sensor ZAs,
 488 but different directions (eastward or westward) differ between morning versus
 489 afternoon based on the direction receiving the most sunlight. At nighttime,
 490 smaller variations among the UHICs as a function of sensor ZAs are observed,
 491 and the results vary by city due to the unique climatic and urban morphology
 492 factors of each, as discussed previously.

493 Fig. 9 presents the maximum SUHI intensity among groups, as estimated

494 by the difference between the maximum and minimum temperature on each
 495 UHIC from Fig. 8. The highest temperatures occur in highly urbanized
 496 regions while the lowest temperatures occur in the most vegetated areas. The
 497 results demonstrate that when angular LST is used to quantify the SUHI,
 498 an uncertainty of up to 2.3 K can be introduced from the anisotropy. The
 499 daytime variation of SUHI is about 2 K, with little difference between Terra
 500 and Aqua overpasses. The nighttime SUHI differences are smaller (about 1 K
 501 in Chicago and 0.4 K in New York). It is noteworthy that the results in Fig. 9
 502 only demonstrate the anisotropic SUHI magnitude using the UHIC method;
 503 for other SUHI indicators (e.g., based on administrative boundaries), the
 504 magnitude of the anisotropic influence may differ.

505 4. Discussion

506 We performed a comprehensive analysis of angular LST from 10-years
 507 of MODIS LST data over two large U.S. cities. The study has a number
 508 of possible limitations. First, this methodology is applicable only to cities
 509 near relatively large and deep water bodies with station observations, which
 510 enables calculation of atmospheric attenuation and weather impacts on an-
 511 gular LSTs. For those cities far away from large water bodies, other reference
 512 locations that feature isotropic properties that are similar to water surfaces
 513 may be used. The atmospheric correction of MODIS LST retrievals is sub-
 514 ject to uncertainty, and it may be possible to minimize atmospheric impacts
 515 through other methods based on the one presented here. Such methodologies

Figure 9: The maximum temperature difference from the UHICs in Fig. 8 for different sensor zenith angles (SZA).

would require further assessment. Second, the effects of differential angular emissivity on LST are not accounted for. Finally, the analyses is based on the statistical distributions from satellite data aggregated over space and time, therefore it does not address the problem of quantifying the instantaneous thermal anisotropy. Each satellite pixel has unique solar and sensor relative positions at each overpass, and the temperature varies in time, however our results represent the general characteristics of LST anisotropy at the metropolitan scale.

The results are comparable to previous studies based on observations of anisotropy from airborne sensors for both day and night (Lagouarde et al., 2004; Lagouarde and Irvine, 2008; Lagouarde et al., 2010, 2012). Similar to our results, those studies demonstrated that angular LST is highly dependent on urban morphology, including building geometry, road and building orientation, and urban canyon materials and structure (Lagouarde et al., 2004; Voogt and Oke, 2003; Voogt, 2008). Moreover, they showed that the sensor and solar relative positions introduce additional complexity to the angular variation of LST during the daytime, resulting in asymmetric temperature features for different sensor ZAs (Lagouarde et al., 2004; Lagouarde and Irvine, 2008; Lagouarde et al., 2010). For nighttime, we found that summer effective directional anisotropies are about 1-2 K higher than what was observed by Lagouarde et al. (2012). Different seasons (their results were for fall and winter) and diverse urban surface structures of urban areas may contribute to the higher nighttime effects.

539 We applied a simplified and integrated indicator, urban land use fraction,
540 to stratify the different intensities of anisotropy according to variations in sur-
541 face properties. The results suggest that this approach provides a reasonable
542 means to distinguish transitions in morphology between rural, suburban and
543 urban areas within a given city (Fig. 5). While there are other ways to cate-
544 gorize intra-urban land use for climate variability studies (Stewart and Oke,
545 2012), we employ urban land use fraction because of its simplicity to apply
546 for other cities: high resolution satellite-retrieved land use data is available
547 globally and updated frequently. This is an important consideration because
548 the relationship between urban land use fraction and anisotropy is likely
549 unique for each city, but that’s partly because land use isn’t the direct driv-
550 ing force for anisotropy, e.g. Krayenhoff and Voogt (2016) showed the linkage
551 of structural parameters to anisotropy.

552 Angular temperature measurements from MODIS are not “correct” or
553 “incorrect” strictly speaking, because they represent “real” temperatures
554 observed from sensors in different directions. However, the analyses de-
555 rived from angular LST may cause biased results due to angular effects.
556 While this paper quantifies the impact of anisotropy on LST estimates from
557 MODIS, at this time MODIS LST data cannot be directly adjusted to ac-
558 count for anisotropy due to the highly spatiotemporally aggregated estimate,
559 and further assessment is required for the possible application for this pur-
560 pose. An accurate adjustment would need to be applied to each pixel of
561 each overpass, to account for the unique anisotropic effects for that pixel.

562 It is therefore worth considering how we might be able to reduce the dif-
563 ferential (in space and time) impacts of anisotropy. Restricting the sensor
564 view angles within a narrow range (often nadir) is one means to minimize
565 differences in LST due to angular effects, which has a long time in practice
566 (Roth et al., 1989; Hu et al., 2014; Monaghan et al., 2014). Another possible
567 means is by temporally compositing images. Temporally composited LSTs
568 are widely used for large-scale or/and long-term analyses (Clinton and Gong,
569 2013; Schwarz et al., 2011; Schwarz and Manceur, 2014). Compositing is a
570 practical approach to reduce the impact of missing LST data due to clouds,
571 and it is also a possible way to mitigate differential LST anisotropy. The tem-
572 poral aggregation does not “cancel” anisotropic features, but the composites
573 provide LST values comprised of a representative sample of various angular
574 effects. This possibly make two or more composite images comparable across
575 time. However, the anisotropic feature is not symmetric at different ZA
576 during the daytime. For example, the “hot-spot” effects will cause different
577 temperatures from opposite directions with similar sensor ZAs. Therefore,
578 the knowledge of anisotropy distribution shape for a given time and surface
579 type as a function of ZA is critical if only a few images are available, be-
580 cause it potentially allows for strategic selection of other view directions to
581 reduce the anisotropy. Another possible compositing approach is to more
582 completely sample the possible ZAs images to construct ‘complete’ urban
583 surface temperature (Voogt and Oke, 1997) by normalizing the results from
584 the shape of anisotropic distribution for view angles. However, in cloudy

regions compositing may not be an effective technique for comparing LST from urban and rural pixels across space because heterogeneous cloud distributions necessitate that different images will comprise the membership of rural and urban pixels in the composite image (Hu and Brunsell, 2013).

5. Conclusions

Satellite-retrieved LST anisotropy was quantified at a metropolitan scale for Chicago and New York using MODIS LST products during the warm months (May-September) for a 10-year period. We proposed a series of adjustments to satellite-retrieved LSTs in order to isolate the anisotropic features from the possible influences of atmospheric attenuation and daily weather variations. The results demonstrate a strong day/night contrast of thermal anisotropy over cities. The daytime effective thermal anisotropy can reach up to 9 K for the most urbanized areas, while the nighttime anisotropic effects are weaker but still discernible. These results are in line with other estimates derived from airborne observations and modeling of urban areas. Given the limitation of the satellite overpass time and azimuthal sampling ability from satellite observations, we observed two anisotropic “hot spot” features during daytime: one corresponds to the sensor-sun geometric effect with a higher proportion of sunlit surface components been seen a given view configuration, and the other occurs when sensor zenith angles are near nadir in the afternoon. Differences in anisotropic features between Chicago and New York emphasize the importance of unique urban morphological features

607 and local geographical controls on the city climate. Hence, the complexity
608 and uniqueness of urban areas globally requires substantial effort to under-
609 stand the anisotropy of LST for given regions. This study is the first of its
610 kind to directly evaluate the influence of anisotropy on satellite-based SUHI
611 measurements, demonstrating that anisotropic effects can modify the SUHI
612 as measured with MODIS LST by 2.3 K, which is about 25-50% of the total
613 magnitude of the SUHI depending on the season and macro-climate setting
614 of the city (Imhoff et al., 2010; Clinton and Gong, 2013).

615 In the future we hope to address some methodological limitations of this
616 work by exploring the use of indicators other than urban land use fraction
617 to distinguish anisotropy, by accounting for emissivity effects on LST, and
618 by modifying our methodology and extending its application to non-coastal
619 cities. In addition to methodological limitations, our results face many un-
620 certainties linked to aggregating the results in space and time. We need
621 to validate our estimates of anisotropic variability with airborne observa-
622 tions or other satellite data. Sensor-view models can simulate anisotropic
623 features at finer time scales, and simultaneously map the anisotropy for all
624 zenith and azimuth angles within a hemispheric field of view, which is a
625 possible tool for the anisotropy adjustment for LST products in the future.
626 However, current modeling techniques face a number of challenges, such as
627 unavailability of facet temperatures (Voogt, 2008), unrepresentative canyon
628 structures (Voogt, 2008; Lagouarde and Irvine, 2008; Lagouarde et al., 2010,
629 2012), poorly understood vegetation effects (Krayenhoff and Voogt, 2007;

630 Voogt, 2008), the uncertainty of emissivity (Voogt, 2008), and the impact
631 of regional and mesoscale weather variations (Krayenhoff and Voogt, 2007).
632 Combining our methodology with modeling approaches may be a promis-
633 ing solution for future anisotropy studies. The ultimate goal is to develop a
634 practical model that is able to adjust temperature from off-nadir to nadir, or
635 vice versa, which will be able to extend the application of satellite-retrieved
636 angular LST to urban areas globally.

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643 **References**

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