Application of airborne remote sensing data on mapping local climate zones: cases of three metropolitan areas of Texas, U.S

Abstract:

Urban and vegetation morphology profiles are important factors in local climate-related studies, but they are not as easily measured as land cover information to study urban landscape at metropolitan area. This study aims to develop a GIS-based Local Climate Zones (LCZs) mapping scheme to map and compare the LCZs for three major metropolises in Texas: Dallas-Fort Worth (DFW), Austin, and San Antonio. Based on an analysis of the land cover and urban morphology, variables including land cover, height of roughness elements, building surface fraction, pervious surface fraction (PSF), and land use planning codes were generated and selected as LCZs classification properties. Then we designed the LCZs mapping scheme with decision-making algorithm was built for LCZs mapping. The key findings of LCZs of our study areas are that: 1) Most of the urbanized area are categorized into LCZ “open” types (characterized by building surface fraction of 15–40% and pervious surface fraction of 30–60%) for all three metropolitan areas with different proportions and spatial diversity; 2) LCZ D Low plants is dominant in areas surrounding DFW, while LCZ A Dense trees and LCZ D Low plants are dominant in Austin and San Antonio with clear regional contrast; 3) LCZs maps are in accordance with the underlying regional environment of the areas. Our study indicated that LiDAR-derived products can support LCZs mapping to identify urban morphological information and standardize the mapping scheme for further comparative studies of metropolitan areas.

Keywords: Local climate zone; urban morphology; urban heat island; LiDAR; Texas

1. Introduction

Currently, more than half the world's population lives in cities, and this proportion is expected to reach 66% by the year 2050 (United Nations, 2014). With urban population growth, the artificial land expands to the surrounding rural land area (Zhao, Jensen, & Zhan, 2017). Urban landscape is characterized by substantial spatial heterogeneity—due in large part to differences

in the configuration and use of these built landscapes. Crucially, variability in urban landscape is linked to the heterogeneity in storage and emittance of the surface energy, wind turbulence, as well as anthropogenic metabolism emission, among other phenomena (Bowler, Buyung-Ali, Knight, & Pullin, 2010; Hart & Sailor, 2008; Mirzaei & Haghighat, 2010). One important ecological consequence of urbanization that relates to this observation is the urban heat island (UHI), which has continuously drawn attention since the first description (Fu & Weng, 2016; Howard, 1818; Imhoff, Zhang, Wolfe, & Bounoua, 2010; Mirzaei, 2015; Oke, 1976; Zhao, Jensen, Weng, & Weaver, 2018). UHI, defined as a city that is warmer than its countryside, generally includes two types: atmospheric UHI (AUHI) and surface UHI (SUHI). AUHI study usually relies on in-situ and/or field measurements at isolated stations and the comparison between urbanized areas and sounding areas, which is also called traditional UHI study. Voogt and Oke (2003) proposed the term SUHI to refer to UHI that is measured with remotely sensed LST data. However, discrete categorization and definitions of urban and rural lands adds uncertainty to traditional UHI measurement. Moreover, individual cities are exposed to diverse local and synoptic factors, which makes UHI studies complex and specific to localities, and therefore difficult for comparison (Ng, 2015). The diversity of size, shape, height, composition, and spatial arrangement of urban canopy components makes it even harder to define a surface datum for atmospheric UHI measurements and urban gradients still cannot sufficiently describe the site topography and local environment (Weng, 2009). That being said, despite the ample attention paid to the UHI over the past two decades and the long history of urban climatology

with site-based measurement, it remains difficult for researchers to obtain the spatial variability of UHI.

To address this issue, the “local climate zone” (LCZ) classification scheme was designed in 2012 to describe urban landscapes from the aspect of the thermal climate characteristics (Stewart & Oke, 2012). Stewart and Oke (2012) defined LCZs as “regions of uniform land cover, surface structure, construction material, and human activity that span hundreds of meters to several kilometers on a horizontal scale” (p. 1884). LCZs mapping aims to characterize the morphology for urban places and locate and build weather stations to capture the heterogeneous nature of urban climate processes. Due to this standardized classification, the LCZs concept may be applied across the landscape in different regions of the world for the comparison of urban climate. Additionally, LCZs mapping can significantly broaden our understanding of UHI mechanisms and mitigation by providing a reasonable sampling framework and additional underlying details for surface-energy balance modeling (Alexander, Mills, & Fealy, 2015) as well as urban climate models (Geletič, Lehnert, Savić, & Milošević, 2018; Martilli, Brousse, & Ching, 2016).

The 17 standard LCZ classes (see Table B1) are determined by their surface characteristics, including: composition (building/tree), structure (permeability), fabric (albedo, thermal admittance), and metabolism (e.g., Table 2 on p. 1885 and Table 3 on p. 1886 of (Stewart &

Oke, 2012)). Unique combinations of these properties provide a distinctive thermal regime for each LCZ (Geletič, Lehnert, & Dobrovolný, 2016; Stewart & Oke, 2012). Researchers have conducted several case studies in cities worldwide to validate the practicability of mapping LCZs. For example, in an effort to build a worldwide LCZs database for UHI-related studies, the WUDAPT (e.g., World Urban Database and Access Portal Tools) project has conducted several studies with free software and data. According to the delineation provided by Geletič and Lehnert (2016) and (Zheng et al., 2017), there are four main methods of LCZs mapping in terms of the data sources and analytical techniques: manual (Leconte, Bouyer, Claverie, & Pétrissans, 2015), remote sensing (Bechtel & Daneke, 2012), GIS-based (Geletič et al., 2016) and combined method (Unger, Lelovics, & Gál, 2014).

To date, there is still no standard or optimal method for LCZs mapping. Among all the published case studies by the WUDAPT initiative and other studies, satellite imagery has provided the main data source to derive surface properties suggested in Table 1, largely because of the time and accuracy limitations of field measurements of surface characteristics used for LCZs mapping (Ng, 2015). Satellite image-based technology has been extensively used for LCZs mapping. Although the WUDAPT method and other straightforward remote sensing classifications provide a fast way to obtain urban morphology information for LCZs mapping (Bechtel & Daneke, 2012; Bechtel, See, Mills, & Foley, 2016; Xu, Ren, Cai, Edward, & Wu, 2017), studies have also indicated non-satisfactory results with the WUDAPT method for high-

density cities. For example, Xu, Ren, Cai, and Wang (2017) evaluated the WUDAPT mapping procedure by Landsat data with remote sensing classification methods (e.g., neural network, support vector machine, maximum likelihood, random forest tree, etc.), and the experimental results showed that the accuracy merely ranged from 59% to 64% in Guangzhou, China.

Some researchers have presented findings using a GIS-based method, whereby a decision-making algorithm delineates LCZs according to thresholds placed on specific geometric and surface cover properties based on the LCZs concept. These studies suggest some advantages of GIS-based methods relative to remote sensing methods, including comprehensiveness of input factors, classification accuracy, standardization, and objectification of the classification procedures (Geletič & Lehnert, 2016; Unger et al., 2014; Wang, Ren, Xu, Lau, & Shi, 2017; Zheng et al., 2017). Aside from the mapping methods, more accurate delineation of LCZ classes requires supplementary information about building and vegetation structure, considering their indispensable roles in the LCZs definitions (Stewart & Oke, 2012). Studies have demonstrated lower-quality LCZs classification results with limited information on urban structure (except the study by Geletič and Lehnert (2016)). For example, LCZs mapping in Guangzhou reached around 60% overall prediction accuracy using the WUDAPT method (Xu, Ren, Cai, Edward, et al., 2017), whereas minimum standard accuracy for LULC investigation is 85% specified by the United States Geological Survey (USGS) classification scheme (Anderson, 1976).

Light detection and ranging (LiDAR) data provide a viable source with which to acquire information on structural characteristics of surface features. However, while LiDAR data have been employed to detect vegetation structure and digitize urban 3D maps, their application for LCZs mapping has rarely been studied, with one published case study at a site of Sydney, Australia (Koc, Osmond, Peters, & Irger, 2017). They proved that LiDAR data are advantageous to build a replicable workflow for LCZs mapping. To assess the utility of LiDAR datasets to contribute to LCZs classification, this study presents a LCZs mapping scheme based on LiDAR datasets and other free data for three major metropolitans in Texas, USA: Dallas-Fort Worth (DFW), Austin, and San Antonio. The LCZs classifications were then mapped and compared in an effort to provide a standardized urban morphology classification for future studies of surface temperature variability and UHI effects.

2. Materials and Methods

2.1. Study area

DFW, Austin, and San Antonio were selected for our LCZs mapping because of their hot and humid summers and population concentration (Fig. 1 and Table 1). However, there have been few UHI studies within these metropolitan areas, and comparisons of UHI results are difficult because of variations in mapping units and land cover characteristics. Located in North Texas, Dallas and nearby Fort Worth were developed as a result of the construction of major railroad lines through the area. Austin, the capital city of Texas, connects the main metropolitan

areas (including Houston) of Texas with each other. San Antonio is situated between the Edwards Plateau and the Gulf Coastal Plains at central Texas.

Figure 1. Location of the three metropolitan study areas in Texas, USA.

Table 1. Population statistics of the study areas from the U.S. Census Bureau.

	Population, Census, April 1, 2010	Land area (square miles), 2010	Estimated population (July 1, 2015)	Housing units (July 1, 2015)	Estimated population change (2010- 2015, %)
Texas Total	25,145,561	261,231.71	27,469,114	10,587,752	9.2
San Antonio	1,327,407	460.93	1,469,845	524,246	10.7
Dallas	1,197,816	340.52	1,300,092	516,639	8.5
Austin	790,390	297.90	931,830	354,241	14.8
Fort Worth	741,206	339.82	833,319	291,086	12.2

2.2. LCZs mapping scheme

The overall LCZs decision-mapping classification was mainly based on the LCZs definition. As showed by Fig. 2, the delineation of LCZs is based on the major properties and the thresholds.

Figure 2. Overall LCZs mapping scheme.

2.2.1. LCZs preliminary classification by surface cover properties

Considering that the original proposal of LCZs mapping is to investigate UHI, individual LCZs are supposed to be constant throughout the year compared to the seasonal variation of the surface and air temperature. LCZs classes can be categorized as two types: “built-up” and “natural”. Hence, a preliminary classification was performed with the aid of 30×30 m resolution 2011 National Land Cover Database (NLCD), the thematic accuracy of which has been established in the literature (Wickham et al., 2017). First, a customized Arcpy Package was designed by the authors to reclassify the surface cover properties from NLCD into LCZs groups or LCZs in the ArcGIS environment. Some land cover classes were directly classified or merged into individual categories of LCZs, while others were classified into LCZ groups (LCZs 1–10 “built-up” types category or LCZ E Bare rock or paved) (Table 2).

Table 2. The look-up table of LCZs pre-classification by NLCD classes.

NLCD code	NLCD class name	LCZ code	LCZ class name
11	Open Water	LCZ G	Water
21	Developed, Open Space		
22	Developed, Low Intensity	LCZs 1-10	“built-up” types
23	Developed, Medium Intensity	LCZ E	Bare rock or paved
24	Developed, High Intensity		
31	Barren land	LCZ E	Bare rock or paved

		LCZ F	Bare soil or sand
41	Deciduous Forest		
42	Evergreen Forest	LCZ A	Dense trees
43	Mixed Forest	LCZ B	Scattered trees
52	Shrub/Scrub	LCZ C	Bush, scrub
71	Grass/Herbaceous		
81	Pasture/Hey		
82	Cultivated Crops	LCZ D	Low plants
90	Woody Wetland		
95	Emergent Herbaceous Wetlands		

2.2.2. LiDAR data acquisition and processing

LiDAR datasets were obtained from the Texas Natural Resources Information System (TNRIS), downloaded manually per tile online, or transferred directly from a hard drive. They were derived from different projects acquired between 2007 and 2013 (Fig. 3).

Figure 3. LiDAR dataset coverages and project names for DEM production and building footprint extraction per metropolitan area.

All LiDAR datasets were delivered with ground points classified. Specific metadata regarding acquisition parameters and subsequent project deliverables are provided in Table B2 with point density, horizontal and vertical accuracies, datum and projection information. Given the variable point density of the different LiDAR acquisitions, digital terrain models (DTMs) with $3\text{ m} \times 3\text{ m}$ and $1\text{ m} \times 1\text{ m}$ resolution were generated for the three study areas using the “LAS Dataset to Raster” tool in ArcGIS 10.5 Conversion Toolbox and “Average Cell Assignment Type” using ground points only. Similarly, the digital surface models (DSMs) were generated with $3\text{ m} \times 3\text{ m}$ and $1\text{ m} \times 1\text{ m}$ resolution and “Maximum Cell Assignment Type” to represent the surface combined ground, built-up, vegetation, etc. DTMs from different sources were merged together after being re-projected to same spatial reference (NAD UTM Zone 14 N) for the three study areas. The same procedures were applied to the DSMs. Then, normalized digital surface models (nDSMs) with $3\text{ m} \times 3\text{ m}$ and $1\text{ m} \times 1\text{ m}$ resolutions were built by subtracting the DTMs from the DSMs. Fig. A1 shows the spatial pattern of nDSMs for the study areas and Fig. A2 provides a detailed illustration of nDSMs for a selected area in San Antonio.

Building footprints are very important to distinguish individual LCZs among the LCZs 1–10 “built-up” types category, in terms of building height and fraction. The available datasets from

the different sources were first checked to avoid the extra work of building footprints extraction. Building footprints of the central and south parts of Austin were created by the City of Austin Enterprise Geospatial Services. They were digitized mainly from 2012/2013 orthoimagery and made available through the official website of the City of Austin, but they did not cover the entire metropolitan area. Similarly, building footprints for the downtown area of Dallas were digitized from 2009 aerial photography and available through “City of Dallas City GIS Services” website, but the coverage extent was very small and not up-to-date.

Here, the buildings footprint for the three metropolitan areas was extracted using the LiDAR mass point clouds. For several projects (e.g., CAPCOG 2007 ” , “CAPCOG 2008 ” , and “FEMA 2011 Comal, Guadalupe”), buildings had not yet been classified from the mass point clouds (Table B2). Also, even though the LiDAR point clouds were already pre-classified for buildings in the StratMap 2010 Bexar LiDAR dataset in San Antonio, we found that most that the data had a high omission error in this project. Hence, building classification was still necessary for this project. The buildings from point clouds for Austin and San Antonio were first classified with point cloud task tool “Planar Point Filter”, in which the parameters were set after several trial and error runs (Table 3). Subsequently, together with the LiDAR projects (e.g., projects in DFW) in which buildings had already been classified, the building outlines were extracted as shapefile polygons from LiDAR data in LP360, a software for the LiDAR data

management and post-processing, with the automated point cloud task tool “Point Group Tracing and Squaring” for the developed areas.

Table 3. Parameter settings for building classification and extraction in LP360 software.

Parameters	Value	Unit
Building Filter: Planar Point Filter		
Minimum and Maximum Building Height	8/6000	Feet
N Threshold	0.40	Feet
Minimum and Maximum Slope	0/45	Degree
Minimum Plane Edge	10	Feet
Maximum Grow Window Area	5000	Square Feet
Plane Fit	0.2	NA
Building Extractor: Point Group Tracing and Squaring		
Max Planar Patch Area	5000	Square Feet
Grow Window Size	5.5	Feet
Trace Window Size	12	Feet
Minimum Area	100	Square Feet
Regularization Angle Degrees	30	Degree

Note: “N Threshold” refers to the distance to consider a point as part of the plane. “Plane Fit” refers to the tightness of the fit of the planar surface.

To assess the building extraction performance, high-resolution 30-cm imagery provided by ERSI ArcGIS was chosen as a base map and overlain by the building points. The result showed that numerous trees were misclassified as buildings, especially in northern Austin and northern San Antonio (Figure 4). Additionally, the buildings points were not fully classified where the buildings were under trees in some mixed development/vegetated areas. From the LCZs definition, single or scattered buildings in undeveloped areas or highly vegetated areas (e.g., a single-family house located in NLCD classes 31-95, and refer to Figure 2 for NLCD distribution for the study areas) were excluded from potential classification as LCZs 1-10 (Table 2). Therefore, to avoid this classification error due to the limitation of the algorithm in software and

insufficient data points due to tree canopy, the buildings located in developed land areas (NLCD 21-24) were only considered and extracted in the subsequent building extraction step.

Figure 4. Errors of building classification for an area in northern San Antonio. Red outlines demonstrate algorithm identification of buildings, while blue circle indicates errors of commission.

To further improve the accuracy of the buildings extraction steps detailed above, we manually interpreted and deleted erroneous building outlines with the aid of high-resolution historical images from Google Earth and base maps in ArcGIS, as well as the above-mentioned building footprints for parts of Dallas and Austin. The algorithm also identified elevated highways and major roads as buildings, and the large extent of the study areas makes it time-intensive to drop them off manually. Considering that the aim of building footprints is to calculate the buildings surface fraction, while the material and shape of these man-made above

ground properties makes them meet the general concept of “buildings”, we did not delete these small proportion of properties from the building footprints.

2.3.2. LCZs mapping and properties generation

Using the reclassified NLCD and LiDAR-derived datasets, seven geometric and surface cover properties (provided in Table B1) were calculated. The range of values for each of property had already been provided by the LCZs definition. We first test whether the codetermined threshold of seven properties could be used directly for LCZs mapping with a fraction of our study area using the “knowledge-based classification” tool in ERDAS IMAGINE 2015. It demonstrated that the definition provide by Stewart and Oke (2012) (e.g., Table 3 on p. 1886) cannot be directly used for LCZs classification, because the thresholds combination of all the properties can lead to a situation in which a substantially redundant area will not belong to any LCZ. A similar issue was also identified in other GIS-based LCZs mapping studies (Geletič & Lehnert, 2016; Zheng et al., 2017). Published case studies confirmed that not all features defined in the LCZs concept are equally important for LCZs mapping (Bechtel et al., 2015), and that not all features can be included in a GIS-based LCZs delineation algorithm (Geletič et al., 2016). According to the analysis by Bechtel et al. (2015), the height of roughness is the most important characteristic of the urban structure while the pervious surface fraction (PSF) is important to represent urban fabric and cover. We referred to recent publications and determined three properties which had been most frequently used for LCZs mapping: height of roughness

(Geletič & Lehnert, 2016; Koc et al., 2017; Unger et al., 2014; Wang et al., 2017; Zheng et al., 2017), building surface fraction (BSF) (Geletič & Lehnert, 2016; Koc et al., 2017; Unger et al., 2014; Wang et al., 2017; Zheng et al., 2017), and pervious surface fraction (PSF) (Geletič & Lehnert, 2016; Koc et al., 2017; Unger et al., 2014; Zheng et al., 2017). Because the combination of PSF, BSF and of Impervious Surface Fraction (ISF) equals to one, which would be a data redundancy issue, the ISF was not included.

The height of roughness elements was considered as the principal properties for LCZs mapping after the pre-classification from NLCD. The height of roughness elements refers to the geometric average of building heights (LCZs 1–10) and tree/plant heights (LCZs A–F). The absolute height of surface objects (e.g., built-up, vegetation, etc.) was calculated based on the nDSMs to extract height of roughness, which was used to subdivide the LCZ 1–10 “built-up” types into three groups (e.g., LCZs 1 and 4 “high-rise”, LCZs 2 and 5 “mid-rise”, as well as LCZs 3, 6, 7, 8 “low-rise” and LCZ 9 Sparsely built) and extract the LCZ D Low plants from the LCZ “natural” types (Fig. 5). BSF refers to the ratio of building plan area to total plan area. The average building surface fraction was calculated as the proportion of building footprints in a 30×30 m pixel area. PSF was calculated as the opposite proportion of ISF, gathered from the 2011 NLCD.

Furthermore, due to the lack of specific information, thermal, radiative, and metabolic properties, which are important to determine a certain class (e.g, LCZ 10 Heavy industry), we checked the City GIS Services websites of the related study areas (e.g. (City of Dallas City GIS Services)), and gathered the city land use planning datasets for recent years. The heavy industry areas were extracted and mapped to LCZ 10 Heavy industry. Together with the height of roughness, those variables delineate the grouped LCZs in the last step according to Table B1.

Sky view factor (SVF), Aspect ratio (H/W), and terrain roughness classes are also defined with the specific threshold for LCZs identification by Stewart and Oke (2012). The spatial variation of SVF is related to the shape and distribution of the ground properties (e.g., trees, buildings, etc.). In this study, the nDSMs with $3\text{ m} \times 3\text{ m}$ resolution was used to calculate SVF using the open source Relief Visualization Toolbox (Relief Visualization Toolbox, 2018). The $3\text{ m} \times 3\text{ m}$ resolution was chosen mainly because of the capability of the tool, and the $3\text{ m} \times 3\text{ m}$ resolution SVF meets our accuracy requirement. Aspect ratio (H/W) refers to the mean height-to-width ratio of street canyons (LCZs 1–7), building spacing (LCZs 8–10), and tree spacing (LCZs A–G). Due to the variation of the city architecture and building geometry, there is no standardized method for calculating aspect ratio, especially for LCZ mapping (Houet & Pigeon, 2011; Zheng et al., 2017). For this study, the maximum height in a 30×30 pixel area based on nDSMs was calculated. Areas with height lower than 0.5 m were assumed to be ground, and the average width of the ground surface in a 30×30 pixel area was calculated based on nDSMs

dataset with $3\text{ m} \times 3\text{ m}$ resolution. Then, the aspect ratio map (maximum height/average width of the ground surface) was calculated as a property for LCZs mapping evaluation according to the LCZs definition. The Davenport roughness classification method has been adopted as the terrain roughness classes for LCZs definition (Davenport, Grimmond, Oke, & Wieringa, 2000; Stewart & Oke, 2012). The values of roughness length were grouped into eight classes of roughness. The roughness classes with this method was defined based on our current database of NLCD and nDSM. Due to the complementarity of ISF and PSF from our data sources, PSF was abandoned for LCZs evaluation.

2.3. Data derivation and preprocessing for LCZs mapping

Figure 2. Land use and land cover distributions of three metropolitan areas derived from NLCD 2011.

2.3.1. Determination of LCZs mapping scale

It was necessary to set a scale for different properties calculations, and the subsequent aggregation to delineate individual LCZs in the final step. The NLCD with 30×30 m resolution was our original data source for LCZs preliminary classification. Meanwhile, the definition of LCZs mentioned uniform region spans “hundreds of meters to several kilometers on a horizontal scale” to ensure the homogeneity of the zones. In climatology, this is often referred to as a scale between micro and meso-scales (Bechtel et al., 2015). This broad range of scale definition allows us to customize the scales for the derivation of properties to map LCZs according to the data sources and urban characteristics. However, it is certain that the smallest unit of LCZs should be a homogenous area in terms of the surface conditions related to the local climate formulation, including building structure, vegetation types, etc.

There is more morphological variation for high density building areas within a certain distance than other areas in the city environment (Zheng et al., 2017). In this study, three sites with the same area located at the most intensely developed land cover area were selected to test the spatial dependency characteristics of the building structure to objectively identify the LCZ mapping scale. We further checked the parameters of the variogram models to get the best fit with the aid of the Geostatistical toolset in ArcGIS 10.5 software.

2.4. Scale selections for GIS-based LCZs mapping

Considering the role of the height of roughness in the overall urban morphology and urban structure, significantly affecting local climate, the major ranges of variograms for building

heights were compared to explore the LCZs mapping scale (Figure 6). By performing an ordinary prediction, the Gaussian process regression was used to fit the experimental variogram to obtain optimized parameters. The variogram shows that the semivariance of the height of buildings increases as the distance of the building increase, especially for San Antonio, and then stays in the sill when the distance reaches to certain extent (e.g., the range of the variogram) (162.87 m, 193.41 m, and 139.18 m for DFW, Austin, and San Antonio, respectively). Hence, the scale of the LCZs mapping should be higher than the maximum of the ranges of the variograms of building heights for the selected areas to ensure homogenous climate zones in terms of the urban morphology.

Additionally, it was also necessary to set a common scale for various parameter calculations to further identify possible LCZs. The maximum resolution of our data sources for LCZs mapping is 30 m (e.g., NLCD). Here, the spatial resolution of 90 m was considered for LCZs parameters generation. Subsequently, to meet the requirement of the homogenous building morphology condition as explored by the variogram models and to facilitate LCZs mapping conveniently and efficiently, a 3×3 cell ($270 \text{ m} \times 270 \text{ m}$) moving window around each cell was used for further aggregation. Hence, in accordance with the proposal of LCZs for urban climate study as a uniform of land cover and surface structure, the scale for our LCZs mapping was determined to be $270 \times 270 \text{ m}$.

Figure 6. Experimental variogram models (left) of building height for selected areas (right).

3. Results

3.1. LCZs mapping result: spatial distribution and comparative analysis

LCZs were identified and tested with our mapping scheme and the threshold defined by Stewart and Oke (2012) (Table B1). Overall, the LCZs maps show a generally similar pattern in all the three metropolitans, with LCZ “built-up” types generally surrounded by LCZs A-G

328 “natural” types (Fig. 7). Google Earth further helped to access the LCZs mapping accuracy by
 329 providing the tools to link with ERDAS and overlay the LCZs mapping results with the historical
 330 imagery. As illustrated profiles of some LCZs in Fig. A3, most of our LCZs were matched
 331 correspondingly with the representative examples shown in Table 2 in p. 1885 of (Stewart &
 332 Oke, 2012). In our mapping, we found that the areas with building fraction <15% are usually
 333 occupied by dense or tall vegetation, leading to the height of roughness elements higher than
 334 15 m (Fig. A3). Thus, the height of roughness threshold was adjusted for LCZ 9 Sparsely built
 335 identification (Table B1).

Figure 7. Spatial distribution of Local Climate Zones (LCZs) for the three metropolitans at Texas. (Note: the labels on the map are the locations of the illustrated sites in Figure A3 with the detailed examination at Google Earth.)

Figure 9. Statistical summary of the area proportion of LCZ types in the respective LCZs maps of three metropolitan areas.

LCZs maps capture most of the underlying land cover and urban morphological characteristics, with <1% of redundant areas which were not assigned to LCZs. We noted that LCZ E Bare rock or paved is mosaicked with LCZ “built-up” types when scaling down to check the LCZs maps in detail, filling in the LCZ 4 Open high-rise in the form of straight lines. The more intensely developed city system in DFW along with transportation construction (car

parking lot, wide traffic roads, railway yards, etc.) lead to a higher percentage of LCZ E Bare rock or paved (e.g., DFW airport is distinguishable in Fig. 7) than the other two metropolitans. For Austin and San Antonio, LCZs “built-up” types are compactly distributed in the central urbanized area, and the surrounding rural areas of these two metropolitans shows a large percentage of LCZ A Dense trees and LCZ B Scattered trees relative to LCZ D Low plants. LCZ A Dense trees is the typical LCZ in the eastern part of the cities, while the southern part is dominated by LCZ B Scattered trees and the western part is occupied by LCZ D Low plants.

In this study, LCZs mapping provides a platform to make a comparative analysis of the urban morphology and vegetation structure of the three metropolitan study areas. Regarding LCZs “built-up” types, there is a tendency that most of the urbanized area is categorized into LCZs “open” types (e.g., LCZ 4 Open high-rise, LCZ 5 Open mid-rise, LCZ 6 Open low-rise), especially for DFW and San Antonio. Overall, DFW shows more diversity in terms of LCZ “built-up” types due to the complex regional character compared to other metropolitan areas. The highest urbanization rate of DFW manifested itself with the highest percentage of LCZ “built-up” types.

Additionally, the LCZs maps indicate an urban development trajectory and the related urban form. DFW has the largest absolute amount and proportion of LCZs 1–10 “built-up” types. It corresponds to the fact that DFW is one of the largest inland metropolitan areas in the country and the economic hub of Texas. The relatively high proportion of LCZ 10 Heavy industry for

DFW also indicates that the historical railroad construction and rapid industrialization led to the development of the DFW metropolis. The LCZs “built-up” types are concentric along the Highway I-35 across Austin, which corresponds with the function of Austin as the hub of communications to link DFW, Houston, and San Antonio. As a fast-growing and economic center similar to DFW, the Austin-Round Rock metropolitan area also has a considerable amount of LCZ 4 Open high-rise with compacted urban morphological structure concentrated on downtown areas. In contrast, the tall buildings in San Antonio are loosely distributed, which, to some extent, lead to the intersection of LCZ 5 Open mid-rise and LCZ 6 Open low-rise. San Antonio metropolitan is predominant by the diversity of building forms, with a strong cultural heritage and slow urban development.

The LCZs “natural” types distribution reflects the slightly different natural environment of the natural land of these three metropolitans. Given the geographical location and the climate environment, DFW is also different from the other two metropolitans regarding LCZs “natural” types diversity. Obviously, LCZ D Low plants is dominant in the surrounding areas of DFW, which corresponds to the flat topology that >90% of the area lies in an elevation ranging from 130 m to 300 m (calculated from DTM) and land coverage with grassland and pasture. In addition, LCZ D Low plants and LCZ G Water also play role in intersecting LCZs 1–10 “built-up types” for the entire DFW and separating the area into four major city centers: Dallas, Fort Worth, Arlington, and Irving in the role of metropolitan “corridors”. Further investigation of

“corridors” at DFW implies that the main rivers, streams (with a length of >100 km), and water bodies lead to the formation of the strip of LCZ D Low plants and LCZ G Water (Fig. A4). Their role of separating LCZs 1–10 “built-up” types in the developed land areas warrants additional investigation, and the role of mitigating surface UHI needs further exploration.

LCZ A-G “natural” types were generally more diversely distributed at Austin and San Antonio. With substantial amount grassland, pasture, and cultivated crops distributed along the majority of peripheries, LCZ D Low plants is the most typical LCZs types of three metropolitan areas (Fig. 8). Furthermore, Austin has the highest percentage of LCZ A Dense tree, followed by San Antonio. Austin and San Antonio are also dominated by LCZ C Bush, scrub. In contrast, it is interesting to note the tiny proportion of LCZ C Bush, scrub at DFW, in accordance with the minimal coverage of NLCD class (e.g., 52 Shrub/Scrub). In addition, all metropolitan areas have slightly few LCZ F Bare soil or sand coverage versus other LCZ “natural” types, indicating that all of the areas are benefited from the LCZ “natural” types with the cooling effect of vegetation and water.

In addition, there is a clear contrast between LCZ A Dense trees and LCZ D Low plants at Austin and San Antonio, which corresponds with the spatial distribution and land coverage by Trees and Grass or pasture. It is first due to the LCZs pre-classification scheme from NLCD. Further investigation indicates that the phenomenon is consistent with the regional geological characteristics. The geological structure of limestone and dolomite combination or limestone and

clay combination at the eastern part of Austin and the northern part of San Antonio contribute to the tree growth and thus the distribution of LCZ A Dense trees, while the geological structure with limestone and sand combination or clay and fine-grained mixed clastic type combination lead to the development of grassland or pasture at western Austin or northwestern San Antonio (Fig. A5).

3.2. Validation of GIS-based LCZs mapping

We examined the SVF, aspect ratio, and terrain roughness of the main LCZs of the study areas to evaluate our LCZs mapping result (Fig. 9 and Table B3). Our findings of the differences of the SVF and aspect ratio are in agreement with results from a prior GIS-based LCZs mapping study (Zheng et al., 2017). SVF thresholds of LCZs urban areas (especially LCZs “compact”) are generally lower than LCZs “natural” types, with noticeable variation among them. The SVF of most of DFW and San Antonio is higher than that of Austin, which also has higher Standard Error of SVF (Table B3). For LCZ “open” types and LCZ C Bush, scrub, the mean SVF values of the study areas are within the threshold of the definition provided in Table B1. On the other hand, the mean value of SVF of LCZ 9 Sparsely built, LCZ A Dense trees, and LCZ G Water are not exactly in accordance with the definition (Table B3). In our SVF calculation, we used a DEM with 3 m resolution and set the diameter to 90 m, which may lead to SVF differences. Also, SVF is specifically related to stations, the aggregation of SVF values for an LCZ would have considerable uncertainty. In addition, we consider the effects introduced by buildings, bridges, or

vegetation for SVF calculation according to the definition, though some studies exclude the impacts of trees when calculating SVF for LCZs “built-up” types delineation, considering that the green cover in suburb areas might affect the calculation (Koc et al., 2017).

Regarding aspect ratio, LCZ 4 Open high-rise is different from others with much higher mean values (0.98, 1.18, and 2.24 for the three study areas). It also shows higher standard deviation than other LCZs “built-up” types due to the variation in height of tall buildings. Similarly, the LCZ A also demonstrate high mean and standard deviation of aspect ratio due to tall trees. However, most of LCZs showed considerable variation and departure from the standard threshold (e.g., LCZ 8 Large low-rise, LCZ 9 Sparsely built, and LCZ A Dense trees, and LCZ G Water) (Table B1 and Table B3). So far, there is no standard method for the aspect ratio calculation, which lead to the differences from thresholds defined by Stewart and Oke (2012). Hence, in future, it is necessary to achieve the consensus in terms of the interpretation of different properties for GIS-based LCZs mapping.

Due to the coarse classification of the terrain roughness classes, its values were assigned with a couple of integer values. Therefore, these value matches the standard threshold defined by the LCZs definition.

Figure 8. Boxplot of LCZ parameters of the main LCZs types of three metropolitans. (Note 1: Please refer to the name of LCZs from Figure 7. Note 2: The line within each box represents the median of LST values at the corresponding LCZ, the bottom of the box indicates the first quartile of LST values, and the top indicates the third quartile of LST values.)

4. Discussion

4.1. Advantages of LiDAR for GIS-based LCZs mapping

LiDAR datasets provide detailed urban geomorphology to analyze LCZs mapping scale. The high horizontal and vertical resolution of the LiDAR dataset is appropriate to calculate the relevant properties. Even though the vertical accuracy of the generated nDSM can be coarser

than the original dataset, the low vegetation and other objects are statistically in residual and they are lower than 3 m, which did not affect our final mapping result. There are different findings for LCZs mapping scale, indicating that spatial characteristics vary worldwide due to urban forms, urban development history, geographical location, and hydrogeological setting. For example, the scales for LCZs mappings have been assigned with 100 m in a suburb area of Sydney, Australia (Koc et al., 2017), and Seoul, South Korea (Lee & Oh, 2017), 120 m in Khartoum, Sudan (Bechtel et al., 2016), and approximately 500 m in Szeged (Unger et al., 2014). In addition, Kotharkar and Bagade (2017) mapped the LCZs of Nagpur, India with different scales (e.g., 250 m, 500 m and 1000 m) to explore the appropriate LCZs zoning unit, and they found that 250 m led to fragmented LCZs maps for the city with scattered distributions of slums. Based on the height of buildings, 270 m was defined as a homogeneous scale in this research, and it is in accordance with the 300 m LCZs mapping scale in Hong Kong, which was based on a more intensive and sophisticated examination of building characteristics (Zheng et al., 2017). The maps of the LCZs mapping properties were generated with the finest resolution as the input data, while in the end, the 270 m $\times$ 270 m moving window around each cell was used for further aggregation to get LCZs mapping. Therefore, the compatibility and rationality of our mapping zoning still need more verification in the future UHI study of the areas.

With detailed urban morphology information provided by LiDAR data, our decision-making algorithm considers land cover, the height of roughness, building surface fraction, pervious surface fraction, and industrial sites from coarse to fine delineation to get LCZs maps. This GIS-based mapping scheme ensures that only one LCZ can be assigned to a given morphological area without “overlaps” (e.g., areas which were assigned to more than one LCZ) or “holes” (e.g., redundant areas which were not assigned to LCZs) caused by parameter combinations of all the LCZs properties (Bechtel et al., 2015). On the other hand, the validation of the GIS-based LCZs mapping result is different from that of the remote sensing LCZs mapping method, which is based on the comparison between the mapping result and the manual interoperation (Geletič & Lehnert, 2016; Xu, Ren, Cai, Edward, & Wu, 2017; Zheng et al., 2017). The comprehensive validation of the imagery classification still need to compare the classified LCZs with manually LCZs classification, while the latter can have a higher uncertainty compared to our GIS-based method itself in this study. Instead, three geometric and surface cover properties (e.g., SVF, H/W, and terrain roughness classes) were included in our LCZs mapping scheme for the evaluation. The statistical summary of their values provided by Table B3 showed that their mean values for most of the major LCZs are in accordance with the standard threshold provided by the LCZs definition (Table B1), which indicates the effectiveness of our LCZs mapping. Since the main propose of LCZs maps is for urban climate studies, a comprehensive examination of LCZs maps would consider the thermal characteristic (e.g., surface or air temperature) in future studies.

4.2. *Uncertainties of the LCZs mapping method*

For the LCZs mapping itself, the LCZ was defined as an area with uniform land cover, surface structure, constructions material, and human activity (Stewart & Oke, 2012). On the one hand, both the urban and natural landscape are heterogeneous, meaning that each LCZs is not an absolute homogenous region and there is no clear boundary between different LCZs. For instance, the LCZ G Water considers different water bodies with the same surface properties in the LCZs definition, given that the LCZs were mainly developed for a city environment. Similarly, the LCZ 9 Sparsely built showed different landscape characteristic for different sites when linking with Google Earth 3D imagery (Fig. A3). Through they all match the LCZs definitions, their corresponding climate can be different due to the different thermal characteristics. LCZ E includes two types of land surface cover: Bare rock and paved. Nevertheless, linking our LCZs maps with Google Earth showed that most LCZ E in these three metropolitans are from urban transportation (roads, highways, parking places, airports, etc.). These examples indicate that some types of LCZs might need to be further sub-classified in terms of LCZs mapping at the metropolitan level or to fit the characteristics of different cities worldwide. We strictly followed the threshold defined by (Stewart & Oke, 2012) for our mapping scheme. For instance, LCZ G water was defined as “Large, open water bodies such as seas and lakes, or small bodies such as rivers, reservoirs, and lagoons” in Table 2 on p. 1885 of (Stewart & Oke, 2012) with zero height of roughness elements. Even through the NLCD code 90 Woody Wetland and NLCD 95 Emergent Herbaceous Wetlands might show the similar thermal

behavior with water to a large extent, they were not classified as LCZ G water. Overall, LCZs mapping is a compromise between the universality and local accuracy.

Additionally, the LCZs definition did not consider the seasonal variation, which might lead to misinterpreted surface property results. Furthermore, the related properties for LCZs mapping were derived from secondary data sources with a time gap. NLCD 2011 data was derived from 2008 to 2010 Landsat data whereas LiDAR projects were conducted by a suite of vendors working for various agencies or clients that all had different accuracy thresholds and acquisition period requirements (Table B2). An example of how the combination of various projects may manifest in the results is for areas dominated by broadleaf deciduous trees or cultivated crops to produce spatial inconsistencies in the output maps.

In terms of the geometric and surface cover properties for LCZs definitions, not all features can be observed straightforwardly by Earth observation techniques. For example, human activities are still challenging to observe from space. We used the land use planning data for the industrial sites to represent the anthropogenic heat release, which does not take other surface properties into account. Furthermore, our study provided evidence that properties in Table B1 cannot be equally utilized to identify an individual LCZ with GIS decision-mapping method. Also, the height of roughness for different elements varies for individual LCZ at our mapping scale, thus the certain threshold indicates low accuracy, which might lead to the accuracy imbalance issue of different factors for further LCZs mapping. In addition, the area along the

LCZs boundary can be considered as fuzzy areas if the local heterogeneity being considered as mentioned, leading to another uncertainty for LCZs delineation. Future work can include the Fuzzy membership classification method or incorporate other remote sensing classification methods to explore the “cut off” values of LCZs properties.

With a high percentage of LCZ A-D in a natural environment and LCZs Open high-rise and mid-rise in urbanized areas, the LCZs maps contribute to the worldwide LCZs studies in a high-density urbanization scenario. LCZs Compact types have been found in cities or mega-regions which are the economic hub of the region or the country, including Singapore (Ng, 2015), Hong Kong (Zheng et al., 2017), the Yangtze River Delta (YRD) (Cai, Ren, Xu, Lau, & Wang, 2017), Wuhan and Guangzhou (Xu, Ren, Cai, Edward, et al., 2017), etc. In contrast, LCZs characteristics of our study areas have relatively low percentages of LCZ compact types but high fragmentation of LCZs “open” types. There are other LCZs maps similar to our LCZs mapping, including Nagpur city (India) with the considerable LCZ 9 Sparingly built (Kotharkar & Bagade, 2017), and Szeged (Hungary) with dominant LCZ 6 Open low-rise followed by LCZ 8 Large low-rise (Unger et al., 2014). Since each city has own size, and development trajectory, and is exposed to diverse local and synoptic factors, the related urban environmental issues are not comparable without a standard datum. Here, the above LCZs comparisons indicate that LCZs mapping can be criteria regarding the land cover character and urban morphology to further

analyze and comprehensively describe the urban climate with heterogeneous human-environment interactions.

5. Conclusions

In this paper, a methodology for LCZs classification was built based on high-resolution airborne remote sensing data, national land cover dataset, and city land use planning data in the three metropolitan areas of Texas, U.S.: DFW, Austin, and San Antonio with different sizes and shape. Compared to the remote sensing method, our LCZs mapping scheme is advantageous for the incorporation of detailed urban and vegetation morphology information with the assistant of LiDAR data at the scope of entire metropolitans. The LCZs mapping scheme in our study indicated that LiDAR-derived products can support GIS-based LCZs mapping to identify urban morphological information and standardize the mapping scheme for comparative studies of metropolitan areas in the USA. Although we intended for an automated GIS-based LCZs mapping method, there are also some heavy manual component in the input data acquisition and processing. Thus, the overall GIS-based LCZs mapping is a mixture of automated and manual processes.

Our LCZs mapping extends the LCZs case studies in the world. The key findings of LCZs of our study areas are that: 1) Most of the urbanized areas are categorized into LCZ “open” types for all three metropolitans with different proportions and spatial diversity, but that DFW shows more diversity in terms of LCZ “built-up” types due to the complex regional character compared

to other metropolitans; 2) LCZ D Low plants is dominant in the surrounding areas of DFW, and LCZ A Dense trees and LCZ D Low plants are dominant in Austin and San Antonio with clear regional contrast; 3) LCZs maps are in accordance with the underlying regional environment and urban development trajectory of three metropolitans.

Besides the function of the LCZs on measuring UHI effects, it is reasonable and necessary to put LCZs mapping studies into a broader urban landscape view to understand the urban heterogeneity characteristic and the spatial distribution of thermal environment. For example, increasingly confronted with urban heat events, the urban planners are being aware of the need of optimizing urban planning processes with respect to urban thermal comfort and local climate (Scherer, Fehrenbach, Beha, & Parlow, 1999). Hence, a further investigation of the thermal behavior characteristic of different LCZs, as the up-to-date classification of urban landscapes, is warranted in the next step. Along with this line, further studies on applying the LCZs mapping results to study UHI formation and evolution are important to fundamentally understand the ways in which elements of the urban ‘surface’ interact with adjacent atmospheric layers.

Appendix A

Figure A1. Normalized digital surface models (nDSMs, unit: meters) with 3m×3m resolution of three metropolitan areas.

Figure A2. Detailed illustration of normalized digital surface models (nDSMs, unit: meters) with 1m×1m resolution for a small area in San Antonio.

DFW

Austin

San
Antonio

LCZ 1 Compact high-rise

LCZ 4 Open high-rise

LCZ 9 Sparsely built

Figure A3. Examples of the typical Local Climate Zones (LCZs) for the three metropolitans.

Figure A4. Major rivers, streams, and water bodies of DFW metropolitan areas. Data is from (Texas Natural Resources Information System (TNRIS), last accessed March 21th, 2018.)

Figure A5. The geological structure of Austin and San Antonio metropolitan. (Data is from U.S Geological Survey.)

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601 **Appendix B**

602 **Table B1.** Local climate zones (LCZs) concepts and the related values of geometric and surface
 603 cover properties.

Code	Local climate zone (LCZ)	Sky view factor (SVF)	Aspect ratio (H/W)	Building surface fraction	Impervious surface fraction (ISF)	Pervious surface fraction (PSF)	Height of roughness elements	Terrain roughness class
LCZ 1	Compact high-rise	0.2–0.4	> 2	40–60	40–60	< 10	> 25	8
LCZ 2	Compact mid-rise	0.3–0.6	0.75–2	40–70	30–50	< 20	10–25	6–7
LCZ 3	Compact low-rise	0.2–0.6	0.75–1.5	40–70	20–50	< 30	3–10	6
LCZ 4	Open high-rise	0.5–0.7	0.75–1.25	20–40	30–40	30–40	> 25	7–8
LCZ 5	Open mid-rise	0.5–0.8	0.3– 0.75	20–40	30–50	20–40	10–25	5–6
LCZ 6	Open low-rise	0.6–0.9	0.3– 0.75	15–25	20–50	30–60	3–10	5–6
LCZ 7	Lightweight low-rise	0.2–0.5	1–2	60–90	< 20	< 30	2–4	4–5
LCZ 8	Large low-rise	> 0.7	0.2–0.4	30–50	40–50	< 20	3–30	5
LCZ 9	Sparsely built	> 0.8	0.2–0.4	5–15	< 20	60–80	3–10	5–6
LCZ 10	Heavy industry	0.6–0.9	0.2–0.5	20–30	20–40	40–50	5–15	5–6
LCZ A	Dense trees	< 0.4	> 1	< 10	< 10	> 90	3–30	8
LCZ B	Scattered trees	0.5–0.8	0.25–0.75	< 10	< 10	> 90	3–15	5–6
LCZ C	Bush, scrub	0.7–0.9	0.25–1.0	< 10	< 10	> 90	< 2	4–5
LCZ D	Low plants	> 0.9	< 0.1	< 10	< 10	> 90	< 1	3–4
LCZ E	Bare rock or paved	> 0.9	< 0.1	< 10	> 90	< 10	< 2.5	1–2
LCZ F	Bare soil or sand	> 0.9	< 0.1	< 10	< 10	> 90	< 2.5	1–2
LCZ G	Water	> 0.9	< 0.1	< 10	< 10	> 90	–	1

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605 **Table B2.** Metadata of LiDAR projects for the study areas.

Project Name	Average Point Spacing (cm)	Horizontal/ Vertical Accuracy (cm, MSE)	Horizontal/ Vertical Datum	Projection	Units	Point Classes
Dallas-Fort Worth						
StratMap 2013 Ellis, Henderson, Hill, Johnson, Navarro	50	NA/ 3.43-6.1	NAD83, NSRS2007/NAVD 88, GEOID 12A	UTM Zone 14N	Meters	1, 2, 3, 4, 5, 6, 7, 9, 13
StratMap 2012 TCEQ Dam Sites	50	75/ 25	NAD83/NAVD88, GEOID 09	UTM Zone 14N	Meters	1, 2, 3, 4, 5, 6, 7, 9, 13
FEMA 2011 Parker	100	60/ 37	NAD83/NAVD88, GEOID 09	UTM Zone 14N	Meters	1, 2, 7, 9, 10, 11
StratMap 2011 Collin, Denton, Kaufman	50	NA/ 6.03-7.13	NAD83/NAVD88, GEOID 09	UTM Zone 14N	Meters	1, 2, 4, 6, 7, 9, 13
Grand Prairie 2009	70	30-45/ 9.1	NAD83/NAVD88, GEOID 03	State Plane Texas North Central	Feet	Ground, man-made, vegetation
StratMap 2009 Dallas	100	NA / 12-15.9	NAD83/NAVD88	UTM Zone 14N	Meters	1, 2, 6, 7, 9, 12, 13
StratMap 2009 Tarrant	50	100/ NA	NAD83/NAVD88, GRS80	UTM Zone 14N	Meters	1, 2, 3, 4, 5, 6, 7, 9
Austin						
CAPCOG 2012 Travis	140	N/A	NAD83/NAVD88	State Plane Texas Central	Feet	1, 2, 3, 4, 5, 6, 7, 9, 11, 15, 17
StratMap 2011 Caldwell, Gonzales	50	75/ 15	NAD83/NAVD88	UTM Zone 14N	Meters	1, 2, 4, 6, 7, 9, 13
CAPCOG 2008 Bastrop, Fayette, Hays	140	100/ 18.5-37	NAD83/NAVD88	State Plane Texas South Central	Feet	Ground/unclassified
CAPCOG 2007 Caldwell, Travis, Williamson	140	100/ 18.5	NAD83/NAVD88	State Plane Texas Central	Feet	Ground/unclassified
San Antonio						
FEMA 2011 Comal, Guadalupe	100	60/ 12.5	NAD83, NSRS2007/NAVD 88, Geoid09	UTM Zone 14N	Meters	1, 2, 7, 9, 10, 11
StratMap 2010 Bexar	50	100/ 19	NAD83/NAVD88, GEOID 09	UTM Zone 14N	Meters	1, 2, 6, 7, 9, 12, 13

CAPCOG 2007

Caldwell, Travis, Williamson -- -- -- -- --

CAPCOG 2008

Bastrop, Fayette, Hays -- -- -- -- --

Notes: 1. NAD refers to North American Datum; UTM refers to Universal Transverse Mercator.

2. “Average Point Spacing” is the square root of the average area per point (the area of the polygon divided by the number of points it contains).

3. Point Classes are based on ASPRS classification: Class 1: Unclassified; Class 2: Bare Earth; Class 3: Low Vegetation; Class 4: Medium Vegetation; Class 5: High Vegetation; Class 6: Buildings; Class 7: Low point/Noise; Class 9: Water; Class 10: Rail; Class 11: Road Surface; Class 12: Overlap; Class 13: Bridges/Culverts; Class 15: Transmission Tower; Class 17: Bridge Deck.

4. “–” refers to “Same as Above”.

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Table B3. Statistical summary of the properties of major LCZs for the three metropolitan areas.

		Mean			Standard Deviation			Standard Error		
		Austin	DFW	San Antonio	Austin	DFW	San Antonio	Austin	DFW	San Antonio
SVF	LCZ 4	0.67	0.72	0.73	0.24	0.15	0.17	0.01	0.00	0.00
	LCZ 5	0.65	0.78	0.76	0.26	0.13	0.15	0.01	0.00	0.00
	LCZ 6	0.66	0.80	0.79	0.25	0.13	0.15	0.01	0.00	0.00
	LCZ 8	0.66	0.83	0.77	0.25	0.12	0.14	0.01	0.01	0.01
	LCZ 9	0.67	0.69	0.76	0.24	0.17	0.16	0.00	0.00	0.00
	LCZ A	0.60	0.71	0.77	0.23	0.16	0.15	0.00	0.00	0.00
	LCZ B	0.71	0.81	0.82	0.25	0.13	0.12	0.00	0.00	0.01
	LCZ C	0.70	0.84	0.79	0.26	0.14	0.14	0.00	0.03	0.00
	LCZ D	0.75	0.84	0.81	0.23	0.15	0.16	0.00	0.00	0.00
	LCZ F	0.75	0.84	0.81	0.23	0.15	0.16	0.00	0.00	0.00
Roughness	LCZ 4	3.82	5.5	5.58	0.47	1.23	0.92	0.01	0.01	0.02
	LCZ 5	3.71	4.48	4.86	0.51	1.26	0.96	0.01	0.01	0.01
	LCZ 6	3.62	4.23	4.53	0.54	1.16	1.04	0.01	0.01	0.02
	LCZ 8	3.53	4.2	4.66	0.58	1.18	1.02	0.01	0.13	0.06
	LCZ 9	0.24	0.08	0.16	0.57	1.06	1.09	0.01	0.01	0.01
	LCZ A	3.03	6.09	7.66	0.2	0.37	0.5	0	0	0
	LCZ B	3.03	4.25	6.86	0.22	0.94	0.44	0	0.02	0.02
	LCZ C	3.01	3.24	4.34	0.14	0.44	0.5	0	0.09	0.01
	LCZ D	3	3.42	3.48	0.12	0.75	0.58	0	0	0.01
	LCZ F	3	3.42	3.48	0.12	0.75	0.58	0	0	0.01
Aspect ratio	LCZ 4	0.98	1.18	2.24	0.93	0.70	3.41	0.02	0.01	0.08
	LCZ 5	0.83	0.86	1.44	0.92	0.58	1.15	0.02	0.01	0.02
	LCZ 6	0.9	0.84	1.38	0.94	0.59	1.53	0.02	0.01	0.03

LCZ 8	1.02	0.99	1.51	1.09	0.75	2.71	0.03	0.08	0.16
LCZ 9	1.23	1.38	1.89	1.05	0.58	2.06	0.02	0	0.03
LCZ A	1.28	1.6	2.35	1.26	0.71	2.50	0.01	0.01	0.02
LCZ B	0.82	0.81	0.94	0.93	0.65	0.97	0.01	0.02	0.05
LCZ C	0.5	0.55	1.32	0.74	0.49	1.70	0.01	0.1	0.02
LCZ D	0.31	0.79	1.66	0.80	0.75	2.53	0.01	0	0.04
LCZ F	0.31	0.79	1.66	0.80	0.75	2.53	0.01	0	0.04

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