1 Mapping Local Climate Zones: A Bibliometric Meta-

2 Analysis and Systematic Review

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ABSTRACT

The local climate zones (LCZ) system proposed by Stewart & Oke (2012) provides a generic clasification of urban and natural landscapes for urban climate research. While a considerable number of studies have carried out LCZ mapping for cities worldwide, there is a lack of a systematic review of different LCZ mapping methods. To address this challenge, this study uses the statistical and meta-analysis methods to comprehensively review 324 LCZ papers during 2012–2020, 202 of which are categorized as LCZ mapping papers. We present a bibliometric analysis of LCZ mapping papers from literature statistics, research topics, city distribution, institutions and cooperation, and research projects. We elaborated on the framework of RS-based LCZ mapping methods from five key compoents (feature sets, classification units, LCZ samples, classification algorithms, and accuracy evaluation), the framework of GIS-based LCZ mapping methods from three key compoents (LCZ parameters, basic spatial units, and classification rules), and the framework of combined LCZ mapping methods. Finally, we discuss several challenges and future directions on data sources, mapping scale, mapping methods, global inter-annual LCZ mapping, and the LCZ system. The research community can benefit from this review on the current research progress and furture directions of LCZ mapping research, which will promote the further development of LCZ research.

KEYWORDS

Local climate zone; LCZ; LCZ mapping; LCZ classification; remote sensing; GIS; literature review; urban climate

1. INTRODUCTION

Under the background of global climate change and rapid urbanization, cities worldwide face increasing major climate risks (IPCC, AR6). The extreme climate events such as heat waves and floods are particularly prominent in urban areas. It is anticipated that by 2050 more than two-thirds of the world's population will reside in cities (United Nations, 2014), and therefore more people, especially vulnerable groups such as the elderly and children, will be at the risk of negative climate effects. In order to deal with the increasingly severe urban climate risks, researchers have conducted extensive and in-depth research on different aspects of urban climate on various temporal and spatial scales through observation and simulation methods (Kleerekoper et al., 2017; Krayenhoff et al., 2018; Manoli et al., 2019; Masson et al., 2020; Sun et al., 2016; Zhao et al., 2021). The particularity of urban climate is closely related to urban morphology and materials of highly heterogeneous artificial structures. Therefore, how to accurately and quantitatively describe urban form and function plays a key role in urban climate research. Traditional urban climate research usually adopts the ‘urban-rural’ dichotomy, which defines urban areas as one category that ignores intra-urban differences. The simple ‘urban-rural’ dichotomy can not meet the urgent requirements of detailed urban morphology for current urban climate research. Therefore, a more reasonable and detailed quantitative description of urban morphology has become a prerequisite for in-depth urban climate research.

In the past decades, researchers have developed several urban zoning schemes to describe the urban form in a more detailed manner (Auer, 1978; Ellefsen, 1991; Grimmond & Oke, 1999; Loridan & Grimmond, 2012; Oke, 2004; Ren et al., 2011;

Stewart & Oke, 2009). Although these urban zoning schemes have promoted urban climate research to a certain extent, they failed to form a unified classification system to be generic and applicable for global cities. Based on previous research on urban climate and urban zoning, Stewart & Oke (2012) proposed the local climate zones (LCZ) as regions of uniform surface cover, structure, material, and human activity that span hundreds of meters to several kilometers in horizontal scale; the classes are local in scale, climatic in nature, and zonal in representation. The standard LCZ set consists of 10 built types labeled as LCZ 1~10, and 7 land cover types labeled as LCZ A~G (Fig. 1). The LCZ system has been widely applied in research fields related to urban climate and urban planning. For urban climate research, the LCZ system provides an important way to analyze the spatiotemporal characteristics and driving mechanisms of urban heat islands. Compared with the widely used remote sensing land cover data, the LCZ system provides detailed urban canopy parameters required by urban climate models. For urban planning, the LCZ system links urban morphology with the local climate, which greatly promotes the development of urban planning strategies that will mitigate negative urban climate effects.

Fig. 1. The 17 standard LCZs. Modified from Stewart & Oke (2012).

Some studies divided meteorological sites into different LCZs based on field surveys (Fenner et al., 2014; Lehnert et al., 2015; Liu et al., 2018; Middel et al., 2014; Müller et al., 2014; Siu & Hart, 2013; Stevan et al., 2013; Stewart et al., 2014; Wang et al., 2016). The LCZ division through field surveys is time-consuming and laborious and can be hardly extended to LCZ mapping on the city scale. To overcome the limitations of field site measurements, remote sensing and GIS data have been utilized for LCZ mapping for cities. At present, a great number of LCZ mapping studies have been reported and different LCZ mapping methods have been proposed. However, there is a lack of systematic analysis of the current research progress and future directions of LCZ mapping research, which has hindered further research on LCZ mapping. Therefore, we used a statistical and meta-analysis method to comprehensively review

113 the LCZ mapping literature during 2012-2020. We present a bibliometric analysis of
114 LCZ mapping research, elaborated on the frameworks of different LCZ mapping
115 methods, and on this basis provided recommendations to address several challenges of
116 LCZ mapping. This work will help scholars quickly obtain abundant literature
117 information on LCZ mapping, master the process and key points of current LCZ
118 mapping methods, and inspire new ideas for future research on LCZ mapping.

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2. LITERATURE SURVEY

We take two steps to search LCZ literature: First, we searched for and scrutinized peer-reviewed LCZ papers during 2012–2020 that contain ‘local climate zone(s)’ and/or ‘LCZ(s)’ in the title, abstract, or keywords via Google Scholar, ISI Web of Knowledge, and Microsoft Academic. Note that doctoral dissertations and non-English journal papers were excluded due to the limitations of accessibility and comprehensibility. Second, we selected those that explained how to classify LCZs for the target city/cities and label them as LCZ mapping papers from the screened LCZ papers. Note that: (i) The papers that directly use previous/existing LCZ maps were excluded from LCZ mapping papers. (ii) Some studies that classify LCZ types for field sites were also excluded from LCZ mapping papers. According to the above two steps, we finally obtained 324 LCZ papers, of which 202 papers were categorized as LCZ mapping papers. Based on the selected LCZ papers, we conducted a bibliometric analysis of the research status from five aspects: literature statistics, research topics, city distribution, institutions and cooperation, and research projects.

2.1. Literature statistics

Since the LCZ system was formally proposed in 2012, the number of LCZ papers has shown an overall growing trend year by year. The progress of LCZ research is mainly reflected in the following two aspects: (i) The number of papers. LCZ mapping has always been a major research focus as its number of papers accounts for more than 50% every year (Fig. 2a). In the early years from 2012 to 2014, the total number of LCZ papers has increased slowly. From 2015, the number of papers grown rapidly

due to the wide application of remote sensing data to LCZ mapping. With the introduction of machine learning algorithms to LCZ mapping, the number of papers has again seen a significant growth since 2018. (ii) The number of literature citations. The pioneering work of [Stewart & Oke \(2012\)](#) has received a steady increasing number of citations year by year ([Fig. 2b](#)), and its total number of citations has reached 1752 by 2020. In addition, the citations of several representative papers of LCZ mapping have shown an overall increasing trend from 2012 to 2020. For example, the two representative papers of RS-based LCZ mapping methods (refer to [Section 3.1](#)), [Bechtel & Daneke \(2012\)](#) and [Bechtel et al. \(2015\)](#), and the representative paper of GIS-based LCZ mapping methods (refer to [Section 3.2](#)), [Lelovics et al. \(2014\)](#), have been increasingly cited.

Fig. 2. The number of LCZ papers during 2012-2020 (a) and the number of citations of four representative LCZ papers according to Web of Science (b).

The number and types of journals or conferences that publish LCZ mapping papers have generally show an increasing trend from 2012 to 2020 ([Fig. 3](#)). The first journal paper on LCZ mapping has been published in IEEE Journal of Selected Topics in

Applied Earth Observations and Remote Sensing ([Bechtel & Daneke, 2012](#)). Overall, Urban Climate ranks the first journal that has published the most papers on LCZ mapping, and IGARSS (International Geoscience and Remote Sensing Symposium), JURSE (Joint Urban Remote Sensing Event), and ICUC (International Conference on Urban Climate) are among the top in the publication of LCZ mapping papers. Several journals and conferences have set special issues for LCZ. For example, Remote Sensing set up a special issue for LCZ in 2015, and ICUC set up special issues for LCZ in 2015 and 2018. In these special issues many papers on LCZ mapping have been published. With the rapid development of LCZ mapping methods, some conferences have directly focused on LCZ mapping in recent years. For example, JURSE (2017) organized a global competition for LCZ mapping based on remote sensing data, and IGARSS set up a special topic for LCZ mapping in 2019.

Fig. 3. The top 18 journals and 8 conferences (in the dashed box) ranked by the total number of LCZ mapping papers during 2012–2020.

2.2. Research topics

LCZ mapping research covers a wide range of keywords in different periods (Fig. 4).

The major research topics include: (i) Data sources. The earliest remote sensing data used for LCZ mapping is Landsat data, and other multisource remote sensing data have been used for LCZ mapping, such as ASTER, Sentinel, SAR, and Lidar data. In recent years, Google Earth Engine has been increasingly used to process plenty of multisource remote sensing data for LCZ mapping. In addition, many GIS data such as building and VGI (volunteered geographic information) data have used for LCZ mapping. (ii) LCZ mapping methods. Both RS-based and GIS-based methods have been used for LCZ mapping. The RS-based LCZ mapping methods has developed from supervised classification methods to object-based image analysis (OBIA) and scene classification methods. The World Urban Database and Access Portal Tools (WUDAPT) project uses the RF classification algorithm for LCZ mapping. After 2017, a variety of classification algorithms have been used for RS-based LCZ mapping, such as CCF, CNN, ResNet, RNN and DNN algorithms.

Fig. 4. The keywords network of LCZ mapping papers during 2012-2020. The node size represents keywords frequency and the node color represents the first year that the keywords appeared in paper.

2.3. City distribution

LCZ mapping has been carried out in almost 300 cities worldwide (Fig. 5). In general, European cities (122) account for the largest proportion (nearly 40%), followed by Asia (94), Africa (37), North America (26), South America (13), and Oceania (3). Among all countries, France and China have the largest number of cities that have carried out LCZ mapping, 48 and 37 respectively. Fig. 5 shows that LCZ mapping cities show a significant growth in 2015 and 2018. Therefore, we divide LCZ mapping cities into the following three stages: (i) Early stage (2012-2014). At this stage, the number of LCZ mapping cities is relatively small, mainly a few megacities in Europe, Asia, and South America. (ii) Development stage (2015-2017). At this stage, the number of LCZ mapping cities increased rapidly, especially in Europe, Asia and North America. In addition to large cities, many small and medium-sized cities have gradually carried out LCZ mapping. (iii) Expansion stage (2018-2020). At this stage, the number of LCZ mapping cities has increased significantly worldwide. The number of LCZ mapping cities in Europe and Asia continues to increase, while the LCZ mapping cities in Africa, North America and South America have become more widespread.

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220 **Fig. 5.** Geographic distribution of LCZ mapping cities. The color represents the year when the first LCZ mapping paper was published. The

221 subfigure in lower left corner presents a zoom in of European cities.

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2.4. Institutions and collaboration

At present, more than 130 institutions around the world have published LCZ mapping papers, among which European and Asian institutions have published relatively more papers (Fig. 6). Overall, the institutions in China (54 papers), Germany (28 papers), France (12 papers), the United States (9 papers), India (8 papers) and Hungary (8 papers) have published relatively more LCZ mapping papers. In China, the Chinese University of Hong Kong published the most LCZ mapping papers (14 papers), followed by Wuhan University (6 papers) and the University of Hong Kong (3 papers). In Germany, the Technical University of Munich and the University of Hamburg have published more LCZ mapping papers, 8 and 7 papers respectively. In France, the National Centre for Scientific Research (CNRS) has published 5 LCZ mapping papers. The University of Szeged in Hungary and Ghent University in Belgium have published 8 and 5 LCZ mapping papers. In India and the United States, although many institutions have published LCZ mapping papers, the amount of papers published by a single institution is small.

Fig. 6. The number of LCZ mapping papers in different countries.

242 Researchers from various institutions around the world have conducted extensive
243 cooperation ([Fig. 7](#)). Among them, Benjamin Bechtel from the Ruhr-University
244 Bochum has the most extensive cooperation with other researchers. For example,
245 Benjamin Bechtel has cooperated closely with Linda See, Gerald Mills, Oscar
246 Brousse, Jason Ching, Matthias Demuzere, Paul Alexander, and Marie-Leen Verdonck
247 in German. They committed to promote the WUDAPT project globally. In China, Ren
248 Chao from the Chinese University of Hong Kong has also cooperated closely with
249 other scholars such as Xu Yong, Wang Ran, Cai Meng, and Edward Ng. In France,
250 Valery Masson from the National Center of Meteorological Research (CNRM) has
251 close cooperation with Julia Hidalgo from Laboratoire Interdisciplinaire Solidarités
252 Sociétés (LISST), because they conducted the MapUCE project. Similarly, Gál T and
253 Unger J from the University of Szeged collaborate frequently to conduct the URBAN-
254 PATH project in Szeged. In addition, Zhu Xiaoxiang from the Technical University of
255 Munich has cooperated closely with Qiu Chunping and Michael Schmitt to conduct
256 LCZ mapping for global cities.

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Fig. 7. Authors network of LCZ mapping papers (each author published more than 2 papers and collaborated more than twice). The node size represents the total number of collaborations and the line width represents collaboration number.

2.5. Research projects

Several research projects have adopted the LCZ framework for mapping (Tab. 1). The WUDAPT project is a community-based project to create LCZ maps for global cities. The WUDAPT project uses RS-based LCZ mapping methods (Section 3.1). The URBAN-PATH project is proposed for the long-term and effective monitoring of the excess heat in Szeged and Novi Sad by installing measurement networks to track the differences between thermal characteristics of the neighborhoods. The URBAN-PATH

project uses GIS-based LCZ mapping methods (Section 3.2). The MapUCE project is proposed to develop a generic and automated method for generating LCZ maps for all cities in France using national databases, including the urban architectural, geographical and sociological parameters necessary for energy and microclimate simulations.

Tab. 1. Research projects related to LCZ mapping.

Project	Duration	Portal website	Reference
WUDAPT	2013-	https://www.wudapt.org/	Ching et al. (2018)
URBAN-PATH	2013-2014	http://en.urban-path.hu/	Unger et al. (2015)
MapUCE	2014-2019	https://mapuce.orbisgis.org/	Masson et al. (2015)

3. LCZ MAPPING METHODS

LCZ mapping methods can generally be divided into three categories: RS-based methods, GIS-based methods, and combined methods of the former two. The basic idea of RS-based LCZ mapping methods is the supervised remote sensing image classification. GIS-based LCZ mapping methods develop from the three-step process when classifying field sites into LCZs guided by [Stewart & Oke \(2012\)](#). The primary objective of combined LCZ mapping methods is to integrate the advantages of RS-based and GIS-based methods. [Fig. 8](#) shows that the three categories of LCZ mapping methods have gone through different developments, but they have shown an overall increasing trend in the past decade. In general, RS-based methods account for the largest proportion in the LCZ mapping literature (64.3%), followed by GIS-based methods (26.5%), and combined methods the least (9.2%). Specifically, the number of RS-based LCZ mapping papers has seen a remarkable growth after the initiative of the WUDAPT project ([Bechtel et al., 2015](#)) and the introduction of state-of-the-art machine learning algorithms in recent years. GIS-based LCZ mapping methods became a research focus after the representative research of [Lelovics et al. \(2014\)](#), and the number of papers has remained stable in recent years. For combined LCZ mapping methods, the number of papers has increased steadily since the representative research of [Gál et al. \(2015\)](#).

Fig. 8. The number and proportion of research literature on RS-based, GIS-based, and combined LCZ mapping methods from 2012 to 2020.

3.1. RS-based LCZ mapping methods

Like remote sensing image classification, the RS-based LCZ mapping methods can be further divided into pixel-based, object-based, and scene-based methods according to different LCZ classification units. The LCZ classification unit is the basic unit on which an LCZ is classified. The pixel-based methods use the pixel as the basic unit and divide each pixel into an LCZ class. The object-based methods use irregular objects composed of pixels as the basic unit, and divide each object into an LCZ class. The scene-based methods use image patches as the basic unit, and divides each image patch into an LCZ class. Compared with pixel-based methods, both object-based and scene-based methods are more in line with the LCZ concept, and exhibit greater potential for LCZ mapping, especially for cities with heterogeneous landscapes. However, the LCZ mapping processes of the two methods are more complicated than pixel-based methods. A literature list of the three categories of RS-based LCZ

mapping methods is provided in [Tab. 2](#).

Currently, RS-based LCZ mapping methods mostly uses pixel-based methods due to the relatively simple mapping process that can be easily applied to cities worldwide. [Bechtel & Daneke \(2012\)](#) proposed an initial framework of pixel-based methods, and on this basis, [Bechtel et al. \(2015\)](#) initiated the WUDAPT project that aims at LCZ mapping of global cities. The main workflow of the WUDAPT LCZ mapping is to select LCZ training areas from Google Earth based on expert knowledge, use Landsat data and the random forest algorithm to classify LCZ types, and iterate the above steps to achieve an accurate LCZ map ([Bechtel et al., 2015](#)). At present, WUDAPT provides level-0 LCZ maps for more than 150 cities around the world; the reader could refer to the WUDAPT website (www.wudapt.org) for updates. [Bechtel et al. \(2019\)](#) systematically evaluated the quality of WUDAPT level-0 LCZ data, and concluded that the LCZ mapping accuracy reached an intermediate level with an overall accuracy of 50-60%. In the future, WUDAPT will provide more detailed and accurate level-1 and level-2 LCZ data ([Ching et al., 2018](#)).

The process of RS-based LCZ mapping methods mainly includes four steps: collect feature sets, determine the LCZ classification unit, select LCZ samples, use classification algorithms to divide LCZs, and evaluate LCZ classification accuracy. Therefore, RS-based methods consist of five key components: feature sets, classification units, LCZ samples, classification algorithms, and accuracy evaluation. Next, we elaborate the five key components covering pixel-based, object-based, and scene-based methods.

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342 **3.1.1. Feature sets**

343 A feature set is a collection of spectral, texture, spatial, and temporal features
344 extracted from multi-source remote sensing data that characterize surface structure,
345 cover, radiative, and thermal properties, etc. Currently, the multispectral remote
346 sensing data with spatial resolution of 10-100 m have been widely used for RS-based
347 LCZ mapping. For example, pixel-based LCZ classification methods usually use
348 Landsat 30-m multispectral data, while object-based and scene-based methods
349 generally use Sentinel-2 10-m multispectral data. Many other remote sensing and GIS
350 data have also been used for RS-based LCZ mapping, such as Sentinel-1 data (Bechtel
351 et al., 2016; Brousse et al., 2019; Hu et al., 2018; Kaloustian et al., 2017), ASTER
352 data (Xu et al., 2017b), RapidEye data (Oxoli et al., 2018), PALSAR-2 data (La et al.,
353 2020), Global Urban Footprint and DMSP/OLS nightlight data (Qiu et al., 2018c),
354 and OpenStreetMap data (Sukhanov et al., 2017; Zhang et al., 2019).

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356 When collecting feature sets, the following aspects need to be considered: (1) Spatial
357 and temporal resolution and availability of multi-source remote sensing data. The
358 remote sensing data used for LCZ classification should have higher spatial resolution
359 than the LCZ definition scale of a minimum diameter of 400–1,000 m recommended
360 by Stewart & Oke (2012). High-resolution remote sensing data can capture surface
361 details, but would probably introduce redundant information that may be detrimental
362 to LCZ classification. In addition, previous studies recommended using remote
363 sensing data covering different seasons for LCZ classification (Bechtel et al., 2015;
364 Qiu et al., 2019). The reason is that land surface properties may change significantly

365 across seasons for most LCZ classes and thus using remote sensing images in a single
366 season may cause uncertainty. On the other hand, remote sensing images covering
367 different seasons enrich feature sets which can improve LCZ classification accuracy
368 and robustness. However, due to the interval between satellite revisit times (e.g., 16
369 days for Landsat) and the influence of clouds, it may be difficult to obtain clear-sky
370 remote sensing images in different seasons. In the absence of remote sensing images
371 during a season, those of neighboring years can be used as an alternative. (2) Feature
372 importance. Some studies have explored the relative importance of each feature to the
373 classification of all LCZs as well as each LCZ. For example, [Bechtel & Daneke](#)
374 [\(2012\)](#) used the minimum redundancy maximal relevance approach to analyze the
375 importance of features derived from IFSAR, Landsat-5, and Landsat-7 data, and
376 reported that the multispectral and thermal features perform better than the features
377 derived from IFSAR data. [Hu et al. \(2018\)](#) compared the importance of polarimetric,
378 local statistical, texture, and morphological features extracted from Sentinel-1 data,
379 and found that the features related to VH polarized data contributed the most to LCZ
380 classification on a global scale. [Xu et al. \(2018\)](#) extracted spectral, thermal, spatial,
381 and temporal features from Landsat-8 and digital surface model (DSM) data, and
382 reported that the spectral feature set is more important than the other feature sets.
383 [Demuzere et al. \(2019\)](#) analyzed the importance of features derived from Landsat-8,
384 Sentinel-1, and DMSP-OLS night-time light data, and found that Sentinel-1
385 backscatter is the most important feature followed by those based on spectral features.
386 [Zhang et al. \(2019\)](#) analyzed the importance of spectral, spatial, and texture features
387 extracted from Landsat-8, Sentinel-2, and OpenStreetMap data, and reported that
388 NDVI and its morphological profiles have higher importance than other features. In

addition to the overall assessment, the importance of each feature to each LCZ class has been investigated by [Xu et al. \(2018\)](#) and [Demuzere et al. \(2019\)](#). On the other hand, some studies have evaluated the LCZ classification accuracy of different combinations of feature sets. For example, [Xu et al. \(2017\)](#) tested six different combinations of spectral and texture features extracted from Landsat and ASTER data, and concluded that the dominant features used to classify LCZs vary from city to city. [Qiu et al. \(2018b\)](#) evaluated different feature combinations derived from Sentinel-2, Landsat-8, global urban footprint (GUF), OpenStreetMap (OSM), nighttime light (NTL) data, and suggested that GUF, OSM and NTL data can contribute to the classification accuracy of some LCZs with relatively few samples. [Demuzere et al. \(2019b\)](#) compared the LCZ classification accuracy of four combinations of features derived from Landsat 8, Sentinel-1, and Sentinel-2 data, and reported that the feature set selected automatically based on the random forest feature importance ranking performs the best. [La et al. \(2020\)](#) compared six combinations of spectral and polarimetric feature sets extracted from Sentinel-2 and PALSAR-2 data, and concluded that integrating polarimetric features can substantially improve classification accuracy compared with the use of spectral features alone.

3.1.2. Classification units

The three categories of RS-based LCZ mapping methods show large differences in determining the unit size. (1) For pixel-based methods, more than 90% of studies set the unit size to 100-150 m. For example, the unit size of the WUDAPT project is 100 m ([Bechtel et al., 2015](#)). In addition, many studies adjusted the LCZ mapping unit size according to the specific conditions of the target city. For example, some studies used

the original 30-m pixel resolution of Landsat data as the classification unit size instead of resampling it to 100 m (Shih et al., 2020; Verdonck et al., 2017; Zonato et al., 2020). (2) For object-based methods, the unit size depends on image segmentation, which is regulated by the scale parameter. For example, Liu et al. (2019) analyzed the sensitivity of LCZ classification accuracy to the segmentation scale, and found that the optimal scale varies from city to city. Simanjuntak et al. (2019) used the multi-resolution image segmentation algorithm and set different scale parameters for different segmentation levels. Collins & Dronova (2019) determined the appropriate minimum segmentation size by testing different segmentation scale parameters. (3) For scene-based methods, the appropriate scene size is usually determined by comparing LCZ classification accuracy of different sizes of image patches. For example, Yoo et al. (2019) compared scene sizes of 10×10 pixels (10-m pixel resolution, the same below) and 30×30 pixels, and reported that the latter achieved higher LCZ classification accuracy. Liu & Shi (2020) tested scene sizes ranging from 10×10 to 96×96 pixels, and found that scene sizes from 32×32 to 64×64 pixels are suitable. Similarly, some studies set the scene size to 32×32 pixels for LCZ classification (Feng et al., 2019; Qiu et al., 2020c; Rosentreter et al., 2020).

3.1.3. LCZ samples

LCZ samples are generally collected from visual interpretation of Google Earth images based on expert knowledge or supplemented by field surveys. When selecting LCZ samples manually, the human influence caused by participants with different backgrounds is unavoidable, which may cause a wide discrepancy in the accuracy of LCZ classification (Bechtel et al., 2017). Considering that the manual selection of

LCZ samples is time-consuming, labor-intensive, and difficult to ensure consistency, it is almost impossible to select LCZ samples for all cities around the world. To deal with this problem, [Zhu et al. \(2020\)](#) built a benchmark LCZ sample set, So2Sat LCZ42. The So2Sat LCZ42 sample set includes a total of 400,673 Sentinel-1 and Sentinel-2 image patches (32×32 pixels in 10-m resolution) collected from 52 cities around the world. This LCZ sample set is labeled by a group of domain experts following a carefully designed workflow and evaluation process, which has an overall confidence level of 85%. The So2Sat LCZ42 data set has been used for LCZ classification in several cities ([Feng et al., 2019](#); [Jing et al., 2019](#); [Qiu et al., 2018c, 2020c](#); [Taubenböck et al., 2020](#); [Yang et al., 2019b](#)). On the other hand, some studies have explored the transferability of LCZ samples. The transferability of LCZ samples refers to the use of LCZ training samples from some cities to classify LCZs for other cities. In the 2017 IEEE GRSS Data Fusion Contest, participants are required to use LCZ training samples from Berlin, Hong Kong, Paris, Rome, and Sao Paulo to conduct LCZ mapping for Amsterdam, Chicago, Madrid and Xi'an ([Yokoya et al., 2018](#)). The top four teams used a variety of classification algorithms deriving from computer vision and machine learning ([dos Anjos et al., 2017](#); [Sukhanov et al., 2017](#); [Xu et al., 2017a](#); [Yokoya et al., 2017](#)). [Bechtel et al. \(2019\)](#) suggested that the use of robust generalized classification algorithms and the incorporation of multi-source data can improve the transferability of LCZ samples. [Demuzere et al. \(2019b\)](#) systematically studied the transferability of LCZ samples on a global scale. Their study shows that the accuracy of city-to-city LCZ mapping can be improved if LCZ samples in the same ecoregion as the target city are used or LCZ samples from several cities are combined together. [Elshamli et al. \(2020\)](#) proposed a scalable yet simple

adaptive multisource domain adaptation (AMDA) framework to address the transferability of LCZ samples. [Rosentreter et al. \(2020\)](#) found that the CNN-based classification methods can be used for LCZ mapping of unknown cities if the LCZ training samples collected from other cities are enough.

3.1.4. Classification algorithms

The pixel-based LCZ mapping methods have used a wide variety of machine learning algorithms to classify LCZs. The WUDAPT project uses the random forest (RF) algorithm. Some studies have improved the WUDAPT LCZ mapping method from different aspects, such as classifying a region instead of each city individually ([Cai et al., 2016, 2018](#); [Wang et al., 2019](#)), adding validation steps ([Danylo et al., 2016](#)), and including neighbourhood information ([Patel et al., 2020](#); [Vandamme et al., 2019](#); [Verdonck et al., 2017](#)). In addition, many other machine learning algorithms have been used for LCZ classification, including naive bayes (NB) ([Bechtel et al., 2016](#); [Bechtel & Daneke, 2012](#)), support vector machine (SVM) ([Bechtel et al., 2016](#); [Bechtel & Daneke, 2012](#); [La et al., 2020](#); [Xu et al., 2018](#)), neural networks (NN) ([Bechtel et al., 2016](#); [Bechtel & Daneke, 2012](#)), canonical correlation forest (CCF) ([Zhang et al., 2019](#)), conditional random field (CRF) ([Zhao et al., 2019b](#)), Markov random field (MRF) ([Tuia et al., 2017](#)), subspace classification ([La et al., 2020](#)), and maximum likelihood (ML) algorithms ([Bechtel et al., 2016](#); [Bechtel & Daneke, 2012](#); [La et al., 2020](#); [Nurwanda & Honjo, 2018](#); [Zhang et al., 2019](#)). Moreover, some state-of-the-art machine learning algorithms such as ensemble learning and deep learning have been used for LCZ mapping. For example, the winning teams of the 2017 IEEE GRSS Data Fusion Contest used a variety of ensemble learning algorithms, such as the

ensemble learning that combines canonical correlation forest (CCF) and rotation forest (RoF) (Yokoya et al., 2017), the multilevel ensemble scheme that combines convolutional neural network (CNN), RF, and gradient boosting machine (Sukhanov et al., 2017), and the ensemble of self-paced co-training, support vector machine (SVM), and multi-layer perceptron (MLP) (Xu et al., 2017a). Many studies compared different machine learning algorithms for LCZ classification, and it can be concluded that their performance varies from city to city (Bechtel et al., 2016; Bechtel & Daneke, 2012; La et al., 2020; Mushore et al., 2019; Xu et al., 2017b, 2018). For example, Bechtel & Daneke (2012) found that RF and NN outperform SVM in Hamburg, Germany, while Xu et al. (2017b) reported that RF and SVM performed slightly better than NN in Guangzhou and Wuhan, China.

The object-based LCZ mapping methods generally use image segmentation algorithms to obtain objects, and then use machine learning algorithms to classify objects into LCZs. For example, Wei & Blaschke (2016) used the multi-resolution segmentation and self-organization map (SOM) algorithms to classify LCZs. dos Anjos et al. (2017) used the multiresolution segmentation and random forest (RF) algorithms for LCZ classification. Simanjuntak et al. (2019) used the multiresolution segmentation algorithm that includes two segmentation levels to classify LCZs. Instead of using high-resolution remote sensing data, Collins & Dronova (2019) explored the potential of object-based LCZ classification using medium-resolution Landsat data. In addition, Liu et al. (2019) proposed an object-based LCZ classification method that uses the multiresolution segmentation and CNN algorithms, which overcomes the discrepancy between the irregular objects resulted from image

segmentation and the rectangular classification unit required by CNN.

The scene-based LCZ mapping methods generally uses CNNs to classify LCZs. Different CNNs have been used for LCZ classification, such as ResNet (Qiu et al., 2018c), Re-ResNet (Qiu et al., 2019; Taubenböck et al., 2020), ResNeXt (Jing et al., 2019), Inception (Xu et al., 2019), DenseNet (Yang et al., 2019b), and VGGNet (Rosentreter et al., 2020). Some studies compared the performance of different CNNs for LCZ classification. For example, Feng et al. (2019) proposed an embranchment DenseNet framework for LCZ classification and achieved higher accuracy than the conventional DenseNet. Qiu et al. (2020) proposed the Sen2LCZ-Net-MF architecture for LCZ classification and achieved higher accuracy than other CNNs such as VGG, ResNet, ResNet, ResNeXt, DenseNet, Xception, and CBAM. In addition, Liu & Shi (2020) proposed the LCZNet architecture for LCZ classification and elaborated the effect of input spectral channels, scene size, network depth, and training set size on LCZ classification accuracy.

3.1.5. Accuracy evaluation

The validation of LCZ classification accuracy mainly include three strategies: (1) The hold-out method. A part of LCZ samples are selected as the training set and the remaining part is used as the validation set. (2) The bootstrapping method. The training set is selected from LCZ samples with replacement and the remaining is selected as the validation set. (3) The cross-validation or k-fold cross validation method. LCZ samples are randomly split up into 'k' groups of which one group is used as the validation set and the rest are used as the training set. This is repeated until

each group has been used as the validation set. The accuracy metrics of LCZ classification mainly include overall accuracy (OA), producer accuracy (PA), user accuracy (UA), Kappa, weighted accuracy (WA), and F1-score that are derived from the confusion matrix between LCZ classification results and validation samples. In addition, the OA of urban LCZs (OA_u) and the OA of urban versus natural LCZs (OA_{bu}) have been used for accuracy evaluation.

OA is usually used to evaluate the overall accuracy of LCZ classification. PA is usually used to evaluate the accuracy of different LCZ classes. PA varies across LCZs for different cities. In general, LCZ A (dense trees), LCZ D (low plants), and LCZ G (water) generally obtain higher PAs than the other LCZs because the three LCZs are usually relatively uniform. On the other hand, LCZ classification accuracy also depends on the performance of classification algorithms and the characteristics of remote sensing data. For classification algorithms, it is difficult to completely avoid the overfitting and class imbalance problems of LCZ training samples (Yokoya et al., 2017). For example, LCZ A (dense trees), LCZ D (low plants) and LCZ G (water) usually have more training samples, while LCZ 1 (compact high-rise) and LCZ 7 (lightweight low-rise) training samples are relatively scarce. For remote sensing data, there are several challenges: (1) Lack of the height information of buildings and vegetation, which probably result in the misclassification of built type LCZs (Cai et al., 2018; Kaloustian & Bechtel, 2016). (2) The phenomenon of ‘the same spectrum of different LCZs’ or ‘different spectrums of the same LCZ’, which, for example, usually causes the confusion between LCZ 8 (large low-rise), LCZ 10 (heavy industry) and LCZ E (bare rock or paved) (Bartasaghi Koc et al., 2017; Verdonck et al., 2017; Xu et

557 [al., 2017b](#)).

Literature	Data	Unit size	Classification algorithms	Accuracy evaluation strategies (metrics)
Pixel-based				
Bechtel & Daneke (2012)	Landsat 5, Landsat 7, IFSAR-NDSM	100 m	ZeroR, Naïve Bayes, Neuronal Network, SVM, RF	Hold-out (OA, UA, PA, Kappa)
Bechtel et al. (2015)	Landsat 5, Landsat 8	100 to 120 m	RF	(OA, UA, PA, Kappa)
Bokva et al. (2015)	Landsat 7		RF	
Bechtel et al. (2016)	Landsat 8, Sentinel-1	120 m	NB, RF, SVM, multilayer perceptron neural network	Hold-out (OA, PA, UA, Kappa)
Brousse et al. (2016)	Landsat 8		WUDAPT	

Cai et al. (2016)	Landsat 8		Improved WUDAPT	Hold-out (OA, PA, UA, Kappa)
Danylo et al. (2016)	Landsat 8	120 m	RF	Hold-out (OA, PA, UA, Kappa)
Kaloustian & Bechtel (2016)	Landsat 8, Sentinel-2	100 m	RF	Bootstrapping (OA, Kappa)
Ren et al. (2016a)	Landsat 8	100 m	WUDAPT	Hold-out (OA, PA, UA, Kappa)
Ren et al. (2016b)		300 m		
Skarbit & Gál (2016)			WUDAPT	
Budhiraja et al. (2017)	Landsat 8		WUDAPT	
Cai et al. (2017)	Landsat 8	100 m	RF	Hold-out (OA, UA, PA, Kappa)
Chen et al. (2017)	Landsat 8		WUDAPT	
Ferreira et al. (2017)	Landsat 8		WUDAPT	Hold-out (OA, PA, UA, Kappa)
Gupta et al. (2017)	Landsat 5, Landsat 8		WUDAPT	

Kaloustian et al. (2017)	Landsat 8, Sentinel-1, Sentinel-2	100 m	RF	Bootstrapping (OA, Kappa)
Shih (2017)	Landsat 8		WUDAPT	
Sukhanov et al. (2017)	Landsat 8, Sentinel-2, OSM	100 m	CNN, RF, Gradient Boosting Machine (GBM)	Cross validation (OA, Kappa)
Tuia et al. (2017)	Rapid-eye, Cartosat-1, OSM	200 m	Markov random field (MRF)	Hold-out (OA, AA, Kappa)
Verdonck et al. (2017)	Landsat 8	30, 100 m	RF	Bootstrapping (OA, F1)
Wang et al. (2017)	Landsat 8	100 m	WUDAPT	
Xu et al. (2017a)	Landsat 8, OSM, Sentinel-2	100 m	extreme gradient boosting (XGBoost), SVM, MLP	(OA, k)
Xu et al. (2017b)	Landsat 8, ASTER	120 m	RF, NN, SVM	Hold-out (OA, k)

Xu et al. (2017c)	Landsat 8	120 m	RF	Hold-out (OA, UA, PA, Kappa)
Yokoya et al. (2017)	Landsat 8, OSM	100 m	CCFs, RoFs	Hold-out (OA, UA, PA, Kappa)
Beck et al. (2018)	Landsat 8	100 m	WUDAPT	
Cai et al. (2018)	Landsat 8	100 m	RF	Hold-out (OA, UA, PA, Kappa)
Chieppa et al. (2018)	Landsat 8		WUDAPT	
Hu et al. (2018)	Landsat 8, Sentinel-1	100 m	CCF	Hold-out (OA, UA, PA, Kappa)
Nurwanda & Honjo (2018)	Landsat 5, Landsat 8		maximum likelihood classification (MLC)	(OA, UA, PA, k)
Nurwanda (2018)				
Oxoli et al. (2018)	Landsat 8, Sentinel-2, Rapid-eye		RF	Hold-out (OA, UA, PA, k)
Richard et al. (2018)	Landsat 8		WUDAPT	
Wang et al. (2018a)	Landsat 8	100 m	RF	Hold-out (OA, UA, PA, k)

Wang et al. (2018c)	Landsat 8	200 m	WUDAPT	
Xu et al. (2018)	Landsat 8, DSM	30 m	RF, SVM	Hold-out (OA, UA, PA)
Ziaul & Pal (2018)	Landsat 5, Landsat 8	100 m	RF	Hold-out (OA, UA, PA, Kappa)
Bechtel et al. (2019)	Landsat 8, Sentinel-2	100 m	WUDAPT	Bootstrapping (OA, WA, Kappa)
Bokwa et al. (2019)			WUDAPT	
Brousse et al. (2019)	Landsat 8, Sentinel-1, DMSP/OLS nighttime lights		WUDAPT	Bootstrapping (OA, OA _u , OA _{bu} , WA, F1-score)
Chen et al. (2019)	Landsat 8	100 m	WUDAPT	
Demuzere et al. (2019b)	Landsat 8, Sentinel-1, DMSP/OLS nighttime lights, global forest canopy height (GFCH), GTOPO30, DSM, DEM	100 m	RF	Bootstrapping (OA, OA _u , OA _{bu} , WA, F1-score)
Demuzere et al. (2019a)				
Eldesoky et al. (2019)	Landsat 8, digital topographic database (DTDB)	30 m	WUDAPT	Bootstrapping (OA, OA _u , PA, Kappa)

Khamchiangta & Dhakal (2019)	Landsat 8		WUDAPT (maximum likelihood)	(OA, Kappa)
Lotfian et al. (2019)	Landsat 8	100 m	RF	Out-of-Bag (OA)
Mouzourides et al. (2019)	Landsat 8	100 m	RF	Hold-out (OA, Kappa)
Mughal et al. (2019)	Landsat 8, building height data		WUDAPT	Hold-out (OA, Kappa)
Mushore et al. (2019)	Landsat 8	30 m	SVM, RF	Hold-out (OA, UA, PA, Kappa)
Odekunle et al. (2019)	Landsat 8		WUDAPT	Hold-out (OA, PA, UA, Kappa)
Pokhrel et al. (2019)	Landsat 8	100 m	WUDAPT	

Pradhesta et al. (2019)	Landsat 8		WUDAPT	
Ren et al. (2019)	Landsat 8, Sentinel-1	100 m	WUDAPT	Hold-out (OA, OA _u , WA)
Rostam & Beck (2019)	Landsat 8	100 m	WUDAPT	
Semenova et al. (2019)	Landsat 7		WUDAPT	
Shi et al. (2019)	Landsat 8	100 m	WUDAPT	Hold-out (OA, Kappa)
Vandamme et al. (2019)	Landsat 7, Landsat 8	100 m	RF	Bootstrapping (OA, F1-score)
Verma et al. (2019)	Sentinel-2	10 m	CNN, ANN, RF, SVM	Hold-out (OA, Kappa, F1-score)
Wang et al. (2019)	Landsat 5, Landsat 8	100 m	RF	Hold-out (OA, UA, PA, Kappa)
Zhang et al. (2019)	Landsat 8, Sentinel-2, OSM	100 m	CCF	Hold-out (OA, UA, PA, Kappa)
Zhao et al. (2019b)	Landsat 8	100 m	CRF, RF, SVM	——(OA, Kappa)

Abougendia et al. (2020)	Landsat 8	100 m	RF	WUDAPT
Anjos et al. (2020)	Landsat 8	100 m	RF	Hold-out (OA, UA, PA, Kappa)
Bande et al. (2020a)	Landsat 8		WUDAPT	
Bande et al. (2020b)				
Berlessova & Konstantinov (2020)	Landsat		WUDAPT	
Brousse et al. (2020)		100 m	RF	Bootstrapping (OA, WA, F1-score)
Chen et al. (2020a)	Landsat 8		WUDAPT	Hold-out (OA)
Colli et al. (2020)	Landsat 8		WUDAPT	
Das & Das (2020)	Landsat 5, Landsat 8	100 m	WUDAPT	Hold-out (OA, UA, PA, Kappa)

Demuzere et al. (2020a)	Landsat 8, Sentinel-1, DMSP/OLS night time lights, GFCH, USGS/GTOPO30, DSM, DEM	100 m	RF	Bootstrapping (OA, OA _u , OA _{bu} , WA, F1-score)
Demuzere et al. (2020b)	Landsat 5, Landsat 7, Landsat 8			
Droste et al. (2020)			WUDAPT	
Fricke et al. (2020)	Landsat 8	100 m	WUDAPT	
La et al. (2020)	Sentinel-2, PALSAR-2	10 m	SVM, MLC, subspace method	Hold-out (OA, UA, PA, Kappa)
Manandhar et al. (2020)	Landsat 8		WUDAPT	
McRae et al. (2020)	Landsat 8	100 m	WUDAPT	
Mu et al. (2020)	Landsat 8		WUDAPT	
Ochola et al. (2020)	Landsat 8	100 m	RF	Hold-out (OA, UA, PA, Kappa)
Patel et al. (2020)	Landsat 8	100 m	RF	Hold-out (OA, UA, PA, Kappa)

Shevchenko et al. (2020)	Landsat 8		WUDAPT	
Shih et al. (2020)	Landsat 8	30 m	WUDAPT	
Varentsov et al. (2020)	Landsat 8, Sentinel-1, Sentinel-2, global forest canopy height (GFCH), DTM, DEM, DSM	100 m	RF	Bootstrapping (OA, OA _u , OA _{bu} , WA, F1-score)
Wang et al. (2020)			WUDAPT	
Yang et al. (2020a)	Landsat	100 m	WUDAPT	Hold-out (OA, UA, PA, Kappa)
Zhao et al. (2020b)			WUDAPT	
Zhou et al. (2020b)	Landsat 8	100 m	RF	Hold-out (OA, UA, PA, Kappa)
Zonato et al. (2020)	Landsat	30 m	WUDAPT	
Object-based				
Wei & Blaschke (2016)	HJ-1B	Segmentation scale=50	Multi-resolution segmentation, Self-	

			Organization Map (SOM)	
dos Anjos et al. (2017)	Landsat 8, Sentinel-2	Segmentation scale=20	Multi-resolution Segmentation, RF	Bootstrapping (OA, Kappa)
Collins & Dronova (2019)	Landsat 5, 8	Segmentation scale=20	Segment Mean Shift tool in ArcGIS, RF	Bootstrapping (OA, PA, UA)
Liu et al. (2019)	Sentinel-1, Sentinel-2, Reflective Optics System Imaging Spectrometer (ROSIS) hyperspectral data	Segmentation scale=30, 20, 8	Multi-resolution segmentation, SVM, RF, CNN	Hold-out (OA, AA, Kappa)
Simanjuntak et al. (2019)	Pleiades, SPOT-6, OpenStreetMap (OSM)	Segmentation scale=10, 300, 500	Multi-resolution segmentation, Rule- set classification	Hold-out (OA, PA, UA, Kappa)
Scene-based				
Leichter et al. (2018)	Sentinel-2, Twitter data	Image patch size 250×250	CNN	Hold-out (OA, F1-score, precision, recall)

		pixels (10-m resolution)		
Qiu et al. (2018a)	Sentinel-2, Landsat 8, Global Urban Footprint (GUF), OSM, VIIRS Nighttime Light (NTL), So2Sat LCZ42 data set	Image patch size 32×32 pixels (10-m resolution)	ResNet	Cross validation (OA, AA, Kappa, WA)
Qiu et al. (2018b)	Sentinel-2, So2Sat LCZ42 data set			Cross validation (OA, AA, Kappa)
Qiu et al. (2018c)	Sentinel-2, Global Urban Footprint (GUF), OSM, So2Sat LCZ42 dataset			
Feng et al. (2019)	Sentinel-1, Sentinel-2, So2Sat LCZ42 data set	Image patch size 32×32 pixels (10-m resolution)	Inception and Densenet based embranchment CNN	Hold-out (average precision)
Jing et al. (2019)	Sentinel-1, Sentinel-2, So2Sat LCZ42 data set	Image patch size 32×32	ResNeXt	Hold-out (OA)

		pixels (10-m resolution)		
Qiu et al. (2019a)	Sentinel-2, So2Sat LCZ42 data set	Image patch size 32×32 pixels (10-m resolution)	Recurrent residual network architecture (Re-ResNet)	Cross validation (OA, Kappa)
Qiu et al. (2019b)			ResNet	
Xu et al. (2019)	Google Street View	Image patch size 640×640 pixels	Inception-v3	Bootstrapping (OA, PA, UA)
Yang et al. (2019b)	Sentinel-2, So2Sat LCZ42 data set	Image patch size 32×32 pixels (10-m resolution)	Multi-Scale Input Spatial Pyramid Pooling Fusion Networks (MSPPF-nets)	Hold-out (precision, recall, F1-score)

Yoo et al. (2019)	Landsat 8	Image patch size 10×10 and 30×30 pixels (10-m resolution)	CNN	Hold-out (OA, PA, UA, F1-score)
Elshamli et al. (2020)	Lansat 8, Sentinel-2	Image patch size 20×20 pixels (30-m resolution)	Deep neural networks (DNN)-based adaptive multisource domain adaptation (AMDA) framework	Hold-out (OA)
Feng et al. (2020)	Sentinel-1, Sentinel-2, So2Sat LCZ42 data set	Image patch size 32×32 pixels (10-m resolution)	DenseNet-based dynamic filter network (DFN)	Hold-out (accuracy, average precision)

Gawlikowski et al. (2020)	Sentinel-1, Sentinel-2, So2Sat LCZ42 dataset	Image patch size 32×32 pixels (10-m resolution)	CNN-based fusion network	Hold-out (OA, AA, Kappa)
Kim et al. (2020)	Sentinel-2	Image patch size 32×32 pixels (10-m resolution)	multi-scale CNN (MSCNN)	Hold-out (OA, Kappa, F1-score)
Liu & Shi (2020)	Sentinel-2	Image patch sizes 10×10, 16×16, 32×32, 64×64 (10-m resolution)	LCZNet	Hold-out (OA, AA, Kappa)
Qiu et al. (2020b)	Sentinel-2, So2Sat LCZ42 data set		Sen2LCZ-Net-MF	Hold-out (OA, AA, WA, Kappa)

Qiu et al. (2020a)		Image patch size 32×32 pixels (10-m resolution)	multi-task learning (MTL)-based CNN	
Rosentreter et al. (2020)	Sentinel-2	Image patch size 32×32 pixels (10-m resolution)	VGGNet	Hold-out (OA, PA, UA)
Taubenböck et al. (2020)	Sentinel-2, So2Sat LCZ42 data set	Image patch size 32×32 pixels (10-m resolution)	Re-ResNet	
Zhao et al. (2020a)	So2Sat LCZ42 data set	Image patch size 32×32	CNN (SeNet, ResNet, ResNeXt)-based circled similarity	Bootstrapping (OA)

		pixels (10-m resolution)	propagation-based domain adaptation (CPDA) method	
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3.2. GIS-based LCZ mapping methods

GIS-based LCZ mapping methods develop from the LCZ classification process of field sites guided by [Stewart & Oke \(2012\)](#). The procedure of GIS-based LCZ mapping methods mainly includes three steps: calculate LCZ parameters, determine the basic spatial unit, and classify LCZs and perform post-processing if necessary. Therefore, GIS-based LCZ mapping methods consist of three key components: LCZ parameters, basic spatial units, and classification rules. It should be noted that the accuracy evaluation of GIS-based LCZ mapping methods is usually not performed, which is significantly different from RS-based methods.

3.2.1. LCZ parameters

[Stewart & Oke \(2012\)](#) defined 10 basic LCZ parameters that characterize four categories of surface physical properties, i.e., surface structure (sky view factor, aspect ratio, height of roughness elements, and terrain roughness class), surface cover (building surface fraction, impervious surface fraction, and pervious surface fraction), surface material (surface admittance and surface albedo), and human activity (anthropogenic heat output). Most studies used the basic LCZ parameters and reference ranges proposed by [Stewart & Oke \(2012\)](#). The commonly used LCZ parameters are surface structure and cover parameters, while surface material and human activity parameters are rarely used ([Tab. 3](#)). However, these rarely used parameters may play a key role in classifying LCZs. For example, for LCZ 6 (open low-rise) and LCZ 10 (heavy industry), the reference ranges of LCZ parameters overlap except the human activity parameter.

Multi-source remote sensing and GIS data have been used for calculating LCZ parameters. For surface structure parameters, the sky view factor (SVF) can be calculated using digital surface model (DSM) (Bartesaghi Koc et al., 2017; Mitraka et al., 2015; Quan, 2019; Zhao et al., 2019a; Zheng et al., 2018), building data (Chen et al., 2020b; Nassar et al., 2016), and Google Street View (Middel et al., 2018). The aspect ratio can be calculated as the mean building height divided by the mean street width using building data (Chen et al., 2020b; Zheng et al., 2018), and as the maximum height divided by average width of ground surface based on the normalized DSM (Zhao et al., 2019a). The height of roughness elements can be calculated as a mean height of buildings weighted by the building footprints using building data (Lelovics et al., 2014; Nassar et al., 2016; Quan, 2019; Zheng et al., 2018). The terrain roughness class can be determined by the Davenport classification method using aerial images, topographic maps, and building data (Lelovics et al., 2014), building data and Landsat 8 data (Chen et al., 2020b), and DSM and land cover data (Zhao et al., 2019a). For the calculation of surface cover parameters, the commonly used data are land cover and building data (Lelovics et al., 2014; Nassar et al., 2016; Quan et al., 2017). For surface material parameters, remotely sensed multispectral data is generally used to characterize surface albedo (Lelovics et al., 2014).

Tab. 3. GIS-based LCZ mapping methods.

Literature	LCZ parameters									
	SVF	AR	BSF	ISF	PSF	HRE	TRC	SAD	SAL	Ah
Parcel-based										
Perera et al. (2013)	√	√	√	√	√	√	√	√	√	√

Lelovics et al. (2014)	√		√	√	√	√	√		√	
Thomas et al. (2014)	√	√	√	√	√	√				
Unger et al. (2014)	√		√	√	√	√	√		√	
Emmanuel & Loconsole (2015)			√			√				
Leconte et al. (2015)	√	√	√	√	√	√	√			
Ndetto & Matzarakis (2015)	√	√		√	√					
Plumejeaud- Perreau et al. (2015)	√	√								√
Šećerov et al. (2015)	√		√	√	√	√	√		√	
Skarbit et al. (2015)	√		√	√	√	√	√		√	
Leconte et al. (2017)	√	√	√	√	√	√	√			
Quan et al. (2017)		√			√	√				
Skarbit et al. (2017)	√		√	√	√	√				
Gonçalves et al. (2018)	√			√			√			
Perera & Emmanuel (2018)	√	√	√	√	√	√	√	√	√	√

Savić et al. (2018)	√		√	√	√	√	√		√	
Wu et al. (2018)	√	√	√	√	√	√				
Hidalgo et al. (2019)						√				
Chen & Huang (2019)	√	√	√	√	√	√	√			
Kwok et al. (2019)						√				
Quan (2019)	√		√	√	√	√				
Rodler & Leduc (2019)	√	√	√	√		√				
Hashemi et al. (2020)	√	√	√	√	√	√		√	√	√
Jin et al. (2020)	√	√	√	√	√	√	√			
Mandelmilch et al. (2020)	√	√	√							
Grid-based										
Lau et al. (2015)	√		√			√				
Mitraka et al. (2015)	√		√	√	√	√			√	
Zheng et al. (2015)			√			√				
Nassar et al. (2016)	√		√	√	√	√				
Geletič & Lehnert (2016)			√	√	√	√				
Geletič et al. (2016)			√	√	√	√				

Lin & Xu (2016)			√	√	√					
Bartesaghi Koc et al. (2017)	√			√	√	√				
Hammerberg et al. (2018)		√	√	√	√	√				
Bartesaghi Koc et al. (2018)	√			√	√	√				
Zhan et al. (2018)	√		√	√	√	√	√	√	√	
Agathangelidis et al. (2019)		√		√	√	√			√	
Cai et al. (2019)	√		√	√		√				
Estacio et al. (2019)	√		√	√	√	√	√		√	
Hu et al. (2019)			√	√	√	√				
Geletić et al. (2019)			√	√	√	√				
Agathangelidis et al. (2020)		√	√	√		√				
Chen et al. (2020b)	√	√	√	√	√	√	√			
Somuncu & Yüksel (2020)			√			√				

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606 3.2.2. Basic spatial units

607 GIS-based LCZ mapping methods usually use two types of basic spatial units, parcel
608 and grid. Here the parcel unit generally refers to lot area polygons (Lelovics et al.,
609 2014; Molnár et al., 2019; Savić et al., 2018; Skarbit et al., 2017, 2015; Unger et al.,
610 2014), blocks (He et al., 2019; Jin et al., 2020; Kwok et al., 2019; Perera &

611 [Emmanuel, 2018; Quan, 2019; Quan et al., 2017; Wu et al., 2018](#)), and urban islets
 612 ([Bocher et al., 2018; Hidalgo et al., 2019; Plumejeaud-Perreau et al., 2015](#)). The
 613 parcel-based LCZ mapping uses line elements such as roads, streets, and rivers as
 614 boundaries, while the grid-based LCZ mapping creates a net of square cells to divide
 615 LCZs. For the two types of spatial units, the methods for determining the appropriate
 616 unit size are different. (1) For the parcel unit, the minimum radius is generally set to
 617 200-500 m as suggested by [Stewart & Oke \(2012\)](#). For example, [Lelovics et al. \(2014\)](#)
 618 set the minimum radius of lot area polygons to 250 m in order to meet the requirement
 619 of large homogeneous areas for establishing LCZs. The same criterion was adopted by
 620 [Wu et al. \(2018\)](#) to define the minimum radius of blocks. [Quan et al. \(2017\)](#) and [Jin et](#)
 621 [al. \(2020\)](#) set the minimum radius of urban blocks to 200-500 m in order to to reduce
 622 the influence of surrounding LCZs. (2) For the grid unit, the appropriate grid size can
 623 be determined by the following strategies: (i) Based on empirical knowledge. This
 624 method has been widely used to determine the grid size ([Agathangelidis et al., 2019;](#)
 625 [Cai et al., 2019; Geletič et al., 2019, 2016; Geletič & Lehnert, 2016; Mitraka et al.,](#)
 626 [2015; Shi et al., 2018; Wang et al., 2018b; Yang et al., 2020c](#)). For example, [Geletic &](#)
 627 [Lehnert \(2016\)](#) chose 100 m as the spatial unit size for three medium-sized cities
 628 (Brno, Hradec Králové, and Olomouc) in Czech Republic, because on this scale the
 629 physical properties of the environment significantly affect local air temperature. [Cai et](#)
 630 [al. \(2019\)](#) selected the grid size of 250 m for the the Yuzhong district of Chongqing,
 631 China, because the correlation between urban morphology factors and LST is more
 632 significant on this spatial scale. (ii) Test different grid sizes for LCZ mapping. For
 633 example, [Hu et al. \(2019\)](#) tested six grid cells (120, 180, 240, 270, 360, and 480 m) to
 634 select the optimal size (240 m). (iii) Based on the semi-variogram model of building

height. For example, the appropriate grid size determined by this method is 300 m for Hong Kong (Zheng et al., 2018), 270 m for Dallas-Fort Worth, Austin, and San Antonio in Texas, US (Zhao et al., 2019a), and 200 m for Chenzhou, China (Chen et al., 2020b).

3.2.3. Classification rules

The direct way to determine LCZ classes is to match the calculated values of LCZ parameters with their reference ranges. This method has been most widely used to distinguish LCZs based on the LCZ parameters provided by Stewart & Oke (2012) or custom parameters (Agathangelidis et al., 2019; Bartesaghi Koc et al., 2018, 2017; Cai et al., 2019; Emmanuel & Loconsole, 2015; Jin et al., 2020; Leconte et al., 2017, 2015; Mandelmilch et al., 2020; Mitraka et al., 2015; Nassar et al., 2016; Ndetto & Matzarakis, 2015; Perera & Emmanuel, 2018; Shi et al., 2018; Thomas et al., 2014; Villadiego & Velay-Dabat, 2014; Wang et al., 2018b; Zheng et al., 2018). In addition, some studies have used other methods to determine LCZ types, such as the score assignment method (Lelovics et al., 2014; Unger et al., 2014), the decision-making algorithm (Chen et al., 2020b; Geletič et al., 2016; Geletič & Lehnert, 2016; Quan, 2019; Zhao et al., 2019a), the multi-dimensional linear interpolation method (Quan et al., 2017), the Naïve Bayes algorithm (Hammerberg et al., 2018), the random forest algorithm (Hu et al., 2019), and the k-means method (Hidalgo et al., 2019; Kwok et al., 2019; Zhan et al., 2018).

The post-processing steps are sometimes required, such as merging unclassified or small-area LCZs into adjacent and similar larger LCZs, to obtain a reasonable LCZ

classification. For example, [Lelovics et al. \(2014\)](#) elaborated on how to merge lot area polygons according to LCZ categories, their locations relative to each other, and the spatial extensions of merged polygons. [Geletic & Lehnert \(2016\)](#) merged small LCZs of less than a hectare into the prevailing LCZ in the neighbourhood. [Wu et al. \(2018\)](#) used a majority filter to determine the dominant LCZ if a small LCZ with a radius less than 250 m is surrounded by larger LCZ clusters. [Jin et al. \(2020\)](#) merged small LCZ blocks with a radius less than 200 m into adjacent larger ones with similar LCZ classes. Note that the improper use of LCZ merging rules may lead to uncertainty. For example, merging a small LCZ B (scattered trees) into the nearby larger LCZ 6 (open low-rise) may sometimes be misleading because the actual LCZ combining the two LCZs could be LCZ 9 (sparsely built).

3.3. Combined LCZ mapping methods

The general idea of combined LCZ mapping methods is to integrate the advantages of RS-based and GIS-based methods. The combined LCZ mapping methods usually use both remote sensing and GIS data, and the mapping unit is usually grid-based. In general, the combined LCZ mapping methods can be divided into two categories ([Tab. 4](#)): (1) The ‘coarse-to-fine’ classification methods. This is to use RS-based methods to preliminarily classify LCZs and then use GIS-based methods to refine LCZ classification. Some studies use GIS-based post-classification filtering to refine RS-based LCZ mapping. For example, [Gál et al. \(2015\)](#) used the GIS-based LCZ aggregation process to refine the RS-based LCZ classification. [He et al. \(2019\)](#) integrated the WUDAPT LCZ mapping with the land parcels divided by road network. On the other hand, some studies use LCZ parameters to assist RS-based LCZ

classification. For example, [Lopes et al. \(2017\)](#) and [Fonte et al. \(2019\)](#) extracted the building surface fraction and impervious surface area information from OpenStreetMap (OSM) data to assist the WUDAPT LCZ mapping. [Zhou et al. \(2020\)](#) extended the WUDAPT LCZ mapping process by adding LCZ parameters to refine LCZ classification. (2) The ‘built type-land cover type’ separation classification methods. A common practice is to identify land cover type LCZs based on the land use and land cover classification, and use LCZ parameters to classify built type LCZs ([Du et al., 2020](#); [Han et al., 2020](#); [Kotharkar & Bagade, 2018](#); [Shi et al., 2018](#); [Wang et al., 2018b](#); [Wicki & Parlow, 2017](#); [Yang et al., 2020b, 2019a](#); [Zhao et al., 2019a](#); [Zheng et al., 2018](#)).

Tab. 4. Combined LCZ mapping methods.

Literature	Classification methods
Gál et al. (2015)	coarse-to-fine
Lopes et al. (2017)	coarse-to-fine
Fonte et al. (2019)	coarse-to-fine
He et al. (2019)	coarse-to-fine
Zhou et al. (2020a)	coarse-to-fine
Wicki & Parlow (2017)	built type-land cover type
Kotharkar & Bagade (2018)	built type-land cover type
Wang et al. (2018b)	built type-land cover type
Zheng et al. (2018)	built type-land cover type
Molnar et al. (2019)	built type-land cover type
Mu et al. (2019)	built type-land cover type
Yang et al. (2019a)	built type-land cover type

Zhao et al. (2019a)	built type-land cover type
Du et al. (2020)	built type-land cover type
Han et al. (2020)	built type-land cover type
Yang et al. (2020b)	built type-land cover type
Yang et al. (2020c)	built type-land cover type

3.4. Comparison of LCZ mapping results

Some studies have compared the LCZ maps generated by RS-based and GIS-based methods in several cities (Gál et al., 2015; Geletić & Lehnert, 2016; Hammerberg et al., 2018; He et al., 2019; Hidalgo et al., 2019; Shi et al., 2018; Wang et al., 2018b). In addition to the difference in the classification process, the RS-based and GIS-based methods also differ in LCZ classification accuracy and LCZ types: (1) LCZ classification accuracy. Some studies reported that GIS-based LCZ mapping methods can obtain better classification results than the WUDAPT LCZ mapping method (Hidalgo et al., 2019; Wang et al., 2018b). For RS-based LCZ mapping methods, object-based and scene-based classification methods usually achieve higher accuracy than pixel-based methods, because the former two use texture and shape features in addition to spectral features for LCZ classification (Liu & Shi, 2020; Rosentreter et al., 2020; Simanjuntak et al., 2019; Yoo et al., 2019). (2) LCZ types. In general, the LCZ types determined by RS-based methods depend on LCZ training samples, which are usually selected from the 17 standard LCZs defined by Stewart and Oke (2012). However, GIS-based methods often face the situation that the calculated LCZ parameters do not match the reference ranges, in which LCZ subclasses will probably be introduced. Some studies reported that the difference between RS-based and GIS-

714 based LCZ classification results reaches 33% in Vienna, Austria ([Hammerberg et al.,](#)
715 [2018](#)) and 49% in Brno, Czech Republic ([Geletič & Lehnert, 2016](#)).

716

717

4. DISCUSSION

Although LCZ mapping has achieved great progress, there are still challenges that need to be addressed. Next, we will provide suggestions to deal with several challenges of LCZ mapping research.

4.1. Data sources

High-resolution and high-precision data that characterize surface structure, cover, material, and human activity lay the groundwork for accurate LCZ mapping. Future work on data sources of LCZ mapping can be carried out from the following aspects:

(1) Exploit the potential of remote sensing and GIS data. Currently, the most widely used remote sensing and GIS data are Landsat multispectral data and urban building data, respectively. Other remote sensing and GIS data are highly encouraged to be used more for LCZ mapping since they could provide a wide variety of useful urban form and function information. For example, high-resolution satellite data such as Sentinel-2, SPOT, Pleiades, and Gaofen data can obtain detailed and accurate surface coverage. Sentinel-1 SAR data can be used to extract surface polarization, texture, and morphology features (Hu et al., 2018). TanDEM-X data can be used to estimate urban building height (Geis et al., 2019). Global Human Settlement Layer and Global Urban Footprint data provide high-resolution maps of human settlements (Esch et al., 2017; Pesaresi et al., 2013). Google Street View can be used to reconstruct 3D urban landscape (Li et al., 2017; Torii et al., 2009). OpenStreetMap data provide detailed urban land use information such as building footprints (Lopes et al., 2017). Heat maps of urban population and traffic congestion can be used to estimate anthropogenic heat.

Many studies have demonstrated that the combination of multi-source remote sensing and GIS data can improve LCZ mapping accuracy (Bechtel et al., 2017; Brousse et al., 2016; Jing et al., 2019; La et al., 2020; Qiu et al., 2018c; Stewart & Oke, 2012; Xu et al., 2018; Yoo et al., 2020). However, using multi-source data with poor data quality and redundant features would probably lead to uncertainty. Therefore, how to select and fuse multi-source data for LCZ mapping needs further investigation. Some considerations for selecting feature sets have been pointed out in Section 3.1.1. (2) Expand the acquisition means of urban data. The following data collection methods can be used: (i) Use unmanned aerial vehicles (UAVs) equipped with remote sensors such as Lidar to acquire high-resolution 3D urban surface information. (ii) Using web crawlers or social networking to collect geospatial big data. For example, use a web crawler to search for building information such as building floors, areas, materials, and functions from a housing trading platform. These data acquisition methods have been initially proved to be feasible, but how to ensure data accuracy and how to process data need to be further explored.

4.2. Mapping scale

Mapping scale is key to cartography. Here the LCZ mapping scale refers to the classification units of RS-based methods (Section 3.1.2) or the basic spatial units of GIS-based methods (Section 3.2.2). In general, five factors need to be considered to determine the appropriate LCZ mapping scale: (1) LCZ definition scale. The LCZ scale ranges from several hundred meters to several kilometers (Stewart & Oke, 2012), i.e., a minimum diameter of 400–1000 m. (2) City size and form. That cities worldwide have great diversity in geographic setting, city size, urban morphology,

and development mode should be considered in LCZ mapping. (3) Spatial resolution of multi-source remote sensing and GIS data. The spatial resolution is required to be high enough to catch the interior form within an LCZ. (4) Classification algorithms. For RS-based methods, the classification unit size should be suitable for the classification algorithm to accurately recognize LCZs. (5) Application requirements. For example, when using an LCZ map as the input to urban climate models (e.g., WRF/UCM, ENVI-met), the LCZ mapping unit needs to match the model scale.

As summarized in [Sections 3.1.2](#) and [3.2.2](#), both qualitative analysis and quantitative methods have been used to determine the LCZ mapping scale. Qualitative analysis empirically determines the LCZ mapping scale by comprehensively weight up the above-mentioned factors. For example, the WUDAPT project defines a uniform LCZ mapping unit size (100 m) to classify LCZs for global cities. Although simplicity and consistency, it may be inappropriate to use a uniform LCZ mapping scale for global cities with great diversity. On the other hand, quantitative methods generally determine the optimal LCZ mapping scale by comparing LCZ classification results of different scales. Compared with qualitative analysis, quantitative methods are more reasonable and generally achieve higher LCZ classification accuracy. Therefore, quantitative methods have become the mainstream to determine the LCZ mapping scale in recent years. However, there are still some challenges in quantitative methods. For example, it is laborious to find the optimal LCZ mapping scale from a range of scales, and thus necessary to form simple standard procedures to determine the LCZ mapping scale for global cities.

4.3. Mapping methods

For RS-based LCZ mapping methods, we provide some future directions on LCZ samples and classification algorithms. (1) For LCZ samples, the following research can be carried out: (i) Assess the impact of LCZ training samples on LCZ classification. The minimum number and area of LCZ training samples required for LCZ classification depend on city size, urban morphology, and machine learning algorithms. The effects of feature redundancy and class imbalance of LCZ training samples on LCZ classification accuracy need to be further investigated for different cities. (ii) Build standard LCZ sample sets. Considering the diversity of global cities, LCZ sample sets can be established on climate zone, country, and continental scales. On the other hand, LCZ sample sets can be constructed based on different remote sensing data such as Landsat or Sentinel data. To establish standard LCZ sample sets needs to address several challenges, such as what criteria to be followed when manually selecting typical LCZ samples based on expert knowledge and how to evaluate the accuracy of LCZ samples. (iii) Explore the transferability of LCZ samples. In addition to the establishment of standard LCZ sample sets, exploring the transferability of LCZ samples is a prerequisite for making full use of LCZ sample sets, which will reduce the huge cost and uncertainty caused by the manual selection of LCZ samples and greatly facilitate global LCZ mapping. The current research on the transferability of LCZ samples is still in its infancy, and further research on this issue can be carried out by combining standard LCZ sample sets with state-of-the-art machine learning algorithms. (2) For LCZ classification algorithms, further research can be conducted to improve pixel-based, object-based, and scene-based LCZ classification methods. The pixel-based methods can be improved by introducing

813 advanced machine learning algorithms and incorporating spatial context information.
814 Compared with pixel-based methods, object- and scene-based LCZ classification
815 methods are relatively less used and need to be extended to many more cities. For
816 object-based LCZ classification, further research can focus on how to effectively
817 segment LCZ objects on different spatial scales (or the effect of segmentation scale on
818 LCZ mapping) and how to deal with the divergence between the irregular objects
819 resulted from image segmentation and the rectangular units required by some
820 advanced machine learning algorithms such as CNNs. For scene-based LCZ
821 classification, future research can introduce more state-of-the-art CNNs and evaluate
822 the effect of scene size and CNN architecture on LCZ classification accuracy.
823
824 For GIS-based LCZ mapping methods, we provide some further research on LCZ
825 parameters and classification rules. (1) For LCZ parameters, the following research
826 can be carried out: (i) Evaluate the importance of LCZ parameters. Since it is difficult
827 to obtain all the data required to quantify all 11 LCZ parameters defined by [Stewart &](#)
828 [Oke \(2012\)](#), determining the key parameters for each LCZ will provide guidance for
829 data collection. (ii) Explore the combination strategies of LCZ parameters. As
830 provided by [Stewart & Oke \(2012\)](#), the reference ranges of LCZ parameters usually
831 overlap among LCZ classes. Therefore, it is worth exploring which LCZ parameters
832 to be combined for distinguishing LCZ classes with overlapping reference values. (2)
833 For LCZ classification rules, the following research can be carried out: (i) Develop
834 LCZ classification methods. How to design effective classification methods based on
835 the importance and combination of LCZ parameters needs further exploration. (ii)
836 Establish LCZ aggregation criteria. Based on the principle of spatial proximity and

similarity, it is necessary to formulate LCZ aggregation criteria on different mapping scales.

For combined LCZ mapping methods, the primary objective is to integrate the advantages of RS-based and GIS-based methods. Further research can be carried out from the following aspects: (i) Explore the advantages of RS-based and GIS-based LCZ mapping methods. Considering that the comparison between RS-based and GIS-based LCZ mapping methods has only been carried out in a few cities, we suggest comparing the LCZ maps generated by the two methods in more cities to gain insights into their strengths and weaknesses. For example, we need to figure out which LCZs could be more accurately classified by which method through extensive research in various cities. (ii) Construct standard frameworks of combined LCZ mapping methods. Currently, the combined LCZ mapping methods mainly adopt two strategies ([Section 3.3](#)), i.e., the ‘built type-land cover type’ dichotomy and coarse-to-fine classification methods. The performance difference between the two integration methods remains uncertain due to a lack of comparison. Considering the large difference between RS-based and GIS-based LCZ mapping methods, how to effectively integrate the two methods requires further investigation. For example, the two LCZ mapping methods could be integrated based on the classification accuracy of each LCZ.

4.4. Global inter-annual LCZ mapping

LCZ mapping for global cities will provide detailed and consistent information on the form and function of cities relevant to urban climate and environment research on a

worldwide basis (Bechtel et al., 2015). Currently, LCZ maps have been generated for more than 150 cities worldwide; the reader could refer to the WUDAPT website (www.wudapt.org) for updates. In addition to classify LCZs for cities individually, LCZ mapping has also been conducted on regional scales such as the Yangtze River Delta (Cai et al., 2018) and the Pearl River Delta (Wang et al., 2019), and on continental scales such as Sub-Saharan Africa (Brousse et al., 2019), Europe (Demuzere et al., 2019a), and the continental United States (Demuzere et al., 2020a). On the other hand, LCZ maps of different years has been generated to reveal urban expansion and intra-urban restructuring (Vandamme et al., 2019; Wang et al., 2019), which will help assess the impact of urbanization on climate and environment and guide urban planning towards sustainable city development. Therefore, global inter-annual LCZ mapping has become an important research trend.

To conduct LCZ mapping on global and inter-annual scales is a huge project, which can benefit from the following aspects: (i) Crowdsourcing. Crowdsourcing provides a simple and effective way to generate LCZ maps as well as collect data for LCZ mapping. Bechtel et al. (2017) assessed the impact of LCZ training samples collected by crowdsourcing on classification accuracy. Their study shows that although crowdsourcing causes wide discrepancies in LCZ mapping results, using multiple crowdsourcing LCZ training samples can improve LCZ classification accuracy. Mhedhbi et al. (2019) collected architectural information on buildings in the Greater Tunis agglomeration by crowdsourcing using the Facebook social network. Demuzere et al. (2020) combined expert and crowd-sourced information to map LCZs for the continental US. (ii) Google Earth Engine (GEE). The GEE platform not only provides

global long-term multi-source remote sensing data, but also supports online processing and visualisation of data (Gorelick et al., 2017). With the GEE platform, recent studies have managed to conduct LCZ mapping and test the transferability of LCZ training samples for several cities (Brousse et al., 2019; Demuzere et al., 2019b; Middel et al., 2018). (iii) State-of-the-art machine learning algorithms. Considering the availability and accessibility of remote sensing data, RS-based LCZ classification is the first choice for global inter-annual LCZ mapping. Since RS-based LCZ classification can be essentially deemed as a kind of remote sensing image recognition, the introduction of state-of-the-art machine learning algorithms can make full use of multi-source data, improve LCZ classification accuracy, and overcome the transferability of LCZ training samples, which will promote global inter-annual LCZ mapping. (iv) Cooperation among LCZ-related research communities and projects. For example, the MapUCE project has completed LCZ mapping for most cities in France, and the URBAN-PATH project has established LCZ-based urban monitoring networks in Szeged and Novi Sad, and these projects can be promoted in other countries. The WUDAPT project can benefit from the cooperation with these projects to construct level 1 and level 2 LCZ database.

4.5. LCZ system

The LCZ system defined by Stewart & Oke (2012) is not generic enough for many cities especially in Asia, Africa and Latin America (Chen et al., 2020b; He et al., 2019; Quan, 2019; Yang et al., 2019a; Zhao et al., 2019a). The reason may be that the standard 17 LCZ classes and 11 physical parameters with the associated reference ranges are mainly based on historical data collected from cities in developed

909 countries, which may not keep up with the rapid urbanization on a global scale.

910

911 To improve the universality of the LCZ system, some adjustment strategies for LCZ

912 classes and parameters could be adopt. For LCZ parameters: (i) Adjust the reference

913 ranges of LCZ parameters. This strategy is to deal with the situations where the

914 calculated LCZ classification indicator deviates from the reference range, or the

915 reference range is too wide compared to the calculated value. Optimizing the

916 reference ranges of LCZ parameters requires statistical analysis on extensive urban

917 data collected from various cities with different backgrounds. (ii) Define new LCZ

918 parameters. This strategy is mainly aimed at situations where the requisite data is not

919 available to calculate some specific LCZ parameters. The introduction of new LCZ

920 parameters is mainly based on the availability of data that indirectly characterize

921 surface structure, cover, material, and human activity, and the ability of new

922 indicators to assist LCZ classification. For example, some remote sensing spectral

923 indexes such as NDVI and NDWI can be used as new LCZ parameters. For LCZ

924 classes, a feasible adjustment strategy is to use LCZ subclasses. As suggested by

925 [Stewart & Oke \(2012\)](#), this strategy can be considered when an LCZ deviates from

926 the standard class set. LCZ subclasses are mainly used for the classification of built

927 LCZ types. The following parameters can be considered to determine the applicable

928 scenarios of LCZ subclasses: (i) The building height variance within an LCZ. For

929 example, LCZ 2₃ (mixed compact midrise and low-rise) can be used when the

930 building height variance of LCZ 2 (compact midrise) reaches a certain threshold,

931 otherwise LCZ 2 is still used. (ii) The area ratio of mixed LCZs. For example, LCZ 3_D

932 (mixed compact low-rise and low plants) is used when the area ratio of LCZ D (low

933 plants) in LCZ 3 (compact low-rise) reaches a certain threshold. Nevertheless, how to
934 determine the appropriate thresholds of these parameters needs further exploration.
935 Although LCZ subclasses can add flexibility to the LCZ system, [Stewart & Oke](#)
936 [\(2012\)](#) recommends that LCZ subclasses should be used cautiously, since creating too
937 many or complex subclasses will hinder comparison and communication.

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5. SUMMARY

Since the LCZ system was proposed by [Stewart & Oke \(2012\)](#) to subdivide urban and rural landscapes in a generic way, the research on LCZ mapping has achieved great progress worldwide. However, a systematic review on different LCZ mapping methods is still lacking, which hinders the further research of LCZ mapping. In response to this challenge, we comprehensively review 202 LCZ mapping papers during 2012–2020, provide bibliometric analysis of LCZ mapping literature, elaborate the frameworks of different LCZ mapping methods, and point out several challenges and future directions on LCZ mapping.

The number of LCZ mapping papers shows an increasing trend from 2012 to 2020. At present, almost 300 cities around the world have carried out LCZ mapping. The existing LCZ mapping methods can be divided into three categories: RS-based, GIS-based, and the combined methods of the two. We dissect the framework of RS-based methods from five aspects: feature sets, LCZ classification units, LCZ samples, LCZ classification algorithms, and accuracy evaluation. The framework of GIS-based methods is elaborated from three aspects: LCZ parameters, basic spatial units, and LCZ classification rules. The combined LCZ mapping methods generally adopt two strategies to integrate RS-based and GIS-based methods. For future research, we point out some recommendations on data sources, LCZ mapping scale, and LCZ mapping process. In addition, we provide some suggestions for global inter-annual LCZ mapping as well as some adjustments to optimize the LCZ system.

This study provides a comprehensive review on the current research progress and

965 future directions of LCZ mapping research, which will greatly promote LCZ
966 mapping research. With the cooperation of participants from different research fields,
967 LCZ mapping is expected to promote urban planning and contribute to the design of
968 mitigation strategies to alleviate negative urban climate effects.

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972 **ACKNOWLEDGMENTS**

973 This research was jointly supported by the National Key R&D Program of China

974 (2017YFA0603604), the Jiangsu Provincial Natural Science Foundation

975 (BK20180009), and the National Natural Science Foundation of China (41671420).

976 We are also grateful for the financial support from the National Youth Talent Support

977 Program of China.

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