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Seven city types representing morphologic configurations of cities across the globe

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ABSTRACT

What we understand by the simple term 'city' is in fact describing highly diverse domains: different economies, demographics, ways of living, land uses, built-up morphologies, among other things. The built landscape alone ranges from low-density, one-storey suburban settlements to high-density accumulations of skyscrapers. Models have repeatedly attempted to describe these various 'city' manifestations and to understand the processes that shape these spatial appearances and patterns. In this paper we analyze the morphological-spatial configurations of urban landscapes. We empirically examine 110 cities distributed around the globe. By using the Local Climate Zones (LCZs) classification scheme, we quantitatively describe morphologic variances of the built landscape within cities. We find seven city types (clusters) that capture the global diversity of spatial urban configurations. These seven types testify in parts to common geographic-cultural spaces. Some are largely congruent with well-known spatial units such as Europe or the Islamic world. In contrast to theoretical city models, however, we also find clusters that are more spatially complex such as African-American or Asian-African clusters. On the one hand, the study confirms that similar cultural, socio-economic, demographic or political conditions in fact do produce similar morphologic-spatial urban configurations. On the other hand, it also shows that there exist similar morphological configurations across geographic-cultural spaces.

1. Introduction

We perceive the city first and foremost through its physical form. When visiting a new city, its spatial structure and its interrelationships appear at first inscrutable. Nevertheless, we expect an underlying spatial order which follows a more universal structural configuration of urban space. A configuration we can understand within the framework of previous experiences. An order that adheres to certain basic principles – a dense, multifunctional city center, an arrangement of subcenters of commerce and industry spread over the city, different densities of living forms, and a generally decreasing density with increasing distance to the center.

Urban geography has long endeavored to uncover rules and general principles of order (e.g. Bettencourt, 2007) and to develop ideal structural models to describe the spatial patterns of cities. As early as the Chicago school, the general spatial order of cities has been conceptualized by observations and theories. Cities were spatially modelled in concentric zones (Burgess, Park, & McKenzie, 1925), sectors (Hoyt, 1939), or multiple nuclei configurations (Harris & Ullman, 1945). The various models created over the years with a claim to universal validity generally refer to social-ecological space, to transport costs, land market and land use, to population density, to functional interdependence, central-local network theory or to diffusion (Hofmeister, 1991). The "Alonso-Mills-Muth" model (Alonso, 1964), as example, has been established with a monocentric character referring to the even distribution of land use within a city as a function of land rents, which decreases with increasing distance from the center (Paulson, 2012). This monocentric character, however, has been questioned by scholars, since a constantly decreasing density with increasing distance to the center no longer adequately reflects today's complex polycentric city patterns (e.g. Adolphson, 2009; Siedentop, Kausch, Einig, & Gössel, 2003). In this regard the "Urban Realms" model tried to capture the simplified representation of the spatial, social, economic and cultural pattern in monocentric models by realms representing more complex polycentric patterns (Vance, 1964). Models that reflect this higher complexity refer to, for instance, effects of economic externalities such as traffic congestion (Anas & Kim, 1996; Fujita & Ogawa, 1982) or indirect utility functions with economic activity to cluster in several

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interacting centers (Anas, Arnott, & Small, 1998; Roca Cladera, Marmolejo Duarte, & Moix, 2009; Solow, 1973). Edge cities have been described, reflecting spatial concentration of office and retail space, often in conjunction with other types of development, including residential, at the nodes of major express highways (Bontje & Burdack, 2005; Garreau, 1991). The unbridled dispersion of economic activity outside the centers as a whole has continued leading to patterns described even as 'beyond polycentricity' (Gordon & Richardson, 1996), often resulting in forms of low dense urban sprawl (Nechyba & Walsh, 2004).

In addition to these more or less universally valid urban structural models, attempts were made to reflect the relationship between global economic forces and the local cultural context. Spatial models are intended to reflect the geographical-cultural diversity by regionally specific features of the urban configuration at the inner-city level (Pacione, 2009). Models for the European (e.g. Lichtenberger, 1972), the US-American (e.g. Hahn, 2014), the Ford-Griffin-Model for Latin America (Griffin & Ford, 1980), the oriental Islamic model (Ehlers, 1993), the African model (UN, 1973), the Chinese city (Gaubatz, 1998), among many others have been conceptualized. Further spatial refinements to urban forms within these large, often continental regions have been developed: For Africa, as example, models for the indigenous city (Krapf-Askari, 1969), the colonial city (Pacione, 2009), the apartheid city (Davies, 1981), among others were conceptualized. The basis for such intercultural comparisons of cities is the division of the earth into cultural areas or cultural earth parts, as it has been done e.g. by Kolb (1962) or Huntington (1997).

Modeling aproaches tried to better understand the complex underlying processes shaping urban patterns. The complexity is also reflected in the fact that, like DNA, each city developed its own unique configuration. The most obvious configuration is the morphologic-spatial structure. It is the direct physical implementation of a complex interrelation of economic, social, demographic, legal, and political systems (Tonkiss, 2013), historical path dependencies (Kostof, 1991) and location factors such as topography or climate (Taubenböck, 2019). This "physicalism" (Batty, 2013) is, on a very generic level, composed of buildings, streets, plots, and open spaces (Kostof, 1991; Salat, 2011). This urban form is designed so differently across the globe that two ends of a morphologic-spatial continuum may be marked by a planned, geometric, regular, low dense arrangement of suburbs with high vegetation fractions and open spaces on the one hand, and informally shaped, organic, irregular, high dense arrangements of shacks in slums basically without open, public space, on the other hand.

However, empirical studies comparing the urban spatial configuration of cities across the globe are few due to data scarcity or data inconsistency. An urgent need for a comprehensive database worldwide that goes beyond an urban footprint analysis with the need to capture the internal structure of cities is formulated (Bechtel et al., 2015). Remote sensing from space is one data source that has the capability to increasingly reduce these data gaps. In the recent past, global mapping products based on Earth observation data with ever better spatial resolutions have emerged (e.g. Esch et al., 2012; Small & Sousa, 2016) and related data-driven urban analysis have been conducted predominantly on urban growth (e.g. Angel, Parent, Civco, Blei, & Potere, 2011; Taubenböck et al., 2012). First models have been developed that allow evaluating the spatial dispersion of urban landscapes on this new empiricism (Taubenböck, Wurm, Geiß, Dech, & Siedentop, 2019). However, at continental or even global scale these analyses are still limited in a thematic sense due to their binary representation of the settlement space. Existing works that analyze and compare the internal morphologic structure of cities using EO-data are so far mostly based on a comparatively small number of cities (e.g. Seto & Fragkias, 2005; Cai, Huang, & Song, 2017; Taubenböck, Standfuß, Wurm, Krehl, & Siedentop, 2017; Wurm et al., 2019) and the specifications of the needed or used input data rarely allow, for several reasons, a global approach. Thus, studies that analyze the intra-urban structure of cities or the conceptualized models of cities in a global empirical comparison on the basis of a consistent data set do not exist so far.

Another challenge for comparative urban research derives from a rather arbitrary use of geographical boundaries for cities or urban landscapes which makes many comparisons inadmissible (e.g. Lechner, Reinke, Wang, & Bastien, 2013; Openshaw, 1983). It has been shown that the commonly used conventional, historical administrative spatial units do represent cities in a world characterized by highly dynamic urbanization less and less (Taubenböck, Weigand, et al., 2019). As a result, geographical knowledge is often distorted by those incomparable spatial baselines.

Against these backgrounds, we aim in this paper for a global empirical analysis on the intra-urban structure of cities using consistent data with comparable spatial baselines. To do so, we characterize the intra-urban morphologic-spatial composition of urban landscapes across the globe. We have selected 110 representative cities. This selection is proportional to the relative global share of urban population per continent, generally selecting the largest cities on each continent and at the same time ensuring a balanced spatial distribution. We classified them according to the classification scheme of the Local Climate Zones (LCZs) (Stewart & Oke, 2012) using remotely sensed data (Qiu, Schmitt, & Zhu, 2019) and we rely on a comparable spatial baseline of city extents (Taubenböck, Weigand, et al., 2019). With it, we specifically ask the following research questions:

- Are intra-urban morphologic configurations of cities across the globe similar or different?
- And, should they be different, do groups form according to geographical and cultural aspects?

2. Conceptualization of the study

The general idea of this study is to quantify intra-urban morphologic-spatial configurations of cities across the globe and to identify groups consisting of similar spatial configurations. This requires a clear definition of the components for analysis and comparison, i.e. we must ensure that we do not use a random *selection of cities* for our experiments, that we do not compare apples with oranges in terms of *thematic content* (i.e. structural classes defining the different morphologic compositions within the urban landscape) and, since space plays a decisive role, that the *spatial units* across cities are comparable.

For a representative *selection of cities* we select cities whose cumulative populations are proportional to city populations on continental level. We base this on statistics from the United Nations (UN, 2018). Beyond, we ensure a balanced spatial distribution across the respective continent. Our object of investigation from the perspective of the *thematic content* is the intra-urban morphologic configuration of an urban landscape. As elements of this configuration we understand homogeneous parcels that contain a similar equipment of space of the built and non-built (non-natural and natural) environment. For this purpose, we adapt the Local Climate Zones (LCZs) scheme as it is a generic, culturally-neutral description of land-use and land-cover (Stewart & Oke, 2012). Although originally developed for studies on urban climate, the classification scheme relies on universal, standardized and measurable parameters of urban form. The classes are based on the characteristics 'density', 'building size' and 'building height' for the built landscape. For the non-built landscape, they are based on the theme (e.g. trees or open spaces). These "*regions of uniform surface cover, structure, material, and human activity span hundreds of meters to several kilometers in horizontal scale*" (Stewart & Oke, 2012). Fig. 1 introduces the 17 thematic LCZs split into ten LCZs defining the built types of the urban landscape and seven LCZs defining the non-built types of the city. In our study we define that different LCZs reflect a different morphologic urban configuration. In consequence, we understand the morphologic urban configuration of cities being similar or different, if the share of specific LCZs is similar or different and/or if the spatial

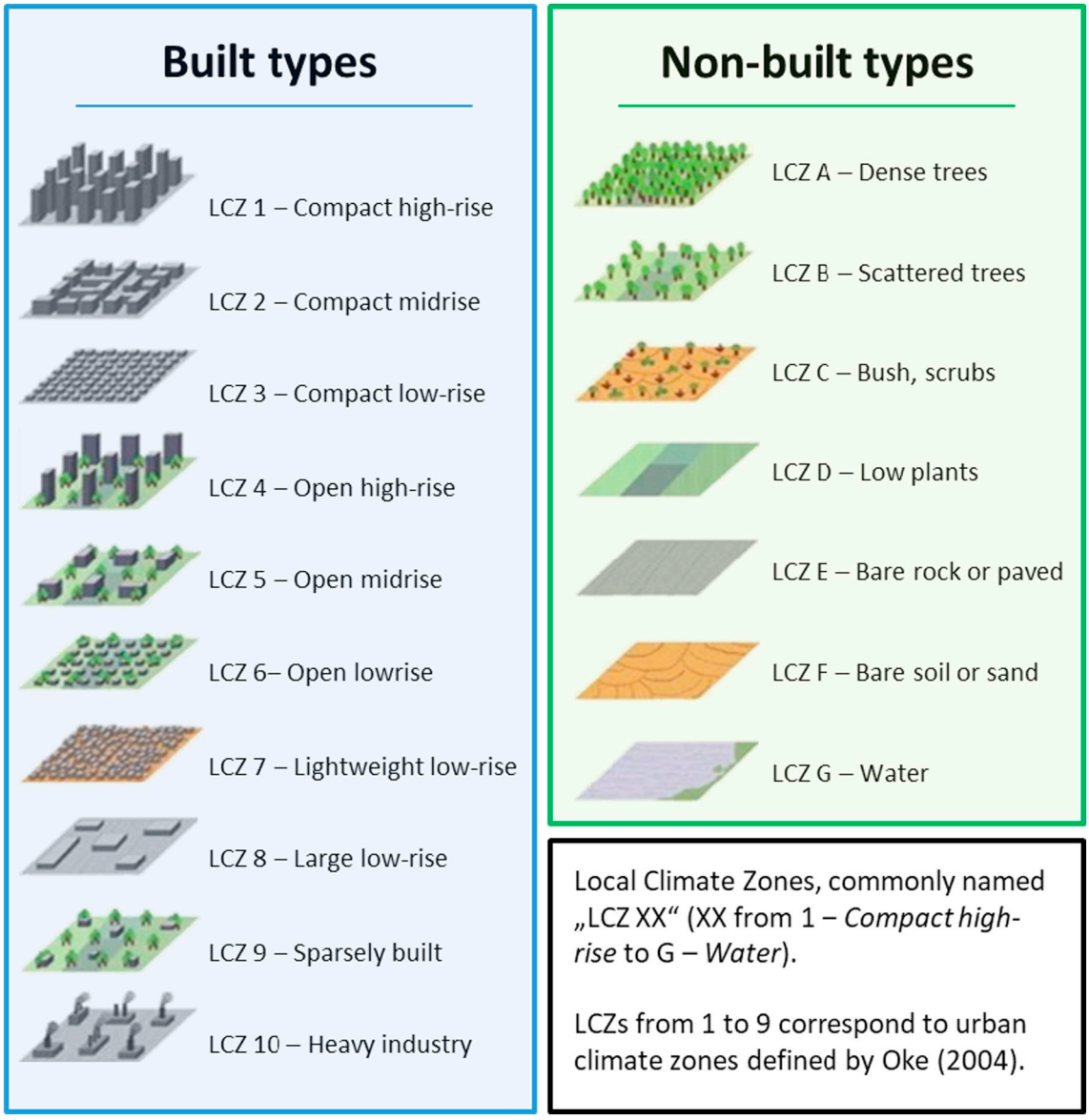


Fig. 1. The 17 Local Climate Zones (LCZs) as a generic, culturally-neutral description of land-use and land-cover. (Based on Stewart & Oke, 2012; Oke, 2004).

distribution of LCZs within cities is similar or different.

For the *spatial units* defining the city extents, we rely on morphological urban areas (MUAs). These encompass the built space of cities independent of administrative/political borders. Since critics question much of existing comparative urban research because of a rather arbitrary use of geographical boundaries (e.g. Lechner et al., 2013; Masucci, Arcaute, Hatna, Stanilov, & Batty, 2015; Taubenböck, Standfuß, Klotz, & Wurm, 2016), we do not use administrative or standardized spatial units, but a consistent delineation of urban from rural areas. We apply the MUAs as provided by Taubenböck, Weigand, et al. (2019). Decisive here is not whether these MUAs capture the urban space in a universal true manner, but that they delimit the urban spaces in a globally consistent manner, which provides the spatial basis for a valid comparison.

3. Study sites, data and methodology

3.1. Study sites

In order to compile a sample of about 100 cities that allows a globally representative evaluation of urban configuration, we have made use of the following considerations: We calculate the relative global share of the urban population per continent using population statistics from the United Nations (UN, 2018). Then we select cities per continent, which in their cumulative number of inhabitants correspond to the relative continental share. In general, we select the largest cities of the continents; however, for a reasonable spatial distribution that ensures all regions are covered, we do not strictly follow the population numbers. However, any selection of cities is naturally not fully proportional to the urban population per continent. Thus, we define an error tolerance of 3% and choose cities that keep the error tolerance low. Based on these considerations, we selected an ensemble of 110 cities. All 110 cities are displayed in Fig. 3 and stated in Table 2.

3.2. Satellite data and classification of LCZs

For the classification of LCZs we rely on multi-seasonal Sentinel-2 satellite data (ESA, 2012). The sensor acquires multi-spectral optical imagery at high spatial resolution of 10, 20 or 60 m with 10 bands in the visible, near infrared, and short wave infrared part of the spectrum.

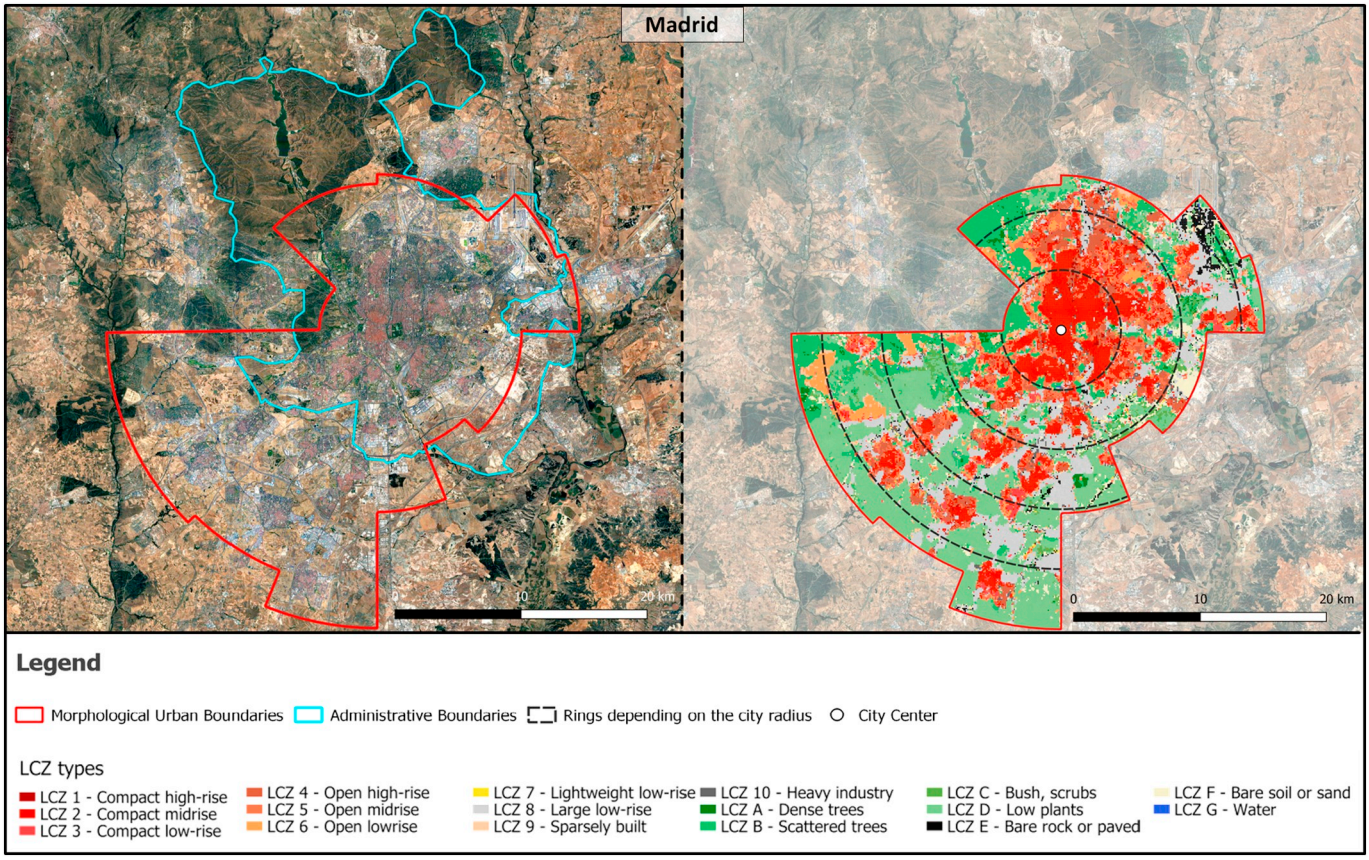


Fig. 2. The morphological urban areas (MUAs) in comparison to administrative unit for the sample city of Madrid (left) and the related classification of LCZs with few sample rings around the defined city center to visualize the spatial concept of the monocentric city model (right).

A recurrent residual network (Re-ResNet) architecture capable of learning a joint spectral-spatial-temporal feature representation within a unitized framework has been exploited and trained on the LCZ42 dataset. The labels for training have been generated manually by 15 domain experts following a carefully designed labeling workflow and evaluation process over a period of six months. The labels are with an overall confidence of 85% based on a rigorous quality assessment (on technical details we refer to Zhu et al., 2019). Afterwards, the trained network is applied to perform the LCZ classification at a resolution of 100 × 100 m per city from seasonal Sentinel-2 images, followed by a majority voting on the multi-seasonal predictions (for details on the classification procedure we refer to Qiu et al., 2019). In Fig. 2 we visually exemplify the LCZ classification.

3.3. Spatial units of analysis

A fundamental challenge for any comparative urban study is the spatial unit to base the empirical investigation on. As introduced above, we apply in our study MUAs as provided by Taubenböck, Weigand, et al. (2019). They understand MUAs as a territorially contiguous settlement area that can be distinguished from low-density peripheral and rural hinterlands along a gradient of decreasing built-up density from the urban center to the periphery. Fig. 2 underpins the spatial discrepancy between the arbitrary administrative units and the MUAs. The exemplified administrative area of Madrid and the respective MUA are very similar around the center. The administrative area, however, includes large non-built forest areas in the northwest that are not considered part of the city in the MUA. At the same time, large suburbs are not considered part of the city by the administrative area in the southwest, while the MUA integrates these built settlement landscapes. By applying the same method to all larger cities worldwide, the provided MUAs are re-territorializing commonly used urban extents. These MUAs constitute a consistent and thus permissible spatial unit for comparative urban research by capturing the built urban space, rather than arbitrary administrative city boundaries or standardized extents.

For analyzing the intra-urban spatial distributions of LCZs, we apply a monocentric city model. Although, as discussed above, this model certainly does not correspond to the many spatial characteristics of the cities investigated here, it allows us to investigate a basic assumption of decreasing densities with a greater distance to the center. And, this model still proves empirical understandability and an explanation of an essential part (at least 80%) of the variation in urbanized land area (e.g. Spivey, 2008) that functions as a theoretical and empirical basis to evaluate intra-urban locations (e.g. McMillen, 2006). As a spatial starting point of the models we rely on the defined center points for each city as provided by the United Nations (2014). We use two different spatial approaches: For a standardized comparison we apply ring models with bandwidths of 100 m to determine the location related to the defined urban center point. For a normalized comparison we apply 100 rings of uniform bandwidths relative to the specific MUA of a city. Fig. 2 exemplifies some sample rings around the defined urban center.

3.4. Methods for comparing landscape configurations of cities

3.4.1. Clustering of cities

We understand the LCZs as the individual building blocks that in their entirety define the morphological-spatial configuration of a city. Against the background of these considerations, we try to identify similarities and differences between urban configurations using two indicators: The *spatial proportions of LCZs* and the *spatial proportions of LCZs depending on their locations within the city*. We want to identify groups for both indicators.

For the *spatial proportions of LCZs*, we count the occurrence (in pixels) of each of the 17 LCZs per city at the spatial unit of MUAs. We apply minimum-maximum normalization to them relative to all cities. With it we produce a 17 dimensional feature space per city (we refer to it as '17f'). To take specifically account of the various city sizes, we derive the spatial share of the 17 LCZs per city from the 17 dimensional feature space and we additionally integrate the 'city size' derived from the MUAs (Taubenböck, Weigand, et al., 2019) as further variable. We apply minimum-maximum normalization to the 'city size' relative to all cities. With it we produce an 18 dimensional feature space per city ('18f').

For the *spatial proportions of LCZs depending on their locations within the city*, we count the occurrence (in pixels) of each of the 17 LCZs per city at the spatial unit of MUAs for each of the 100 concentrical rings of relative width using our monocentric city models. As above, we apply minimum-maximum normalization to them relative to the basic population, i.e. all cities. With it, we produce a 1700 dimensional feature space per city ('1700f'). In addition, we derive the spatial share of the 17 LCZs per ring from the 1700 dimensional feature space and we also integrate the size of the city based on the size of MUAs. We apply minimum-maximum normalization to the 'city size' relative to all cities. With it, we produce a 1701 dimensional feature space per city ('1701f').

With it four features spaces are at our disposal. This allows us to find various clusters of similar proportions of the various LCZs in the first place, and to find various clusters of similar proportions of the various LCZs with respect to their spatial location within the urban landscape in the second place. For clustering we apply two unsupervised methods: k-means (Hartigan & Wong, 1979) and expectation-maximization algorithms (Dempster, Laird, & Rubin, 1977), where we assume a model of type "EII" (Spherical distribution, Equal Volume, Equal shape, without specification of orientation). Both algorithms apply centers of clusters to model the data; however, k-means tends to find clusters of comparable spatial extent; the expectation-maximization allows clusters to have different extents. Expectation-maximization can detect clusters partially mixed in the feature space; k-means, in comparison, tends to find clusters with more neighborhood-oriented logics.

In unsupervised clustering methods, the number of clusters is not known a priori. For determining the optimal number of clusters we rely on the gap statistics algorithm (Tibshinari, Walther, & Hastie, 2001). We apply 100 random launches with different seeds. To define the amount of clusters for all four feature spaces (17 and 18-dimensional as well as 1700 and 1701-dimensional) we calculate the average from the 100 launches. As a result, we plot the determined particular clusters on a world map.

3.4.2. Correlation of identified clusters to geographical-cultural spaces

The clustering results (based on the four feature spaces and the two clustering methods) differ in composition and thus their spatial expression. It is not a priori clear which clusters are our target. As in this study we want to focus on whether groups are emerging that correspond or come close to predefined geographical-cultural spaces we evaluate our resulting clusters in relation to geographical/cultural regions based on those defined by Huntington (1997). He divided the world basically into the following geographical/cultural regions – Western, Latin American, Orthodox, Islamic, Sinic, Buddhist, Japanese, Hindu, African (cf. Fig. 1A, Appendix). It is perfectly clear to us that this division into regions is problematic. Distinct cultural boundaries do not exist in the present day and are oversimplifying the complexity of our globalized world (e.g. Berman, 2003). However, the underlying argument of using these geographical/cultural regions in our study is that, as assumed in many studies, similar cultural, demographic, socio-economic and political conditions produce similar spatial patterns. This is reflected by specific city models designed for different cultural circles assuming they influence the morphologic-spatial configuration of cities (e.g. Hahn, 2014; Griffin & Ford, 1980). Against this background, we want to take a closer look at the clustering that comes closest to this geographical and cultural division.

To identify this clustering, we apply the Simpson Evenness Index (SIEI) (Simpson, 1949), which defines the probability that two sub-units (in our case the cities) of the landscape (in our case the geographic-cultural region), selected at random, belong to different types (in our case the clusters). The SIEI is defined as

$$SIEI_{geographic/cultural\ zone_i} = \frac{1 - \sum_{k=1}^{7} \left(\frac{number\ of\ cities\ of\ cluster\ k}{number\ of\ cities\ in\ i} \right) 2}{1 - \left(\frac{1}{7} \right)}$$

producing values from 0 to 1; with 0 indicating there is only one cluster present in the respective region and 1 indicating there is an even repartition of all clusters in the respective region. In other words the lower the value, the higher the congruency.

3.4.3. Morphologic descriptions of clusters

Based on the analysis above, we continue this study with only one clustering result having highest congruency to geographical/cultural regions as defined by Huntington (1997). The idea now is to characterize these resulting clusters in their morphologic-spatial configuration. To do so, we apply four elements: 1) The *average size of the cities*, a parameter which was not tackled by theoretical models; 2) the *share of built* versus *non-built up LCZs*, a parameter to assess the intensity of used urban space; 3) *distributions of LCZ shares* within the respective MUAs as the main information on the structural configuration of the cities; we illustrate the internal variability per cluster in boxplots; 4) and, the *volume density gradients* from the center to the peripheries, a parameter to describe the distribution of the usage of space within the urban landscape. For the latter, we transfer the LCZs into measures of three-dimensional built-up density. We extract the building surface fraction and the height of roughness element (as provided in Stewart & Oke, 2012) per LCZ. For each grid, we calculate the approximated built-up volume by multiplying the building surface fraction with the provided height of roughness elements. We aggregate all resulting built-up volumes from the grid level to the corresponding ring of the monocentric city model. From it we calculate the average built-up volume along the gradient from the defined city center to the peripheries of the MUAs for each of the resulting clusters. We display the resulting density gradients per cluster in two different ways – absolute and normalized. In absolute manner, we derive for each city and every ring (100 m of width) of the monocentric city model the average built-up volume. For the clusters we rescale the resulting values of the built-up volumes to 0 (minimum value) and 100 (maximum value) and plot the clusters' depending on the absolute distance to the center (x-axis from 0 to the maximal radius of the city). In the normalized manner, we derive for each city 100 individual rings varying in widths depending on the particular city radius as defined by the MUAs. From it we calculate the average built-up volume for each of the clusters and rescale the values as done above. We then plot the clusters' built-up volume depending on the relative distance to the center (x-axis from 0 to 100% of the maximal radius of the city).

We illustrate one representative city per cluster in a LCZ map, we plot the distribution of LCZs within the clusters, we describe the main morphologic-spatial characteristics of this cluster and we name the cluster according to urban geographical features.

4. Results

4.1. City clusters and their geographic-cultural expression

The gap statistics algorithm suggests in principle, for all four features spaces, the 17 and 18-dimensional and the 1700 and 1701-dimensional feature space, that on average seven clusters best group the data. As a consequence, the input data of LCZ classifications, the spatial baseline of the MUAs, the introduced methodological approach, and

Table 1
Results of the weighted Simpson Evenness Index based on the different feature spaces (17-, and 18-dimensional features (17f, 18f), and 1700-, and 1701-dimensional features (1700f, 1701f)) and the different clustering methods (k-means, expectation-maximization).

Method used	Weighted SIEI
k-Means & 17f	0.81
k-Means & 18f	**0.77**
k-Means & 1700f	0.82
k-Means & 1701f	0.82
Expectation-maximization & 17f	0.79
Expectation-maximization & 18f	0.83
Expectation-maximization & 1700f	0.87
Expectation-maximization & 1701f	0.82

application onto these sample cities indicate that seven types of morphological-spatial city configurations generally allow capturing the built appearance of cities on our globe.

Based on this, we have systematically tested the different methods for clustering (k-means and expectation-maximization) onto the different feature spaces (17 and 18-dimensional as well as 1700 and 1701-dimensional) for the a priori defined seven clusters. Of course, the resulting groups are not so unambiguous that the results remain the same regardless of the feature space or method. Since we want to find out in this study whether similar groups are emerging that are similar to predefined geographical-cultural regions as proposed by Huntington (1997), we continue from here with the result that shows the greatest possible similarity to the geographical-cultural region. By weighting the Simpson Evenness Index by the number of cities in each region, we find the 18-dimensionsal feature space using the k-means algorithm provides highest congruence to the suggested geographical-cultural regions (Table 1).

This empirical analysis according to physical equipment and spatial distribution for cities on our globe shows that whether we consider only the proportions of the LCZs or whether we consider the proportions of the LCZs as a function of their relative position relative to the center, or whether we apply k-means or expectation-maximization as clustering methods, we find slightly different spatial compositions of the seven clusters. Nevertheless, we generally also see the geographical-cultural clusters remain comparatively constant. Relative to our best result (k-means, 18f), we observe the greatest match of classes if we leave the feature space the same. Applying the expectation-maximization algorithm on the 18-dimensionsal feature we have an 80% match in the class assignment of the cities (cf. Fig. 2A, Appendix). But even if we vary the feature space (k-means, 1701f), compared to our best result (k-means, 18f), there is still a 60.9% agreement in the class assignment of the cities. For the latter example, still 66 of our 110 sample cities remain in the same cluster constituting similar geographical-cultural regions.

If we plot the best results on the world map (18f and k-means), we can see certain spatial distributions of the clusters, which obviously represent in parts geographical-cultural spaces (Fig. 3). This is a first clear indication that the geographical regions, their cultural and historical background do influence the morphologic-spatial appearance of cities.

In a first step, we describe the geographical distribution of the identified clusters. The morphological specifics of the identified clusters are introduced below in Section 4.2.

Cluster 1: mainly **Asian and African cities**

Of the 22 cities in this cluster, 19 are located in Africa and Asia (10 in Africa, 9 in Asia with 5 of them in India). Many cities have a colonial or dominion heritage. It should also be mentioned here that also two cities from South America and one from Europe are belonging to this cluster.

Cluster 2: mainly **Asian and American cities**

Of the 15 cities in this cluster, 9 are from Asia and 5 are from America. The only exception here is Melbourne in Australia.

Cluster 3: dominated by **European cities**

21 out of 29 cities belonging to this cluster are on the European continent. Of the 22 European cities that are part of our entire sample, 21 belong to this cluster (the only exception is Bucharest belonging to Cluster 1). It is also worth mentioning that contrary to our expectations some cities like Addis Ababa in Ethiopia or Wuhan in China also belong to this cluster.

Cluster 4: mainly **Eastern African and Eastern Asian cities**

Of the 20 cities in this cluster, 10 are located in Africa. It is striking that all these cities are located in (south-)eastern parts of Africa. 8 cities are located in Asia, mainly in far Eastern parts and one city (Port-au-Prince) belongs to America and one (Sydney) to Australia. It is interesting to note that most of the cities here do have a colonialist legacy.

Cluster 5: dominated by **cities of central Africa**

8 out of 10 cities of this cluster are located in Central Africa - distributed from west to east. Just one from Oceania (Port Moresby) and 1 from Asia (Poona) add to it. Again, most of the cities here do have a colonialist legacy.

Cluster 6: **Cities of the Islamic world**

It is noteworthy that all cities in this cluster are exclusively located in the Islamic region from Ouagadougou to the Hindu Kush. 9 cities (5 in northern parts of Africa and 4 in the Middle East) define this cluster. In this region, two cities part of our sample – Bagdad and Riyadh – do not belong to this cluster.

Cluster 7: consisting of **very large cities**

This cluster contains only 5 cities. All of these five cities are mega cities with four of them located in Eastern Asia. The remaining one (Los Angeles) is from America. They all are very large cities and assume that the share of LCZs could be characteristic for these mega cities.

All in all, we draw the following interim conclusion from this empirical analysis according to physical equipment and spatial distribution for cities on our globe: In many theory-based studies, city models are strictly constituted according to more or less accepted geographical spaces. This empirical analysis, however, shows that these geographical spaces represent a unit that is too simplified and too generalized. Here historical path dependencies such as colonial influences or economic situations overlap with many other factors and influence the constitution of the built city. But it remains undisputed that geographical-cultural spaces are reflected in the morphological configuration of cities (and yes, outliers do exist). The *European city model* (Cluster 3) and the *Islamic city model* (Cluster 6), as presented in many theoretical models, are clearly identified by this empirical investigation. City configurations that apply mainly to *Central Africa* (Cluster 5) could be localized. However, other clusters are found that cannot be assigned so clearly to only single geographical-cultural area. Clusters are identified whose similar morphologic-spatial urban characteristics appear predominantly in cities located at different continents: *Asian and African* (Cluster 1), *Asian and American* (Cluster 2) cities. For the first case –Asian and African–, a further cluster is identified which takes a clear spatial concentration on the eastern parts within the particular continents (Cluster 4). Despite some geographical outliers of these clusters, we find there are cultural spaces that seem to have a clear influence on the morphologic-spatial configuration of cities (Figs. 3 and 4).

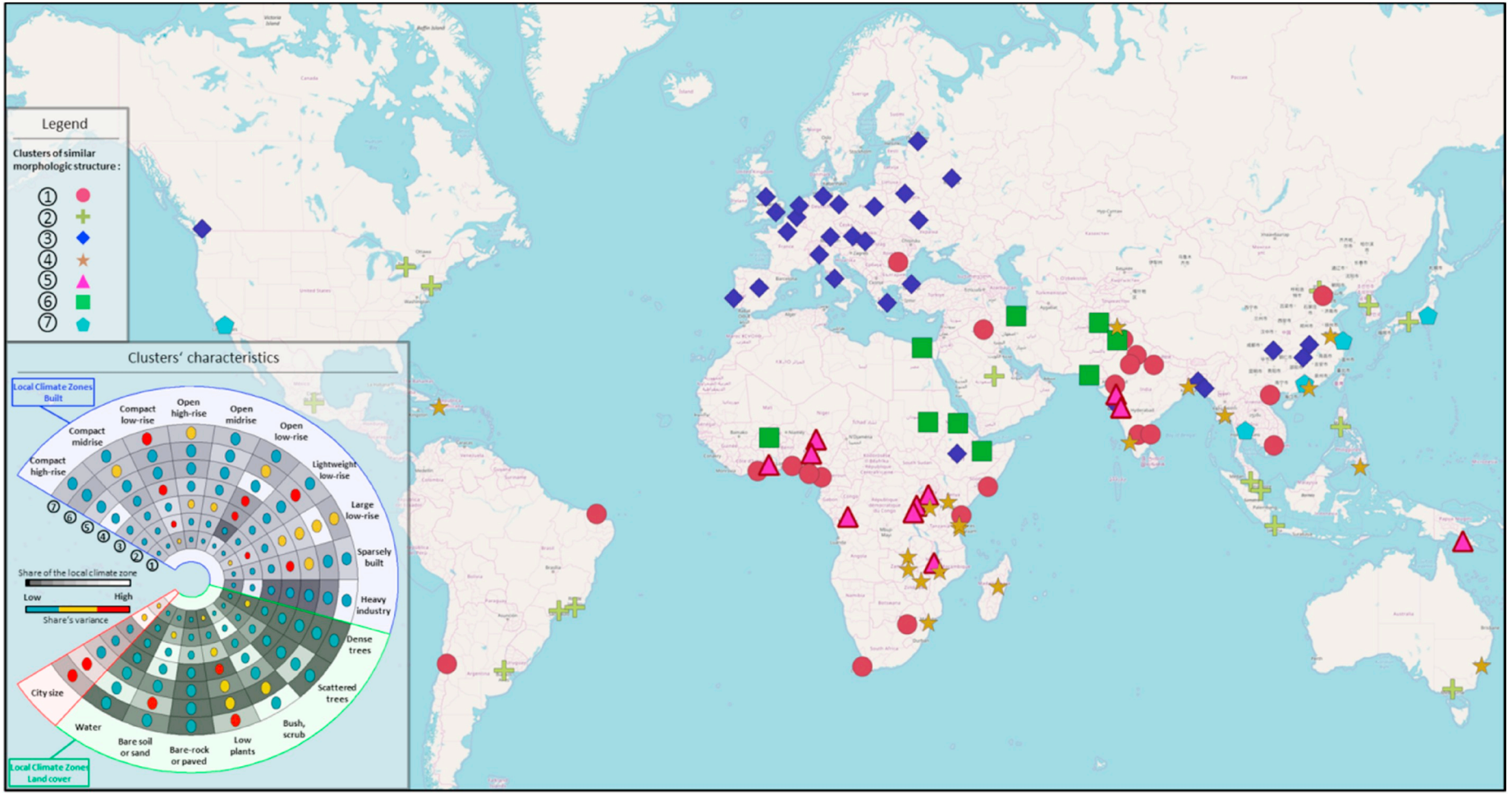


Fig. 3. Seven resulting clusters based on the k-means algorithm using the 18 dimensional feature space (consisting of 17 LCZs as well as city size as features) at the spatial unit of the morphological urban areas. The seven clusters are presented in their global distribution and by their cluster characteristics: For the latter, we compute average and standard deviation of the share of the 18 features. We divide the diagram in seven rings, one for each cluster. We divide the rings in 18 radials sectors, one for each feature. Thus, we obtain $18 * 7$ cells, each related to one cluster and one feature. On each cell we plot a gray shade related to the share of this individual feature in the cluster: white is high, black is low. On each cell we plot a colored pastille related to the standard deviation across the cities in the respective cluster of the share of this individual feature. Red is high, blue is low. We arrange the clusters in this diagram so that the closest neighbors in the diagram are also the closest neighbors in the feature space. This means fewer differences between clusters that are neighbors in the diagram. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.2. Seven city clusters and their morphological configurations

In the following we present the morphologic specifics of the seven clusters based on the 18-dimensional feature space and the k-means algorithm. For the morphologic-spatial characterization we apply the four elements, size of the cities, the share of built versus non-built up LCZs, the general shares of LCZs and, the volume density gradient.

In Fig. 4 we illustrate the cartographic results of the LCZ classification for one representative city per cluster as well as box plots showing the distributions of LCZs. We also illustrate the three dimensional volume density by density gradients from the urban center towards the peripheries (Fig. 5). We do so for the standardized and for the normalized distances.

Cluster 1: (mainly **Asian and African cities**)
Medium large cities of low structural variability, medium compact, low-rise

Cities of this cluster have on average a radius of 14.9 km. With it, this clusters features cities in a medium size among the seven clusters. Structurally, these cities show an average share of 35% of non-built up land. This ratio seems to be rather typical for cities across the globe as four out of the seven clusters show values between 31 and 35%. The structural variability of these cities is low. Three LCZs, which together account for about 61% of the MUAs, dominate the structural configuration: low plants (LCZ-D with 25% on median), large low-rise (LCZ8; 24%), and compact low rise (LCZ3; 12%). The remaining LCZs cover without exception less than 5% each of the urban area. From the point of view of spatial statistics, this class has the greatest similarity with cluster 2.

Uniform density decrease (abs.) and convex gradient (normalized)

For cluster 1 we measure the expected decreasing built-up volume density gradient with increasing distance to the center. The general volume density for these cities, however, is just above average among all clusters (Fig. 5). It is remarkable that when we evaluate the normalized approach, we do not get a flattening curve towards the urban periphery, but a rising curve outside the city center which eventually decreases again on the edges of town. In other words, in comparison to other clusters, the drop in density is less pronounced and the urban morphology remains relatively constant within the MUA.

Cluster 2: (mainly **Asian and American cities**)
Large cities of medium structural variability, medium compact, low-rise

With 25.1 km radius on average, this cluster contains large cities compared to other clusters. The share of non-built up is with 31% still in a medium range. While this cluster features one LCZ that stands out in terms of spatial shares (large low-rise structure (LCZ8) accounting for 28% of the MUAs), more other LCZs have higher spatial proportions compared to cluster 1 (compact low rise (LCZ3; 13%), low plants (LCZ-D; 12%), open low rise (LCZ6; 7%), sparsely built low rise (LCZ9; 7%), dense (LCZ-A; 5%) and scattered trees (LCZ-B; 4%)) (Fig. 4). From the point of view of spatial statistics, this class has among the remaining clusters (3–7) the highest similarity with cluster 3.

Concave decreasing density gradient (abs. and normalized)

The volume density of the built-up in the center is on average comparatively high in this cluster and we measure a continuously decreasing, concave density gradient towards the periphery (Fig. 5a). A specific characteristic here is the comparatively high volume density at a long distance from the center (even at 25 km at over 20%), which is an indication that there are many very large cities in the cluster. This is also represented in the normalized density gradient showing a relative increase in the periphery (Fig. 5b).

Cluster 3 (dominated by **European cities**)
Medium-sized cities of high structural variability, medium compact, mid-rise

With 13.7 km radius on average, this cluster contains medium sized cities compared to other clusters. This morphological configuration consists of a generally medium share of non-built up (31%). This cluster features no dominance of one or few LCZs, but more balanced shares of LCZs: Open low rise (LCZ6; 15%), large low-rise (LCZ8; 15%), low plants (LCZ-D; 13%), open mid-rise (LCZ5; 10%), compact mid-rise (LCZ2; 6%), dense (LCZ-A; 6%) and scattered trees (LCZ-B; 4%) show the high structural variability. From the point of view of spatial statistics, this cluster has the among the remaining clusters (4–7) highest similarity with cluster 4.

Strongly decreasing, concave uniform density gradient (abs. and normalized)

The volume density gradient of this cluster comes closest to the generalized assumption that a continuous decrease from the center to the periphery exists. The volume density in the center is very high in this cluster and we observe the steepest decrease among all clusters with increasing standardized distances from the center (Fig. 5a). And, we observe an even and continuous decrease in density using relative distances to the center, too (Fig. 5b).

Cluster 4: (mainly **Eastern African and Eastern Asian cities**)
Small cities of high structural variability, low compact, low-rise

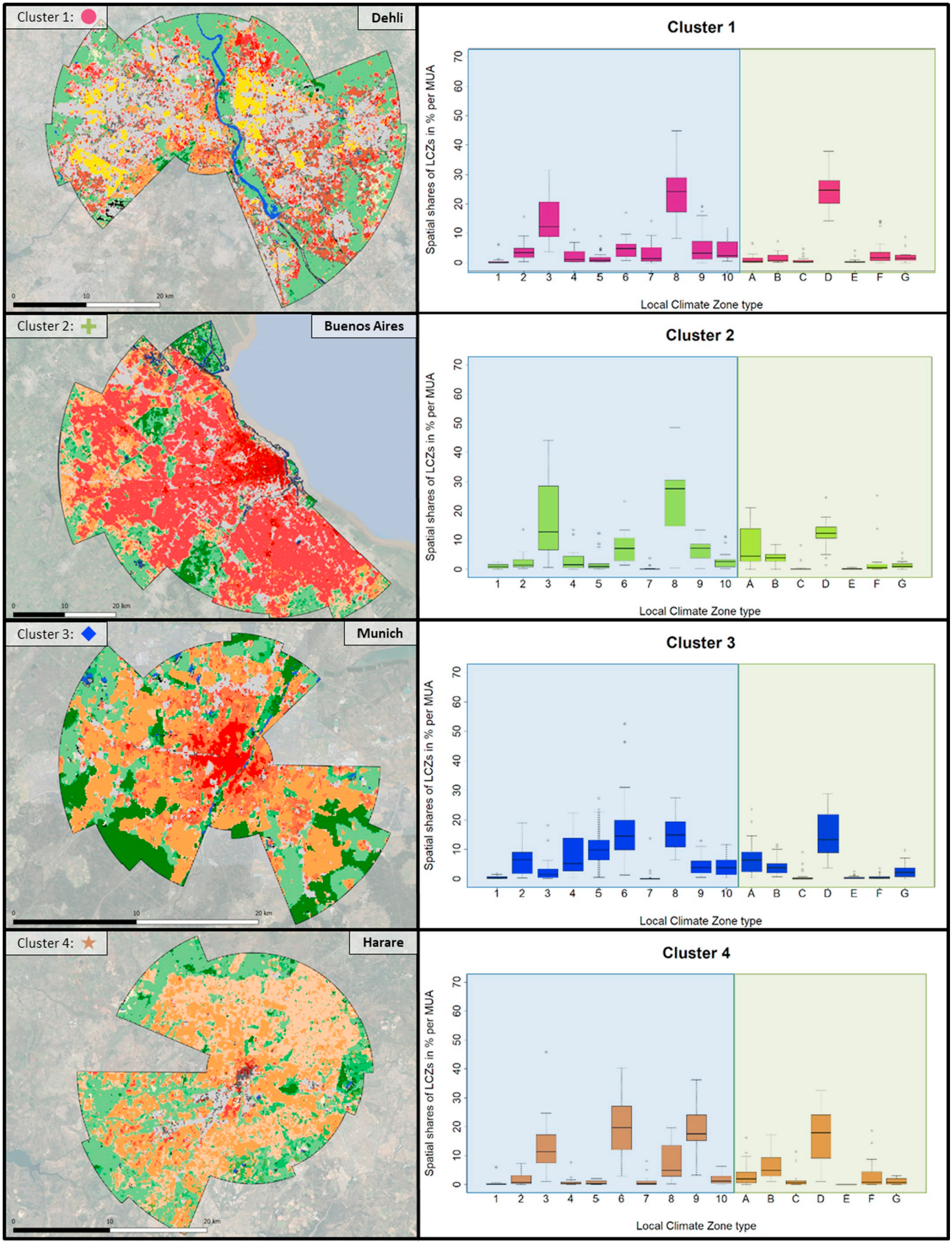
With 12.2 km radius on average, this cluster contains small sized cities among our clusters. The share of non-built up is with 32% again in a medium range. This cluster features no dominance of one LCZ but a high structural variability: open low rise (LCZ6; 20%), low plants (LCZ-D; 18%), sparsely built (LCZ9; 18%), compact low rise (LCZ3; 11%), scattered trees (LCZ-B; 5%) and large low-rise (LCZ8; 5%) are the six classes featuring highest shares. Statistically, this cluster has the among the remaining clusters (5–7) highest similarity with cluster 5.

Strongly decreasing, non-uniform density gradient (abs.) and change from decreasing to increasing gradient (normalized)

The standardized volume density gradient of this cluster features a high drop in density outside the center with a lower drop in the peripheries. The relative density gradient reveals a comparatively high density in the periphery and an unconventional increase relative to all clusters towards the periphery (Fig. 5).

Cluster 5: (dominated by **cities of central Africa**)
Small-sized cities of medium structural variability, low compact, low-rise

With 11.8 km radius on average, this cluster contains the smallest sized cities among our clusters. The share of non-built up is here with 57% large, i.e. the general structure of these cities differs significantly to clusters 1–4. The large amount of undeveloped land is generating a less intense usage of urban space. This cluster features an exceptional proportion of one non-built LCZ: low plants (LCZ-D; 47%) defines the pattern. In the built domain, the shares of individual LCZs are exceptionally small: large low-rise (LCZ8; 8%), compact low rise (LCZ3; 11%), open low rise (LCZ6; 10%), sparsely built (LCZ9; 10%). Many LCZs do not exist at all. Statistically, this cluster has among the remaining clusters (6, 7) highest similarity with cluster 6.



(caption on next page)

Fig. 4. The seven resulting clusters based on the k-means algorithm using the 18 dimensional feature spaces consisting of 17 LCZs and city size at the spatial unit of the morphological urban areas.

Uniform density decrease (abs.) and increasing gradient (normalized)

This cluster features lowest volume densities across all clusters independent from the location within the city. The standardized volume density gradient features the expected continuous decrease towards the periphery starting at the lowest measured rate of 32% of the maximum density measured across all cities. Interestingly, the relative density gradient reveals an increase relative to other clusters towards the edges of towns.

Cluster 6: (dominated by **cities of the Islamic world**)
Medium-sized cities of high structural variability, medium compact, low-rise

With 15.8 km radius on average, this cluster contains medium sized cities. The share of non-built up is with 62% the largest of all clusters; a structural configuration that leaves a large part of the urban landscape undeveloped. So, this cluster shows large shares of non-built up LCZs: Bare soil or sand (LCZ-F; 29%) and low plants (LCZ-D; 19%) are dominating. In the built types individual LCZs feature on median comparatively small shares. Compact mid-rise (LCZ2; 3%), compact low rise (LCZ3; 3%), open low rise (LCZ6; 3%), large low-rise (LCZ8; 4%), sparsely built (LCZ9; 3%) and heavy industry (LCZ10; 3%).

Uniform density decrease (abs.) and basically constant gradient below average (normalized)

The volume density gradient features a continuous and uniform decrease in density towards the periphery. The relative volume density gradient reveals a cluster consistently below average densities across clusters.

Cluster 7: (consisting of **very large cities**)
Very large cities of low structural variability, medium compact, mid-rise

With 37.4 km radius on average, this cluster contains by far the largest cities among our clusters. The share of non-built up is with 26% the lowest of all clusters and reveals highly developed urban spaces. In this cluster two LCZs cover more than 50% of the entire MUAs. In the built domain large low-rise (LCZ8; 33%) dominates the physical configuration of the cities. In the non-built domain, low plants (LCZ-D) cover 20%. Other LCZs (3, 4, 5, 6, 9 and 10) are in the range of 2.5–8%. It is noteworthy that even for these very large cities, the compact high-rise (LCZ1; 1%) occupies only a small proportion of the urban area (albeit more than in the other clusters).

Concave density gradient (abs. and normalized)

Volume density is highest in the center among all clusters and due to the city sizes in this cluster the gradient is, in comparison to others, featuring a lower decrease with remarkable densities even 50 km from the city center. Due to this, the relative density gradient reveals a strongly concave shape with significant relative increases in density compared to other clusters.

Summarizing, Table 2 provides a detailed overview of the seven clusters with highest congruence to geographical-cultural regions. The associated cities, the geographical allocation and their physical characteristics in terms of LCZs and density are provided.

We conclude that based on these specific data, these methods, these spatial units, we find *seven clusters* (or city types) represent the morphologic-spatial configuration of cities worldwide. And these seven clusters do related in parts to geographical-cultural regions.

5. Discussion

Cities are diverse – in their economic, social, demographic, administrative, political structure, but also in their atmospheres, in their daily routines, in their sound volumes or smells; and, of course, also in their physical appearance, i.e. the built and non-built urban landscape. The morphologic-spatial appearance is naturally only one part reflecting this diversity; yet, it defines many routines and modes of operation of a city (e.g. Glaeser, 2010). In this study we have filtered out similarities of built landscapes of cities across the world and formed groups that represent different morphologic-spatial types.

City models, as mentioned in the Introduction, are based mainly on observations and theories. They rely comparatively little on truly consistent empirical data, which are suitable for comparison. Our study is based on consistent, structural knowledge of the built landscape based on a uniform concept. The structural knowledge is derived from remote sensing data. This enables a new empirical approach to analyze city theories and models.

It may not come as a surprise, but this study shows that the theoretical spatial model concepts of cities and the seven spatial city types (clusters) determined from our empirical work have common features; however, differences also become apparent.

With respect to our *first research question* – are intra-urban morphologic configurations of cities across the globe similar or different – we empirically find that different morphologic-spatial configurations of cities across the globe exist. Against the often stated narrative of 'homogenization' (e.g. Gordon & Cox, 2012), we found here a large structural variation. In general, seven clusters of morphologic city models have been statistically identified representing the various morphological appearances of cities across our globe.

The *second research question* – do groups form according to geographical and cultural aspects (with the underlying assumption that similar processes produce similar spatial patterns) – cannot be answered so unambiguously. On the one hand, we find clusters of cities that show structural similarities in our global sample and correspond to the often proposed geographical-cultural aspects. The European, the Islamic and the central African model are the representatives of this group. On the other hand, we identify groups in this study that surprise us with regard to a geographical-cultural classification: The 'Asian and African', the 'Asian and American', and the 'Eastern African and Eastern Asian' clusters that have, to the knowledge of the authors, never been identified explicitly with respect to similar morphological-spatial configurations. These clusters suggest that there are indeed urban configurations in which cities are more similar across continents than to cities in geographically and culturally closer regions. City models that generate themselves exclusively from these geographical-cultural spaces thus seem to represent reality in an over-simplified way.

However, our results are, and this must be discussed here, also fraught with uncertainty. The uncertainties are derived from the following points: 1) inaccuracies in the classification products, 2) the applied classification scheme of LCZs, 3) the spatial units of measurement, 4) the general spatial entity of MUAs, and 5) the selection of cities: 1) The input LCZ classifications have an overall accuracy of 87.3 and a kappa value of 0.65. Overall accuracies among the thematic classes vary significantly. 65.1% for the 'LCZ-C – bush, scrub' up to 99.3% for 'LCZ-G – water' in the natural domain and, as examples in the built domain 0.58 for the 'LCZ-6 – open low-rise' to 0.87 for 'LCZ-8 – large low-rise'. Although these are fair numbers, the effects of misclassifications to the derivation of clusters is unknown. Furthermore, it

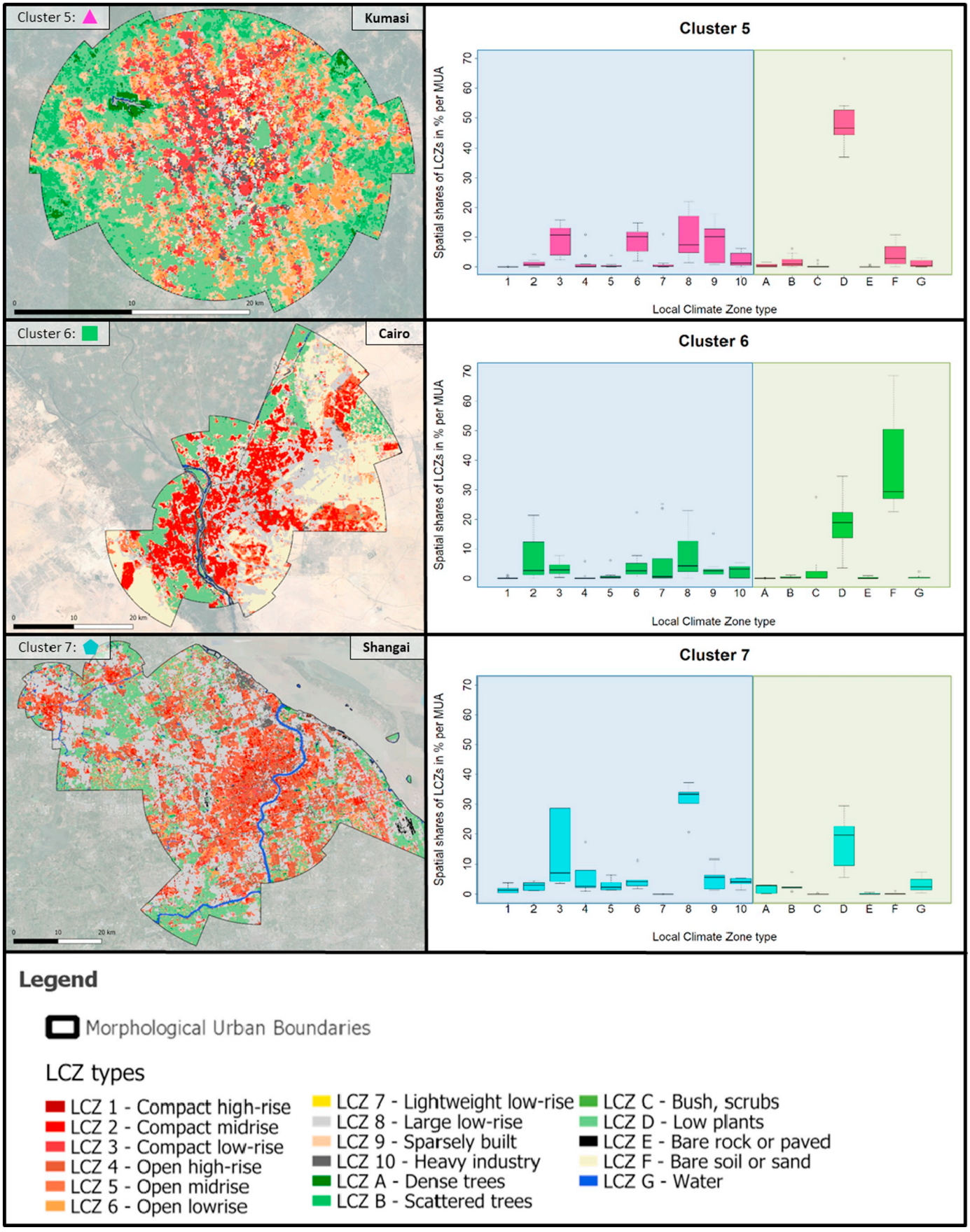


Fig. 4. (*continued*)

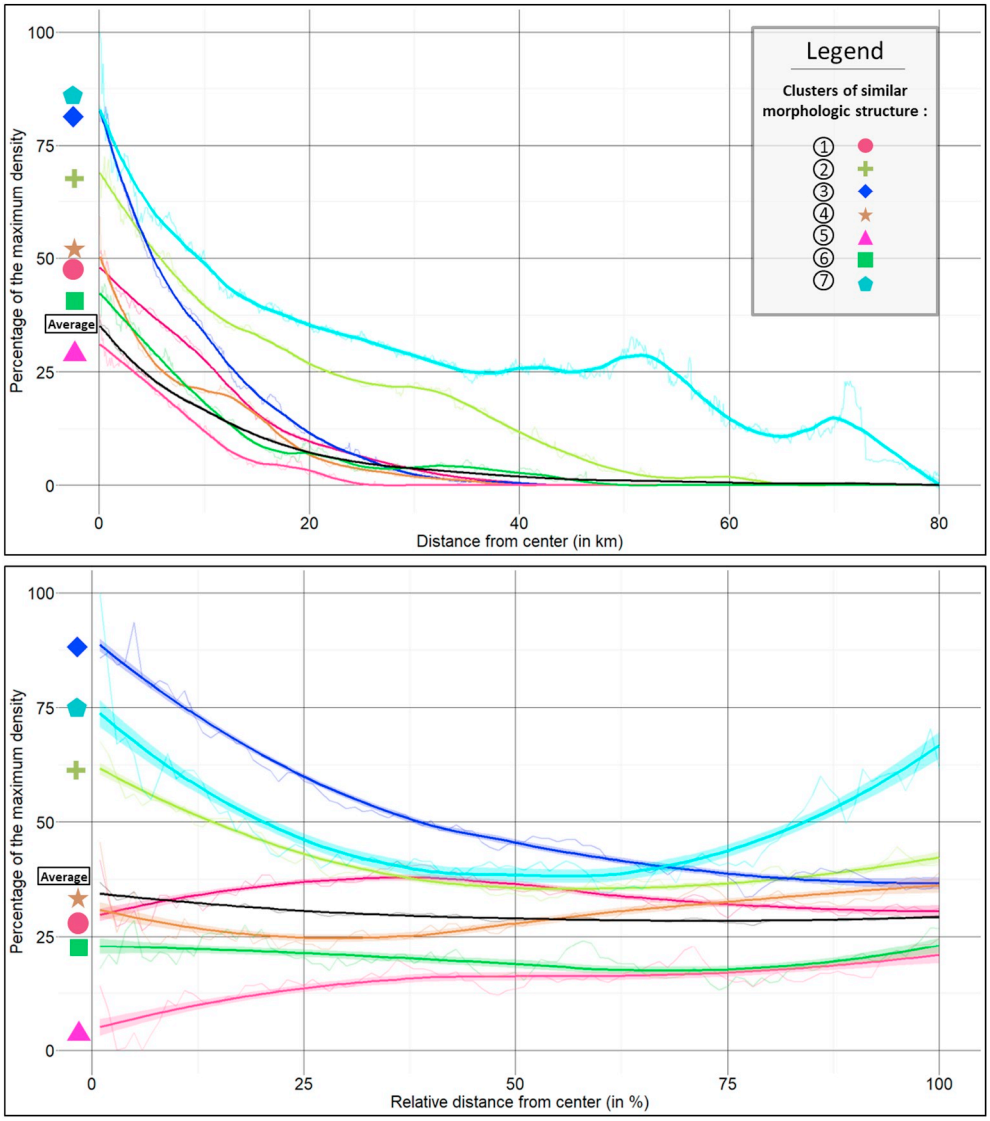


Fig. 5. Volume density gradients of the seven resulting clusters (k-means algorithm; 18f feature space, spatial entity MUAs) standardized distances (top) as well as normalized distances (bottom) from the city center.

must be stated that the LCZ classifications from Sentinel-2 data are two-dimensional. The derivation of built-up volumes is purely based on a statistical approach derived from the concept of Stewart and Oke (2012) and thus contains further unknown uncertainties. 2) The applied classification scheme of LCZs is a concept aggregating the structures to a larger spatial unit, in our case a standardized raster of 100 × 100 m. In this spatial generalization, small-scale, structural transitions or invariances are lost, of course, due to an averaging effect in the classification process demanding for a discrete LCZ class. Beyond this, we must be aware that although LCZs are generic, culturally-neutral descriptions of land-use and land-cover, we cannot rule out that morphologically similar areas exhibit different meanings in different cities or areas. 3) The spatial units of measurement we applied rely on a monocentric city model. While it is still a well-accepted approach (e.g. Spivey, 2008), it is once again a generalized assumption that structural peculiarities, especially in the periphery, are masked by averaging. 4) Beyond, although the MUAs are consistently derived and thus form a comparable basis (Taubenböck, Weigand, et al., 2019), they are only one way of delineating urban from rural. A different setting allowing larger or smaller MUAs, while still being designed consistent, might have effects on the resulting clusters. We do have tested in our study also administrative city units as well as standardized circles as spatial extents; the resulting clusters, however, were geographically not as congruent with the geographic-cultural regions used, and thus we disregarded them in this paper. And, our analysis is based on the fact that the extent used for the cities, except for the class 'water', which is eliminated, is flat and therefore the same. However, topographic, economic-specifics, historic path-dependencies such as colonial influences or any other related possible effects shaping the configurations of cities have not been considered in this analysis. These things may counteract geographic-cultural processes, but the effect is unknown to us. 5) Last but not least, our analysis relies on 110 cities. While this is a large sample, with a proven representative distribution across the globe relative to continental urban population shares, a smaller or a larger sample, might also affect the resulting clusters. All in all, we conclude that based on our particular data and methods, we think the resulting seven clusters are one reasonable possibility of describing the city configurations across the globe in a transparent way that reveal that geographical-cultural aspects influence their spatial configuration; but, these seven clusters are neither the only possibility nor the universal best fit for a reality probably more complex.

When we close our eyes and think of big cities on our planet, the often appearing feature in our mind is a high-rise skyline. This often feeds the feeling that cities are becoming more and more homogeneous. However, the

Table 2
Overview of the Clusters (C), the containing cities depending on the feature space (18f), and their geographical allocation and spatial features.

Cluster	Cities (k-means, 18-dimensional feature space)	Geographic-cultural allocation	LCZ features	Density features
1	Abidjan, Ahmadabad, Baghdad, Bangalore, Bucharest, Cape Town, Chennai, Delhi, Douala, Fortaleza, Ha Noi, Ho Chi Minh City, Jaipur, Johannesburg, Lagos, Lahore, Lucknow, Mogadishu, Mombasa, Port Harcourt, Santiago, Tianjin	Mainly **Asian and African** cities	Low structural variability, medium compact, low-rise, medium shares of open space	Uniform density decrease (abs.) and convex gradient (norm.)
2	Beijing, Buenos Aires, Jakarta, Kuala Lumpur, Manila, Melbourne, Mexico City, New York, Osaka, Rio De Janeiro, Riyadh, Sao Paulo, Seoul, Singapore, Toronto	Mainly **Asian and American** cities	Medium structural variability, medium compact, low-rise, medium shares of open space	Concave decreasing density gradient (abs. and norm.)
3	Addis Ababa, Amsterdam, Athens, Berlin, Brussels, Budapest, Changsha, Chittagong, Chongqing, Dhaka, Hamburg, Istanbul, Kiev, Lisbon, London, Madrid, Manchester, Milan, Minsk, Moscow, Mumbai, Munich, Paris, Rome, Saint Petersburg, Vancouver, Vienna, Warsaw, Wuhan	Dominated by **European** Cities	High structural variability, medium compact, mid-rise, medium shares of open space	Model-like, strongly decreasing, concave uniform density gradient (abs. & norm.)
4	Antananarivo, Blantyre, Calcutta, Calicut, Dar Es Salaam, General Santos City, Harare, Hong Kong, Islamabad, Kitwe, Lusaka, Maputo, Mwanza, Nairobi, Nanjing, Port Au Prince, Sydney, Yangon, Zanzibar	Mainly **Eastern African & Eastern Asian** Cities	High structural variability, low compact, low-rise, medium shares of open space	Strongly decreasing, non-uniform gradient (abs.) and change from decreasing to increasing gradient (norm.)
5	Abuja, Bujumbura, Kampala, Kano, Kigali, Kinshasa, Kumasi, Lilongwe, Poona, Port Moresby, Surat	Dominated by **Central Africa** cities	Medium structural variability, low compact, low-rise, high shares of non-built space	Uniform decrease (abs.) and increasing gradient (norm.)
6	Asmara, Cairo, Faisalabad, Hargeysa, Kabul, Karachi, Khartoum, Ouagadougou, Tehran	Dominated by cities of the **Islamic world**	High structural variability, medium compact, low-rise, very high shares of non-built space	Uniform decrease (abs.) and basically constant gradient below average (norm.)
7	Bangkok, Guangzhou, Los Angeles, Shanghai, Tokyo	Consisting of some **Very large cities**	Low structural variability, medium compact, mid-rise, lowest shares of open space	Concave density gradient (abs. and norm.)

related morphological class (LCZ1 – compact highrise) plays almost no role in the morphologic-spatial composition of cities, since their spatial proportions usually make up only about 1% of the MUAS. And this focus on the most conspicuous morphological manifestations, but extremely underrepresented in the urban landscape as a whole, probably also obstructs the feeling that there is a wide range of urban configurations worldwide. On our global analysis seven clusters with still a large variation in themselves are the result. Even if we, for instance, find the European cluster relatively homogeneous within our global sample, other studies reveal, looking only at a sample of European cities, that a large variety exists also within Europe (e.g. Scharz, 2010; Siedentop & Fina, 2012; Taubenböck, Gerten, Rusche, Siedentop, & Wurm, 2019). This clearly shows that the generalization of the clusters here as done by our study is on a highly aggregated level. Cities like Mumbai and Hamburg fall into one cluster. However, this is legitimate as geographically motivated city models have always adopted this high abstraction level. The fact that similar morphological structures produce very different atmospheres, life routines or many other things (as Mumbai and Hamburg testify) is not the issue here and goes without saying. This study is exclusively about morphologic-spatial manifestations. Given these variations, the identified seven clusters allow us to take a novel look at city configurations and their geographic distributions across our planet. We must not forget that the generalized models conceal regional specifics of urbanization processes that often materialize in highly site-specific urban outcomes that are incompatible with the model.

6. Conclusion and outlook

Science, but also reports or popular rankings have always tried to fit the diversity of our urban landscapes into generalizing and thus simplifying models. This study shows with novel data from remote sensing an improved empiricism to identify morphologic-spatial characteristics for such models across the globe. And the realization that geographic-cultural characteristics can be empirically proven with regard to morphological urban configurations is a confirmation of a long-held observation. At the same time, however, it also shows that morphological urban configurations also have similarities across geographical-cultural spaces. Understanding and fathoming these will be part of future research tasks. With a large database of 110 globally distributed cities, selected in proportion to the urban population per continent, we can principally make generalizable statements at global level. Nevertheless, an expansion of the empirical basis remains necessary. In times of 'Big Data' this study is only a beginning to master this complexity with more precise classifications, more cities, or alternative methods. It may be a basis to more systematically analyze which forms and models work better or worse.

Firmly convinced that the spatial-morphological configuration of cities makes a decisive contribution to whether cities offer quality of life, whether they are socially acceptable, ecologically sustainable or economically successful, this study attempts to create a spatial-morphological basis to examine these questions more systematically: In the hope of better understanding urban space as the theatre of life and thus being able to make it more livable.

CRediT authorship contribution statement

H. Taubenböck: Conceptualization, Methodology, Formal analysis, Visualization, Writing - original draft. **H. Debray**:Conceptualization, Methodology, Formal analysis, Visualization, Writing - review & editing. **C. Qiu**:Data curation, Validation, Writing - review & editing. **M. Schmitt**:Data curation, Validation, Writing - review & editing. **Y. Wang**: Data curation, Validation, Writing - review & editing. **X.X. Zhu**: Data curation, Validation, Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

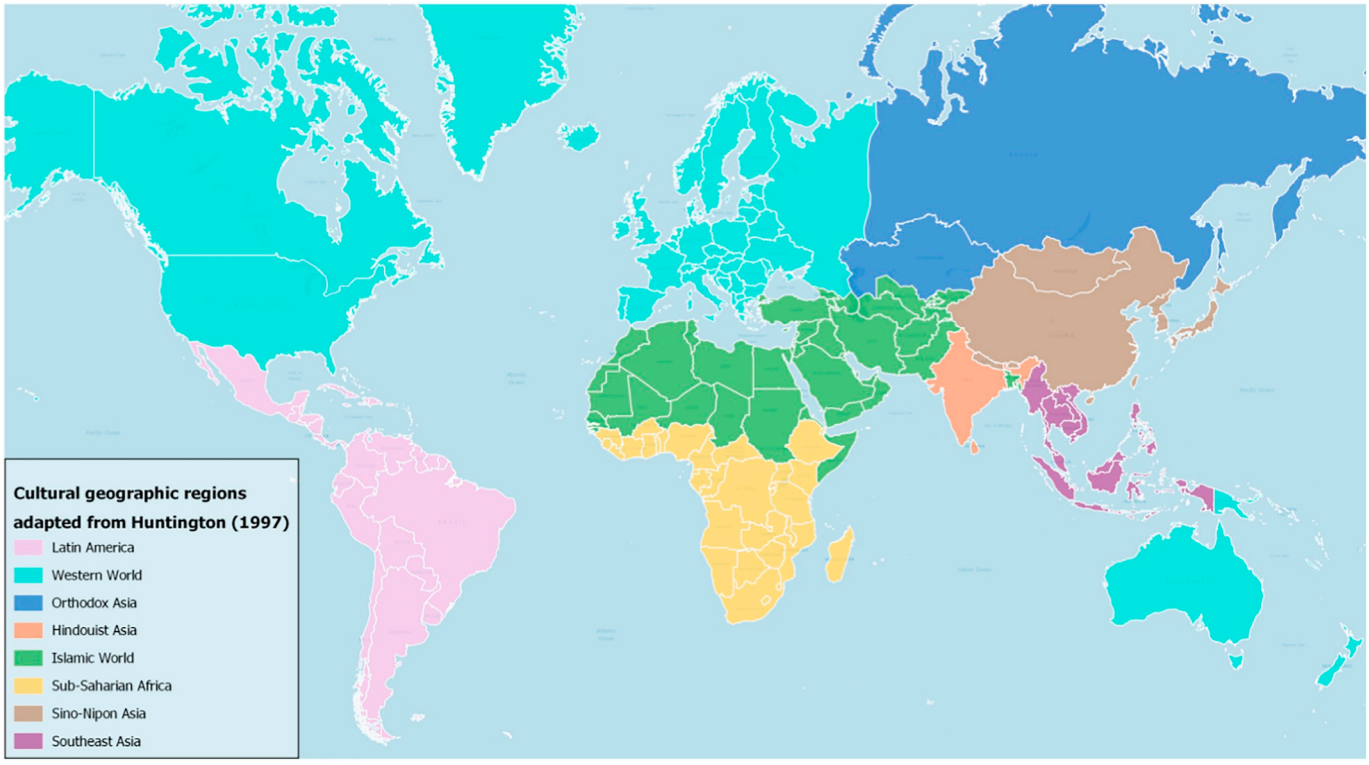

Fig. 1A, Appendix. Cultural-geographic regions adapted from Huntington (1997).

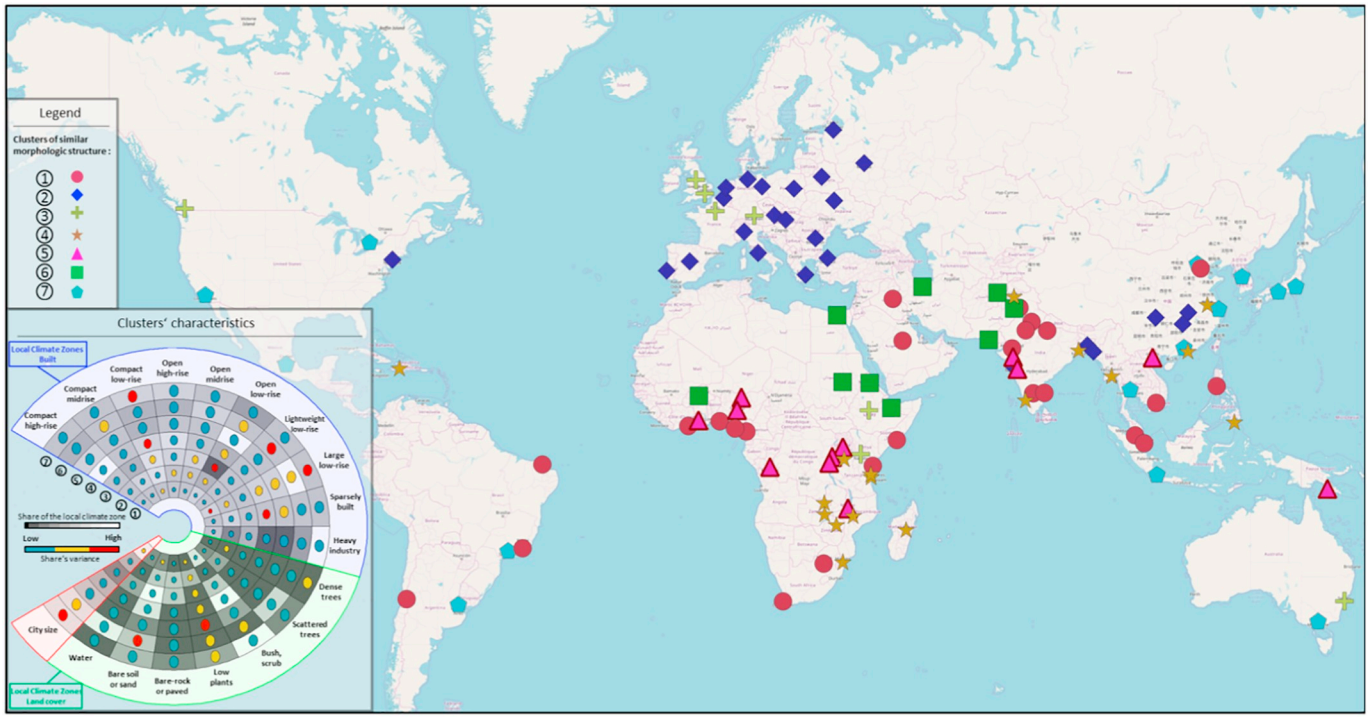

Fig. 2A, Appendix. Seven resulting clusters based on the expectation-maximization algorithm using the 18 dimensional feature space (consisting of 17 LCZs as well as city size as features) at the spatial unit of the morphological urban areas.

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