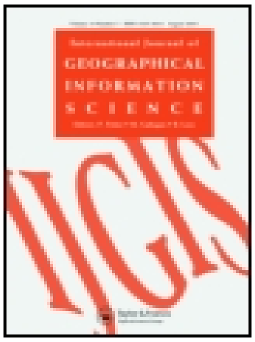

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RESEARCH ARTICLE

Are all cities with similar urban form or not? Redefining cities with ubiquitous points of interest and evaluating them with indicators at city and block levels in China

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ABSTRACT

Urban forms reflect spatial structures of cities, which have been consciously and dramatically changing in China. Fast urbanisation may lead to similar urban forms due to similar habits and strategies of city planning. However, whether urban forms in China are identical or significantly different has not been empirically investigated. In this paper, urban forms are investigated based on two spatial units: city and block. The boundaries of natural cities in terms of the density of human settlements and activities are delineated with the concept of 'redefined city' using points of interests (POIs), and blocks are determined by road networks. Urban forms are characterised by city-block two-level spatial morphologies. Further, redefined cities are classified into four hierarchies to examine the effects of different city development stages on urban forms. The spatial morphology is explained by urbanisation variables to understand the effects. Results show that the urban forms are spatially clustered from the perspective of city-block two-level morphologies. Urban forms tend to be similar within the same hierarchies, but significantly varied among different hierarchies, which is closely related to the development stages. Additionally, the spatial dimensional indicators of urbanisation could explain 41% of the spatial morphology of redefined cities.

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KEYWORDS
Urban form; redefined city; POI density; spatial morphology; urbanisation

1. Introduction

Reasonable concepts and measures of urban form are difficult to be determined to reflect both overall and local distributions of human and socio-economic activities. Traditionally, cities are defined based on administrative boundaries, such as municipalities, prefectural cities and country-level cities in China. However, modern city systems are complex and consist of strongly interrelated components, including human networks and their links with the built and natural environments (Chase-Dunn and Jorgenson 2002, Bettencourt and West 2010, Taubenböck *et al.* 2017, Zou *et al.* 2017). In addition, urban morphology and clustered functional areas have been dramatically changed during the past decades due to the rapid urbanisation process globally (Taubenböck *et al.* 2012, Moghadam and Helbich 2013,

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Ramachandra *et al*. 2015, Melchiorri *et al*. 2018), especially in China (Ma and Wu 2004, Wang *et al*. 2005, Feng and Liu 2007, Zhou and Ye 2013). Thus, there is an apparent inconsistency between traditional administrative boundaries of cities and the real densely populated or functional central urban extent. For instance, the settlement pattern in reality can cover several administrative cities, or it might be a small part of an administrative city. For the measures of urban form, analysis based on a single spatial scale, e.g. city level, is lack of comprehensive understanding of the complex city systems (Batty 2008, 2013a, 2013b). Urban forms reflect the spatial structure of cities and it is a basic issue of analysing social and economic problems of cities (Poelmans and Van Rompaey 2010, Webster 2010, Song *et al*. 2018b). To comprehensively depict spatial structure of city systems, the assessment of urban forms should involve both the morphological characteristics of city boundaries and the functional areas inside cities. Therefore, this study will redefine city extent to reflect their morphology and functional central areas, and evaluate urban forms at both city and block levels.

In general, a city is defined from three perspectives: a morphological area with a certain population density or built-up region, a functional urban area covering core and peripheral scopes, and an administrative unit (Long 2016). Since the administrative boundaries of cities cannot reflect the urban central regions with dense human and socio-economic activities, data-driven methods are increasingly used to investigate real city systems in recent researches (Long *et al*. 2016). In data-driven studies, urban central regions are outlined by proxy variables of human and socio-economic activities with multi-source data, including remote sensing images (Cai *et al*. 2017, Huang *et al*. 2018), population density (Chi *et al*. 2015, Jin *et al*. 2017), built-up regions (Xu 2007), road networks (Long 2016), points of interest (POIs) (Jin *et al*. 2017) and geotagged social media data (Shelton *et al*. 2015, Chua *et al*. 2016). In most of these studies, city boundary setting is universally default as administrative unit to explore the clustered regions with dense human activities and investigate active urban central areas (Long *et al*. 2016). As a result, since urban forms which correspond to the constitution of reality may cover a part of administrative unit or many administrative cities, it is not appropriate to address issues of real urban forms.

In addition, it is still a debatable problem that urban forms tend to be diverse or similar due to continuous and dramatic changes during rapid urbanisation, especially in developing nations such as China. From the perspective of urban planning, urbanisation usually leads to similar urban forms especially in developing and active urban regions. This phenomenon is commonly caused by the habits of city planning, similar policies for city development, living and cognitive habits of residents (Stoyanov and Frantz 2006). Small area-based analysis of urban form demonstrates that urban structure tended to be stable over a decade due to a job-housing balance, although this area was continuously growing (Horner 2007). However, from the perspective of human's movement, urbanisation also may lead to different urban structures due to various needs of residents (Doxiadis 1968). The histories of city forming and development are significantly different, which means that the urban forms are diverse, since the changes of urban forms are bound to have various historical reasons. Further, global climate change and its related events such as sea level rise and extreme weather also urge new living environment and city planning (Hamin and Gurran 2009). Thus, the interaction between urban development and climate change enables sustainability to become a key issue of new approaches for the development of urban form, the size, scale and shape of cities (Landsberg 1970, Batty 2008, Grimm *et al*. 2008). It is noted that with the integrated impacts of historical trajectories in urban development and socio-economic factors, urban forms of European cities, especially those located in the western and northern regions, are more like Unites States, Australian and New Zealand cities, but significantly different with Asian cities (Huang *et al*. 2007). While, other researchers still believe that sprawl urban forms in the United States are distinct with compact cities in Europe (Brueckner 2000, Johnson 2001).

Urban patterns can be measured from the geographical, geometric, topological, typological and morphological perspectives (Marshall 2004). The geographical measures are usually the administrative boundaries, which describe urban patterns by the territorial jurisdiction (Cai *et al*. 2017). The geometric measures primarily describe the shape and structure of road network pattern to estimate traffic flows and assess road designs (Marshall 2004). The topological measures can depict the spatial contiguity among road network, or between road network and land use (Jiang and Claramunt 2004). The topological analysis has broad applications, such as transport geography, built environment and infrastructure management (Marshall 2004, Jiang 2007). The typological analysis exams urban road network from a typological space which includes various road types and classification systems (Louf and Barthelemy 2014).

A popular method of sprawling urban forms is to quantify spatial morphology of urban outlines or boundaries (Zhou and Ye 2013). Urban spatial morphology is affected by city planning and construction, and conversely, urban development also has influence on the spatial morphology. The commonly used indicators for capturing urban spatial morphology include fractal dimension (Niemeyer *et al*. 1984, Shen 2002, Frankhauser 2015), compact ratio (Liu *et al*. 2003) and shape factor (Haggett *et al*. 1977). Compared with the basic measures of urban forms, such as length, area and density, fractal dimension is used to differentiate shapes of cities which tend to be circle or striped, and it is more efficient in describing space filling of urban evolution (Shen 2002, Zhou and Ye 2013). Compact ratio can describe the closeness of various parts of cities, and it reveals the conditions of energy consumption, transport convenience and the distributions of urban district functions (Zhou and Ye 2013). Shape factor tends to reveal a city with single centre for development or diverse distributions of urban district functions with multiple functional centres (Haggett *et al*. 1977). While, urban forms are not only presented by the boundaries of the whole cities, but also reflected from the forms and distributions of blocks inside cities (Louf and Barthelemy 2014). Urban boundary represents the characteristics of urban spatial morphology, but it is limited in capturing the spatial structure inside cities. A common block distribution pattern is that the blocks with identical or similar functions are clustered (Yuan *et al*. 2012). Road networks are a simple view of cities to depict the spatial structure and organisation inside cities, helping to understand of urban forming mechanisms (Southworth and Ben-Joseph 2013, Song *et al*. 2018c). From the perspective of human eye, road networks-based blocks are detailed and practical for the description of urban inside structure instead of road networks itself, which are equivalent in addressing this issue (Louf and Barthelemy 2014, Taubenböck *et al*. 2016). Thus, blocks in each city can be recognised based on the road networks. Most of previous studies quantify urban forms with merely one aspect of spatial morphologies of cities, whole cities or blocks inside cities, but few of them consider both spatial scales simultaneously. This paper assesses urban forms involving both city-level and block-level spatial morphologies, and the integrated measures can characterise urban forms to reflect both overall and local distributions of human and socio-economic activities.

In this paper, to quantitatively and reasonably reveal whether all cities are of similar urban forms or not, cities are redefined to reflect their real and natural central regions, and spatial morphology is computed with both city-level and block-level indicators. The natural cities are the naturally and objectively delineated urban extent in terms of the density of human settlements and activities (Jiang and Jia 2011, Jiang and Liu 2012, Jiang and Miao 2015, Jiang *et al*. 2015, Bergs 2018), which are usually quantified by population data and the proxy variables of human activities, such as nightlight images and web-based geospatial big data (Jiang and Ren 2018, Song *et al*. 2018a). The redefined cities present the urban central regions with relatively high density of human activities in the natural cities. Spatial morphologies at both city and block levels are evaluated with the variables 'fractal dimension', 'compact ratio' and 'shape factor'. Spatial patterns of both morphologies are explored using a spatial autocorrelation method, respectively. Then cities are classified using clustering methods according to both the city-level and block-level spatial morphologies information. Further, the spatial differences among cities are explored based on the spatial dimensional indicators of urbanisation, including POI density, area, population density, road junction density and distance to the nearest city.

This paper is organised as follows. Section 2 describes study area and data and Section 3 elaborates methods of redefining and assessing city systems. In Section 4, analysis results in each step are presented. Sections 5 and 6 propose discussion and conclusion of this study, respectively.

2. Study area and data

2.1. *City system in China*

City system in China is spatially defined as administrative city boundaries for the management and statistics, which is different with the metropolitan statistical areas in the United States and Australia, and the functional urban areas in European Union countries (Long 2016, Jin *et al*. 2017). Under the definition of a city system, there are 657 cities with three hierarchies in 2011 in China, including four national municipalities, 284 prefecture-level cities and 369 county-level cities (Ministry of Housing and Urban-rural Development of the People's Republic of China (MOHURD) 2011b). This system lists cities with relative large urban areas, dense population and high socio-economic status, but this system can't reflect all the real urban central extent. In 2011, total built-up area of 657 cities is 43 603 km^2, accounting for 23.75% of the whole areas of cities (Ministry of Housing and Urban-rural Development of the People's Republic of China (MOHURD) 2011b). In addition to these urban areas, there are still built-up regions of 17 376 km^2 in other 1 627 counties and 33 860 km^2 in towns (Ministry of Housing and Urban-rural Development of the People's Republic of China (MOHURD) 2011a). This means that the city system in China includes sub-urban and rural areas within the administrative cities, but doesn't cover all prefecture-level and county-level urban regions. In this paper, the cities are redefined as the real spatially closely connected urban central regions where population is dense, human activities are abundant and active, and built environment and infrastructure conditions are relatively complete. Thus, the redefined cities will cover all the central urban extent across China, which might vary in different hierarchies in the administrative city system.

2.2. *Points of interest (POIs) and road networks*

POIs and road networks are utilised to define urban regions and blocks inside cities. POIs are the accurate locations of important and hotspot urban infrastructures, such as hotels, schools, hospitals and industries, so they are usually regarded as useful and self-defined components in the urban management systems (Man *et al*. 2012). Thus, in this paper, POIs are a proper proxy variable for capturing active human activities and residential development (Chi *et al*. 2015), and it is used to outline boundaries of redefined cities. POIs across China in 2011 are collected and geo-coded by business cataloguing websites to recognise the boundaries of urban regions in China. The quality of POIs is secured through random manual checks. There are totally 2,581,382 POIs in China, and the average POI density is 0.269 points per square kilometres. POIs present the locations of urban functions such as shopping, public administration, education, government buildings, etc. Road networks data include highways, national roads, provincial roads, county roads and urban expressways. Figure 1 shows the spatial distributions of POIs

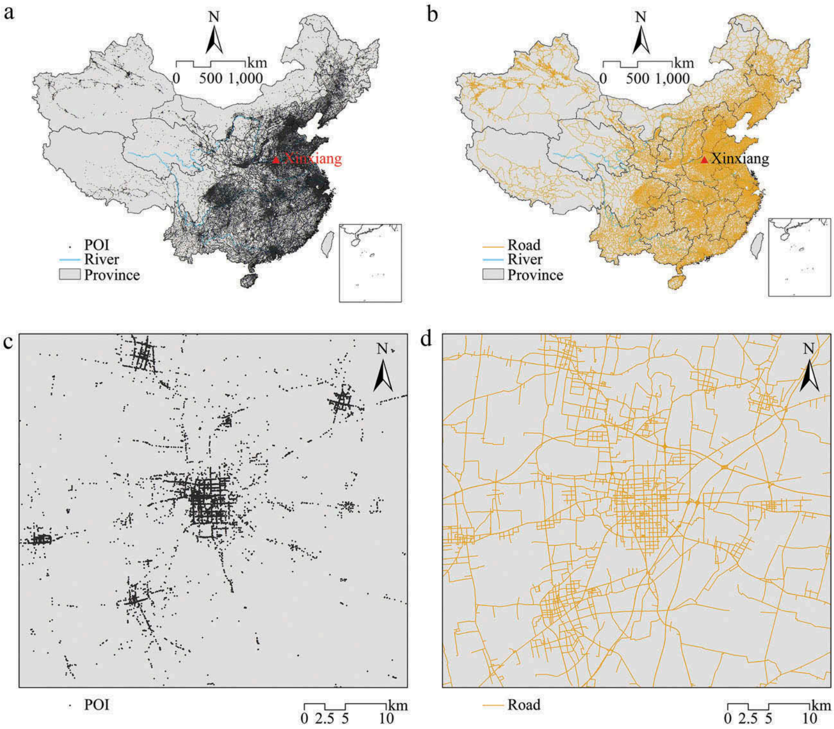

Figure 1. Spatial distributions of POIs and road networks data in China (a and b), and within an example region surrounding Xinxiang, a prefectural level city in Henan province (c and d).

and road networks in China and within an example region surrounding Xinxiang, a prefectural level city in Henan province.

2.3. *Data for quantifying urbanisation*

Urbanisation is quantified by considering the city size, active level of human activities, urban infrastructure conditions and the relationships with surrounding cities. City size is computed as area (km^2) of a redefined city. Human activities are depicted with POI density (points/km^2) and population density (persons/km^2). Population data is sourced from China Temporal Datasets in 2010 with the spatial resolution of 100 m (Gaughan 2015). Urban infrastructure conditions are described with a proxy variable of road junction density (junction/km^2). There are 2,728,143 road junctions across China in 2011, which is provided by Beijing City Lab (Long 2014). Road junction density of a city is computed with the total number of road junctions within the city divided by the city area. The spatial relationship between a redefined city and its surrounding cities is quantified with the Euclidean distance from the geometric centre of this city to the centre of nearest city (km).

3. Methods of redefining and assessing city systems

3.1. *Method outline*

This paper aims to answer the question that whether urban forms are all identical in China. To study the similarities and differences of the urban forms, city systems are redefined to outline the natural central urban regions, the spatial morphology is characterised, and the cities are classified based on the morphology of urban forms. There are primarily three stages of this research as shown in Figure 2. First, city systems are redefined with POIs to depict the central urban regions whose boundaries are developing naturally instead of outlined by administrative necessities. Then, spatial morphologies of cities are characterised by both city-level and block-level morphological indicators. Finally, redefined cities are classified according to the city and block two-level morphology to investigate whether urban forms tend to be similar or not. To validate the hierarchy result, the spatial differences among various hierarchies of cities are explored considering the relationships between the integrated spatial morphology and corresponding spatial dimensional indicators of urbanisation.

3.2. *Redefining cities*

The process of redefining cities is to generate boundaries of urban central regions of natural cities using POIs. Figure 3 shows the process of redefining cities with the example region around Xinxiang, which consists of the following five steps. The first step is to calculate POI density and generate POI density map with Kernel density functions with the spatial resolution of 500 m. The resolution around 500 m can statistically summarise points and it is proper and commonly used for generating raster products across China, e.g. land surface temperature, forest coverage (Li *et al.* 2017), land cover (Gong *et al.* 2013), gross domestic product (GDP) (Liu *et al.* 2005) and population estimations (Fu *et al.* 2014).

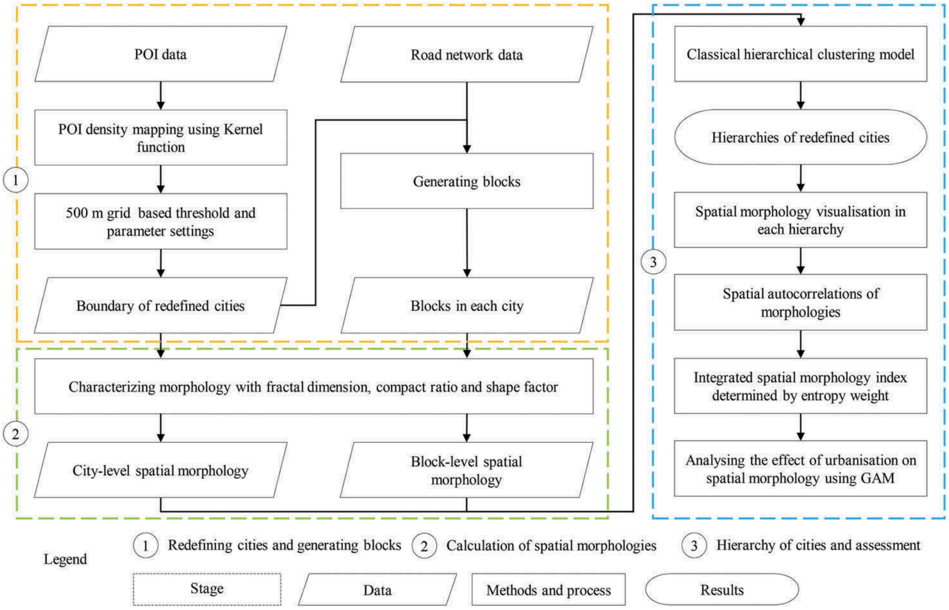
POI data
Road network data
POI density mapping using Kernel function
Generating blocks
500 m grid based threshold and parameter settings
Boundary of redefined cities
Blocks in each city
Characterizing morphology with fractal dimension, compact ratio and shape factor
City-level spatial morphology
Block-level spatial morphology
Classical hierarchical clustering model
Hierarchies of redefined cities
Spatial morphology visualisation in each hierarchy
Spatial autocorrelations of morphologies
Integrated spatial morphology index determined by entropy weight
Analysing the effect of urbanisation on spatial morphology using GAM
①
②
③
Legend
① Redefining cities and generating blocks
② Calculation of spatial morphologies
③ Hierarchy of cities and assessment
Stage
Data
Methods and process
Results

Figure 2. Schematic overview of redefined cities and blocks based hierarchy of urban spatial morphology.

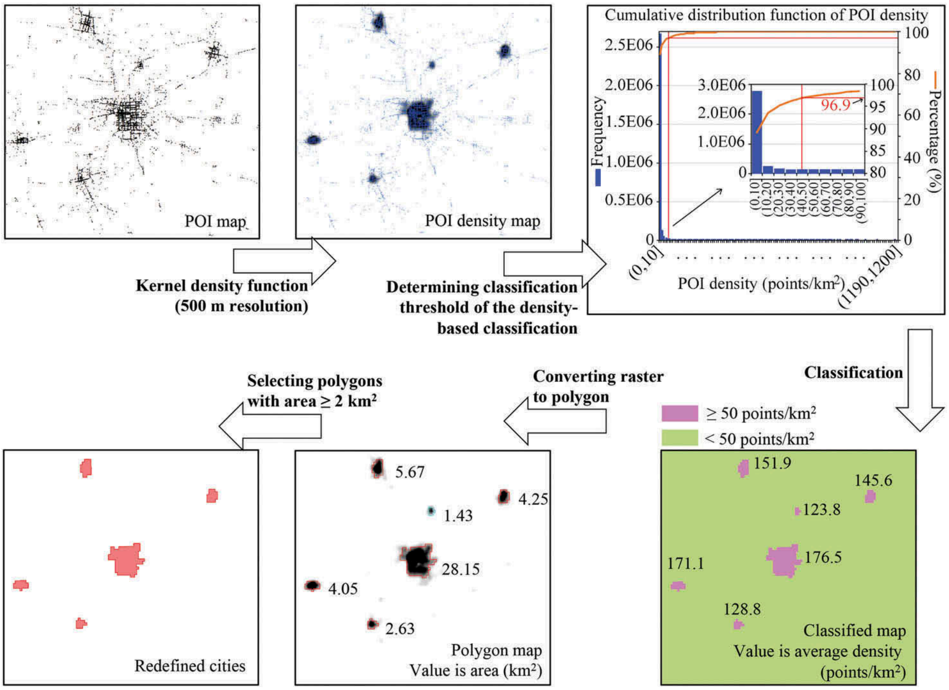
POI map
POI density map
Cumulative distribution function of POI density
2.5E06
2.0E06
1.5E06
1.0E06
0.5E06
0
Frequency
100
80
60
40
20
0
Percentage (%)
3.0E06
2.0E06
1.0E06
0
100
95
90
85
80
96.9
(0,10]
(10,20]
(20,30]
(30,40]
(40,50]
(50,60]
(60,70]
(70,80]
(80,90]
(90,100]
(0,10]
(1190,1200]
POI density (points/km²)
Kernel density function (500 m resolution)
Determining classification threshold of the density-based classification
Classification
Converting raster to polygon
Selecting polygons with area ≥ 2 km²
≥ 50 points/km²
< 50 points/km²
151.9
145.6
123.8
176.5
171.1
128.8
Classified map
Value is average density (points/km²)
5.67
4.25
1.43
28.15
4.05
2.63
Polygon map
Value is area (km²)
Redefined cities

Figure 3. Process of POI-based redefining cities with an example region surrounding Xinxiang, a prefectural level city in Henan province.

Second, before classifying the central urban regions and other areas, the classification threshold should be determined for the density-based classification. A cumulative distribution function (CDF) of POI density is utilised to describe and differentiate the spatial variations of POI density from the central urban regions to the outer areas. A larger CDF value indicates a more central urban region, and the difference between urban central regions and outer areas are presented by the changes of CDF of POI density. When the change of CDF tends to be small enough, which is set as 0.5% in the study, the classification threshold is determined. If the change is too large, some urban central regions will not be included. If the change is too small, many outer areas will be treated as urban central regions. In the study, based on the 500-m grid POI density map, the frequency and CDF are computed with the interval of 10 points/km^2 from 0 to the maximum density 1199.58 points/km^2, which are summarised in Table 1. In Figure 3 and Table 1, the change of CDF of POI density is significantly reduced at the beginning intervals, but it gets small when the POI density is higher than 50 points/km^2. The changes of the CDF of POI density lower than 50 points/km^2 are all larger than 0.5%, where the change from $(30, 40]$ to $(40, 50]$ is 0.64%, but the changes of the CDF of POI density higher than 50 points/km^2 are smaller than 0.5%, where the change from $(40, 50]$ to $(50, 60]$ is 0.47%. The grids with POI density lower than 50 points/km^2 account for 96.9% of all density grids, and that higher than 50 points/km^2 account for 3.1%. As a result, when the classification threshold is 50 points/km^2, the percentage of urban central region areas is 3.1%. On one hand, if the threshold is higher than 50 points/km^2, the grids with POI density will cover fewer urban central regions and some areas that should be urban central regions are not included. For instance, when the threshold is 60 points/km^2, 15.0% of the areas $((3.11\% - 2.65\%)/3.11\%)$ that should be urban central regions are removed. On the other hand, if the threshold is lower than 50 points/km^2 (e.g. 40 points/km^2), the urban central regions will include at least 17.1% of the areas $((3.75\% - 3.11\%)/3.75\%)$ that should be outer areas. Thus, the boundary of the central urban regions is defined and determined by the conditions that local POI density is set as at least 50 points/km^2. This POI density threshold differentiates the urban central regions where POIs are grid distributed and other areas where POIs are linearly or sparse distributed.

Table 1. Summary of cumulative distribution function (CDF) of POI density for the selection of classification threshold of urban central regions.

Threshold of POI density (points/km^2)	Cumulative distribution function (CDF)	Change of CDF	Percentage of urban central region areas
$(0, 10]$	89.18%	/	10.82%
$(10, 20]$	93.59%	4.42%	6.41%
$(20, 30]$	95.30%	1.70%	4.70%
$(30, 40]$	96.25%	0.95%	3.75%
$(40, 50]$	**96.89%**	**0.64%**	**3.11%**
$(50, 60]$	97.35%	0.47%	2.65%
$(60, 70]$	97.71%	0.36%	2.29%
$(70, 80]$	98.00%	0.29%	2.00%
$(80, 90]$	98.24%	0.24%	1.76%
$(90, 100]$	98.44%	0.20%	1.56%
…	…	…	…
$(1190, 1200]$	100.00%	0.00%	0.00%

The third step is to classify the central urban regions and other areas with the POI density map and the selected classification threshold. The fourth step is converting raster map to polygons to derive the initial city boundaries. Finally, cities with areas smaller than 2 km^2 are removed, which means the redefined cities contain at least a main street of 2 km in the urban central regions. Thus, the POI density-based boundaries of redefined cities are determined, which presents the urban central regions of natural cities.

3.3. *Characterising cities and blocks*

Three indicators are used to capture the spatial morphology of redefined cities, including fractal dimension, compact ratio and shape factor. Analysing fractal dimension of urban space is a focus of depicting urban morphology (Niemeyer *et al*. 1984, Shen 2002, Frankhauser 2015). In this research, a variable-sized grid method is used to estimate fractal dimension within the city boundary. The urban extent is covered by grids with varying sizes. When the grid side length l varies, the number of grids covering urban boundary $N(l)$ and number of grids covering the whole urban extent $B(l)$ have to be changed. According to fractal theory, $lnN(l) = C + DlnB(l)^{1/2}$, where C is constant and D is the dimension of city boundary. The varying side lengths enable a series of point pairs $\left(lnN(l), lnB(l)^{1/2}\right)$. Thus the estimation of D is the slope of linear regression for these point pairs. A large D value means the urban form is more fractal, and urban development tends to be more diverse (Figure 4).

Compact ratio is another indicator for depicting urban spatial morphology (Liu *et al*. 2003). Compact ratio r of urban boundary is calculated as $r = 2\sqrt{\pi A}/P$, where A is urban area and P is perimeter of boundary. A high r value represents the compact urban form

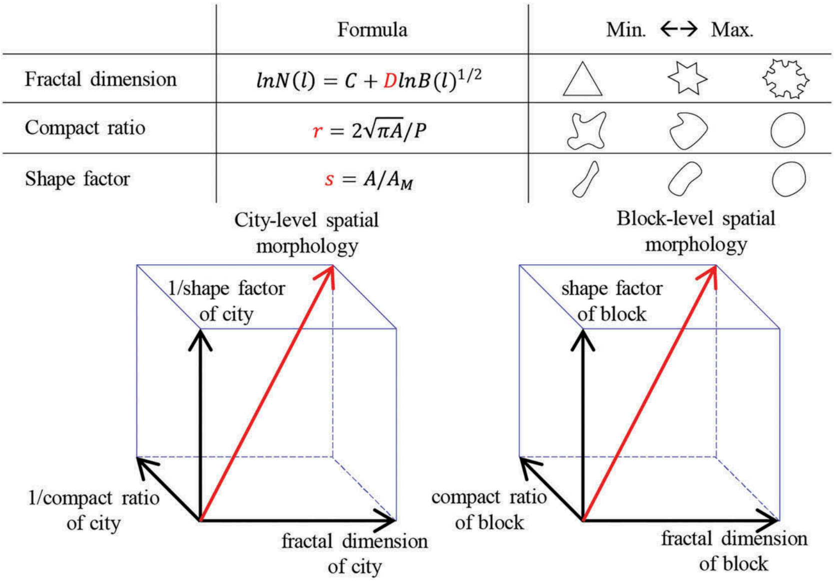
Formula
Min. ←→ Max.
Fractal dimension
$lnN(l) = C + DlnB(l)^{1/2}$
Compact ratio
$r = 2\sqrt{\pi A}/P$
Shape factor
$s = A/A_M$
City-level spatial morphology
1/shape factor of city
1/compact ratio of city
fractal dimension of city
Block-level spatial morphology
shape factor of block
compact ratio of block
fractal dimension of block

Figure 4. Schematic diagram of relationships between city/block-level spatial morphology and corresponding indicators.

that tends to be a circle, while a low one means the urban form is narrow and long. Actually, both high and low compact ratios have their respective advantages. High compact ratios enable the close connection among various parts of cities, which could reduce energy consumption and improve transport convenience (Newman and Kenworthy 1999, Shim *et al*. 2006) (Figure 4). For low compact ratios, urban district functions are more apparent.

A third characterisation of urban form is its shape factor s, which is calculated as the ratio between urban area A and the area of the circumscribed circle M, $s = A/A_M$ (Haggett *et al*. 1977). Usually the shape factor is smaller than one, and a smaller one means the more anisotropic the urban form is (Figure 4). An anisotropic urban form may be characterised as diverse distribution of urban district functions and multiple centres of development.

Further, three spatial morphology indicators, including fractal dimension, compact ratio and shape factor, are also used for characterising blocks. In this research, both city-level and block-level spatial morphologies are integrated to capture urban forms. The relations of both kinds of indicators are shown in Figure 4. A larger city-level spatial morphology is composed by larger fractal dimension (Cfd), reciprocal compact ratio (1/Ccr) and reciprocal shape factor (1/Csf), which indicates that the form of central urban region is more fractal, less compact and more unevenly distributed due to more fixed district functions. Meanwhile, a larger block-level spatial morphology, consisting of reciprocal fractal dimension (1/Bfd), compact ratio (Bcr) and shape factor (Bsf), reveals more spatially clustered and compact spatial structures and block organisations with identical functional blocks.

3.4. *Hierarchy of cities and validation*

To investigate whether urban forms are all similar or not, the redefined cities are classified using cluster analysis for the city and block two-level spatial morphologies. The city clusters represent the similarities or differences of spatial morphologies among cities. Cities within the same hierarchy are of similar urban forms, and cities in different hierarchies are of distinct urban forms. Two primary methods of clustering are hierarchical clustering and k-means clustering. There are a lot of assumptions in k-means clustering. For instance, number of clusters is a pre-specified and fixed value k, computation objective is minimising the sum of squared errors (SSE), variables should be of spherical distribution, all variables have the same variance or importance for clustering, and all k clusters have the same prior probability (Hartigan and Wong 1979, Kanungo *et al*. 2002). Compared with k-means clustering, hierarchical clustering is flexible in choosing the number of clusters and has weaker assumptions, so it is commonly used in urban planning field. Unlike k-means runs clustering process with a single step, hierarchical clustering runs a series of partitions ranging from N clusters each involving one object to a single cluster with all objects. Thus, the hierarchical clustering method is used to classify redefined cities with the variables of city-level and block-level spatial morphological indicators. The multicollinearity of variables is tested using condition numbers before hierarchical clustering analysis.

In addition, to understand the potential reasons of the similarities or differences of urban forms, the contributions of urbanisation on central urban forms are computed, which includes the following three steps. First, an integrated spatial morphology indicator is calculated by a sum of weighted city-level and block-level spatial morphologies for describing the overall forms of the redefined cities. During the calculation, both city-level and block-level spatial morphologies are normalised to variables raging from 0 to 1, and the weights of variables are computed using an entropy weighting method. The entropy weighting method based on entropy information theory is efficient in inferring the useful information of variables (Chen *et al.* 2018, Xie *et al.* 2018). Thus, the entropy weights indicate the relative amount of useful information and relative importance of variables. Next, urbanisation of redefined cities is quantified with the city size, active level of human activities, urban infrastructure conditions and the relationships with surrounding cities. Finally, a generalised additive model (GAM) is utilised to calculate the deviance explained by each urbanisation variable. It could depict both linear and nonlinear relationships between independent variables and responses through non-parametric smoothing functions (Hastie and Tibshirani 1990, Strawa *et al.* 2011, Li *et al.* 2013, Song *et al.* 2016, Wu *et al.* 2017). GAM is a reliable and flexible approach for exploring statistical relationships, computing contributions of potential variables and making predictions (Song *et al.* 2015, 2017).

4. Results

4.1. *Redefined cities and their characteristics*

In this study, 2005 redefined cities in China (see Figure 5(a)) are derived from POI density map with the Kernel density functions. As a result, each city covers at least 170 POIs and areas of 2 km^2, and the minimum mean POI density of redefined cities is 78.66 points per square kilometres. Correspondingly, the averaged POI densities in cities are mapped in Figure 5(b), showing that high POI densities appear in south-eastern China along the ocean and western China, while low-density cities are primarily located in northern China. To explain the process of this study, four cities are selected as examples, including the redefined cities around Beijing, Hohhot, Xinxiang and Jiujiang. These four cities are used as exemplars since they are of distinct city sizes, varied patterns of road networks, and distributed in different regions in China. Their locations are shown in Figure 5(a). Beijing is a typical large city in China. The urban central area of the redefined city is 503.21 km^2 covering 4.94 million inhabitants, 89 101 POIs and 46 872 road junctions. Hohhot is a provincial capital located in northern China. Area, population and number of POIs in Hohhot are nearly one-tenth of those in Beijing, and number of road junctions is about one-twentieth of that in Beijing. Xinxiang and Jiujiang are both prefecture-level cities. Xinxiang is in plain area and the middle part of China, so its road networks are grid distributed. Jiujiang locates on the southern shores of the Yangtze River in southern China, and its road networks are irregularly distributed due to dense river net. The relationships between city boundaries and POI density are mapped in Figure 5(c-f).

The redefined cities reflect the urban central regions with dense human and socio-economic activities. Their boundaries are very likely inconsistent with the administrative boundaries. To illustrate this concern, the spatial relative relations of urban central regions presented by the concept of the spatial redefined city extents are compared with the administrative county boundaries and primary cities locations, including capital, provincial capitals, prefecture-level cities and districts/countries (Figure 6). For the four example cities, the central urban regions are generally composed by multiple nearby cities instead

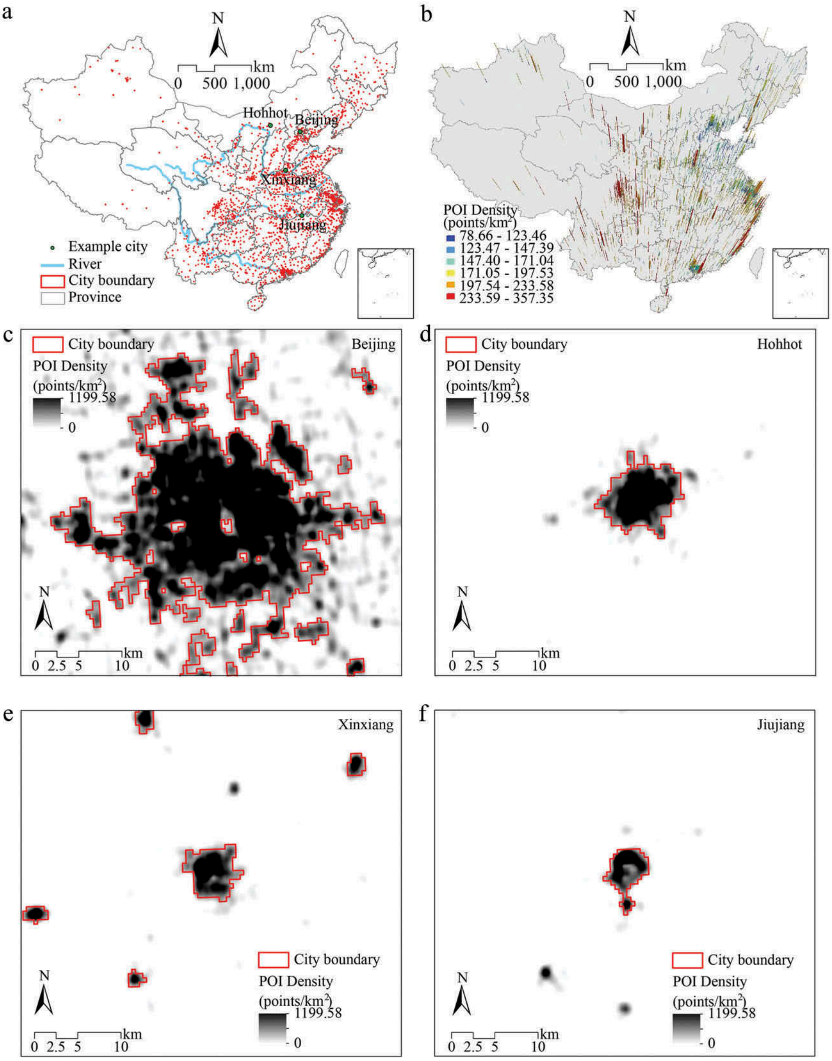
a
N
0 500 1,000 km
Hohhot
Beijing
Xinxiang
Jiujiang
Example city
River
City boundary
Province
b
N
0 500 1,000 km
POI Density
(points/km^2)
78.66 - 123.46
123.47 - 147.39
147.40 - 171.04
171.05 - 197.53
197.54 - 233.58
233.59 - 357.35
c
City boundary
POI Density
(points/km^2)
1199.58
0
Beijing
N
0 2.5 5 10 km
d
City boundary
POI Density
(points/km^2)
1199.58
0
Hohhot
N
0 2.5 5 10 km
e
Xinxiang
City boundary
POI Density
(points/km^2)
1199.58
0
N
0 2.5 5 10 km
f
Jiujiang
City boundary
POI Density
(points/km^2)
1199.58
0
N
0 2.5 5 10 km

Figure 5. Boundaries of redefined cities based on POI kernel density map. Distribution of redefined cities (a), map of mean POI densities in cities (b), and the relationships between city boundaries and POI density in four example cities, Beijing (c), Hohhot (d), Xinxiang (e) and Jiujiang (f).

of a single one. While surrounding the four example cities, there are still many cities that their geographic locations are consistent with administrative cities. In addition, the inconsistency between redefined city boundaries and administrative boundaries or locations also appears in two kinds of cases. One is that the places are recognised as redefined cities but they are not administrative cities shown in Figure 6(a), the other one is the contrary case that the places are not redefined cities but practically they are administrative cities as shown in Figure 6(b-d). This inconsistency demonstrates the redefined cities represent the central, active and continuously developing urban regions.

The city-level spatial morphology indicators of redefined cities, including fractal dimension, compact ratio and shape factor, are mapped in Figure 7(a,c,e). To learn the spatial

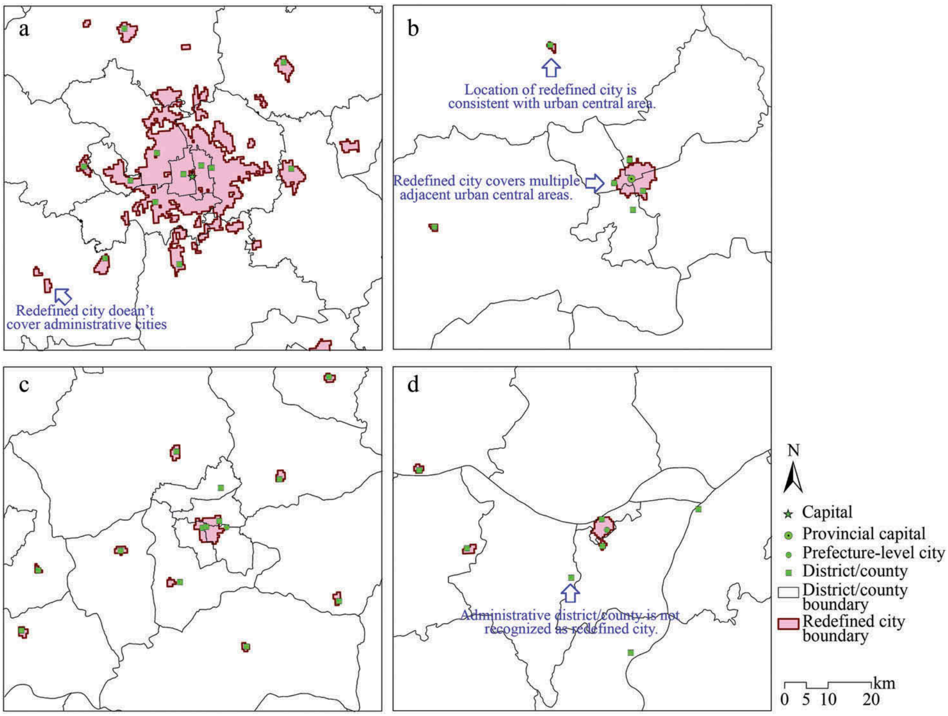
a
Redefined city doean't cover administrative cities
b
Location of redefined city is consistent with urban central area.
Redefined city covers multiple adjacent urban central areas.
c
d
Administrative district/county is not recognized as redefined city.
N
Capital
Provincial capital
Prefecture-level city
District/county
District/county boundary
Redefined city boundary
km
0 5 10 20

Figure 6. The relationships between redefined city boundaries and administrative boundaries/locations around four example cities, Beijing (a), Hohhot (b), Xinxiang (c) and Jiujiang (d).

difference of spatial morphology in redefined cities, local spatial autocorrelation of each indicator is tested by a local indicator of spatial association (LISA) (Anselin 1995), which are mapped in Figure 7(b,d,f). The maps of LISA show the hot-spot clusters (high-high, H-H) and cold-spot clusters (low-low, L-L) of redefined cities, where hot-spot clusters mean the value of a spatial morphology indicator of a city is high and the indicator values of its adjacent cities are also high, and cold-spot clusters have the contrary meaning (Ge *et al.* 2017). In general, hotspot cities are located in southern part of China and cold-spot cities are in northern part of China, but the distributions of three indicators are distinct. The forms of cites in southern part of China are more fractal, disperse and banded compared with those in northern part of China. A direct reason of this phenomenon is the topographical difference. Northern China Plain and North-eastern China Plain are two primary plains distributed in northern part of China, leading to free radial development of cities. On the contrary, the topography of southern part of China is characterised as dense river networks and hilly areas. Thus, the central cities would expand along rivers and hills, causing their complex fractal, disperse and banded forms.

4.2. *Blocks and their characteristics*

With the help of road networks data, 154 871 blocks are generated within all 2005 redefined cities in China. Similarly, four example urban regions are used to explain the block-level analysis. The blocks in the four example cities are illustrated in Figure 8. The total number of

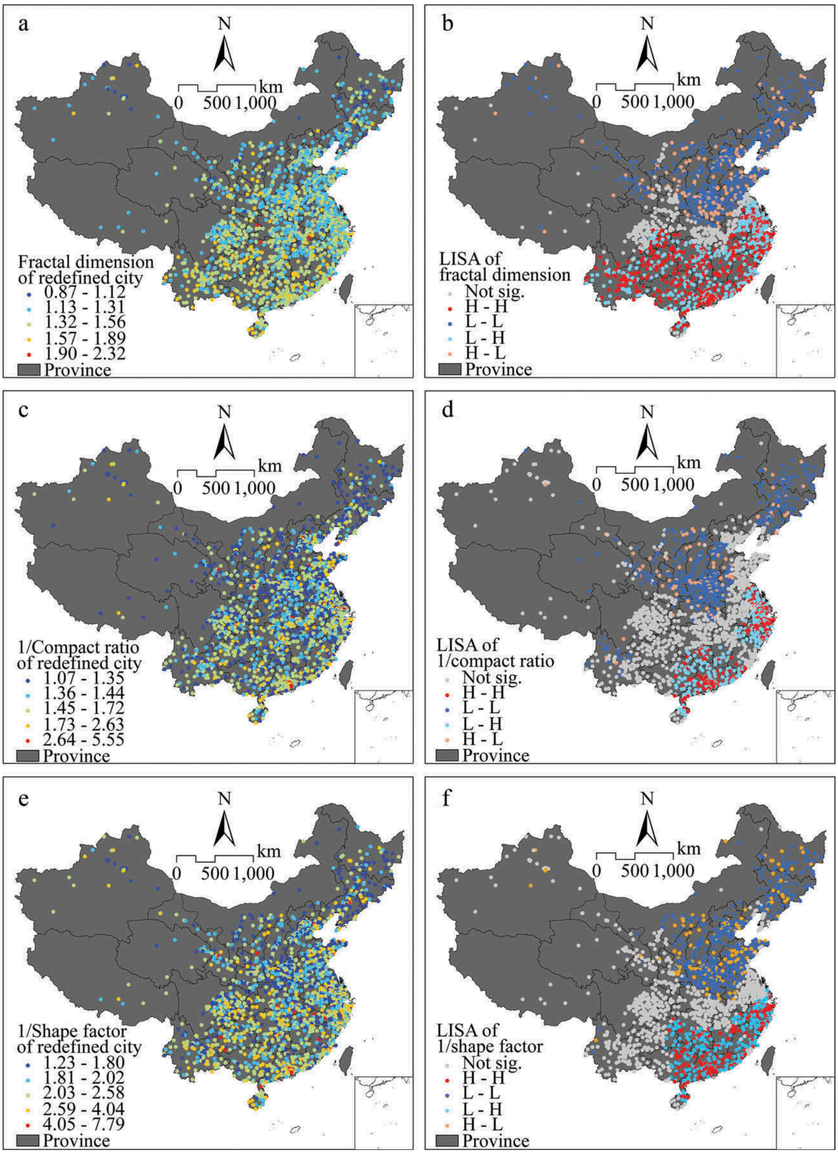
a
N
km
0 500 1,000
Fractal dimension of redefined city
● 0.87 - 1.12
● 1.13 - 1.31
● 1.32 - 1.56
● 1.57 - 1.89
● 1.90 - 2.32
Province
b
LISA of fractal dimension
● Not sig.
● H - H
● L - L
● L - H
● H - L
Province
c
1/Compact ratio of redefined city
● 1.07 - 1.35
● 1.36 - 1.44
● 1.45 - 1.72
● 1.73 - 2.63
● 2.64 - 5.55
Province
d
LISA of 1/compact ratio
● Not sig.
● H - H
● L - L
● L - H
● H - L
Province
e
1/Shape factor of redefined city
● 1.23 - 1.80
● 1.81 - 2.02
● 2.03 - 2.58
● 2.59 - 4.04
● 4.05 - 7.79
Province
f
LISA of 1/shape factor
● Not sig.
● H - H
● L - L
● L - H
● H - L
Province

Figure 7. City-level spatial morphology indicators in 2005 redefined cities in China, fractal dimension (a), 1/compact ratio (b) and 1/shape factor (e) of cities, and their LISA maps (b, d and f).

blocks of four example redefined cities of Beijing, Hohhot, Xinxiang and Jiujiang are 3536, 329, 123 and 131, respectively. From the intuitive point of view, the spatial morphologies of road networks-based blocks are significantly different among four cities.

The spatial morphology is also computed for blocks in all redefined cities in China. Figure 9 shows the distributions of three block-level indicators, fractal dimension, compact ratio and shape factor, in four example redefined cities. Within a city, the block forms are varied across the central urban region, which is related to the topography, functions of blocks and urban structure design (Bosselmann 2012). To capture

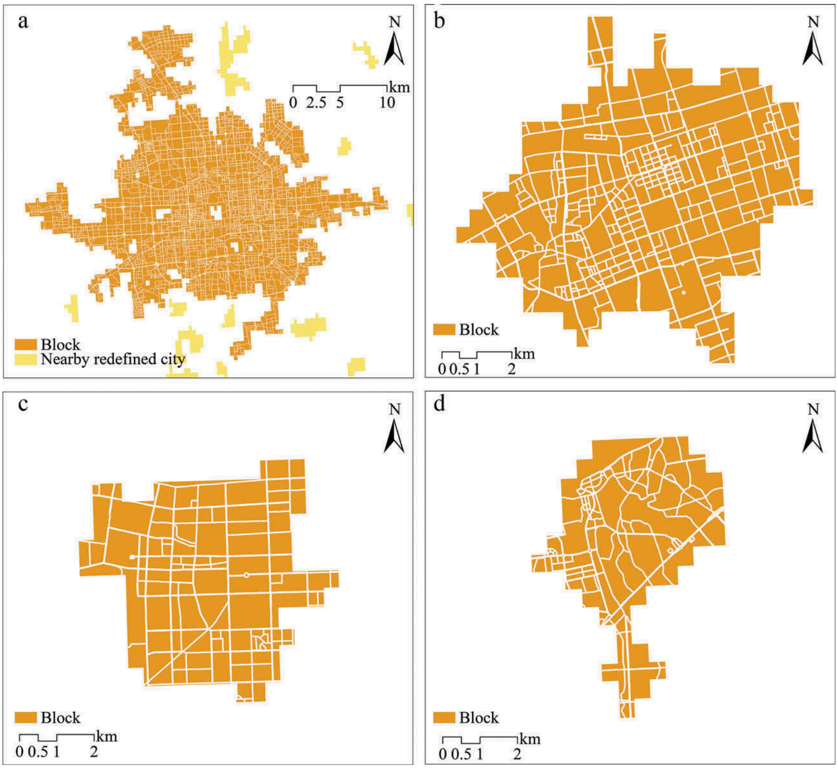

Figure 8. Road networks based blocks in four example cities, Beijing (a), Hohhot (b), Xinxiang (c) and Jiujiang (d).

the integrated performance of block-level spatial morphology, the indicators are summarised with mean values for each city. As shown in Figure 9(m-o), the statistical summaries by boxplots reflect the statistical difference of the indicators in various cities besides the spatial difference shown in the maps. According to the urban forms defined by block-level morphology illustrated in Figure 4, a larger mean or median block-level spatial morphology indicator demonstrates a more clustered urban inside structure and organisation, and a more compact form of urban functional areas. The urban inside structure in Xinxiang is more compact than that in other cities, and the land resources with similar functions are more clustered organised. The inside structure in Beijing is continuously changing, parts of functional areas are still moving and central regions are expanding with different magnitudes and speeds especially in newly developing regions (Chen and Wang 2013, Long *et al*. 2013, Wu *et al*. 2015), even though the inside structure in some regions are mature and robust. Both topology and the development of functional areas have influence on the inside structure of Jiujiang. All four example cities are in river network, but Jiujiang is located near Yangtze River and its river network is much denser than others.

Correspondingly, block-level spatial morphology indicators are summarised within each redefined city, and the spatial autocorrelations of mean morphological indicators are tested by LISA (Figure 10). Results demonstrate that hotspot cities of reciprocal of fractal dimension and compact ratio of blocks locate in northern and north-eastern

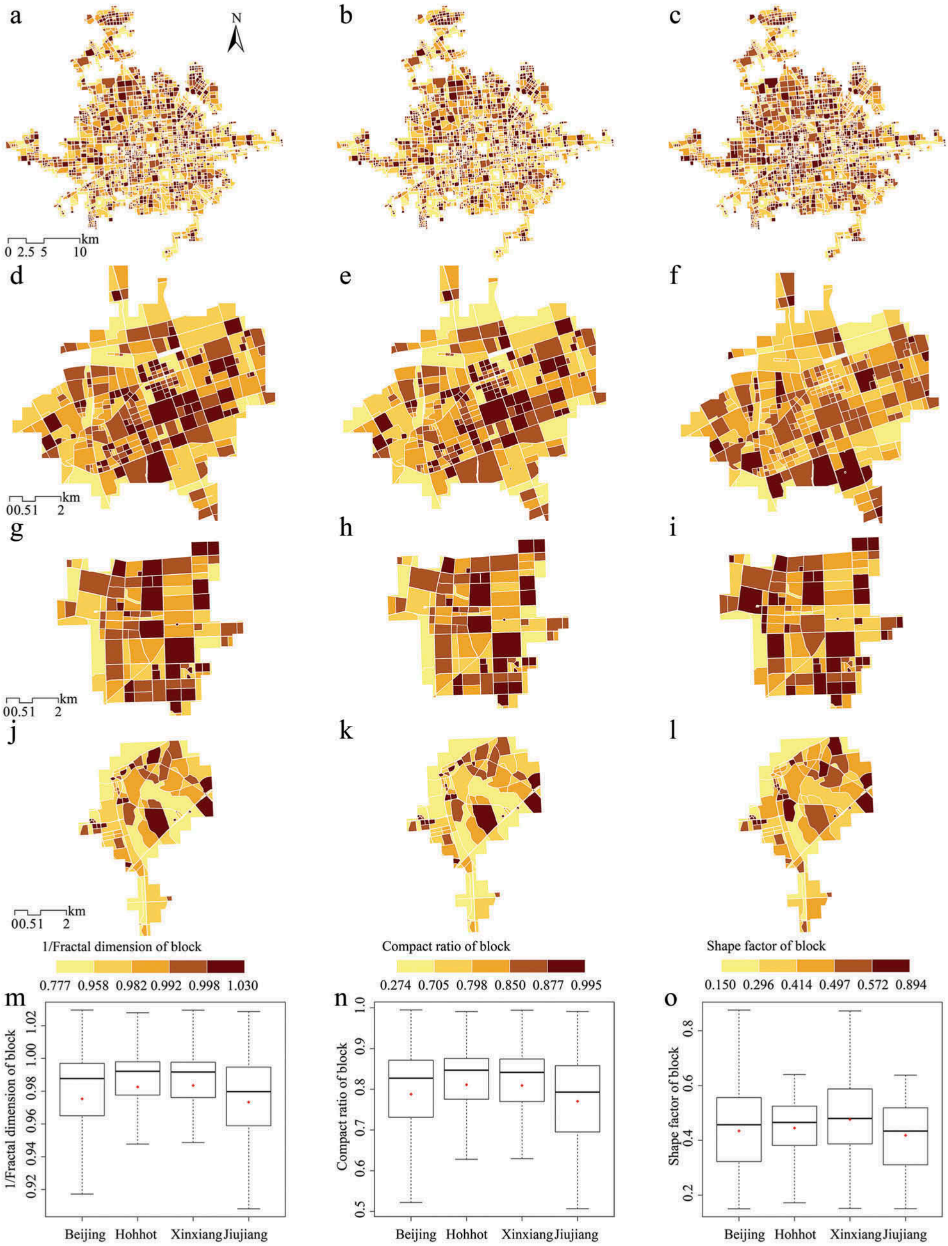
a
b
c
N
0 2.5 5 10 km
d
e
f
00.51 2 km
g
h
i
00.51 2 km
j
k
l
00.51 2 km
1/Fractal dimension of block
0.777 0.958 0.982 0.992 0.998 1.030
Compact ratio of block
0.274 0.705 0.798 0.850 0.877 0.995
Shape factor of block
0.150 0.296 0.414 0.497 0.572 0.894
m
1/Fractal dimension of block
0.92 0.94 0.96 0.98 1.00 1.02
n
Compact ratio of block
0.5 0.6 0.7 0.8 0.9 1.0
o
Shape factor of block
0.2 0.4 0.6 0.8
Beijing Hohhot Xinxiang Jiujiang

Figure 9. Maps of block-level spatial morphology indicators in four example cities (a–l) and their statistical summaries (m–o).

China, while cold-spot clusters locate in the western part especially south-western China. Hotspot cities of shape factor are distributed in northern China, and cold-spot ones are north-eastern and south-western China. Different from the spatial clustering patterns of city-level morphology indicators, clustering patterns of block-level morphology indicators are caused by various reasons such as histories, local culture, recent fast urbanisation, urban renewal, etc.

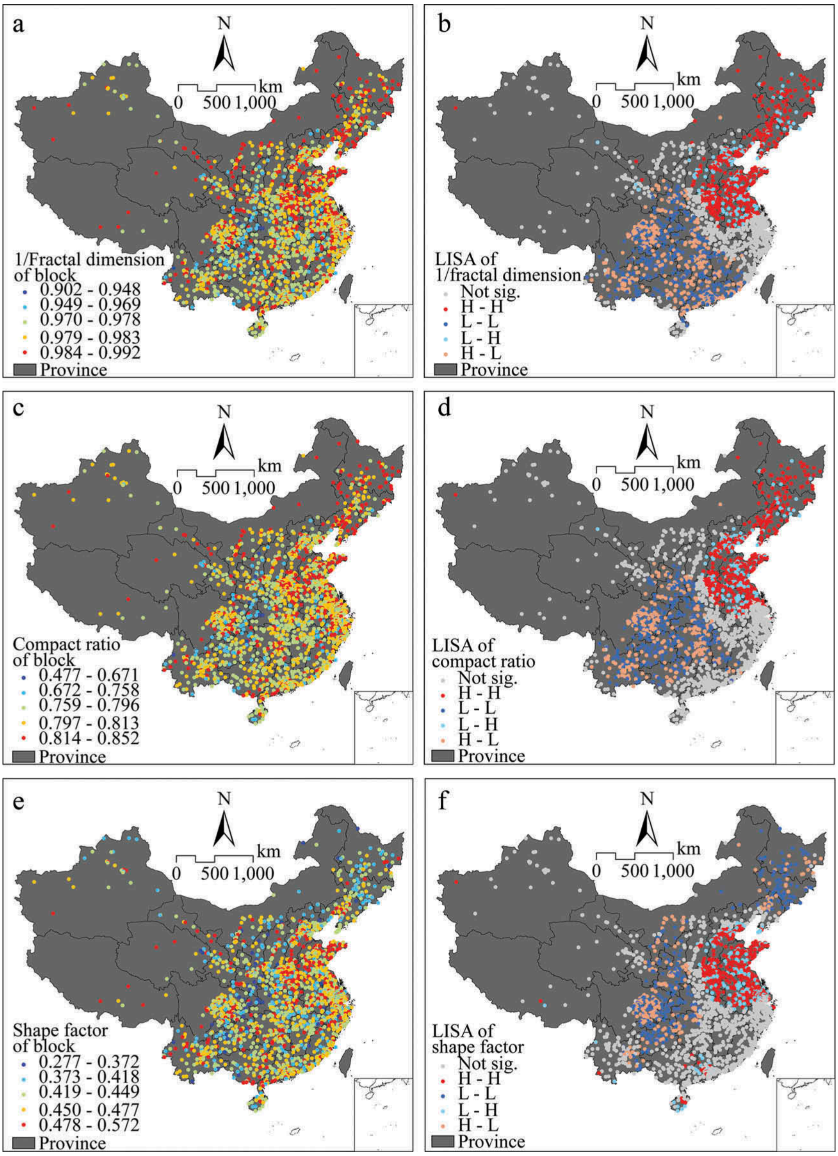
a
N
km
0 500 1,000
1/Fractal dimension of block
0.902 - 0.948
0.949 - 0.969
0.970 - 0.978
0.979 - 0.983
0.984 - 0.992
Province
b
N
km
0 500 1,000
LISA of 1/fractal dimension
Not sig.
H - H
L - L
L - H
H - L
Province
c
N
km
0 500 1,000
Compact ratio of block
0.477 - 0.671
0.672 - 0.758
0.759 - 0.796
0.797 - 0.813
0.814 - 0.852
Province
d
N
km
0 500 1,000
LISA of compact ratio
Not sig.
H - H
L - L
L - H
H - L
Province
e
N
km
0 500 1,000
Shape factor of block
0.277 - 0.372
0.373 - 0.418
0.419 - 0.449
0.450 - 0.477
0.478 - 0.572
Province
f
N
km
0 500 1,000
LISA of shape factor
Not sig.
H - H
L - L
L - H
H - L
Province

Figure 10. Block-level spatial morphology indicators in 2005 redefined cities in China, 1/fractal dimension (a), compact ratio (b) and shape factor (e) of blocks, and their LISA maps (b, d and f).

4.3. *Hierarchies of redefined cities*

4.3.1. *Similarities and differences among hierarchies*

With the above analysis and results, urban forms of redefined cities are sprawled by three city-level and three block-level spatial morphology indicators, which are summarised in Table 2. The condition number-based multicollinearity test shows that there is no harmful multicollinearity between pairs of indicators. Based on these spatial morphology indicators, redefined cities are classified into four hierarchies to investigate the differences of forms of urban central extent in China. The four hierarchies are

Table 2. Spatial morphology indicators of redefined cities and urban blocks.

Variable		Code	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Number
City-level spatial morphology	Fractal dimension	Cfd	0.87	1.25	1.35	1.37	1.47	2.32	2005
	Compact ratio (reciprocal)	1/Ccr	1.07	1.33	1.43	1.52	1.58	5.55	2005
	Shape factor (reciprocal)	1/Csf	1.23	1.82	2.07	2.25	2.50	7.79	2005
Block-level spatial morphology	Fractal dimension (reciprocal)	/	0.77	0.97	0.99	0.98	1.00	1.03	154 871
	Compact ratio	/	0.25	0.75	0.84	0.80	0.87	1.00	154 871
	Shape factor	/	0.15	0.36	0.47	0.45	0.55	0.95	154 871
Summarised block-level spatial morphology in redefined city	Fractal dimension (reciprocal)	1/Bfd	0.90	0.98	0.98	0.98	0.98	0.99	2005
	Compact ratio	Bcr	0.48	0.78	0.80	0.79	0.81	0.85	2005
	Shape factor	Bsf	0.28	0.43	0.45	0.44	0.47	0.57	2005

selected in terms of the four combinations of city-level and block-level morphology indicators, including (1) high city-level and high block-level, (2) high city-level and low block-level, (3) low city-level and high block-level and (4) low city-level and low block-level morphology indicators. Results show that the characteristics of the cities within four hierarchies are generally consistent with the four combinations. Figure 11 shows the spatial morphology-based hierarchies and their distributions. Among four hierarchies, 26.8% of cities belong to hierarchy 1. Hierarchy 1 represents the active and function diversified cities, including capital, provincial capitals and primary cities in China. Hierarchy 2 and 3 are two kinds of primary cities, accounting for 33.9% and 23.2% of all 2005 redefined cities. Among them, hierarchy 2 is the cities with relatively

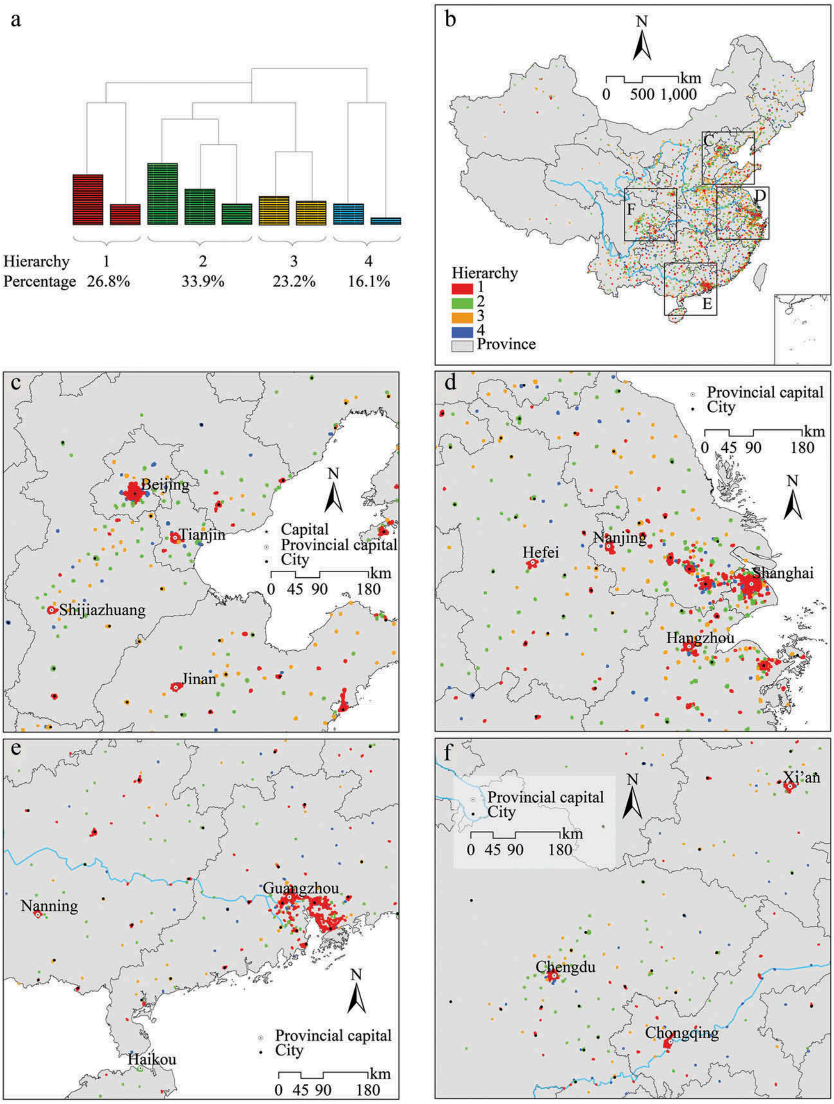
a
Hierarchy 1 2 3 4
Percentage 26.8% 33.9% 23.2% 16.1%
b
N
0 500 1,000 km
C
D
F
E
Hierarchy
🟥 1
🟩 2
🟧 3
🟦 4
▢ Province
c
Beijing
Tianjin
Shijiazhuang
Jinan
N
Capital
Provincial capital
City
0 45 90 180 km
d
Provincial capital
City
0 45 90 180 km
N
Hefei
Nanjing
Shanghai
Hangzhou
e
Nanning
Guangzhou
Haikou
N
Provincial capital
City
0 45 90 180 km
f
Provincial capital
City
0 45 90 180 km
N
Xi'an
Chengdu
Chongqing

Figure 11. Spatial morphology determined hierarchies of redefined cities. Four hierarchies and their percentages (a), their spatial distributions (b) and four enlarged regions (c–f).

high city-level values of spatial morphology indicators but relatively low block-level values, and hierarchy 3 has the contrary conditions. They both have developing potential from the perspective of city planning and construction. Hierarchy 4 accounts for 16.1% and is relatively undeveloped cities or cities at an early development stage. Relatively undeveloped cities are located far from other cities, and the cities at an early development stage are located near previous three kinds of cities, especially the cities belong to hierarchy 1 as shown in Figure 11(c–f).

4.3.2. *Integrated spatial morphology*

With the aim to understand the urban forms of redefined cities, an integrated spatial morphology (ISM) indicator is computed by entropy weighting method. The entropy weights of Cfd, 1/Ccr, 1/Csf, 1/Bfd, Bcr and Bsf are 0.129, 0.440, 0.360, 0.009, 0.009 and 0.053. Thus, the city-level and block-level spatial morphology indicators contribute 92.9% and 7.1% to ISM, respectively. The summarised ISM indicator is mapped in Figure 12, which indicates the differences of ISM among four hierarchies. In general, ISM in hierarchy 1 is the highest and that in hierarchy 3 is the lowest. The cities with higher ISM tend to be mega cities in China. This result is consistent with the descriptions for four hierarchies. Additionally, ISMs of cities in the southern part are generally higher than those in northern China.

Urban forms of the redefined cities that quantified by the ISM also reflect the distributions of functional areas in cities. The high city-level ISM shows that the

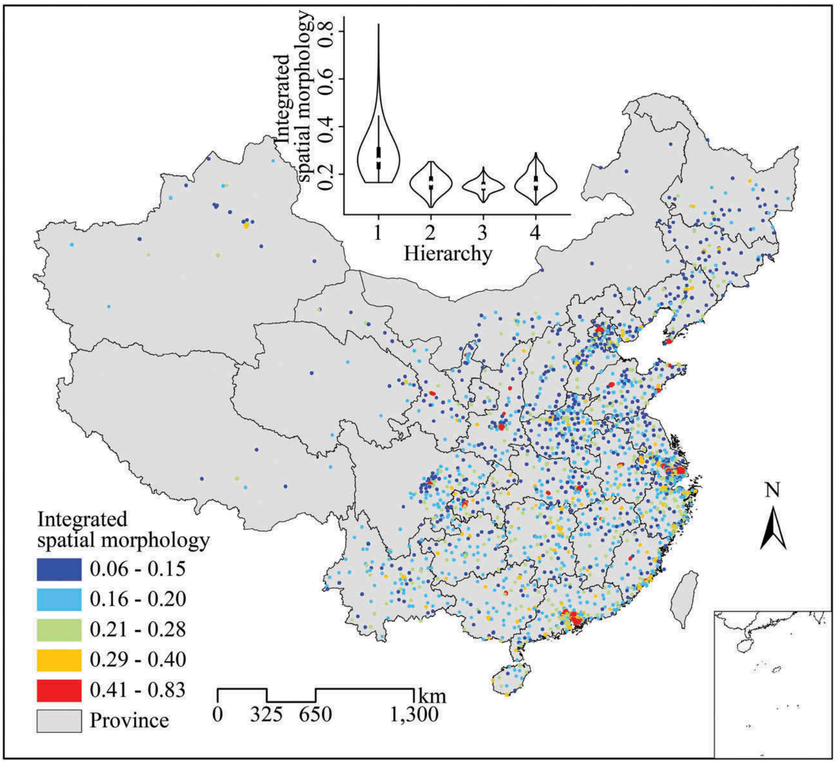

Figure 12. Integrated spatial morphology indicator and its summary in each hierarchy.

functional areas are relatively more comprehensive and industrial structures are more diversified, and the high block-level ISM reveals that the regions of certain industries and functions are more clustered. Figure 13(a) shows the relationship between city-level and block-level ISMs. The large cities are primarily distributed in hierarchy 1, and their city-level ISMs are relatively higher than other cities. For these cities, block-level ISM is negatively associated with city-level ISM, which means that the high diversity of functions and industrial structures might lead to the loss of developing locally clustered regions of certain functions. In addition, cities in hierarchy 2 have moderate block-level ISM, and the block-level and city-level ISMs are positively correlated. In these cities, the overall and local developments are promoted by each other.

Further, the ISM is compared with the city size, which is a more general and straight forward indicator that reflects the scale of a city and the commuting structure inside city (Louail *et al*. 2015). Figure 13(b) shows the significantly positive relationships between POI densities and areas of the redefined cities in all four hierarchies. Figure 13(c-f) show the relationships between city size and ISMs. City-level, block-level and overall ISMs are all increased with the growing of city size, except for the block-level ISM of cities in hierarchy 3. For most of cities, the enlarged city size is associated with the urban development or rapid urbanisation, where the functional areas and industrial structures

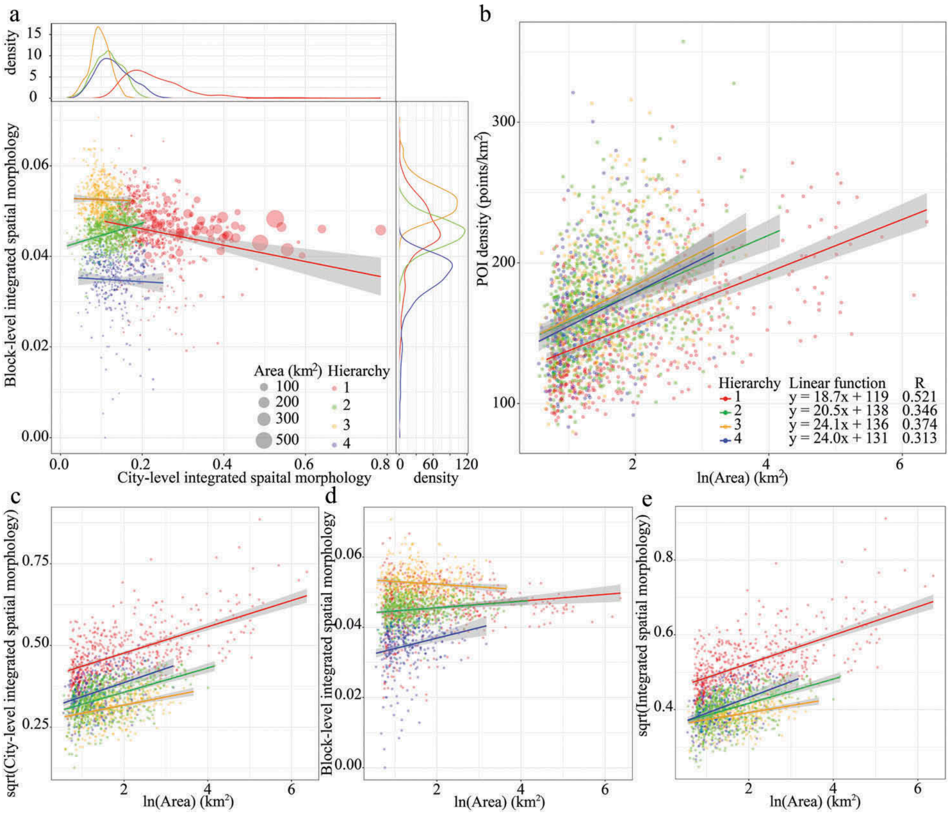

Figure 13. Relationships between areas of redefined cities and characteristics of functional regions quantified by POI density and integrated spatial morphology.

become more diverse. However, the cities in hierarchy 3 are characterised with high block-level ISM and low city-level ISM, so they have advantages over one or several clustered functional areas, but are limited in various industrial structures. Thus, for these cities, the increase of city size is not benefit for the development of locally clustered functional areas.

4.4. *Impacts of urbanisation on urban forms*

Spatial dimensional variables of urbanisation include POI density, area, population density, road junction density within each redefined city and distance to the nearest cities, which are listed and summarised in Table 3. The impact of each urbanisation variable on the integrated indicator is determined by GAM, and the deviance explained by each variable is listed in Table 4. Urbanisation can explain 41.0% of the differences of spatial morphology among redefined cities. The area of one city reflects its spatial scale, which is significantly related to the spatial morphology with the deviance explained of 30.37%. POI density and the distance to the nearest city contribute 9.62% to spatial morphology together. The deviances explained by urbanisation in four hierarchies are different, ranging from 15.6% to 44.6%, due to the various stages of urban development. For hierarchy 1, 3 and 4, area is still the most important contributor of spatial morphology to differentiate cities, but the key factor of the spatial morphology in cities of hierarchy 2 is the distance with the nearest city. Thus, the development of cities of hierarchy 2 significantly relies on the surrounding fast developing or developed cities. POIs are a primary contributor to the urban forms besides the variable of area for the cities of hierarchy 1. POI presents the distributions of the primary functional areas and the regions with active human activities, so the cities of hierarchy 1 are at fast growing stage. Results also show that cities of hierarchy 3 and 4 are at initially significant developing stage. In these cities, expanding land use is still the primary approach for the development. For cities of hierarchy 3, urbanisation variables are limited in explaining urban forms. Considering the descriptions of hierarchy 3, the block-level spatial morphology performs well but city-level one is weak. This means the inside structure

Table 3. Statistical summary of urbanisation variables in redefined cities.

Variable	Code	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Number
POI density (points/km^2)	poid	78.66	137.11	160.99	165.20	188.64	357.35	2005
Area of redefined city (km^2)	area	2.03	2.63	3.85	8.32	6.89	536.83	2005
Population density (persons/km^2)	popd	15.6	701.1	1758.6	2794.2	4363.3	19,124.4	2005
Road junction density (junctions/km^2)	jncd	4.94	26.94	37.04	39.64	49.83	130.32	2005
Distance to nearest city (km)	dnc	0.02	0.08	0.21	0.26	0.33	4.59	2005

Table 4. Integrated spatial morphology indicator explained by urbanisation variables.

			Deviance explained by each variable				
Hierarchy	R^2	Total deviance explained	poid	area	popd	jncd	dnc
All	0.403	41.00%	6.58%	30.37%	0.51%	0.51%	3.04%
Hierarchy 1	0.429	44.60%	4.56%	38.17%	0.21%	0.00%	1.66%
Hierarchy 2	0.240	25.70%	2.57%	2.57%	0.73%	2.57%	17.26%
Hierarchy 3	0.133	15.60%	0.80%	12.71%	0.13%	2.01%	0.00%
Hierarchy 4	0.262	31.30%	4.41%	15.05%	5.42%	3.41%	3.01%

and distribution is relatively good but urban development is slow. For cities of hierarchy 4, all urbanisation variables besides area play important roles in the total deviance, which demonstrates that both human activities and infrastructure construction have significant influence on the early development stage of urbanisation process.

5. Discussion

5.1. *Are urban forms all identical?*

Compared with traditional definition of city systems whose spatial scales are outlined by administrative boundaries, the concept of the spatially redefined city systems draws city boundaries using POIs in terms of the naturally developed spatial structures of cities, e.g. urban function agglomeration pattern. Urban forms are quantified with two-level spatial morphology indicators from the perspectives of both cities and blocks. Results of spatial autocorrelations of single indicators show significant local clustering of cities in China, which means that the forms of cities within the same spatial clusters are similar, but the forms of cities in different clusters are varied. Further, the integration of both levels of spatial morphologies helps classify the cities into four significantly differentiated hierarchies. Within each hierarchy, urban forms are similar or identical, but they are distinct at city level, block level or both levels in different hierarchies.

The similarities of cities in the same hierarchy, or the differences of cities in different hierarchies, are correlated with human activities and corresponding built and natural environment, which usually reflect the level of urbanisation process. Thus, the relationships between urban forms together with their similarities or differences and the level of urbanisation are assessed using nonparametric models. The level of urbanisation is considered with proxy variables from the aspects of spatial scale of central urban regions, human density, active human activities, infrastructure construction conditions and inter-city spatial relations. The two-level spatial morphology analysis for all redefined cities and each hierarchy of cities demonstrate that urbanisation could explain 41% of the variations of urban forms. The variations of urban forms that cannot be explained by urbanisation might relate to the habits of city planning, policies for city development, living and cognitive habits of residents, the histories of city forming and development, global climate change and its related events such as sea level rise and extreme weather (Doxiadis 1968, Stoyanov and Frantz 2006, Hamin and Gurran 2009).

Among urbanisation variables of the urban forms, the spatial scale of cities is a primary factor at the developed stage and early development stage, but it is not the main driver at fast developing stage, especially for the cities that the development closely relies on surrounding developed and fast-growing cities. In addition, the performance of human activities is a key factor for the urban form and urbanisation relationships of developed and fast-growing cities. For the cities at an early stage of development, infrastructure construction conditions are of significance for the development of urban forms together with human activities.

5.2. *Academic contributions*

This paper proposes a POI-based method to redefine cities to outline the urban central regions with dense human and socio-economic activities, and identifies the similarities and differences among cities using spatial morphological methods with the consideration of urban structure and distributions of functional areas inside cities. The contributions of this study are listed as follows.

First, cities are redefined with widespread popular data using simple and direct methods. Compared with traditional definition of city systems, the redefined cities reveal the real spatially closely connected urban central regions. This redefinition of cities is particularly essential in China due to the apparent inconsistency between administrative cities and the real extent of cities. China is a fast-developing nation, and it is undergoing the extensive and profound urbanisation. Urban forms are significantly varied during the past decades, and they are still greatly changing now. Data-driven methods for redefining cities are practical and essential for understanding the rapid urbanisation in China.

Second, spatial morphology of urban forms is quantified using two-level urban form indicators (city level and block level). The two-level methodology considers both the spatial morphology at city scale and that of blocks within cities. Compared with previous studies that consider urban morphology from one perspective of morphologies, the integration of city-level and block-level morphologies is critical in investigating conditions of urban development and distributions of functional regions. The integration is also benefit for more comprehensive understanding of both overall and local development of industrial structure.

Third, this study tries to answer the question that whether all cities are with similar urban form or not. To answer this question, redefined cities are classified based on their city-level and block-level spatial morphologies, an integrated indicator of spatial morphology (ISM) is computed, and the difference of ISMs among cities is explained by urbanisation. Results show that urban forms tend to be similar for cities within the same hierarchy, but they are significantly distinct for cities in different hierarchies, i.e. different development stages, industrial structures, and distributions of functional areas.

Finally, these findings have potentially practical applications on nation-wide understanding of characteristics of urban forms, the development of city systems, and the distributions of different functional regions inside cities. Especially, city development and level of urbanisation are unbalanced in China. The issues of urban forms, the distributions inside cities and their factors are complex and affected mutually. The two-level methodology enables the integration of different spatial scale considerations and provides a solution for addressing these complex and interactively affected problems. The spatial morphology analysis of the redefined cities also reveals the characteristics of urbanisation at the spatial dimension of different Chinese cities. For the cities at different development stages, the conditions, opportunities and challenges of the urbanisation are varied and diverse, but they tend to be similar for the cities at the identical urbanisation stages.

5.3. *Limitations and future work*

There are still some limitations in this research. In this research, there is an assumption that a higher city-level spatial morphology indicator reveals the more fractal, less compact and more diverse distributed form of central urban region due to more determined district functions, and that a higher block-level indicator indicates a more clustered and compact spatial structure and distribution of blocks with identical functions. This assumption is based on the fact that most of cities have been fast developing in China. However, in different cities, especially the central regions, both dispersed and clustered urban forms have their advantages and disadvantages. Therefore, future studies might exam urban forms with the assumption that the whole or parts of a certain nation are not at the fast-developing stage.

6. Conclusion

This research proposes the concept of redefined city systems, featuring agglomerated urban functions, to answer the question that whether urban forms are all identical in China. A POI density-based data-driven method is utilised to redefine cities to outline the natural central urban regions. The redefined cities are the places where population is dense, human activities are abundant and active, and built environment and infrastructure conditions are relatively complete. For the identified 2005 redefined cities in China, urban forms are quantitatively evaluated using two-level spatial morphology indicators at both city and block levels. As such, the urban forms are not only evaluated by the urban developing conditions from the perspective of the geometry of city boundaries, but also related to morphology of functional regions inside cities. Different spatial morphologies could be explained by the conditions of topography, urban development, local history and culture, and city design strategies. To understand the similarities and differences of urban forms, the redefined cities are classified into four hierarchies, the spatial morphology indicators are summarised to an integrated morphology indicator, and the contribution of urbanisation on the urban forms is assessed. Results show that the urban forms are similar within a hierarchy, but they are significantly different among different hierarchies, due to the various development stages, structures and distributions of functional areas within cities, and the levels of urbanisation. In the study, the optimisation levels of functional areas within cities are assessed with the spatial morphology of redefined cities. The integrated morphology reveals the characteristics of functional areas distributions of a city, where a higher city-level morphology indicates more comprehensive functional areas with diversified industrial structure, and a higher block-level morphology reveals more concentrated region for a certain industry or function. Results show that the North-eastern and Northern China have a higher city-level morphology than south-western regions, southern areas have a higher block-level morphology than northern parts, and the capital, provincial capitals and cities with high level of urbanisation usually have relatively high integrated spatial morphology. For the redefined cities, spatial dimensional indicators of urbanisation could explain 41% of the spatial morphology of cities, where with the increase of city size, distributions of functional areas within urban central regions tend to be more optimised. Among four hierarchies of cities, the city area is a key contributor to the spatial morphology for actively developed and cities at an early development stage. The development of cities with limited intra-urban spatial structure significantly relies on surrounding fast developing and developed cities. The development of cities with weak city-level spatial morphology has weak relationship with urbanisation process.

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