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Rediscovering Chinese cities through the lens of land-use patterns

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ABSTRACT

Urbanization is a complex spatial phenomenon involving significant compositions and interactions in land use. Yet, only few studies have quantitatively examined multidimensional urban land-use patterns with insights into land use policy, particularly in the context of China's rapid urbanization process. This paper aims to investigate the urban land-use patterns in China by employing multiple measurements with multi-sourced data, including Spatial Entropy and Dissimilarity Index, and a combination of cellular-automata (CA) modeling and Structural Equation Modeling (SEM). The results show that land-use patterns in China are characterized from more mixed (Beijing, Shanghai) to less segregated (Xiangyang, Tangshan, and Guiyang), and the most segregated (Chongqing), which can be categorized into three typical types: economically led, government led, and geographically constrained. The findings also indicate that residential sector has correlation with GDP and urban built-up area; public sector is driven by GDP, urban built-up area, and paved road area; and commercial sector is related to GDP and paved road area. Furthermore, land-use patterns are not only determined by economic forces, but also subject to China's land policies that formulated based on its unique social and political characteristics. It reveals the complex spatial characterization of urbanization in China, where government still plays an important role in facilitating the land use allocation. The research sheds light on understanding land use policy for land-use patterns reconfiguration in the context of New-Type Urbanization towards better planning and governance.

1. Introduction

In the past two decades, measuring the composition and configuration of land use is the most frequently debated subject in urban planning and land use policy, specifically, describing the features of land use pattern (Alberti and Waddell, 2000; Ewing and Cervero, 2010; Song et al., 2013; Gehrke and Clifton, 2017). Rapid urbanization has profoundly changed land use pattern in China, which vice versa exerts influence on socio-economic development, population growth, city growth, etc. (Liu et al., 2014). Urbanization has been a prominent phenomenon in China's economic development since the country adopted the "reform and opening" policy in 1978. The urban population of China has researched to 813.47 million (58.52%) in 2017 (National Bureau of Statistics of China, 2018). With the power devolving gradually from the central government to the municipalities, land-use patterns and urbanization processes of China's cities have undergone fundamental transformation (Gaubatz, 1999; Lang et al., 2016a,b). Such transition of Chinese cities to more post-industrial forms is much like that seen in the USA, Canada, Australia, and Europe (Schneider et al., 2005), of which our understanding is still inadequate (Batty, 2008).

Unfolding complex urbanization makes it clear that the quantitative understanding, optimization, and adjustment of land use pattern of cities is a major issue for sustainable land use (Verburg et al., 2004). Urban spatial restructuring of land-use patterns have been analyzed for the past few decades, seen in such studies as Li and Yeh's (2004) study of the spatial structuring of land-use patterns in the Pearl River Delta of South China; Liu et al.'s (2010) exploration of the impact of land-use changes on sustainability in Jiangsu Province; Long and Zhang's (2015) discussion of land-use pattern scenarios; Kuang et al.'s (2016) examination of the driving forces behind rapid and massive urbanization and industrialization in China. Nevertheless, the lack of solid understanding of land-use patterns issues makes it difficult to address the ongoing challenges of the volatility and complexity of land use policy in China (Long, 2014). Therefore, the situation poses a number of challenging questions to the country: 1) How to correctly depict the general situation of urbanization and consequential spatial phenomenon in China? 2) How to adapt a quantitative approach to address the distinctive features of land-use patterns in Chinese cities? and 3) what are the underlying drivers of forming land-use patterns?

Land use pattern forms the basic spatial layout of a city as a result of the interactions of government intervention and market forces. The

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Fig. 1. Locations of study cities.

driving factors that influence the magnitude and extent of land-use patterns are often related to the functioning of local and national policy and demographic conditions (Verburg et al., 2004). From urban planning perspective, the land-use patterns represent the structural and functional differences of socio-economic development. Researchers have recently formulated a foundation to understand the causes and consequences of land-use formation and the simplified mechanisms that facilitates the optimization of land-use patterns and allocation of land resources (Long et al., 2012a,b; Long and Zhang, 2015). Previous studies limited their focus to changes in land use (Longley and Mesev, 2000), yet few studies have quantified land use mix and sprawl degree in urban China (Tian et al., 2017), understood uneven urban expansion with natural cities (Long et al., 2018), and examined the relationship between land-use patterns and a suite of social and economic underlying factors (Comer and Greene, 2015), as well as related planning and policy affects urbanization and shapes land-use patterns (Wei and Zhang, 2012).

Measuring urban land-use patterns is a key part of spatial metrics (Herold et al., 2005) that are commonly used to quantify the shapes and patterns of a city (Hargis et al., 1998). Recent studies have emphasized the use of spatial metrics to assess land-use patterns and interpret their planning policy (Seto and Fragkias, 2005; Tsai, 2005; Song et al., 2013; Lang et al., 2016a,b; Gehrke and Clifton, 2017). As an effective spatial metrics, entropy has provided us a powerful tool for researching the spatial organization of cities (Batty and Longley, 1994), characterizing urban form (Schneider and Woodcock, 2008; Taubenböck et al., 2009), representing the heterogeneous characteristics of urban area (Alberti and Waddell, 2000), and quantifying the degree of mix and sprawl (Ewing and Cervero, 2010). In addition, researchers have employed dissimilarity index to detailed characterize the spatial allocation of land use diversity (Ewing and Cervero, 2010) and entropy to evaluate the degree of urban sprawl (Li et al., 2013).

Spatial Entropy (SE) measures the degree of urban sprawl (Batty, 1976) and determines urbanization occurs in a compact or expansive (aggregate or dispersed) mode (Jiao, 2015), while Dissimilarity Index (DI) helps to define the efficiency of mixing land-use sectors and measure the degree of evenness in the distribution of land use (Decraene et al., 2013b). The combination of these two measures provides a straightforward method to investigate the urban land-use patterns that results from dispersion and segregation mechanisms. The importance of this cellular automata (CA) model emphasizes the reconstruction of cities from the bottom-up with SE and DI values. Thus, in this research, we are adapting Decraene et al.'s (2013b) CA model to study a selection of Chinese cities.

This paper attempts to integrate the use of CA, Python, ArcGIS, and R Programming and addresses the following research objectives: 1) to quantify urban land-use patterns through SE and DI; 2) to identify the interconnected major urban factors for the formation of land-use patterns; and 3) to investigate the relationship between the emerging land-use patterns and its associated land use policy. China's rapid urbanization is often accompanied with a lack of competent control and regulation, leading to informal development and incompatible land use function. For stimulating sustainable development at the new agenda of China New-Type Urbanization (Lang et al., 2016a,b), a better understanding of land-use patterns and its driving forces are the key to empowering local governance and implementing effective and well-timed land use policy. Therefore, this study contributes to enlighten the applicability of analysis generalization to land use policy corroborating within the planning literature.

To begin with, the preceding part of this paper introduced of urbanization and spatial metrics. In the following section, the study area is presented along with methods for processing of the data. The issues of measurements and their applications in the analysis and modeling of urban land use are discussed. This section also describes the measurements in detail, including their mathematical formulae. The findings are presented in Section 3. Section 4 begins with an interpretation of land-use patterns, followed by an analysis of the corresponding influence factors. In Section 5, conclusions are drawn with reference to the mechanisms of urbanization and recommendations for selecting appropriate planning policies are provided for future use.

2. Data and analysis

2.1. Cities

This study examined a total of 61 Chinese cities (Fig. 1), ranging across 3 levels: namely megacities (first-tier cities, n = 7), provincial capital cities (second-tier cities, n = 21), and prefecture-level cities (third-tier cities, n = 33). The selected cities from the 3 levels, which can representationally illustrate the general features of urban land-use variation in diversified scales, help to propose a mechanism for the formation of land-use patterns in China. The quality and availability of data also influenced the selection of sample cities in that a city must have enough urban parcels to characterize each individual city's land-use pattern. The study cities include Hong Kong and the top 60 cities in Mainland China, according to an order list in which cities have a total count of valid urban land parcels above 200. These selected cities were recognized and verified through a criterion built on automated identification and characterization of parcels (AICP) method detailed in a previous study (Liu and Long, 2016).

Numerous Chinese cities have experienced fast and unbalanced development. In order to promote or restrict urban growth, the central government has divided cities into different tiers for decision-making and management. The structural hierarchy of the administrative divisions of China includes three classifications for cities and excludes the county level cities: 1) Directly controlled municipalities of China (megacities), identified as first-tier cities 2) The provincial capital cities (large-medium cities), representing second-tier cities; and 3) The prefectural-level cities (medium cites), the third-tier cities. First-tier cities represent the most developed areas of the country with the most affluent and sophisticated growth that typifies the driving forces of China's urbanization. These first-tier cities have the most potential to attract growth. Second-tier cities have come to represent some of the fastest growing areas with growth trends that mimic those of first-tier cities. Third-tier cities generally lag behind other two tiers of cities in terms of economic growth and urban development, although many of them are considered to be economically and historically important.

2.2. Data processing

The analytical scope of this paper includes the utilization of urban land-use data based on AICP with Ordnance Survey Map of road networks and Points of Interest (POIs), which is built through the method developed in a previous study (Liu and Long, 2016). The AICP method provides vector GIS data for all study cities from which to extract urban land-use patterns. Urban land use in every city was generated as a pile of land parcels from the Ordnance-based vector map (Ordnance 2012), which essentially reflects the real-world urban area. The data were processed in ArcGIS for classification and color definition pixel by pixel, which were converted into color-coded raster images as base maps with a spatial resolution of 8 m per pixel. Each parcel of urban land was defined through a continuous urban area bounded by the actual roads in Ordnance Survey Map. Land use for individual parcels was determined by the dominant POI types within the parcels. POIs synthesized from online business catalogue (2013) were aggregated into eight general categories (i.e. commercial sites, office building/space, transport facilities, government, education, residence communities, green space, and others). High-quality land-use status quo maps were acquired for the cities in 2010 for data validation as gathered from local planning authorities. However, due to data availability, this manual comparison for land use parcel identification was only performed in a 1/10 scale of the total cities. Even though each classified image might have some potential errors in accuracy, road networks in the ordnance survey map and land-use zoning map were taken to verify and ensure overall data quality and relevance. Urban land area, urban population, GDP and paved road area data were obtained from the China Urban Statistical Yearbook (National Bureau of Statistics of China, 2018).

2.3. Analysis

Characterizing the overall dynamics of land-use patterns, the base map accordingly reflects the observed land-use configuration. In this study, three main types of land use are employed as parameters to reconstruct urban land-use classifications from the data based on the base map: $T_{Residential}$ (residential communities) indicated in blue, $T_{Commercial}$ (businesses, retail buildings, firms, etc.) indicated in green, T_{Public} (governmental and educational areas, etc.) indicated in red. While T_{others} (manufacturing, utilities, infrastructure, warehouses, etc.) and undevelopable land (water, reserved lands, forests, etc.) are colored yellow, they are excluded from the calculations. A cell of each land-use type $T_{[R,\ C,\ P]}$ (where R = residential, C = commercial, P = Public) is then calculated from the data on the base map. All cells are the total number of land-use parcels that are extracted from the base map.

In order to examine the differences in entropy among different cities, the CA model was applied to compute the entropy for the cells, where a land plot unit is a pixel of 64 m^2 of a given land-use sector in each city map. In Decraene et al. (2013a), a series of experiments were conducted to evaluate and identify a sufficient and suitable spatial resolution to measure spatial entropy and to demonstrate land-use plots. When considering a frame length value of pixels, a comparable degree of spatial entropy and dissimilarity index were examined against the varying frame length. There is no noticeable distinction when a land parcel is larger than 128 by 128 m. Similarly, when it is smaller than 32 by 32 m, no differences can be noted. This suggests that a parcel at 8 by 8 m should be considered. It is also observed that the frame areas with a value of 32 pixels or lower are too small to encompass different land-use types. When the frame areas are greater or equal to 128 pixels, the results change significantly. Therefore, a frame of 64 pixels (8 by 8 pixels per frame, pixel length = 8 m) is best for the calculation and characterization of land-use patterns. In this research, a suitable length of frame is $l = 8$ pixels (64 m), whereas 64m^2 per pixel is set for computing each cell in the CA models.

The spatial entropy, $SE_T\ (M)$ given in Eq. (1), provides information about the degree of spatial concentration or dispersion for different land-use types among N cells across urban areas. City maps are divided into k frames as a regular grid, in which of each frame is constituted of $N_k = l\ x\ l$ land plots (pixels). City maps were color-coded according to land-use types, where a cell of land is categorized by its color value. Spatial entropy, utilized to evaluate the degree of spreading for land-use type T in a city, is defined as:

$$SE_T(M) = -\sum_k \left[p_k \ln(p_k) + (1-p_k)\ln(1-p_k)\right] \tag{1}$$

$$p_k = t/N_k \tag{2}$$

where P_k is the intensity of pixels corresponding to land-use type T (Eq. (2)), and t is the number of pixels of type T found in the i^{th} ($i = 1, 2\ldots k$) frame. SE varies between 0 and 1. When $SE_T\ (M) = 1$, type T pixels are dispersed throughout all of the frames. Whereas, when $SE_T\ (M) = 0$, this indicates that sectors of type T are concentrated within a small cluster. Larger entropy values signify higher levels of urban sprawl. An increase in entropy value indicates that there has been an increase in dispersed urban land use, and the city has experienced expansion.

Entropy Index and Dissimilarity Index can be computed as an approach to measure heterogeneity or fragmentation (Song et al., 2013). Mixed land use is a key characteristic of neo-traditional planning, therefore, DI is used to understand the balance of different kinds of land use. In Eq. (3), the DI is employed to characterize the degree of segregation and represent variation in different land-use sectors. The DI between land-use sectors, T_1 and T_2, is given as:

$$DI_{(T_1 T_2)} = \frac{1}{2}\sum_{i=1}^{k}\left|\frac{t_{1_i}}{N_{T_1}} - \frac{t_{2_i}}{N_{T_2}}\right| \tag{3}$$

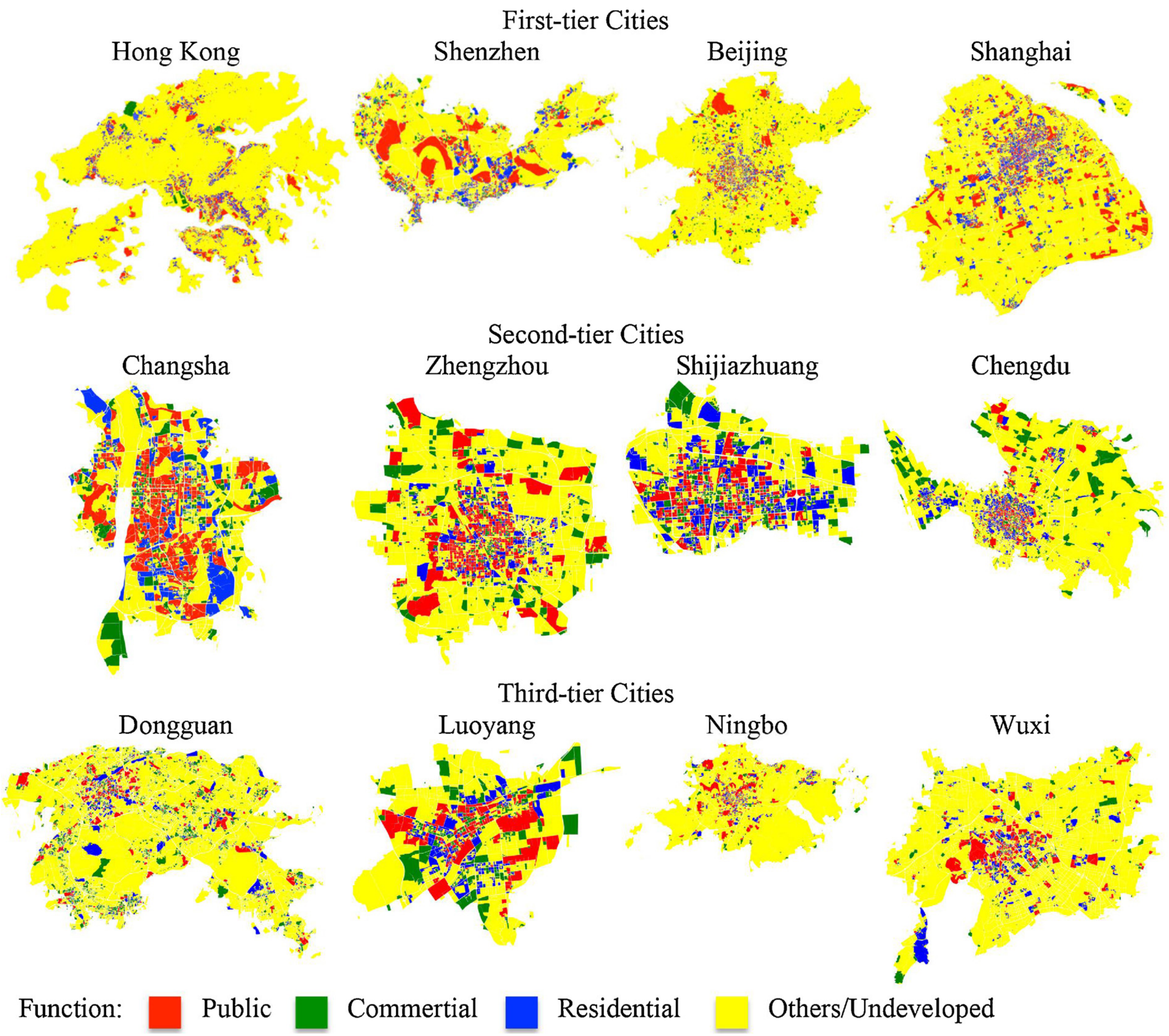


Fig. 2. Typical classifications of land-use patterns. (For interpretation of the references to colour in the text, the reader is referred to the web version of this article).

where k is the total frames in each city map, and N_T is the total number of pixels of land-use sector T found in each frame, while t_1 and t_2 represent the number of pixels of land use sector T_1 and T_2 in each corresponding frame. The value DI $_{(T1/T2)} = 1$, implies that land-use sectors T_1 and T_2 are fully segregated, with a single land-use type dominating in each frame, whereas DI $_{(T1/T2)} = 0$ indicates an equal distribution of both land-use sectors throughout all of the frames. Lastly, urban populations, urban areas, urban built-up areas, GDP, and paved road area are five significant factors in the distinction of a city. We explored the correlations among SE, DI, urban land area, urban population, GDP, and paved road area to achieve an in-depth understanding of their impacts on urban land use.

3. Findings

3.1. Generalization of land-use patterns through SE and DI

To reflect the balance and patterns of land use, two quantitative approaches, SE and DI, were used to classify and analyze the urban features. Fig. 2 provides a general representation of the typical land-use classifications for a few selected cities in this study. The classifications clearly depict the features of each city that were extracted from the base map, where the residential, commercial and public land-use sectors are the aggregations of relevant sub-categories in which land-use categories that are not directly related to the above mentioned sectors were discarded. The given pixels of blue, green, red, and yellow correspond to residential, commercial, public, other and undeveloped functioning sectors, respectively. Lower SE values indicate aggregated development, while higher values indicate dispersed development. The DI is a distinctive characteristic that clearly highlights the segregation of land use. See Fig. 3 for details and the model concept.

Table 1 lists the top 10 cities in each category ranked based on their normalized SE and DI values. The appearance of each cities differs widely. A relatively low DI is observed for large cities, such as Beijing and Shanghai. In contrast, smaller cities, namely Xiangyang, Tangshan, and Guiyang, present higher DI values. While Chongqing as a larger city from the perspectives of both population and urban area, it has a higher DI value. It is also noted that the city of Chongqing emerges as the city in China with the most segregated development. Its $D_{R|P}$ and $D_{R|C}$ are relatively higher, of which T_R to T_P and T_R to T_C are more segregated than the rest of cities in China. The primary reason for this result is the implementation of a planning layout emphasizing the separation of land use, e.g. zoning, which has been rigidly enhanced through planning authorities on the national and local levels. Historically, the early stages of development of China's programming economy and the mode of the Soviet planning system shaped the current situation, although China has begun to adjust and reform its planning and administration system. Hong Kong is distinctive by consistently exhibiting a lower degree of DI (less segregated) but higher degree of SE (more spread out) in comparison with other cities. The city of Hong Kong exhibits higher

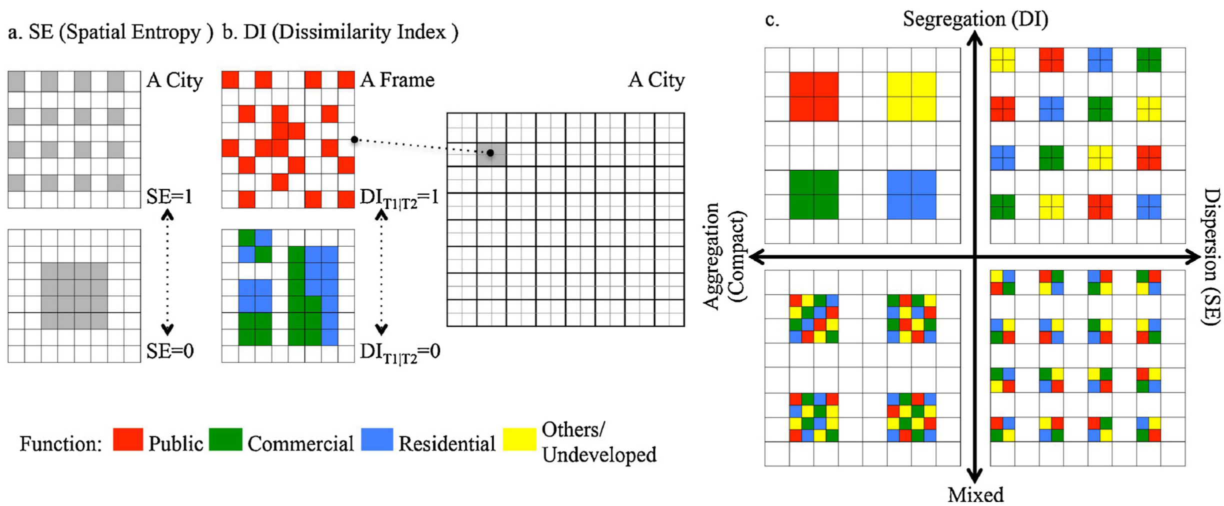


Fig. 3. Geometric prototypes of land-use pattern, (a) the degree of spatial entropy (SE) denotes aggregate (compact) land use; (b) the degree of dissimilarity index (DI) indicates segregation/mixed land use ($DI_{T1|T2}$ = 1 implies the presence of a singular type of land use such as T_{Public} dominates a given frame rather than $T_{Commercial}$ or $T_{Residential}$. $DI_{T1|T2}$ = 0 entails mixed land use, such as $T_{Commercial}$ evenly distributed with another type of land use $T_{Residential}$.); and (c) multi-dimensional indices.

entropy value, but has developed a highly concentrated urban space due to limited land availability. It is well attested that this city is the most densely populated city in the world with a highly concentrated city center and sub-centers. Developable lands are dispersed throughout the territory. The developed areas of Hong Kong have scattered and spread throughout its entire urban area, even though most parcels of built-up land are high density. Thus, in respect to developed-area distribution, Hong Kong is defined as having sprawl, and its SE value is comparatively high. The populated sub-centers are separated by country parks and conservation areas. Therefore, Hong Kong is recognized as a unique case.

Table 2 gives an overall understanding of the top 10 cities ranked in each category of aggregation to disperse and segregation to mixed land use according to mechanism elaborated in Fig. 3. For example, Dongguan is greatly dispersed but retains a mostly even distribution of land use. However, Shijiazhuang shows dispersed land use, but has mixed land use. Larger cities exhibit higher degrees of dispersal than smaller cities, although topographic considerations are important as in the case of Hong Kong. Finally, it is notable that Hong Kong is the only city selected that does not follow a Chinese zoning map (Urban Master Plan and Regulate Detailed Planning). The potential implications of this fact need to be investigated further.

Table 2
City ranking for top 10 cities according to aggregation vs. dispersion, and segregation vs. mixing.

Aggregation	Disperse	Segregation	Mix
Luoyang	Hong Kong	Chongqing	Shanghai
Guiyang	Dongguan	Xiangyang	Shijiazhuang
Hohhot	Shijiazhuang	Tangshan	Changzhou
Xiangyang	Shanghai	Guiyang	Shenzhen
Jingzhou	Wenzhou	Changchun	Hong Kong
Liaoyang	Changzhou	Luoyang	Dongguan
Tangshan	Beijing	Wuhan	Beijing
Nantong	Suzhou	Jingzhou	Baotou
Weihai	Lanzhou	Xuzhou	Wenzhou

Table 1
Results summary for the first 10 cities under each variable of normalized value.

SE_R	SE_C	SE_P	SE_{Mean}	$DI_{R\|C}$	$DI_{C\|P}$	$DI_{R\|P}$	DI_{Mean}
Hong Kong	Dongguan	Hong Kong	Hong Kong	Chongqing	Xiangyang	Tangshan	Chongqing
1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Wenzhou	Shijiazhuang	Shijiazhuang	Dongguan	Xianyang	Datong	Chongqing	Xianyang
.74	.63	.88	.091	1.00	.97	.99	1.00
Lanzhou	Shanghai	Dongguan	Shijiazhuang	Changchun	Wuhan	Xianyang	Tangshan
.62	.60	.67	.85	.99	.97	.96	.98
Changzhou	Zhongshan	Shanghai	Shanghai	Guiyang	Changchun	Jiangmen	Guiyang
.55	.58	.64	.78	.98	.96	.95	.96
Shanghai	Beijing	Changzhou	Wenzhou	Haikou	Qingdao	Yangzhou	Changchun
.54	.50	.59	.76	.97	.93	.95	.95
Baotou	Shenzhen	Urumqi	Changzhou	Zhanjiang	Chongqing	Weihai	Luoyang
.52	.49	.56	.71	.97	.92	.93	.92
Shijiazhuang	Changzhou	Qingdao	Beijing	Wuhan	Haikou	Xuzhou	Wuhan
.51	.48	.51	.65	.96	.91	.93	.92
Beijing	Wenzhou	Suzhou	Suzhou	Tangshan	Guiyang	Luoyang	Jingzhou
.50	.46	.50	.59	.96	.91	.92	.91
Nanjing	Suzhou	Lanzhou	Lanzhou	Jingzhou	Luoyang	Guiyang	Xuzhou
.50	.45	.49	.59	.95	.91	.92	.89
Suzhou	Baotou	Beijing	Baotou	Datong	Zhanjiang	Yancheng	Datong
.42	.40	.47	.59	.91	.90	.91	.88

Note: SE (spatial entropy), DI (dissimilarity index), R (residential), C (commercial), P (public), M (mean).

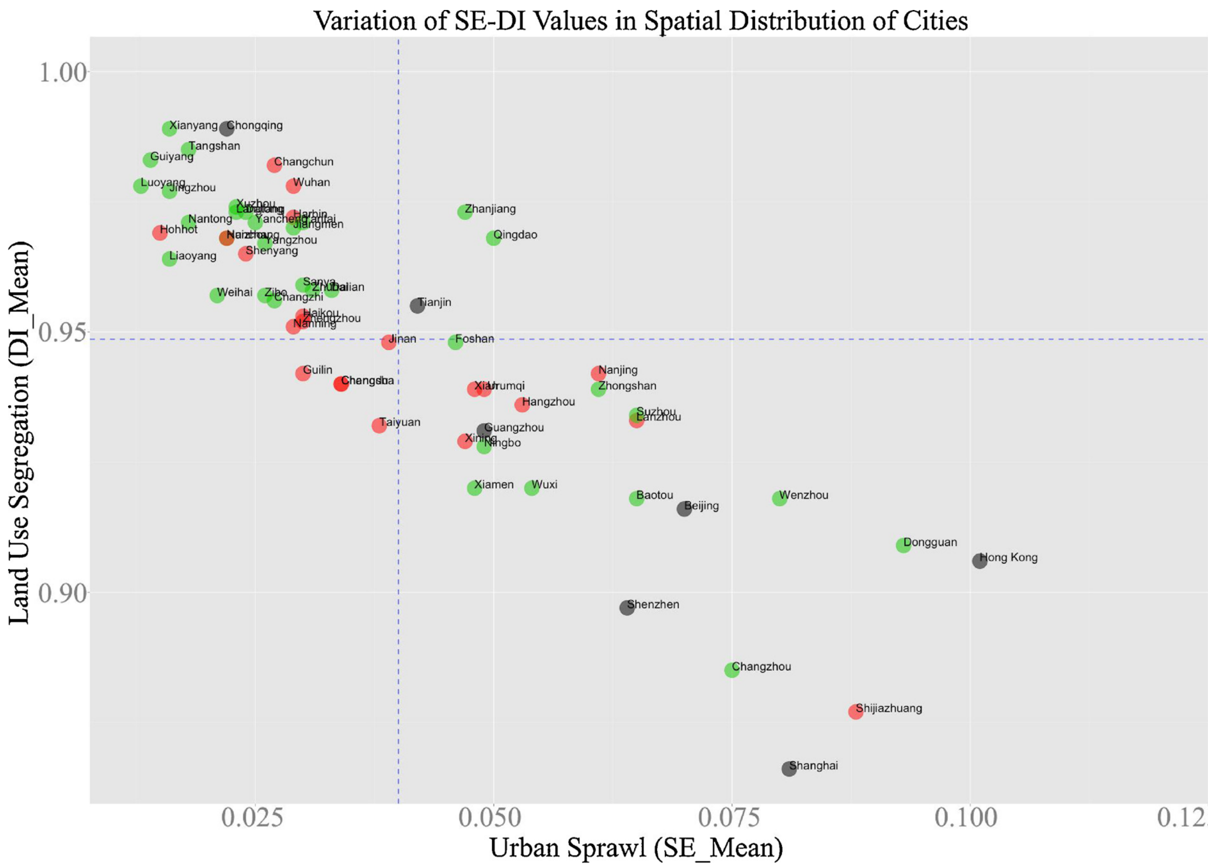


Fig. 4. The variation of SE-DI (spatial entropy-dissimilarity index) values for evaluating spatially differentiated cities. First-tier city (black dots), second-tier cities (red dots), third-tier cities (green dots). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

3.2. Differences of distribution in urban land-use patterns

The combination analysis of SE-DI combination best differentiates cities in terms of urban land-use patterns. Fig. 4 differentiates the selected cities by the combination of both SE and DI in terms of degree of segregation and dispersion. The dashed blue line signifies the mean value of SE and DI, which divides cities into four distribution zones, reflecting distinct characters of land-use patterns. Cities in the upper-right zone show a pattern of dispersion and segregation; cities in the upper-left zone exhibit a pattern of concentration, but segregation; cities in lower left zone have a pattern of concentration and mixed land use; cities in the lower-right zone display a pattern of mixed land use, but dispersion. It can be seen that the dispersed cities are accompanied with a decrease in segregation. Most of the cities are located in the lower-right zone and upper-left zone, which implies that, in general, cities that are more spread out have mixed land use, and vice versa. Beijing, Shanghai, Shenzhen, Guangzhou, and Hong Kong are quite spread out urban areas with highly mixed land use. Chongqing also has a high DI value but has no obvious spread urban area owing to the restrictions of natural environment, which surrounds the territory with continuous mountains and rivers (see Table 2).

Fig. 5 further shows the geographical distribution of the differently tiered cities according to the SE_{Mean} (Fig. 5a) and DI_{Mean} (Fig. 5b) values. According to the multi-factors assessment, Fig. 6 depicts the three tiers of Chinese cities differentiated by their SE and DI values. Fig. 6a presents megacities and prefecture cities, which have more residential land because first-tier cities need to absorb a large number of migrants and provide enough residences for them. On the other hand, third-tier cities need to attract investment, and residential-district development is the fastest and most direct way of increasing local GDP. Similarly, first-tier cities are the most vibrant for their economic functions and show a high SE_C in Fig. 6a. Meanwhile, as was detailed in the previous section, first-tier cities emphasize government-led development by increasing public functions in the new areas. Not surprisingly in Fig. 6a, a more stable urban land-use pattern is seen among provincial cities. In Fig. 6b, a prominent mixed land use is seen for all land sectors in the first-tier cities. In contrast, the urban land-use patterns of second and third-tier cities with higher *DI* values do not manifest mixed land use. Large cities tend to have lower DI values. It can be concluded that multiple urban and functional districts can be observed in the relatively large cities due to the presence of multiple city cores, while small cities would exhibit a distinct singular city core. Larger cities are more driven by SE_R, followed by SE_C and SE_P, while second-tier and third-tier cities associate with the same evidence. SE_R indicates a high value with third-tier cities. Meanwhile, $DI_{R|C}$ has the highest value with second-tier cities. $DI_{C|P}$ have highest value with first-tier cities and third-tier cities. $DI_{R|P}$ shows the lowest all cities, which implies more mixed residential and public land use. On top of that, this result again shows that public sectors stimulate city size, and residential sectors are associated with public sectors in a reciprocal relationship according to both volume and location. In other words, the residential and public sectors are equally dispersed throughout cities. That is to say that residential districts are consistently developed in accordance with the amount of public land-use development. This consistent development occurs because land use in the public sector usually serves as a catalyst for the promotion of residential investment for development in new urban areas, or to provide supplementary services to the existing residential communities.

3.3. Relationships between urban land-use patterns and their driving factors

Fig. 7 shows plots of SE and DI values in relation to urban land area, urban population, GDP, and paved road area (PRA). The plots estimate

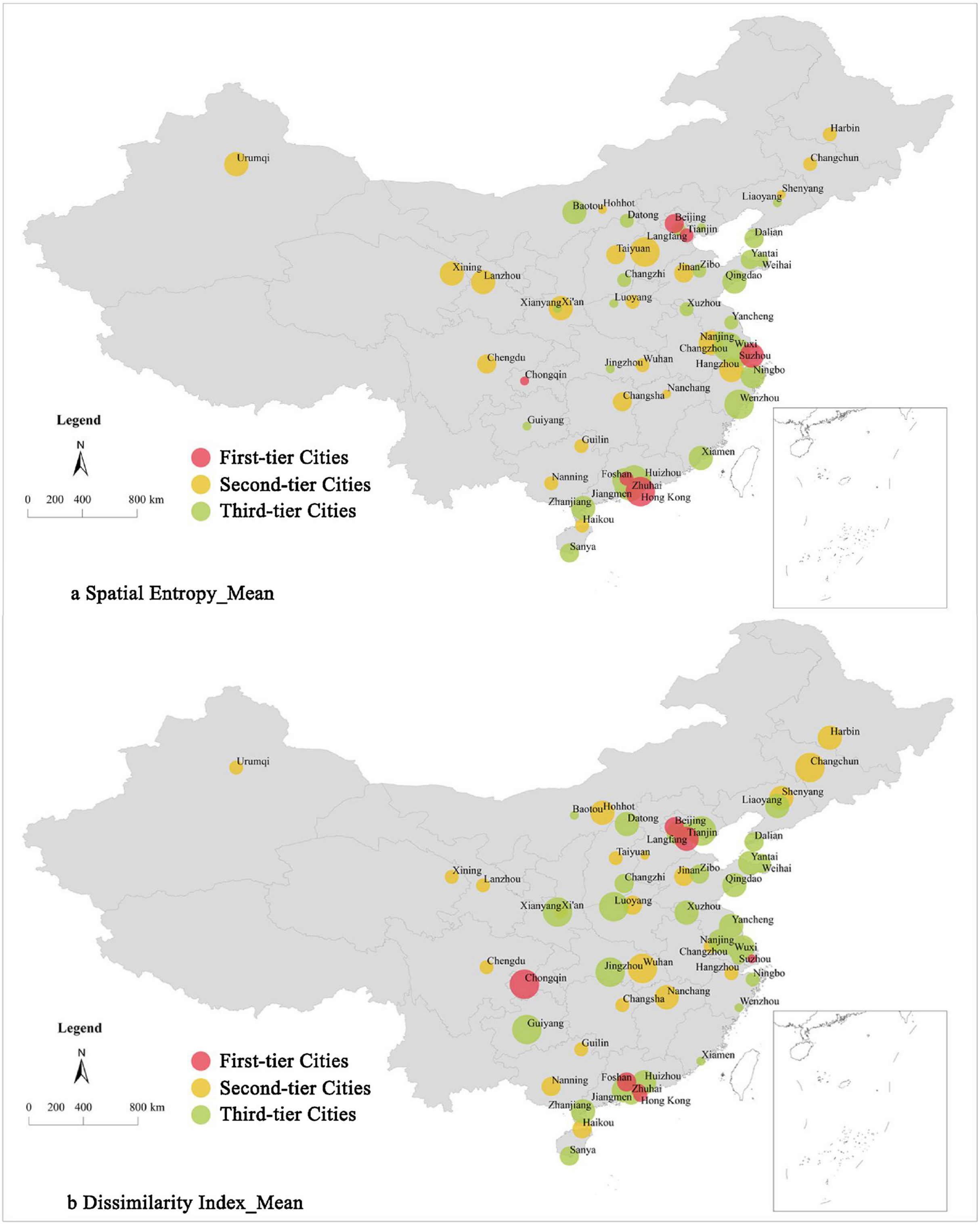


Fig. 5. Geographical distribution of cities indicating SE-DI value.

how dispersed the urban land uses of Chinese cities are in relation to urban factors. An increase in the SE value of a city means that the compactness of a city is decreasing and the city is possibly sprawling. The SE values of cities in the upper left area of the plot are larger, and the corresponding cities can be considered to be characterized by a more expanded form (Fig. 7a–d). Particularly, it can be inferred that the cities with higher SE values have a larger footprint. By combining a summary of the results shown in Fig. 7 and multiple regression in Structural equation modeling (SEM), Table 3 indicates the significance degree of correlation. SE_R has positive correlation to GDP and to urban built-up area with high coefficient estimates (0.887 and 0.622 respectively). For example, regarding the coefficient estimates, we can see that one unit increase in standardized GDP increases 0.887 unit in standardized SE_R. Similarly, one unit increase in standardized Urban Built-up Area decreases -0.622 unit in standardized SE_R. Furthermore, SE_C is significantly driven by GDP and PRA (coefficient estimates at

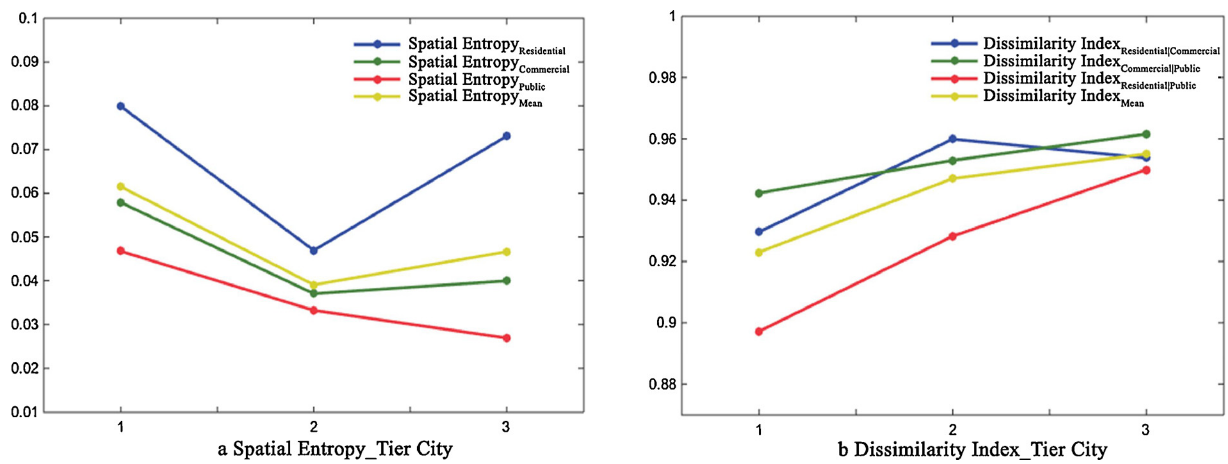


Fig. 6. Variations in urban land use among Chinese tiered cities.

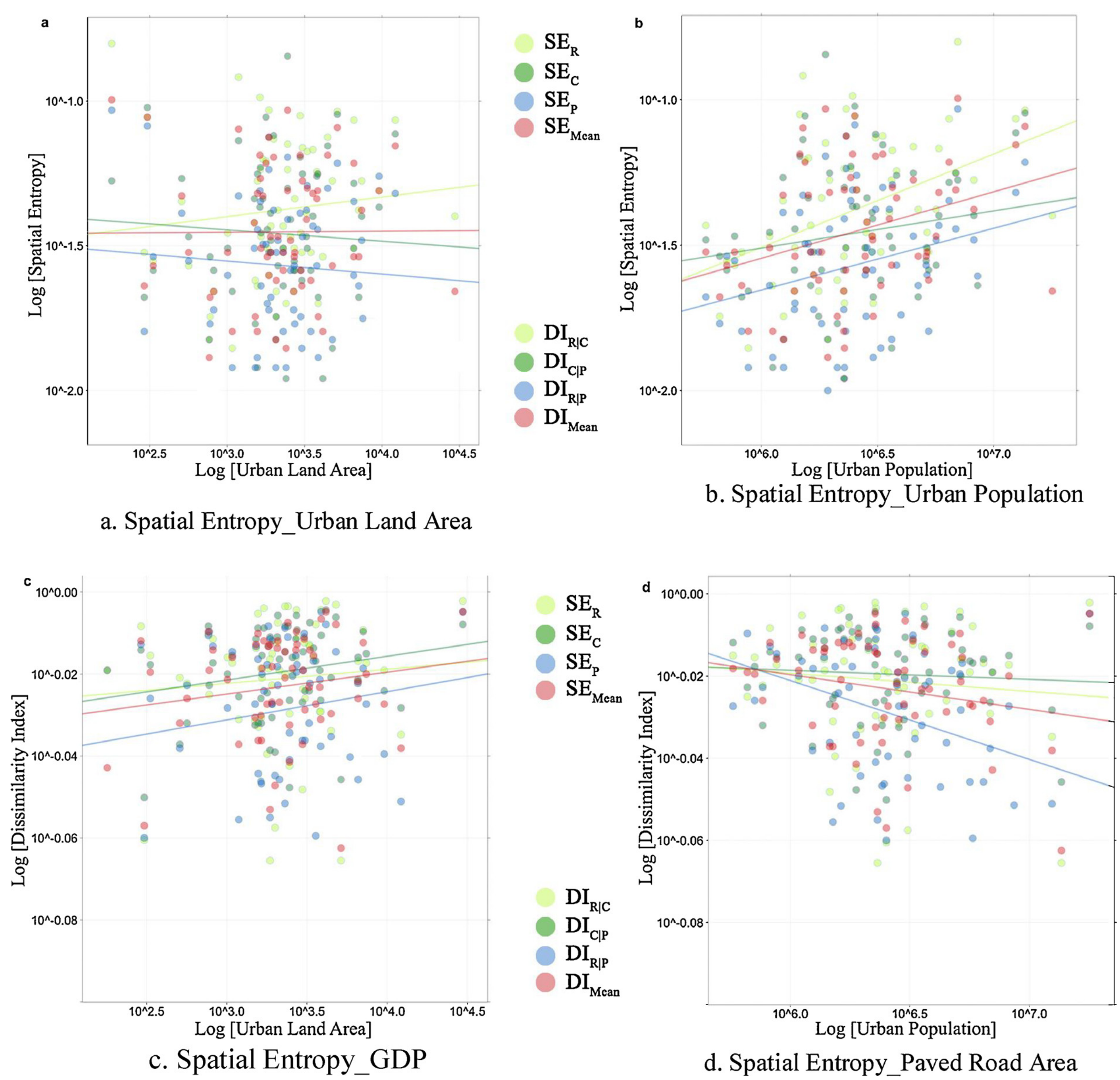
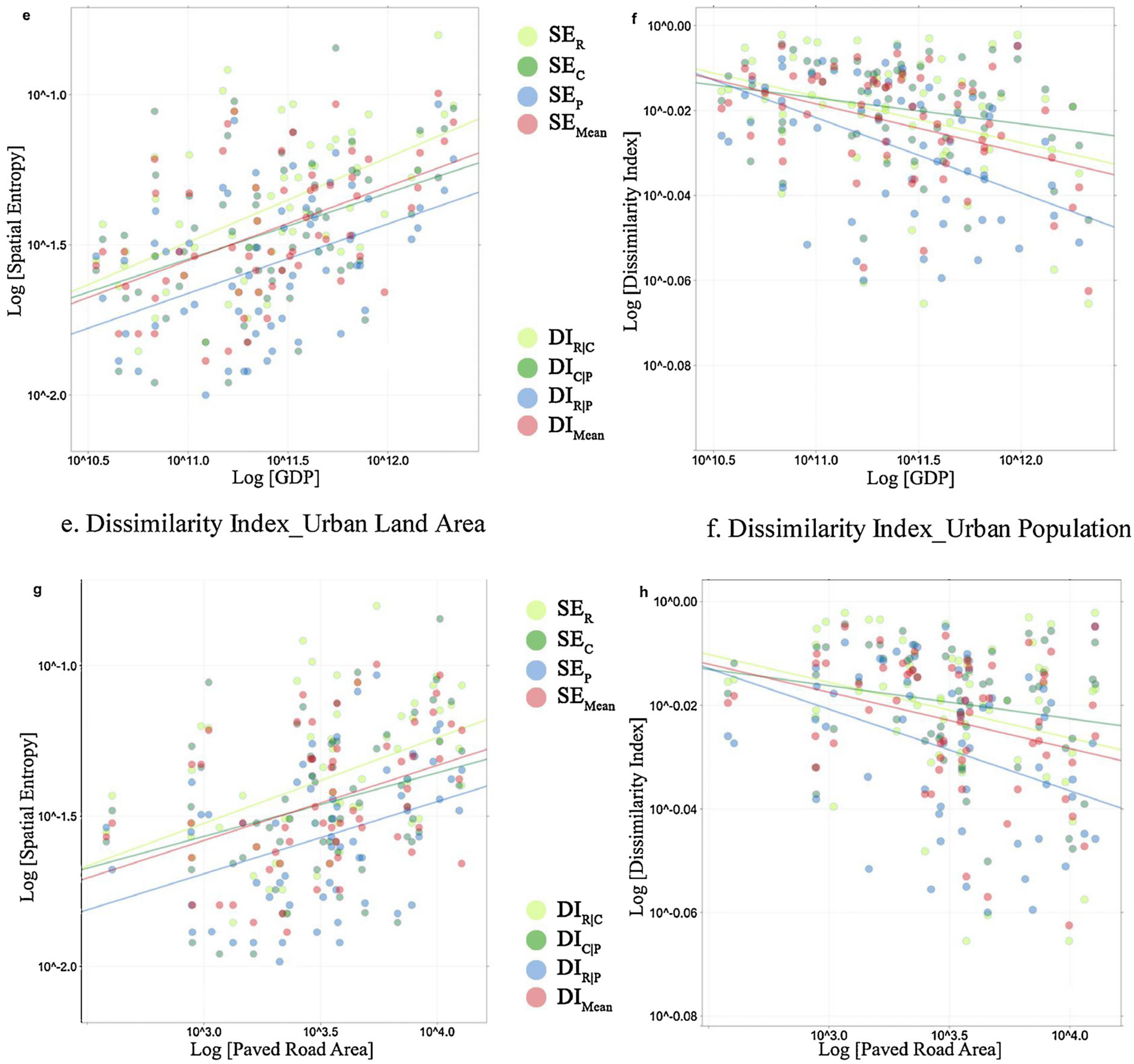


Fig. 7. Double logarithm plots of the comparison of SE (spatial entropy) and DI (dissimilarity index) values of cities (x-axis: urban land area, urban population, GDP, and paved road area; y-axis: SE and DI value).



e. Dissimilarity Index_Urban Land Area

f. Dissimilarity Index_Urban Population

g. Dissimilarity Index_GDP

h. Dissimilarity Index_Paved Road Area

Fig. 7. (*continued*)

0.802 and 0.428 respectively). In other words, the commercial sector is usually a concentrated development with easy access to road networks, which in turn attracts more economic production and commercial activity. Meanwhile, SE_P is positively influenced by urban built-up area, GDP, and PRA (coefficient estimates at 0.771, 0.778, and 0.403 respectively). That public land use is consistently developed in accordance with the amount of GDP and PRA. This consistent development occurs because land use in the public sector usually serves as a catalyst for GDP increase and for the promotion of infrastructure investment in new urban areas, or to provide supplementary services to the existing communities.

In respect to the DI values shown in Fig. 7e–h, higher DI values denote aggravated segregation. Because DI introduces the degree of segregation of different types of land use, the evenness or unevenness of urban land use can be evaluated. Table 3 indicates GDP to be the most influential in reducing the segregation of land use in $DI_{R|C}$, $DI_{C|P}$, and $DI_{R|P}$ (coefficient estimates at -0.765, -0.398, and -0.590 respectively). Urban Built-up Area shows positive significance of correlation to $DI_{R|P}$ (coefficient estimates at 0.432). Table 4 summarizes the correlations among independent variables regarding urban factors. From Table 4, we can see that all the variables are strongly correlated at 0.01 level. This implies that the chosen independent variables are interrelated and the chosen independent variables can be used to describe the dependent variable. We use SRMR and GFI as criteria to test Goodness-of-Fit Test with SRMR = 0.000 and GFI = 1.000, which implies that Structural Equation Modeling (SEM) is quite suitable in this analysis.

4. Implications and discussion

4.1. Characterization of urban land-use patterns

Land-use patterns reflect the arrangement of different types of land use and indicate where to allocate land associated with city development. The findings clearly prove that cities experience crucial dispersion of land use in the public sector (high SE_P), as most new urban areas are initially urbanized with public investment. The government has played an important role in stimulating, restricting, and allocating land use. Many Chinese cities released their peripheral land or rural land for real estate development of residential clusters (high SE_R). Hereafter, the land use of urban fringes was adjusted from agricultural land to built-up area that lead to a more dispersed landscape of urban central areas. The results also reveal the essential origin of Chinese urbanization. For

Table 3
Summaries of significance from structural equation modeling (SEM) analysis.

		Regression Weights			Standardized Regression Weights
		S.E.	C.R.	P	Estimate
Spatial Entropy_Residential	Urban Population	.000	−.348	.728	−.106
	Urban Area	.000	.301	.764	.064
	Urban Built-up Area	.000	2.414	.016**	.622
	GDP	.000	3.559	***	.887
	PRA	.000	1.120	.263	.214
Spatial Entropy_Commercial	Urban Population	.000	−1.405	.160	−.448
	Urban Area	.000	.241	.809	.053
	Urban Built-up Area	.000	1.409	.159	.380
	GDP	.000	3.078	.002***	.802
	PRA	.000	2.139	.032**	.428
Spatial Entropy_Public	Urban Population	.000	−.758	.449	−.226
	Urban Area	.000	.090	.928	.019
	Urban Built-up Area	.000	3.057	.002***	.771
	GDP	.000	3.193	.001***	.778
	PRA	.000	2.149	.032**	.403
Mean_SE	Urban Population	.000	−.944	.345	−.281
	Urban Area	.000	.260	.795	.054
	Urban Built-up Area	.000	2.502	.012**	.629
	GDP	.000	3.747	***	.910
	PRA	.000	1.974	.048**	.368
Dissimilarity_RC	Urban Population	.000	1.325	.185	.440
	Urban Area	.000	.357	.721	.082
	Urban Built-up Area	.000	−.165	.869	−.046
	GDP	.000	−2.822	.005***	−.765
	PRA	.000	−.281	.778	−.059
Dissimilarity_CP	Urban Population	.000	.989	.323	.340
	Urban Area	.000	.628	.530	.150
	Urban Built-up Area	.000	.437	.662	.127
	GDP	.000	−1.417	.056*	−.398
	PRA	.000	−.738	.461	−.159
Dissimilarity_RP	Urban Population	.000	−.455	.649	−.131
	Urban Area	.000	1.604	.109	.320
	Urban Built-up Area	.000	1.777	.076*	.432
	GDP	.000	−2.515	.012**	−.590
	PRA	.000	−.438	.662	−.079
Mean_D	Urban Population	.000	.678	.498	.209
	Urban Area	.000	1.038	.299	.223
	Urban Built-up Area	.000	.833	.405	.217
	GDP	.000	−2.716	.007***	−.685
	PRA	.000	−.542	.588	−.105

Note: Correlation significance level is at the *** < 0.01, ** < 0.05, * < 0.1. SE for spatial entropy, RC for residential and commercial, CP for commercial and public, RP for residential and public, D for dissimilarity, and PRA for paved road area.

Table 4
Summaries of covariation from structural equation modeling (SEM) analysis.

		Covariances				Correlations
		Estimate	S.E.	C.R.	P	Estimate
Urban Area	Urban Population	9,724,095.789	2,060,343.418	4.720	***	.768
Urban Population	Urban Built-up Area	705,386.896	140,726.454	5.012	***	.849
Urban Population	GDP	115,599,183,163.760	24,156,651,333.718	4.785	***	.786
Urban Population	PRA	7,666,402.223	1,666,537.988	4.600	***	.738
Urban Population	Class	−1,519.765	339.685	−4.474	***	−.708
Urban Area	Urban Built-up Area	705,546.816	166,617.242	4.235	***	.653
Urban Area	GDP	70,751,917,362.820	26,335,661,726.563	2.687	.007	.370
Urban Area	PRA	7,053,061.631	1,966,994.076	3.586	***	.522
Urban Area	Class	−1,194.657	392.181	−3.046	.002	−.428
Urban Built-up Area	GDP	10,092,239,590.405	2,080,614,495.422	4.851	***	.803
Urban Built-up Area	PRA	735,863.191	148,780.786	4.946	***	.830
Urban Built-up Area	Class	−133.108	29.258	−4.549	***	−.726
GDP	PRA	119,708,441,918.745	25,491,253,519.317	4.696	***	.762
GDP	Class	−23,467,815.189	5,172,624.430	−4.537	***	−.723
PRA	Class	−1,426.695	348.570	−4.093	***	−.622

Note: * indicates a significant level according to SEM, significance tested (***correlation at $p < 0.01$, ** correlation at $p < 0.05$, * correlation at $p < 0.1$). Model Fit Summary GFI 1.000, SRMR, 0.000. PRA for paved road area.

instance, Beijing, Shanghai, and Hong Kong have higher spatial entropies (*SE*) (see Table 1). These cities have powerful municipality authorities, where the government determines land release or acts as a catalyst for development in new districts. Nonetheless, with lower spatial entropy in commercial sector (SE_C), Hong Kong has concentrated its commercial centers in a few districts, such as Tsim Sha Tsui, Central, and Causeway. This concentration arises from the city's aims to provide people with more housing and support public services under the circumstances of extremely limited land resources.

The current separation of land use is a result of traditional planning and economic marketization, exacerbated by the natural environment. It is necessary to note that office and commercial developments have an economic advantage in locations close to the city center, whereas industrial development is pushed farther away towards the suburban areas. Residential development is most likely to take place in between the city center and industrial development. This evidence suggests the strong influence of market-driving forces on the spatial separation of urban land-use patterns. In addition, cities with environmental restrictions on urban development have several dispersed developed areas, each with independent functions. Dongguan, as an example, has not divided its city into towns of urban administrative districts (shixiaqu) nor set up counties (shixiaxian), but the municipality has direct jurisdiction over towns (shixiazhen). In this manner, each independent town urbanizes alone, separating the whole city domain and resulting in well-balanced functions. For this reason, Dongguan is on both lists of high dispersion and mixed land use (see Table 2).

Our analysis of the variation of urban land use in major Chinese cities shows that each individual city has a distinctly different land-use pattern, ranging from more mixed (Beijing, Shanghai) to less segregated (Xiangyang, Tangshan, and Guiyang), and the most segregated (Chongqing). From the above analysis, the spatial characterization of urban land-use patterns in China can be categorized into three typical types: (1) economically led (Shanghai) (2) government led (Dongguan) and (3) geographically constrained (Hong Kong and Chongqing).

4.2. Characteristics of urban land-use patterns among cities of different tiers

In the urban system of China, tiered cities that are defined by the State Council have a major impact on land-use patterns, owing to the spatial distribution of land resources and population mobility. Administrative intervention in city development, particularly by ways of land acquisition and fiscal support, is in line with the national policy for urban hierarchy systems. Furthermore, the strict hierarchy of the land-use planning system and the restriction on population migration resulted in relatively undifferentiated urban patterns within the same tier of cities (Seto and Fragkias, 2005). There are some subtle differences between cities. The first-tier cities and third-tier cities remain the most dispersed and the most segregated, respectively, in terms of land pattern. First-tier cities have a higher degree of mixing, but also have higher dispersion than the two other tiers. Third-tier cities are more driven by residential sectors (SE_R), which need increased real estate development in order to guarantee their fiscal resources and stimulate city growth.

In general, larger cities would acquire a more mixed urban land-use patterns in the course of time (Wang et al., 2016). More specifically, Chinese cities originally have much more separated functional layouts, but cities have been developing very rapidly during in the last three decades, particularly among the first-tier cities. They have either absorbed a variety of land-use areas within the existing city layout, or added a large amount of additional land-use areas of various types. Because of the influx of migrants into big cities, the process of mixing land use in larger cities is generally faster than that in smaller cities. We can assume that land-use mixing declines from the city cores to the outskirts. Whereas, in spite of being a first-tier city, Chongqing is a mountain city surrounded by undevelopable land, which limits expansion in comparison to other first-tier cities. Meanwhile, Chongqing is separated into different clusters of land use. That is why it has higher DI and SE values.

Based on the above SEM analysis results (Table 3), we can explicitly perceive that GDP is increasing with urban expansion in terms of SE_R, SE_C, SE_P; urban built-up area is growing with SE_R and SE_P; paved road area is extending in accordance with SE_C *and* SE_P. The observations imply that GDP booming is the fundamental inducement for urban sprawl or city expansion in China, where infrastructure construction incipiently takes initiatives through public sector investment and consequentially induces commercial sector development, especially for new area development in Chinese cities. As a result of infrastructure driving public land use development, along with which residential development rise, urban built-up area increased and cities expanded. This is one of the representative images of China's urbanization process for decades. The social-economic prosperity has given rise to more mixed land use development, that is higher GDP a city has, the lower Dissimilarity it is associated with, in terms of $DI_{R|C}$, $DI_{C|P}$, $DI_{R|P}$ (seen from Table 3). Alternatively, cities who promote mixed land use or is moving towards mixture development, can seat about more economy outputs and lead to more economic activities.

4.3. Planning and design towards mixed and compact land-use patterns

The conventional wisdom of planning, long adopted by most planners and government agencies, has advocated for the separation of urban and rural land-use systems and population registration systems (Li et al., 2010). After decades of urbanization, the emergence of land-use patterns, which are driven by land-use policy, local economic development, and direct investments, characterizes the restructuring of the urban land use in China over the last 30 years. The above results indicate that land-use patterns are affected by natural environment, administrative adjustment, and the spatial arrangement of Chinese zoning districts (Urban Master Plan and Regulate Detailed Plan). The contributions and the widespread adoption of zoning trends over time have resulted in not just the separation of land uses, but increasingly the separation of urban land uses into large, homogeneous districts (Song et al., 2013). However, the overly strict separation of land uses through zoning has the consequence that planners and local decision makers would like to change the zoning laws. The question is when and how to shift towards smarter urban land use. Multiple plans (including National Economic and Social Development Planning, Urban and Rural Planning, Land Use Planning, Ecological and Environmental Protection Planning, and other plans) results in difficult coordination for planning implementation. Thus, the Ministry of Natural Resources of China was newly established in 2018 to uniformly exercise all responsibilities of land use and spatial planning, ecological and agricultural protection and restoration, and to promote the multiple-plan integration program.

The decision of land use policy generates physical land use patterns through planning made by the government. Thus, planning and design for formulating mixed and aggregated land use patterns need strong legal binding force for policy support (Lang et al., 2018). At present, only a few cities in China, including Beijing, Shanghai, Nanjing and Shenzhen, have issued local regulations for mixed and compact land use. For example, the Provision of Shenzhen Urban Planning Standards and Guidelines (2016) stipulates that urban planning and land use layout should give priority to compact development. For example, the industrial buildings are mixed with commercial buildings, with the assembly line above the second floor. Land use is relatively intensive with mixed housing, employment, activities, and public services. Plans on mixed and compact land use issued by some cities in China are brief and need to be further expanded in the legal planning system.

5. Conclusion

Understanding how cities urbanized is vital and can be accomplished using a computer model that can reconstruct cities from bottom up to investigate fundamental urbanization mechanisms. Much of the existing literature has discussed the negative effects of the proliferation of urbanization. However, there is a general lack of research on the development of methods to quantify and compare land-use patterns shaped by urbanization. This study applies an integrated and quantitative method to investigate urban land-use patterns through automatic categorization, identification, and characterization of the existing land-use patterns in Chinese cities. By linking planning data, the Ordnance Survey, Python Programming, ArcGIS, SPSS, R Programming, and cellular automata modeling with socio-economic data sets, we developed Spatial Entropy and Dissimilarity Index (SE-DI) to capture, quantify, and understand the patterns of urban land use and link them to the urban planning background. This study contributes to the body of urban planning knowledge by calculating urban land-use patterns, revealing its driving forces, and presenting implications for policy and practice. Evidence from this study may help inform urban planners and decision-makers to formulate planning policy and guide practice away to promote urban infill development and mixed land use.

A comparative evaluation of land-use patterns reveals the distinct driving-forces of urbanization simultaneously at work and can lead to far-reaching policy implications. We have compared spatial patterns of cities by studying six independent attributes (SE_R, SE_C, SE_P, SE_{Mean}, $DI_{R|C}$, $DI_{C|P}$, $DI_{R|P}$, DI_{Mean}) of actual land use, followed by integration with statistical data. The findings indicate that SE_R has relatively higher positive correlation with GDP and urban built-up area; SE_P development is fundamentally driven by GDP, urban built-up area, and paved road area; and SE_C is closely related to GDP and paved road area. In addition, the key to linking urbanization and land-use patterns lies in the recognition of the spatial relationships of urban hierarchies. The changing land-use patterns in China have been influenced by the natural environment, administrative adjustment, entrepreneurial governments, and the spatial arrangement of Chinese zoning districts. Yet, such a government-led urbanization approach in China relies on both the will of decision makers and government intention, but neglects the fundamental law that peripheral areas have close dependent relationships with relevant core areas.

In summary, the driving forces on land use pattern are the results of combined impacts of planning policy, the regional development policy, the urbanization policy, and land use policy. What is more, intensive land use policy and compatible mixed land use planning are indeed required to shape our lives to encourage mixed land-use patterns and reduce urban sprawl for urban vitality and sustainability. To highlight the continued prospect for sustainable land use policy, this study delivers an empirical analysis and contributes to the knowledge by measuring urban land-use patterns and by addressing urban planning concerns. We should develop further research that deals with different cultural and regimes with respect to such urban land-use patterns.

Declaration of interest statement

The authors declare that they do not have any conflict of interest involvement in this manuscript.

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