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Live-Work-Play Centers of Chinese cities: Identification and temporal evolution with emerging data

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ABSTRACT

The Live-Work-Play (LWP) center, as a more comprehensive profile of a city center, has attracted increasing attention in recent years. This paper proposes a straightforward framework for identifying and evaluating LWP centers using ubiquitously available points of interest (POIs) as a proxy for urban function. The framework is then applied to 285 Chinese cities. The results show that 35 Chinese cities in 2014 had polycentric urban structures, increasing from 23 cities in 2009. The temporal evolution of the LWP centers of Chinese cities can be better understood as three types of evolution, differentiated by the number of LWP centers, their morphology and location. First, more polycentric cities emerged in 2014 in comparison with 2009. Second, the morphological change type can be further classified as "relative dispersion", "relative concentration", and "absolute concentration". Third, the location change type can be classified into five types: displacement, division, fusion, emerging, and recession. In the final experiment, the regression results show that larger population and greater road junction density significantly contribute to LWP center formation.

1. Introduction

Urban spatial structure has always been an important issue in the academic fields of urban planning, urban economy and geography. Extensive studies of urban structure focus on two aspects, namely the morphological dimension, which indicates spatial distribution of centers, and the functional dimension, which indicates the relationship between centers (Burger & Meijers, 2012; Vasanen, 2012). However, most empirical studies only focus on single attributes (Zhong et al., 2017), such as population (Li, Li, Long, & Dang, 2016; Liu & Wang, 2016), employment (Giuliano & Small, 1991; McMillen & Smith, 2003) or the built environment (Taubenböck, Standfuß, Wurm, Krehl, & Siedentop, 2017; Yang & Shi, 2014), without accounting for the comprehensive function of centers. The density and diversity of human activities are then included in the identification of urban functional centers in order to extend the understanding of how urban structure influences daily life (Batty, Besussi, Maat, & Harts, 2004; Cai, Huang, & Song, 2017; Zhong et al., 2017). It is widely accepted that urban centers are characterized by a high diversity of human activities which indicates the multifunctionality of centers, since mixed-use has been advocated as "an established planning principle", mainly owing to theories of New Urbanism (Grant, 2002).

The concept of Live-Work-Play centers (LWP) represents the multifunctionality of centers and can be described from three perspectives, including "the center's population, the activities occurring in the center, or the physical feature[s] of the center itself" (Malizia & Song, 2016). Malizia and Song (2016) focus on the physical aspects of LWP centers and define them as compact, dense, diverse, mixed-use, connected and walkable areas. Consistent with their definition, this study identifies LWP centers from the perspective of human activities as areas with the highest levels of multifunctionality.

There has been limited research into LWP centers, especially for large city systems that include many size varying cities. Emerging data, such as data on points of interest (POIs), can provide a useful lens for identifying and evaluating the LWP centers from the perspective of human activities. POIs that are ubiquitously available enable researchers to expand the scope of their studies from single cities to national and international, multi-city studies. This study proposes a straightforward methodological framework for identifying and evaluating LWP centers using POIs and comprehensively applies the framework to the entire Chinese city system. This study answers the following questions: (1) how polycentric are Chinese cities, (2) what are the precise boundaries of LWP centers in central cities, (3) what patterns do the LWP centers follow in their evolution, and (4) what factors have led to the polycentricity of Chinese cities. As a prelude, two clarifications are made, the first regarding the debate on functionality versus

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morphology and the other regarding the issue of scale (Van Meeteren, Poorthuis, Derudder, & Witlox, 2016). This study focuses on the morphological dimension of urban spatial structure in intra-city scale.

After the literature review in Section 2, Section 3 introduces the study area and data used, and Section 4 outlines the methodology of urban center identification following an examination of the advantages and disadvantages of pre-existing methods. Section 5 presents the research results, including the LWP centers identified in 2009 and 2014, their geographical boundaries, and the evolution patterns of LWP centers in China based on the changes from 2009 to 2014, as well as the factors that determine the polycentric urban structure of Chinese cities. Lastly is the conclusion and discussion in Section 6.

2. Literature review

2.1. Methods of center identification

It is noticeable that different methods of center identification make use of different data types. This study highlights four major types of data – employment, population, built environment, and human activity data, as follows.

(1) The field of urban economics has contributed three major categories of quantitative methods to identify centers using employment data based on the concept of the subcenter "defined as an area with significantly higher employment densities than surrounding areas" that is "large enough to have a significant effect on the overall spatial structure" (McMillen & Smith, 2003).

The first category is based on minimum cutoff point of number and density of employees in an area, and was developed by Giuliano and Small (1991) and adopted extensively in subsequent studies (Anderson & Bogart, 2001; Bogart & Ferry, 1999; Cervero & Wu, 1997, 1998; Giuliano, Redfearn, Agarwal, Li, & Zhuang, 2007; McMillen & McDonald, 1998; Pan & Ma, 2006). Giuliano and Small (1991) identified a center as a cluster of contiguous tracts that have a minimum employment density of D, and a minimum total employment of E. The thresholds set for those two indicators produce the most prominent differences between studies that use similar methods. Giuliano and Small (1991) set the minimum employment density as 10 employees per acre and minimum total employment as 10,000 employees. Bogart and Ferry (1999) used the same total minimum employee threshold but a lower employment density of 8 employees per acre, while Cervero and Wu (1997) had a still lower minimum employment density of 7 employees per acre. McMillen and McDonald (1998), in contrast, increased the threshold for two special areas in order to produce reasonable results. Absent of a unified method for determining an appropriate threshold, the identified results remain sensitive to the density cutoff and the spatial scale of the analysis (Anas et al., 1998). Some studies thus have relied upon uniquely discrepant thresholds in order to lower their impact on results. For instance, McMillen (2003) used four different values for density cutoff across five cities, and Liu and Wang (2016) used a lower threshold for China's five largest cities than for its other cities.

The second category is "based on estimation of density gradients to identify potential centers" (Agarwal et al., 2012). Unlike the first method, which requires a uniform, predetermined minimum cutoff, this identifies potential centers via density peaks. McDonald (1987) used a regression of the natural logarithm of employment density on the distance to CBD to discover local peaks and take them as potential subcenters. Craig and Ng (2001) identified subcenters by exploiting the tracts with the densest employment. However, local knowledge has generally been required for achieving accuracy in the selection of sites with a large employment size. Therefore, this method is not efficient when applied to a larger number of cities.

The third category comprises "various two-step methods using locally weighted regression (LWR) to smooth the density surface and then identify centers" (Agarwal et al., 2012). McMillen and McDonald (1997) first adopted a nonparametric procedure using LWR estimates of employment density. McMillen (2001) then popularized it by proposing a two-stage nonparametric procedure. The first stage uses LWR to calculate the predicted value of the natural logarithm of employment density for each observation within an urban area. The second stage uses regression to identify subcenters that have statistically significant effects on employment density. McMillen (2003) further improved the second stage by defining a subcenter as a group of contiguous sites provided by the first stage for which the total number of employees exceeded 10,000. Essentially, the procedure, improved by McMillen (2003), combines the method based on the minimum cutoff point of employment from Giuliano and Small (1991) with the two-stage method. This combined method has been adopted by McMillen and Smith (2003) to identify subcenters for 62 large American urban areas. Lee (2007) further revised McMillen and Smith's method, as well as Giuliano and Small's method to identify centers in 1980, 1990 and 2000 for selected metropolitan areas in the US.

(2) Some studies have adopted data reflecting population distribution to identify centers. Li et al. (2016) utilized the Baidu (the most popular search engine in China) heatmap[1] to identify city centers for 658 cites in China automatically. Liu and Wang (2016) employed detailed gridded population data to identify centers, and further explored the polycentricity of 318 Chinese prefectures. Those new data make the procedure for center identification applicable to a large number of cities and regions, and do not require much local knowledge.

(3) The built environment is a good indicator of how urban space is actually organized, especially in its morphological dimension. For example, Yang and Shi (2014) evaluated the height and intensity of public service facilities and set thresholds for both indicators to identify centers. Taubenböck et al. (2017) use 3D building models derived from remote sensing data and define a center as a high urban mass concentration, which they argue can be a reasonable proxy for employment density data. Cai et al. (2017) combined nighttime light imagery with social media check-in maps to locate (sub)centers, and they declared that those data can be valid substitutes for population or human activities. Given those empirical studies, it is believed that there is much more potential to be explored in examining the built environment for the research related to urban structure.

(4) Similar to the built environment methods, human activities determine how urban space is utilized, implying how the urban structures operate. Thurstain-Goodwin and Unwin (2000) established an index called "index of town centeredness", which combines four key indicators - economy, property, diversity of use, and visitor attractions - to represent the characteristics of a city center. Instead of setting a threshold, the centers were delineated from the peaks of a continuous surface called "Intensity of Town Centeredness", which integrated the surface of each indicator generated by means of Kernel Density Estimation. A similar method was also adopted by Borruso and Porceddu (2009) using the geographical location of human activities to generate a density surface, and by Hollenstein and Purves (2010) who used georeferenced images from Flickr. Inspired by emerging large-scale data on human activities, Zhong et al. (2017) adopted travel survey data to identify functional urban centers considering both density and diversity of human activities. Sun, Fan, Li, and Zipf (2016) provided a new approach that applied a new type of movement data generated from location-based social network use. It can be used not only to accurately identify city centers, but also to delineate the city center with a precise boundary. However, existing empirical studies fall short on the partiality of human activities, and normally do not cover the majority of urban functions.

[1] Baidu Heatmap: a map that displays population density and flow speed of population with different colors and lightness, and the map is generated based on location information of smart phone users when they visit Apps supported by Baidu, such as a Search engine, Map, Weather, Music, or other App.

2.2. Impact factors for polycentricity

In addition to the identification of city centers, the questions of how the polycentric urban structure forms and what factors contribute to the total count of city centers are also the concern of scholars. Anas et al. (1998) have pointed out that explanations of polycentricity center on agglomeration economies. When the negative effect of diseconomies of scale begin to outweigh the positive effect of scale economies, multi-centers emerge.

The diseconomy of scale usually refers to increasing transportation cost or commuting cost (Anas & Kim, 1996; Fujita, Krugman, & Mori, 1999; Helsley & Sullivan, 1991; Konishi, 2000). As Helsley and Sullivan (1991) have demonstrated, "in a growing city, subcenters arise from the tradeoff between external scale economies in production and diseconomies of scale in transportation". Other studies have come to similar conclusions. Anas and Kim (1996) developed a computable general equilibrium model verifying that traffic congestion and employment locations are endogenous, concluding that the number of centers increases with higher traffic congestion. Giuliano, Redfearn, Agarwal, and He (2012) examined the impact of accessibility on the growth of employment centers in the Los Angeles region and confirmed a significant relationship between network accessibility and center growth.

In addition to transportation, increasing population also threatens scale economies because population growth is highly integrated with transportation and commuting cost. "Population growth eventually exhausts scale economies from concentrated activity and centers become uniformly distributed" (Anas & Kim, 1996). The monocentric urban configuration cannot stay at equilibrium "when [a] city's population and commuting rate change" (Fujita & Ogawa, 1982). Based on Fujita and Ogawa (1982)'s model that the number of subcenters tends to rise with population and commuting cost, McMillen and Smith (2003) tested the impact of both population and commuting cost by estimating a Poisson model. Their results show that these two variables explain most of the variation in the number of subcenters.

3. Study area and data

3.1. Study area

This study focuses on the 285 cities at the prefectural, or higher, level in China, including four municipalities under the management of the central government, 15 sub-provincial cities, 17 other provincial capital cities, and 247 prefecture-level cities.

Most of the existing studies on Chinese cities examine the administrative area of cities rather than the spatial entity or the functional urban area of cities, thus making cross-comparisons of Chinese cities difficult due to the varied hinterland ratio of each city. For instance, Beijing is composed of the central city, new cities, and large towns, each of which could be regarded as cities when compared to the scale of western cities, more details for this problem have been highlighted by Long (2016). To cope with this problem, this research restricts the scale to the intra-city by extracting the central areas of all 285 cities, namely the central cities, and takes them as its study area. Firstly, the urbanized areas of all cities are identified (also see Long, Zhai, Shen, & Ye, 2017, about this data source) using data from Landsat TM images from 2010 by Liu et al. (2014), and then the largest parts of all cities' urbanized areas are extracted as central cities automatically. Additionally, a manual check for most of the cities is carried out to verify that this criterion for determining central cities is corroborated by those cities' master plans. Exception only exists in those cities whose central cities are divided by rivers or mountains, and those are then corrected individually.

Table 1
Categories of POIs in 2014.

Category	Sub-category	Counts	Total
Live	Residential community	166,187	186,330
	Community service	20,143	
Work	Company	487,948	1,808,704
	Office building	35,064	
	Financial service	173,811	
	Legal service	18,416	
	Government institution	133,020	
	Education institution	179,818	
	Medical institution	218,537	
	Others	562,090	
Play	Commercial sites	1,474,630	2,547,284
	Catering sites	555,024	
	Entertainment	383,666	
	Hotel	117,864	
	Tourism	16,100	
Transport facility	–	281,943	281,943

3.2. Points of interest (POIs) in 2014 and 2009

All of the POIs located in the central cities for 2014 and 2009 are gathered and geo-coded by business cataloguing websites. The data quality is ensured through manual checking of POIs, which have been selected randomly across the country (also see Long, 2016). The initial POI dataset contains two levels of categories – 396 types in the second level representing all of the different functions that a city can serve and 16 categories in the top level. Through a process of trial and error, the final classifications are converted into the following 16 categories[2]: the residential community, community services, companies, office buildings, financial services, legal services, governmental institutions, educational institutions, medical institutions, commercial sites, catering sites, entertainment, hotels, tourism, transport facilities, and other facilities. The 16 categories of POIs are sorted into "Live", "Work", and "Play", respectively (Table 1), based on their main functions. Three declarations must be explained beforehand. First, POIs representing transport facilities are not classified into any category of "Live", "Work" or "Play". Second, counts of the POIs of "Live" are much fewer than the other two categories, but in relation to the floor space and population of "Residential community", it is high enough to represent the value of "Live". Third, even though the POIs have been classified to the extent possible, there are admittedly some types of POIs that are multi-functional in themselves and do not easily fall into one single function. For example, sub-categories of "Play" such as "Commercial site", "Catering site", and "Entertainment", also account for a certain percentage of employment, however its main function is asserted to balance more characteristics of "Play" than "Work" for the whole city.

4. Method

This study has two major aims: the first is to identify the LWP centers of 285 Chinese cities, and the second is to explore the potential variables that lead to polycentricity.

For the first aim, local POI density peaks are used as the main index to identify the center(s) for each city. The point density within each central city is computed in order to generate a contiguous density surface for every city, and is then classified into eight classes with Natural Breaks (Jenks). With the area threshold set to a minimum of 10 ha,[3] potential centers are given from the top class of each density surface and the boundary of each center is generated automatically at the same time. To differentiate the main center and sub-center among potential centers, we take both area and POI density into consideration.

[2] The classification may be slightly different from other research, such as Yao et al. (2017) which have 20 categories of POIs, due to different data sources.

[3] According to the empirical results, there exist some tricky patches that have top POI density, but are too small to be identified as centers. The purpose of setting a threshold of 10 ha is to avoid mistaking these patches as LWP centers.

Normally, the main centers are centers that show both the largest area and highest density, however, when area difference between the centers is huge, the one which has a much larger area than others will be identified as the main center even though it may have comparatively lower POI density. When the area difference between centers is < 20%, priority is given to centers that have larger POI density as main centers even though they may have a smaller area.

The method proposed has four advantages. First, as diverse as the POI categories are, the data adopted in this research covers the majority of the functions a city can serve. Centers identified in this study are function-intensive and consistent with the definition of the LWP center. Second, the main index used – local POI density peaks – makes the procedure of identification insensitive to the spatial scale, further avoiding the need for setting arbitrary thresholds. Third, this method makes it possible to identify centers for all cities and produce reasonable results without local knowledge. Forth, this procedure can be run automatically for a large number of cities.

For the second aim, a regression analysis is adopted. To explore the impact factors leading to polycentric cities, a number of potential independent variables are selected based on existing studies that include three categories: factors of transportation and population, natural factors, and economic factors. Table 2 lists the data description or source of all independent variables and year of the source data used. The dependent variable is the number of LWP centers for each city in 2014. It is self-evident that the number of LWP centers is a simple count, which indicates that a Poisson regression is the most appropriate approach. Poisson regression is often used for modeling count data and has a number of useful extensions for count models. The validity of the Poisson regression has also been verified in existing research, such as McMillen and Smith (2003). Therefore, the Poisson regression is used to explore the impact factors.

5. Results

5.1. The profile of LWP centers in 2014 and 2009

The results show that 35 cities in 2014 had more than one LWP center, compared with 23 in 2009. The spatial distribution of those polycentric cities in 2014 and 2009 is shown in Fig. 1.

Among the 35 polycentric cities from 2014, 9 of them had three LWP centers, and 26 had two LWP centers. Meanwhile, among the 23 polycentric cities from 2009, only 4 of them had three LWP centers, and 19 had two LWP centers. The spatial distribution maps for all polycentric cities for 2014 and 2009 are shown in Fig. 2 (scale varies among cities in the figure).

5.2. Changes of LWP centers between 2014 and 2009

Based on the LWP centers identified in 2014 and 2009, significant changes in three aspects – number, morphology and location - are highlighted to explore the temporal evolution of LWP centers in China.

5.2.1. Number changes of LWP centers

There is a general trend towards polycentricity in Chinese cities, even though most cities still showed one LWP center for both years and the maximum number of centers remained at 3. Specifically, changes in the number of LWP centers from 2009 to 2014 can be categorized into three types: unchanged, increased and decreased. Table 3 lists all types of changes emerging during this period. From 2009 to 2014, 25 cities increased their number of LWP centers and 11 cities had fewer centers, while the rest did not change. Notably, 20 cities grew from monocentric cities into polycentric cities, while 8 cities reversed from polycentric cities to monocentric cities. Polycentricity can be deemed unstable, but the general trend of Chinese cities tends towards a higher number of LWP centers.

5.2.2. Morphological changes of LWP centers

The basic morphological changes of centers are reflected in aspects of land scale and land use intensity, and can then be measured by indicators such as the differences in total area and average Floor Area Ratio (FAR) (Hu, Yang, & Shi, 2016). As a reference, the difference in the total area of the center is used to show the changing scale, but FAR difference is replaced with the POI density ratio of LWP centers to reveal the changing intensity. It is clear that changing FAR for POI density is not an equivalent substitution because the number of POIs could fluctuate for reasons independent of the changing area or FAR. LWP centers focus on urban functions represented by POIs, so changes in POI density will be more pivotal where the morphological evolution of the LWP centers is accounted for. Since changes in the number of LWP centers are diverse, only the main centers of the polycentric cities and centers of the monocentric cities are extracted to calculate the area difference and POI density ratio of LWP centers.

(1) Scale change: most city centers increased in size between 2009 and 2014, but 76 city centers shrank. Center shrinkage is not necessarily a phenomenon restricted to small cities; larger cities, such as Shijiazhuang, Zhengzhou, Guangzhou, Shenyang and Shenzhen et al., also experienced shrinking LWP centers.

Statistical results indicate that the size of LWP centers for most of

Table 2
The potential variables contributing to polycentricity.

Category	Variables	Description or source	Reference
Population and transportation	Population	Total population within the central city in 2010	Konishi, 2000; Helsley & Sullivan, 1991; Anas & Kim, 1996; Fujita et al., 1999; Giuliano et al., 2012; McMillen & Smith, 2003
	Population density	Total population within the central city/area of central city in 2010	
	Road density	Total length of urban roads within central district/area of central city in 2014	
	Road junction density	Total amount of road junction within central district/area of central city in 2014	
Natural factors	Whether the central city is divided by rivers or mountains	–	McMillen & Smith, 2003
	Proportion of area within central city whose slopes are < 15%.	According to, China's *Code for vertical planning on urban and rural development land* (CJJ83-2016), the planned slope of a central city should be < 15%.	–
Economic factors	Employment density	Total employment/area of administrative area. Data of total employment and administrative area from statistical yearbook of each province in 2014, http://data.cnki.net/	–
	Per capita income	Statistical yearbook of each province in 2014, http://data.cnki.net/	Fujita & Ogawa, 1982; McMillen & Smith, 2003
	Tertiary industry as percentage of GDP	Statistical yearbook of each province in 2014, http://data.cnki.net/	–

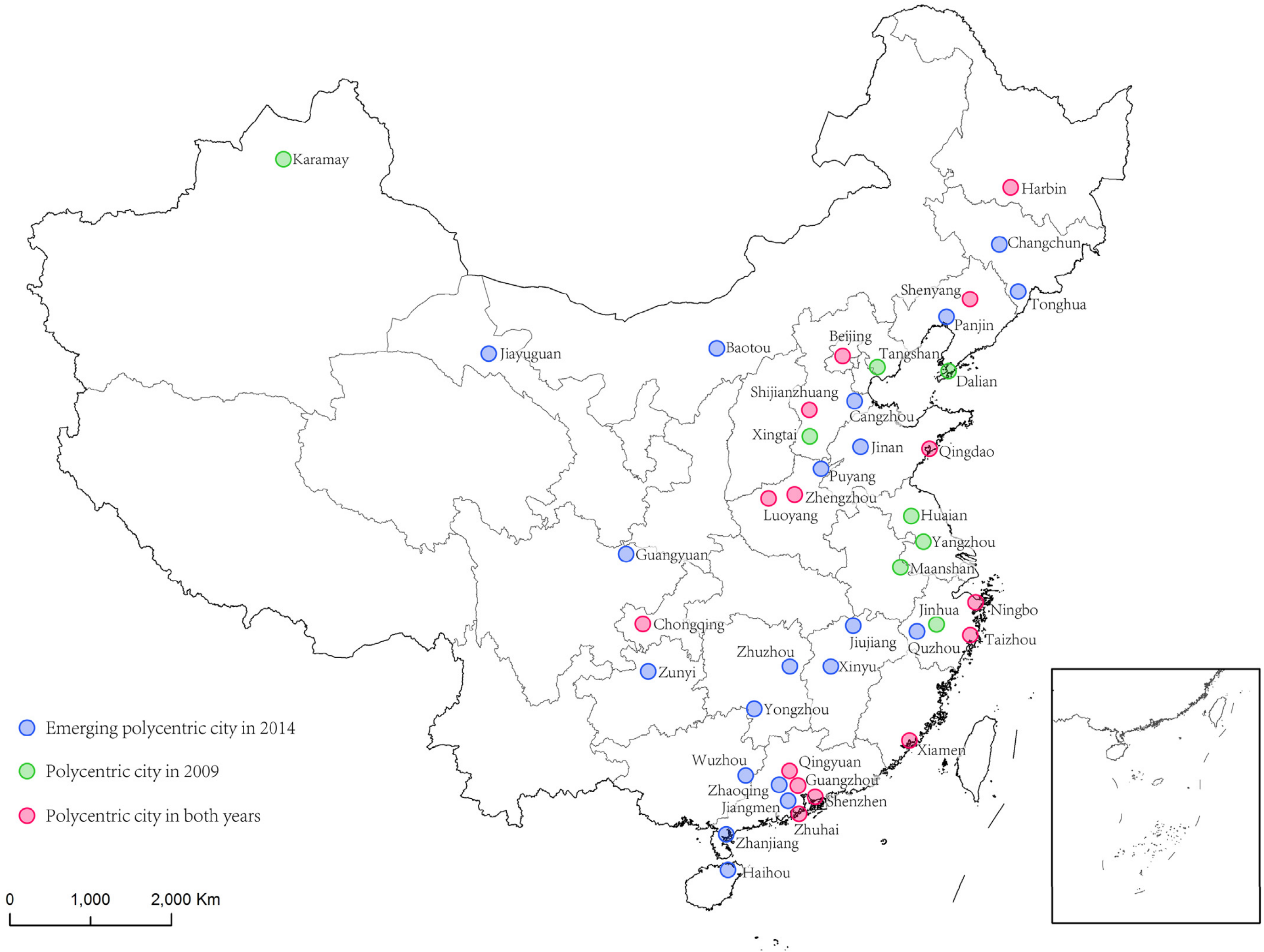

Fig. 1. Distribution of polycentric cities in 2014 and 2009.

the cities did not dramatically change. The rate of area change of LWP centers for more than half of all the cities was < 20%, and more than 80% of the cities changed less than 50%.

(2) Intensity change: Whether growing or shrinking, all LWP centers' POI densities increased. Except for a few cities experiencing extreme growth, most centers had increased POI density in a reasonable extent. The average ratio was 5.097.

Two types of morphological changes can be derived when combining the scale change and intensity change together. One is POI densification with center growth and the other is POI densification with shrinking centers. For the first type, POIs gather faster at the periphery of the original center in order to reach the same class as the original center. LWP centers expand under these conditions. For the second type, there are two possible explanations for the changing periphery of the new centers. One possibility, challenging the first type, is that POIs gather faster at the new center than on its periphery. The other possibility is that, instead of gathering at the periphery of the new center, POI density is decreasing there. Both of these possibilities explain the greater difference between the new center and its periphery and the shrinking LWP center.

The two types of morphological changes may suggest different phases of LWP center development. Theoretically, the morphological relationship between center and its periphery shows similarity to the relationship between the urban central city and its suburban area. Therefore, the process of urban development is used as a reference to verify whether the above morphological changes imply different phases of LWP center development.

The urban evolution model proposed by Peter Hall (1984) has been widely acknowledged (Xu, Zhou, & Ning, 2009). Based on dynamic migration between urban central city and suburban areas, the process of urban evolution can be divided into six phases, which are “concentration with loss”, “absolute concentration”, “relative concentration”, “relative dispersion”, “absolute dispersion”, and “dispersion with loss”. In this study, a variety of POIs, including employment, residence and public service, are used to represent population distribution indirectly. The six phases of urban evolution are thus used to understand the development of LWP centers. According to the above description, the first type of center, which experiences POI densification with center growth, is at the “relative dispersion” phase, and the second type of center, which experiences POI densification with a shrinking center, is either at the phase of “relative concentration” if the periphery becomes densified, or of “absolute concentration” if sparse.

5.2.3. Location changes of LWP centers

As previously noted, location change is detected upon close examination of all centers' areas. Five types of location change for LWP centers are generalized, which are displacement, division, fusion, emerging and recession (Fig. 3), where the most common location change is the displacement type, followed by the emerging type. Not all LWP centers encountered location changes, and most LWP centers simply grow or shrink concentrically. There is also another type of transition where the main LWP center and LWP subcenter switch roles.

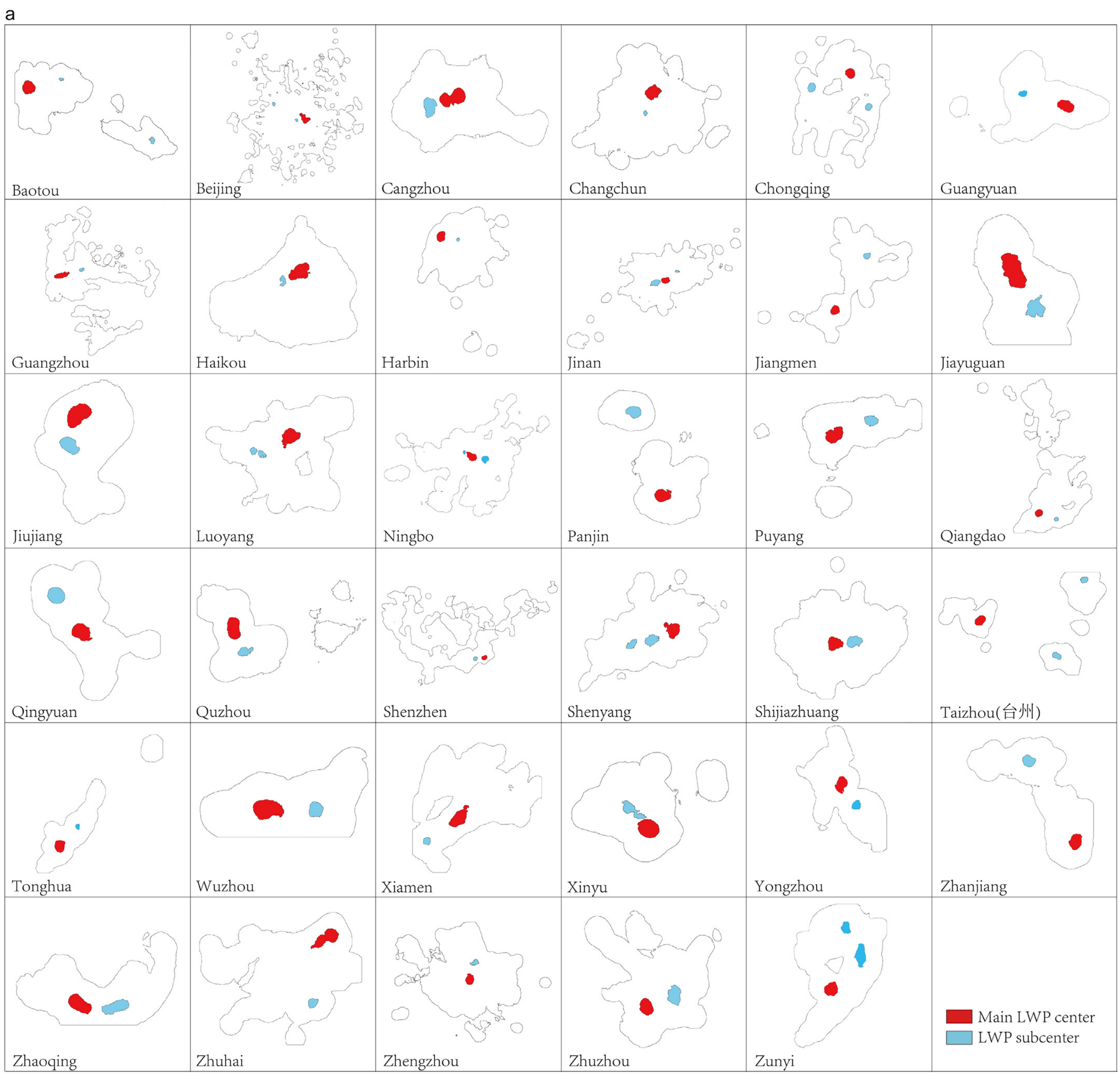

Fig. 2. Polycentric cities in 2014 (a) and 2009 (b).

Between 2009 and 2014, this transition type is represented by cities such as Shijiazhuang, but they are not included in the location change types because they do not represent a simple morphological change.

Except for the Displacement type, all other four types of change are related to a changing number of LWP centers. Specifically, the Fusion and Recession types lead to a decreasing number of centers, and the Division and Emerging types lead to an increasing number of centers. In order to understand how the number of LWP centers change along with the location change, the centroid of each LWP center of polycentric cities from 2014 is extracted and the average distance between LWP centers is calculated for each city. The statistical results show that the average distance of LWP centers within cities is < 3 km in 54% of all cities and < 5 km in 74%, which indicates that LWP centers are located close to each other in the majority of cities. As demonstrated above, Chinese cities tend to develop more centers over time. Combining those evidences, it points to a trend of LWP centers emerging in close proximity to each other, impacting the process of center formation and center growth. This trend is the subject of the following section.

5.3. Impact factors for polycentricity in China

Regression analysis is used to explore the factors that determine the polycentricity of Chinese cities. The Moran's I is first measured for all 285 cities and the result shows that the Moran's I is not significant (with p-value = 0.89 and z-score = 0.14), which means that there is not significant spatial autocorrelation among cities to guarantee their independence in the regression model.

OLS regression is attempted first, but the results show poor performance with *adjusted* R^2 = 0.11. The Poisson model is then evaluated through the Goodness of Fit table generated by SPSS. The conclusion is that the Poisson model fits well since the goodness-of-fit chi-squared test is not statistically significant (with 260 degrees of freedom, p = 1).

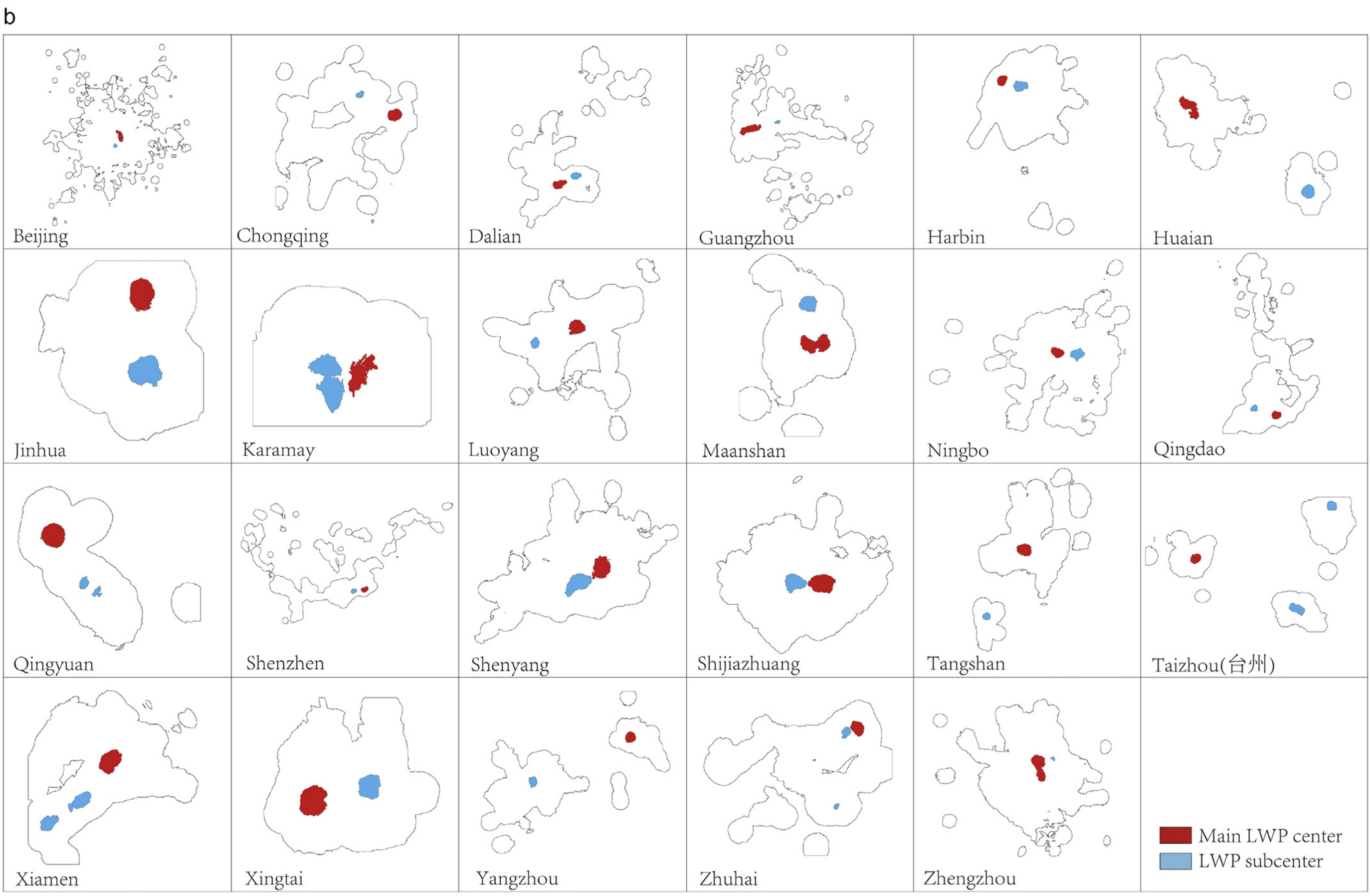

Fig. 2. (*continued*)

Table 3
Changes in numbers of LWP centers from 2009 to 2014.

Type of change	Number of centers		Number of cities	Total
	2009	2014		
Unchanged	1	1	242	249
	2	2	6	
	3	3	1	
Increased	1	2	17	25
	1	3	3	
	2	3	5	
Decreased	3	2	3	11
	2	1	8	
	3	1	0	

To sum up, the Poisson model fits reasonably well in this research.

The Poisson regression results are presented in Table 4. Population and road junction density are proven to be the main determinants of LWP subcenter formation, both of which show positive correlations with the number of LWP centers. In other words, both larger population size and higher road junction density tend to increase the number of subcenters. Other variables are statistically insignificant.

The results are partially consistent with those of McMillen and Smith (2003) regarding population, however, the road junction density results differ. Higher road junction density generally raises accessibility in centers, making POIs more accessible (Shen & Karimi, 2016), and higher accessibility further decreases commuting cost. In short, higher road junction density means lower commuting cost. The Poisson regression results therefore suggest that LWP subcenters arise in the central city as the commuting costs decrease, whereas McMillen and Smith came to the conclusion that "higher commuting costs increase the expected number of subcenters".

The difference in study areas may offer an explanation for why the two studies draw opposite conclusions. McMillen and Smith (2003) use large American urban areas, which largely compare to administrative areas of a city in the Chinese context. As demonstrated in Section 3, an administrative area includes more than one district. Higher commuting costs usually mean lower accessibility and may cause smaller districts to develop their own centers, which become subcenters in the administrative area, distinct from the main center in central cities. Additionally, subcenters tend to develop independently, rather than relying on main centers, partly due to low accessibility preventing support from the centers.

Within a contiguous built-up area, such as the central city, a cooperative relationship must be established among centers, including between main centers and subcenters, in order to develop multi-centers. Higher commuting costs render one-way communication from periphery to main center (the monocentric form) more cost-effective, pushing the main center towards dominance and reducing the necessity of the subcenter. Conversely, lower commuting costs derived from higher accessibility promote the organization of all centers into collaborative networks that contribute to subcenter formation. This conclusion also supports the assumption made in Section 5.2 that LWP centers tend to emerge in close proximity to each other so as to benefit from the higher accessibility. Therefore, the conclusion that the number of LWP centers in a central city increases as the commuting cost decreases is well-founded.

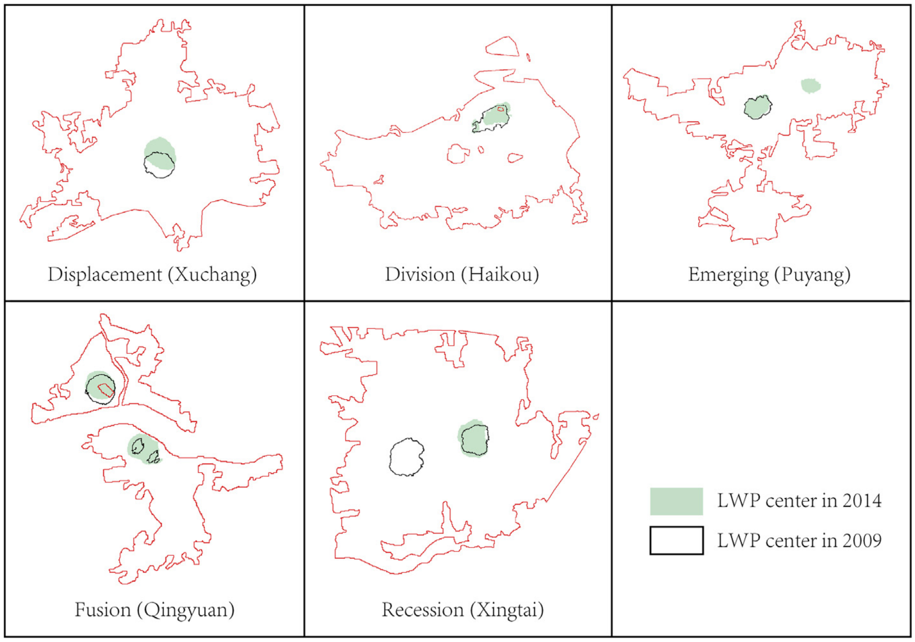

Fig. 3. Examples of location change.

Table 4
Poisson regression results.

Variable	Coefficient	Significance
(Intercept)	0.521 (0.5374)	0.332
No natural barriers	−0.046 (0.0476)	0.330
Tertiary industry as percentage to GDP	0.000 (0.0014)	0.903
Per capita income	0.085 (0.0625)	0.172
Employment density	1.275E-5 (4.8972E-5)	0.795
Slope ≤ 15%	−0.005 (0.0048)	0.299
Population	0.000 (0.0002)	0.035
Pop density	0.024 (0.0499)	0.629
Road junction density	0.006 (0.0029)	0.029
Road density	−0.041 (0.0257)	0.107

Note: numbers in parentheses are the standard error of each independent variable.

6. Conclusions and discussion

6.1. Concluding remarks

This paper has explored the urban structure of Chinese cities based on the concept of LWP centers, function-intensive centers that are of great importance for urban planning and urban spatial studies. Benefiting from the ubiquitously available points of interest data, a proxy for urban function (Gao, Janowicz, & Couclelis, 2017; Yuan, Zheng, & Xie, 2012), LWP centers are identified from the perspective of human activities through the straightforward method proposed, and the temporal evolution of LWP centers in China has been explored. The identification results show that there were 35 polycentric cities in 2014 and 23 in 2009. Based on multi-year identification, the evolution of Chinese LWP centers is identified through three aspects, namely the number of LWP centers, their morphology, and location. Regarding the first, 25 cities developed more LWP centers between 2009 and 2014, 11 cities had fewer centers, and the rest did not change. 20 cities grew from monocentric cities into polycentric cities, which indicates that Chinese cities are trending towards polycentricity. However, exceptions also exist where some cities lost their LWP subcenters and even regressed into monocentric cities. Secondly, regarding the morphology of LWP centers, two changes were witnessed in the combined evidence from the change in scale and intensity of LWP centers, POI densification with center growth and center shrinkage. Three phases of LWP center development are then inferred from the two morphological changes; taking the urban evolution model as reference, these phases are described as “relative dispersion”, “relative concentration” and “absolute concentration” respectively. Third, regarding the location of LWP centers, five types of location change are generalized as displacement, division, fusion, emerging and recession, and the statistical results indicate that LWP centers tend to cluster close together in most cities. In addition to the observations made through LWP center identification and delineation, the factors contributing to the process of LWP center formation is explored through Poisson regression. The results show that larger population and higher road junction density are the main determinants that have significant impact and also validate the assumption that new LWP centers tend to emerge in close spatial proximity to existing centers.

6.2. Academic contributions

There are three major academic contributions to this study. First, the definition of LWP center indicates the multifunctionality of city centers, but the traditional methods concerning single attributes, such as employment, population or the built environment, are not sufficient for their identification. The data used in this research, POIs, which represent the majority of the city functions, enabled the identification of LWP centers. Secondly, this procedure for LWP center identification avoids some of the potential problems that plague existing methods, such as arbitrariness of threshold setting and sensitivity to the spatial scale. Due to the advantages of this procedure, it was possible to conduct the research for a large number of cities, thus providing a great opportunity for understanding how the urban spatial structure has been evolving in China. Third, one of the main characteristics that distinguishes this study is the use of the central city as the study area, rather than the administrative boundaries of cities in China, thus enabling the analysis of a more objective city system in China that accounts for the differences between Chinese cities and cities in western countries.

6.3. Potential bias and future study

There are several potential biases in this study and room for future research. The method proposed in this paper only considers area and

POI density of the LWP centers in its differentiation of main center and subcenter, however, there are alternative approaches for validating that separation, such as integrating land use types derived from remote sensing images.

The number of POIs in LWP centers in each category is highly correlated with the total numbers for each category in central cities, especially for the “Work” and “Play” POIs, with the coefficients being 0.86 and 0.85, respectively, while the proportion of each category in LWP centers shows less correlation with the proportion of each category in central cities, where the coefficient is 0.60. Therefore, questions such as whether different categories of POIs should be treated differently and how to weight them need further exploration.

When emerging data, such as POIs, enables the exploration of new dimensions of urban structure, it also confronts us with challenges of finding appropriate ways to utilize it. This study attempts to break new ground by utilizing new data, but confines the focus to the morphological dimension of urban spatial structure at the intra-city scale. Nevertheless, the partiality of such an attempt needs to be acknowledged. Within all LWP centers, the POIs of “Live” account for the least as expected. As explained in Section 3.2, the number of “Live” POIs are much fewer than for the other two categories, but they possess large floor space and population. As for the POIs of “Work” and “Play”, results show that, except for Beijing, all other cities have more “Play” POIs than “Work” POIs in their LWP centers, and the amount of “Play” POIs is more than twice as many as “Work” POIs in about 64% of all cities. Since the focus of this research is on the morphological change of LWP centers, future research is needed to address the above phenomenon.

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