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The spatial restructuring and determinants of industrial landscape in a mega city under rapid urbanization

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ABSTRACT

we analyzed the evolution of industrial land use in the Shanghai's central city since 1947, with a more detailed analysis of determinants of change in the expanded city area since the economic reform for 2002–2009 and 2009–2016. Relying on land use data extracted from satellite images, air photos, and historic land use maps produced by local experts, we find that industrial land in the central area of Shanghai increased from 1947 to 1993 but declined from 2002 to 2016. The spatial form was transformed from scattered small industrial land pieces interspersed with other types of urban land within the urban core to a polycentric pattern of large patches with greater distances between patches. Using a binary spatial logistic regression on data from 2002 to 2009 and 2009–2016 for an extended area beyond Shanghai's central city, we found that major spatial determinants contributing to the recent conversion of Shanghai's industrial land include land price, the existing industrial land, and the planning policies for both periods and additionally distance to main transport station and economic development level for the period of 2009–2016. Moreover, patches affiliated with different sizes of industrial areas were driven by different sets of spatial determinants. Both large-size patches (>0.1 km^2) and small-size patches (<0.05 km^2) seem to be very sensitive to all spatial determinants, i.e., distances to major roads and to major station, economic development level, existing industrial land, land price, and planning policy, except economic development level for large patches for 2002–2009 and for small-size patches for 2009–2016. Our study provides valuable insights for planners as it highlighted important variables that land use planning can focus in order to achieve effective industrial land conversion. Our study also offers an example of utilizing different sources of data and methods for analyzing a specific type of urban land use change.

1. Introduction

Urbanization and urban land transformation in both the developed and developing countries are closely associated with industrialization and the relocation, expansion, and transformation of industrial land (Davis, 1965; Gollin, Jedwab, & Vollrath, 2016; Leigh & Hoelzel, 2012; Zhang, Yue, Liu, Fan, & Wei, 2018). In the developing world, industrial land conversion has been closely associated with industrialization and economic opportunity, where inter-regional competition has led to a price war in industrial land and low industrial land prices often also resulted in urban sprawl (Gao, Liu, & Dunford, 2014; He, Wei, & Xie, 2008; Liu, Yue, Fan, Peng, & Zhang, 2016; Wu, Zhang, Skitmore, Song,

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& Hui, 2014). Since the economic reform of 1978, Chinese cities have experienced unprecedented urbanization, with the urbanization ratio, i.e., the percentage of urban population of the total population, leaping from 18% in 1978 to over 58% in 2017 (NBS, 2018). The industrial sector played a crucial role in both urban expansion and urban spatial restructuring and the planned industrial development zones have contributed significantly to the urban expansion and urban spatial restructuring (Ma and Wu, 2005). The expansion of the manufacturing sector in Chinese cities has been enabled by enterprises set up through private investment and foreign direct investment (FDI), in addition to the relocation of state owned enterprises from city cores to the extended territory of suburban areas (Ma and Wu, 2005; Wei, Yuan, & Liao, 2013, and 2016, 2010; Zhang et al., 2018).

Chinese cities intrigued the scholars also by their various stages of industrialization. While many Chinese cities have experienced rapid industrialization, a substantial number of Chinese cities, including Shanghai, have experienced relocations of their manufacturing sector to suburbs or even other cities. The manufacturing sector has experienced decentralization from the city center to suburban locations to form agglomeration clusters (Gao et al., 2014; He et al., 2008), including Hangzhou (Duan, Verburg, Zhang, & Yu, 2004; Feng et al., 2005; Liu et al., 2016; Yue, Liu, & Fan, 2010; Zhang et al., 2018), Nanjing (Gao & Yuan, 2017), and Beijing (Gao et al., 2014). Although Shanghai is the largest manufacturing center in China, little English literature on industrial relocation and spatial determinants exist.

As for spatial determinants for industrial land conversion, location factors such as accessibility to market, resources, and labor, economic development, neighborhood situation, and market have been emphasized (Colwella & Munnekeb, 1997; Huang, Cheng, & Zhong, 2009; Qin, Zhang, Huang, & Pu, 2005; Wang, Miao, & Chen, 2007). These determinants were guided by the neoclassicial location theories which indicate that industries tends to locate at where maximum profits can be achieved by the minimal cost (Hayter, 1997; Smith, 1966; Weber, 1929). Moreover, agglomeration economy on manufacturing restructuring, i.e., a large number of companies locating close to one other can lead to cost reduction and gain in efficiency, is highlighted by the new economic geography model that uses sophisticated spatial modeling to explain uneven development and the emergence of industrial clusters (Krugman, 1991). In addition to these market factors, studies on manufacturing relocation in Chinese cities have emphasized the institutional factors, such as development zone, industrial land planning, on industrial land conversion for industrial locations (Wei et al., 2013, 2016, 2010; Gao et al., 2014; Gao & Yuan, 2017; He et al., 2008; Yuan, Wei, & Chen, 2014; Zhang et al., 2018).

Despite the importance of the manufacturing sector for urban economic development and industrial land for urban land transformation in the developing world, there are few quantitative studies that specifically investigate the transformation urban industrial land or to analyze the spatial determinants for the industrial land conversion of mega cities, especially in rapidly urbanizing countries such as China (Zhang et al., 2018). Two major gaps that need special attention. First, most existing studies on China's industrialization focused on enterprise-based studies (Zhang et al., 2018), thus lacking a geographic perspective, i.e., a spatio-temporal pattern of industrial land of Chinese cities. Second, while some studies examined spatial pattern and analyzed spatial determinants for industrial land conversion, the analysis has rather short time span and it is not clear whether or not the government control has been effective in the long-term in guiding the industrial land development, especially vis-à-vis the market force.

This paper assess the urban industrial land transformation and analyze its spatial determinants of Chinese cities by using Shanghai, China's economic center and the largest and earliest manufacturing base since the 1800s, as a case. Here we defined industrial land as land used predominantly for manufacturing purposes. In our classification, industrial lands include not only land for production and storage, but also transportation facilities of ports, railways, and stations located inside of the industrial land patches specifically used for manufacturing. We address the following research questions:

1. What has been the evolutionary pattern of Shanghai's urban industrial land since 1947? How has the evolution been related to the manufacturing policies and economic priorities of the city?
2. What spatial factors have driven the recent industrial land conversion (from 2002 to 2009 and from 2009 to 2016) of Shanghai? Especially, what is the role of spatial planning?

We assessed the evolution of urban industrial land in Shanghai using satellite imagery and land use data and described its characteristics by using several well-known landscape metrics. We then identified major spatial determinants in urban industrial land conversion processes using a logistic model. Our research will contribute to an improved understanding of spatio-temporal pattern and spatial determinants of industrial land in rapidly urbanizing China.

2. Study area, data, and methodology

2.1. Study area

Located at the confluence of the Yangtze River and the East China Sea, Shanghai consists of a peninsula between the Yangtze River and the Hangzhou Bay and several islands in the Yangtze River, including Chongming, Changxing, and Hengsha (Fig. 1) (Yue, Fan, Wei, & Qi, 2014). As the largest city in China with a population of 24 million in 2017, the city has a total area of 6340.5 km^2 and is situated on an alluvial plain with an average elevation of 4 m above sea level (Shanghai Bureau of Statistics, 2018). Huangpu river, a tributary of Yangtze river, divides the city core into two parts, (1) the west of the river that has been the city center since the nineteenth century, and (2) the east of the river, the newly developed Pudong Area since the 1990s (Fan, Xu, Yue, & Chen, 2017b). Within the subtropical monsoon climate zone, Shanghai has distinct four seasons with hot, humid summers and cool, wet winters. The rapid expansion of urban built-up area, its determinants, and its impacts has been well documented for Shanghai (e.g., Fan et al., 2017a & 2017b; Han, Hayashi, & Cao, 2009; Mei, Zhu, Cheng, & Sun, 1997; Xu, Liao, Shen, Zhang, & Mei, 2007; Yue et al., 2014). Urban built-up area in Shanghai grew more than seven times in 30 years, from 76 km^2 in 1979 to 1462 km^2 in 2008 (Yue et al., 2014). Shanghai's fast urbanization is found to be closely associated with economic development, particularly the dynamics of the manufacturing sector, and has brought distinct environmental consequences at the district level (Yue et al., 2014). Furthermore, spatial land planning has affected Shanghai's urban spatial restructuring and industrial land evolution (Ning, 2006; Zeng, 2001). Population, economics, and transportation are the primary spatial determinants for the growth in urban land use in Shanghai from the end of the 1970s to the 2000s (Han et al., 2009; Xu et al., 2007).

Shanghai was forced to open as a port city for foreign trade after China signed the Nanjing Treaty with the United Kingdom in 1842. Although at the time only a small fishing village, it quickly became the most important trading/commercial port city in the lower Yangtze River Delta. Manufacturing boomed, as the city benefited from the investment of both Chinese nationals and foreigners. Many factories, first of their respective types were established in Shanghai, such as, the first papermaking factory by a domestic investor in 1884, the first textile factory by a domestic investor in 1889, the first tobacco factory by a USA investor in 1894, and the first flour production factory by a German investor in 1894 (Gong, 2007). Shanghai achieved its leadership position in China's manufacturing in 1933, when it produced 51% of China's manufacturing output, possessing 43% of China's manufacturing workers and 40% of China's manufacturing assets (Gong, 2007). In 1949, industrial land was concentrated in the former foreign concession areas, centered around the Huangpu District (Fig. 1), with three main areas (1) Yangpu industrial area of 928 ha of textile, printing and

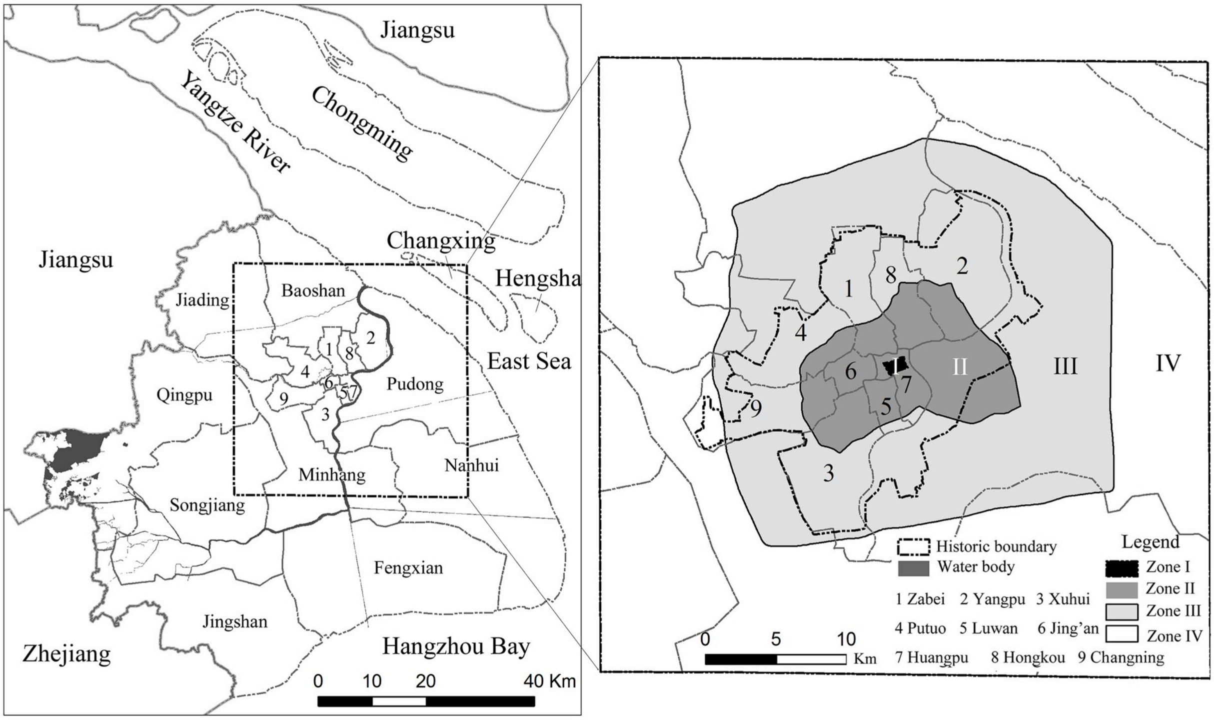

Fig. 1. Study area of Shanghai. The area of 284 km^2, is enclosed by the dashed line (historic boundary) and most of it falls within the Outer Ring Road, including nine central city districts (as indicated by # 1 to # 9 in the legend), and part of the Pudong new district.

dyeing, and machinery manufacturing, (2) Putuo industrial area of 586 ha of textile, printing and dyeing, and grain milling, and (3) Hunan industrial area of 200 ha of ship-building manufacturing, all located along the Huangpu River. Currently, four main industrial clusters are located in the four corners of Shanghai's suburbs: the steel cluster in the north (Baoshan), the petrochemical cluster in the south (Jinshan), the automobile cluster in the west (Jiading), and the high-tech manufacturing cluster in the east (Pudong).

Since historic industrial land data from 1947 to the 1990s are only available for the urban core, we will examine the evolution of the industrial land in the urban core area, defined in Fig. 1. The area is enclosed by the dashed line (historic boundary) and most of it falls within the Outer Ring Road. With a total area of 284 km^2, it includes nine central city districts, namely, Huangpu, Luwan, Xuhui, Changning, Jing'an, Yangpu, Hongkou, Zhabei, Putuo, and part of the Pudong new district. The urban core area clearly is only a very small portion of the entire city and will limit our study because we will not be able to capture the whole picture of the industrial land transformation in Shanghai, particularly the expanded industrial area in Shanghai's suburbs. Nevertheless, as the urban core area of Shanghai has experienced the most intensive conversion from industrial land to non-industrial land, we feel our assessment can provide significant insights of Shanghai's urban industrial land use change.

For our logistic regression model on explanatory determinants for industrial land conversion, we were able to extend our study area much larger than the area for the evolution of urban industrial land, due to the availability of land and other data of 2002, 2009, and 2016 (see the enlarged rectangle portion of Fig. 1). With an area of 1720 km^2, this extended area covers nine central urban districts mentioned above, and partial areas of eight outer districts, i.e., Baoshan, Jiading, Qingpu, Pudong, Songjiang, Nanhui, Minhang, and Changxing Island of Chongming County.

2.2. Data and methodology

2.2.1. Industrial land use data

For historical industrial land dynamic analysis, we use the existing land use maps from 1947 to 2002 (1947, 1958, 1964, 1979, 1984, 1993, 1996 and 2002) that were produced by a research group in East China Normal University. While the 1947 dataset was directly digitized from the land survey map of 1947, the other seven temporal datasets were products of aerial remote sensing surveys of land use in Shanghai. The land use classification scheme was built based on the standard land use classification (GBJ 50137) issued in 2011 by the Ministry of Construction, China (Ministry of Construction, 2011). We extracted industrial land maps from the land use maps. The land planning data of 2020 was digitalized from the land use planning map published by Shanghai Municipal Planning Bureau (Shanghai Urban Planning Bureau, 1999) and used to extract data of planned industrial land.

We derived 2009 industrial land information from a scene of Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER) Level 1B satellite image (date: October 20, 2009; resolution: 15m). The selected ASTER image was clear and nearly free of cloud. COST model was adopted in the atmospheric correction process after the radiometric correction (Chavez, 1996). The resultant image was geometric corrected and rectified with an UTM WGS84 projection (Zone 51N) according to 2002 georeferenced Landsat TM image (ASTER Science Team, 1996; Richards & Jia, 2006). Based on same standard land use classification (GBJ 137–90), we modified our 2009 classification scheme to six main types: water body, green land, farmland, urban built-up, industrial land, and transportation land based on spectral response. Based on the corrected reflectance image and the prior knowledge about the ground truth, we designed a classification scheme of six land types and sampled for each land type. Maximum likelihood classifier was used to classify different land types. The spectral signatures of six land use types were extracted by using the maximum likelihood algorithm with ERDAS 9.1 software. Urbanized lands, except for industrial and transportation purposes, were classified as urban built-up land. The observations and investigations from two field trips conducted in 2010 and 2011 revealed that the industrial lands in Shanghai after 2000 have unique characteristics as the following: 1) in most cases, they are relative far away from the city proper and close to freeways or highways; 2) the industrial buildings/facilities generally tend to have the blue steel roof as this is the normal practice for industrial buildings in Shanghai, making the industrial lands significantly different from other types of urban built-up land; 3) they tend to cluster together, possibly due to the municipal policies that encourage concentration of industrial land use. Using the ground reference data collected during our field trips and high-resolution images from Google Earth, we also conducted an overlay examination to classification for each land type to visually evaluate the classification accuracy and made manual revision when necessary. After a preliminary supervised classification, an elimination procedure was conducted to merge very small patches (<8 pixels).

We randomly sampled 4000 points with a distance of greater or equal to 50 m to assess the accuracy of our classification. We used both the widely adopted kappa coefficient and Pontius Matrix value for our accuracy assessment (Pontius & Millones, 2011). The overall kappa value of our land use classification is 0.80; the kappa value for the industrial land is 85%; and the overall agreement for our classification and the industrial land is 85%. We then extracted the industrial land of 2009 from the classified land use map. For 2016 land use data, we obtained it from Shanghai Municipal Government. While the land use classification data used in this study is from different sources, land use classification is consistent. Furthermore, the definition of industrial land has little change and the classification standard for industrial land is always similar, this can be verified from the spatial distribution industrial land of different years. In order to eliminate the influence caused by stochastic factors such as the tiny patches, we also deleted the patches with area of less than 100 m^2. Therefore, the different datasets does not impact on our goal of revealing of the spatial evolution of industrial land in Shanghai.

2.2.2. Four concentric zones

In light of the conventional divisions of Shanghai city in previous research, a zone delineation system was proposed based on the roads' configuration (Han et al., 2009; Ma, 2009; Ning, 2006; Shanghai Urban Planning Bureau, 1999; Xu et al., 2007). Traditionally, Shanghai has been divided into two parts: one is the area inside the Outer Ring Road, called "central city", the other is the area outside the Outer Ring Road, called suburbs (Ning, 2006). The central city can be further divided into three parts: the area inside the Outer Ring Road as the "central city", the area inside the Inner Ring Road as the "urban core", and the area in the center of the "urban core" as the central business district (CBD) (Ma, 2009; Shanghai Urban Planning Bureau, 1999). Inner Ring Road and the Outer Ring Road are important dividers for spatial policies (Ma, 2009; Ning, 2006; Shanghai Urban Planning Bureau, 1999). For instance, spatial policies aim to "relocate industrial enterprises in the urban core (inside the Inner Ring Road) to make room for service sectors such as finance, commerce and trade" (Ma, 2009). Therefore, for the ease of comparison and to demonstrate the decentralization trend of urban industrial land, we divided the urban core area into four different concentric zones (Fig. 1):

1. Zone 1 (central business district or the CBD zone): the area bounded by People's Square in the west, the Bund in the east, Nanjing Road in the north, and Huaihai Road in the south;
2. Zone 2 (Inner Zone): the area inside of the Inner Ring Road, but outside of the CBD zone;
3. Zone 3 (In-Out Zone): the area between the Inner Ring Road and the Outer Ring Road; and
4. Zone 4 (Outer Zone): the area between the Outer Ring Road and our study area of logistic regression

2.3. Identifying major spatial determinants of urban industrial land conversion

Logistic regression models have been widely used to empirically validate hypothesis concerning the determinants of urban development (Braimoh & Onishi, 2007; Verburg, van Eck, de Nijs, Dijst, & Schot, 2004; Wu, 1998). In this paper, we focus on examining the conversion from non-industrial land to industrial land, rather than vice versa, due to the critical role of industrial land conversion in the expansion of urban built-up area in Chinese cities (Wu, 1998). Therefore, we set the dependent variable Y as a presence or absence event where Y = 1 means a given pixel (20m × 20m) was converted from non-industrial to industrial land from 2002 to 2009 and Y = 0 means the land remained as non-industrial land during the period. Thus P (Y = 1) means the probability of the pixel transforming from non-industrial land to industrial land use; the odds, denoted as P(Y = 1)/[1- P(Y = 1)], is the ratio of the probability that Y = 1 to the probability that Y≠1. The logistic regression model is denoted as follows (Menard, 2001):

$$logit(Y) = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + e \tag{1}$$

where logit (Y), the natural logarithm of the odds, is expressed as a linear combination function of the explanatory variables x_i. Parameters β_i are the regression coefficients to be estimated. The logit (Y) can be transformed back to the probability of (Y = 1):

$$P(Y=1) = \exp\left(\widehat{\beta}_0 + \sum_{i=1}^{n} \widehat{\beta}_i x_i\right) \Big/ \left[1 + \exp\left(\widehat{\beta}_0 + \sum_{i=1}^{n} \widehat{\beta}_i x_i\right)\right] \tag{2}$$

where the estimated values are indicated by the hat notations in Equation (2). To test the hypothesis on the impact of independent variables on industrial land use change, a positive sign of the coefficient means that an increase in the independent variable increases the probability of land use change from non-industrial to industrial. In contrast, a negative sign means the opposite, i.e., the increase in the independent variable decreases the probability of land use change from non-industrial to industrial, whereas the value of zero means an increase in the independent variable does not change the probability of land use change from non-industrial to industrial.

We computed Moran's I values with different weight distances (4 km, 5 km, 6 km, and 10 km) to evaluate the spatial autocorrelation of the dependent variables and found little spatial autocorrelations of the variables. We further used a spatial sampling method to reduce the potential bias in estimating the logistic model as a result of any remaining spatial autocorrelation in the data (Anselin, 1988; Cheng & Masser, 2003). After implementing a 100m systematic sampling, i.e., sampling at an interval of 100 m × 100 m, we applied stratified random sampling to choose roughly 2% of points of land with no industrial conversion (1928), roughly 5% of points for each subset, i.e., 2264, 2778, and 1030 points for large-, medium-, and small-size affiliation industrial land, respectively, resulting in a total of 8000 points (see Section 2.5 for definitions of large-, medium-, and small-size affiliation industrial land).

2.4. Independent variables

Neoclassical location theory assumes the firm or factory makes an optimal decision in location to minimize costs or maximize profits, especially minimizing the transportation cost of raw material and final product (Hayter, 1997; Smith, 1966; Weber, 1929). Based on our literature review on similar studies on industrial land conversion (Colwella & Munnekeb, 1997; Huang et al., 2009; Qin et al., 2005; Wang et al., 2007; Zhang et al., 2018), we selected independent variables that represent influences of accessibility, access to labor, economic development, neighborhood situation, and market and planning for our logistic regression (Table 1a; Fig. 2). First, as accessibility is central to create urban structure (Braimoh & Onishi, 2007; Clark, 2000), transportation cost should be considered. Therefore, we calculated the total travel time to the CBD (T_TIME) through an accumulative summation of the time cost for each grid cell. We generated the cost distance data by using the road network data extracted from the land use maps of 2002 & 2009 of Shanghai, the statistics on the vehicle speed in four zones of Shanghai (Wu & Qi, 2002) and data on the walking speed of the pedestrian (Knoblauch, Letrucha, & Nitzburg, 1996). We also include other independent variables of accessibility, i.e., the distance to major road (D_MRD) and the distance to five major stations and ports in Shanghai (D_Station), including Hongqiao and Pudong International airports, Shanghai and Shanghai South railway stations, and Waigaoqiao Port (Fig. 2).

Second, access to labor may constitute an important determinant for industrial location. Due to the limitation of the data on workers' residence, we use the population density (POP) as a proxy for labor, despite the fact that the residences of some workers can be distant from the industrial locations. Although other studies, such as Han et al. (2009), have found that population is an important spatial determinant for urban expansion in Chinese cities, we are aware of the endogeneity issues related to this variable. Industries may appear in locations where many workers reside, but it is not clear if workers attract industries or industries attract workers. Nevertheless, since we used the population data of 2000 & 2010 from the census, it is unlikely that the population of 2000 & 2010 could be affected by the industrial land conversion that occurred later. We also recognize the complicated effects that the population density might have on industrial sites. On the one hand, a high population density could mean the availability of labor; on the other hand, a high population density may discourage industrial development due to the high land cost or the limited availability of land in the area as the high population density attracts other types of urban land uses, such as commercial or residential land. Based on the population census data of 2000 and 2010 at the neighborhood level, we interpolated population density with a Kriging method (Smith, Goodchild, & Longley, 2007; Yue et al., 2010).

Third, economic development, here indicated by GDP per capita, can have a mixed effect on industrial land conversion. High GDP per capita usually means that the area is equipped with enough resources for industrial development, but it also means that the area may have the preference for developing a service sector. Alternatively, low GDP per capita may imply that the area has limited resources or infrastructure for industrial development; it could also mean that the area is eager to use industrial development as a way to boost economic growth. We are aware of the endogeneity issue with this indicator, as areas mostly occupied by the industrial land might lead to different GDP values than areas mostly occupied by the residential land, making it difficult to evaluate GDP per capita as a potential driver of industrialization. Despite the endogeneity issue, like other similar studies (e.g., Han et al., 2009), we decided to include this independent variable in our model and used the data of GDP per capita of the starting year, at the urban district level (Shanghai Bureau of Statistics, 2002; 2009), since GDP per capita in the starting year is unlikely to be affected by the industrial land conversion afterwards. Based on the GDP per capita data of 2002 & 2009 at the district level, we converted GDP per capita at each district into ArcGIS grid form directly.

Fourth, we include two neighborhood indices, the density of the land that can be potentially converted to the industrial land (POTENTIAL) and the density of the existing industrial land (IND), to investigate the influences of neighborhood configurations. As indicated by Braimoh and Onishi (2007), Caruso, Rounsevell, and Cojocaru (2005; 2007), and Verburg et al. (2004), urban land transformation is affected by neighborhood configurations and the industrial land conversion is not an exception. First, industrial land conversion is constrained by the density of the potential land, i.e., the land that can be potentially converted to the industrial land in the neighborhood. In this paper, potential land does not include the land that is impossible to be converted to the industrial land, such as residential land, water bodies, or land prohibited from industrial land conversion by government laws or regulations. It should be noted that Shanghai is designated as one of the prioritized areas for urbanization in China. There are few regulations on urban land conversion and almost no area is preserved for agriculture land conservation in the study area for the logistic regression; reserved agricultural land is mainly located in outer suburbs such as Chongming, Jinshan, and Qingpu (Shanghai Planning Bureau, 1999). Second, classical and modern location theories have emphasized the agglomeration and clustering tendency of industries (Arthur, 1987; Krugman, 1991; Marshall, 1920; Porter, 1990). Therefore, we are particularly interested in the influence of the density of the existing industrial land, referring to the percentage of the existing industrial land in the 1 km^2 cell in 2002 and 2009, on the industrial land conversion of 2002–2009 and 2009–2016. Similar to other variables such as population density, we used the density of the existing industrial land (IND) of 2002 & 2009. We calculated IND and POTENTIAL as the percentages of industrial land and agricultural land in 1 km $\times$ 1 km grid cells.

Finally, we included independent variables of land price (L_PRICE) and spatial planning policy (POLICY) to evaluate the influence of the market force and the impact of the government planning in our logistic regression models. The cost of land may serve as an important determinant for urban land conversion (Liu, Yue, & Fan, 2011), including industrial land. For instance, the high cost of land near the CBD may be a great deterrent for industrial land conversion. We used an independent variable L_PRICE to represent the land price so that the market influence can be evaluated. We generated our land price data by interpolation based on land transactions from 2005 to 2006 and from 2013 to 2014 in Shanghai, published by the Bureau of Housing and Urban-Rural Development, Shanghai. Furthermore, although China is in the process of transitioning into a market economy, local spatial planning remains vital to the urban development of Chinese cities. The municipal governments usually establish a spatial preference for different land uses through their land use planning maps. To assess the effectiveness of spatial policy on industrial land, we use a proxy POLICY variable (Caruso et al., 2005). We extract the industrial land from the 1999's land use plan map of Shanghai (Shanghai Urban Planning Bureau, 1999). If part or all of the sample's land belongs to planned industrial land, the value for POLICY will be "1", otherwise, it will have a value of 0.

To deal with possible collinearities, we performed a correlation analysis and noticed that some variables are highly correlated, although their coefficients haven't reached the threshold value of 0.8 except the correlation between POP and T_TIME for 2009–2016 (Table 1b). We conducted collinearity diagnostics to further analyze the issue (Table 1c). We adopted the threshold value of 0.6 for tolerance to identify unacceptable collinearities (Brower, Aldrich, Robinson, Zucker, & Greden, 2001; Chan, 2004). Both exercises indicate that the variables POP, POTENTIAL, and T_TIME have significant collinearities with other variables. We therefore removed these three variables in our logistic regression.

2.5. Spatial determinants for different size of patches

As our historic analysis indicates that patches of industrial land become more concentrated and larger over time, it would be interesting to investigate whether or not the industrial land conversion of patches affiliated with different sizes of industrial areas may be driven by different sets of spatial determinants. We therefore classified the converted industrial land according to the sizes of their attached industrial areas of 2009 for the analysis of 2002–2009, namely patches affiliated with large-, medium-, small-size industrial areas. If the industrial area in 2009 is greater than 0.1 km^2, any newly converted patch that belongs to this industrial area is categorized as a large-size affiliation patch. If the industrial area in 2009 is smaller or equal to 0.05 km^2, any newly converted patch that belongs to this industrial area is classified as a

Table 1
Logistic regression and independent variables used.

a) Descriptive statistics of independent variables

Variable name	Description	Source	Pre-processing method	Year	Mean	Std. Dev.	Min	Max
T_TIME	Accumulative time cost to CBD (hours)	Road network extracted from the land use map of Shanghai, 2002&2009	Calculated the time cost travel to CBD by using spatial analysis tool	2002	0.72	0.28	0	2.46
				2009	0.54	0.19	0.01	1.09
D_MRD	Distance to major roads (km)	Land use map of Shanghai, 2002&2009	Calculated the distance to the nearest main road for each cell	2002	0.88	0.79	0	7.89
				2009	0.63	0.56	0	3.88
D_Station	Distance to main transport stations and ports (km)	Generated the data layer of stations and ports by ourselves	Calculated the Euclidean distance to the nearest station or port	2002	10.36	4.52	0.2	26.2
				2009	10.48	5.04	0	26.51
GDP	GDP per capita (10,000 RMB/person)	GDP data at district unit from the yearbook of Shanghai (Shanghai Bureau of Statistics, 2002&2009)	Manually input and convert to ArcGIS grid	2002	3.68	2.25	0.52	7.25
				2009	7.33	2.45	4.39	24.31
POP	Population density (10,000 people/km^2)	2000&2010 National Census data at street (Jiedao) unit from National Bureau of Statistics, 2000&2010	Used interpolation of street centroid to create the population density surface based on thepopulation density measured in the street	2000	1.04	0.9	0.11	5.59
				2010	1.50	0.90	0.16	5.54
L_PRICE	Land cost per (1,000RMB/m^2)	Land transaction data (BHPS, 2005–2006&2013–2014)	located the land transaction records and interpolated with the Kriging method to create the raster data of land price	2005–2006	5.58	4.81	0.29	51.1
				2013–2014	17.30	20.34	1.93	115.62
IND	Percentage of existing industrial land in the cell (%)	Land use map of Shanghai, 2002&2009	Calculated for all spatial units of 1 km^2 net by using the 2002 land use data.	2002	22.83	19.49	0	95
				2009	19.98	14.79	0	98
POTENTIAL	Percentage of potential land that can be transformed to industrial land (%)	Land use map of Shanghai, 2002&2009	Calculated for all spatial units of 1 km^2 net by using the 2002 land use data.	2002	30.93	24.44	0	94
				2009	14.69	15.91	0	73
POLICY	Dummy variable for whether or not the cell falls in 2020's plan for industrial land	2020's land planning map (Shanghai Urban Planning Bureau, 1999)	Digitalized from 2020's land planning map	1999	0.12	0.32	0	1

b. Correlation analysis for independent variables for all patches (2002–2009 and 2009–2016)

2002–2009

	T_TIME	D_MRD	D_Station	GDP	POP	L_PRICE	IND	POTENTIAL	POLICY
T_TIME	1								
D_MRD	***0.5142***	1							
D_Station	0.4593	0.1359	1						
GDP	0.2916	−0.0429	0.0798	1					
POP	***−0.7073***	−0.2374	***−0.6199***	−0.268	1				
L_PRICE	**−0.553**	−0.2117	−0.4656	−0.1127	***0.771***	1			
IND	−0.2955	−0.1653	−0.2438	−0.0725	0.1747	0.0135	1		
POTENTIAL	***0.5972***	0.3224	***0.509***	0.2321	***−0.6139***	−0.4466	***−0.5619***	1	
POLICY	−0.1216	−0.0728	−0.1115	−0.0256	0.1248	0.0457	0.3717	−0.2773	1

2009–2016

	T_TIME	**D_MRD**	**D_Station**	**GDP**	**POP**	**L_PRICE**	**IND**	**POTENTIAL**	**POLICY**
T_TIME	1								
D_MRD	0.3781	1							
D_Station	***0.7469***	0.1986	1						
GDP	−0.1219	−0.1115	−0.0681	1					
POP	***−0.8709***	−0.3243	***−0.6731***	0.1279	1				
L_PRICE	***−0.6883***	−0.2452	−0.3817	0.4135	***0.6836***	1			
IND	0.1723	0.0442	0.1087	−0.2642	−0.2202	−0.3073	1		
POTENTIAL	***0.7575***	0.3304	***0.6228***	−0.0089	***−0.708***	−0.4555	−0.1179	1	
POLICY	−0.0642	−0.0375	−0.0762	0.0052	0.0685	0.03	0.1565	−0.1358	1

Note: 1. Bolded values are larger than 0.5.

c. Collinearity diagnostics for all patches (2002–2009 and 2009–2016)

Variable	VIF		SQRT VIF		Tolerance		R-Squared	
	02–09	09–16	02–09	09–16	02–09	09–16	02–09	09–16
D_MRD	1.08	1.08	1.04	1.04	0.9225	0.9249	0.0775	0.0751
D_Station	1.38	1.21	1.17	1.1	0.7267	0.8285	0.2733	0.1715
GDP	1.03	1.25	1.01	1.12	0.9755	0.7978	0.0245	0.2022
L_PRICE	1.36	1.53	1.17	1.24	0.7357	0.6546	0.2643	0.3454
IND	1.27	1.17	1.13	1.08	0.7857	0.8545	0.2143	0.1455
POLICY	1.16	1.04	1.08	1.02	0.8602	0.9631	0.1398	0.0369

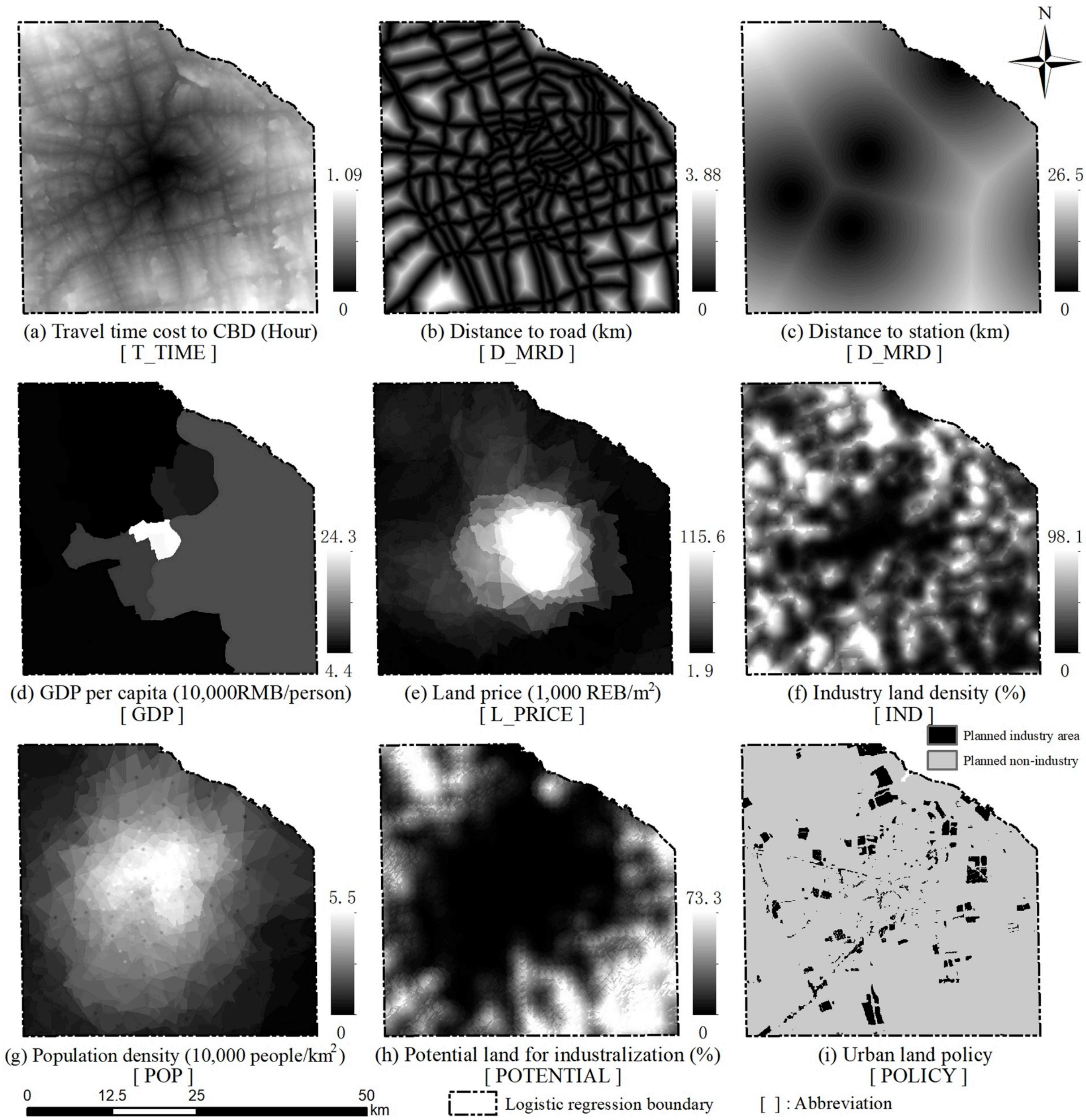

Fig. 2. Explanatory variables of industrial land conversion, including (a) travel time cost to CBD, (b) distance to road, (c) distance to station, (d) GDP per capita, (e) land price, (f) industrial land density, (g) population density, (h) potential land for industrialization, and (i) urban land policy.

small-size affiliation patch. The rest of the patches, i.e., those are affiliated with the industrial area greater than 0.05 km^2 but smaller than or equal to 0.1 km^2 are the medium-size affiliation patches. We then randomly selected roughly 5% points from each of the large-, medium- and small-size affiliation patches and applied the same logistic regression model for points in each category. For the period of 2009–2016, we used the same method and classified converted industrial land according to the sizes of their attached industrial areas of 2016. To ensure the balanced sample numbers for all categories, we chose the dividing line of patch sizes through the analysis of histogram distribution.

3. Results

3.1. Historic industrial land use change in Shanghai

Shanghai's industrial land increased rapidly from 1947 to 1993 but decreased from 2002 to 2016 (Table 2). Shanghai's total industrial land in the historical study area expanded almost 4 times from 13.99 km^2 in

Table 2
Area of industrial land in Inner Zone (Zone 2) and Outer Zone (Zone 3), 1947–2016, km^2, (%) of industrial land in the zone.

	1947	1958	1964	1984	1993	2002	2009	2016
ZONE 2	9.23 (9.1%)	10.24 (10.1%)	13.87 (13.7%)	15.81 (15.6%)	14.85 (14.6%)	9.05 (8.9%)	4.34 (4.3%)	3.28 (3.19%)
ZONE 3	4.76 (2.7%)	8.86 (5.0%)	22.9 (13.0%)	35.89 (20.4%)	37.94 (21.5%)	40.93 (23.2%)	31.33 (17.8%)	21.93 (12.13%)
Total	13.99 (5.0%)	19.1 (6.9%)	36.76 (13.2%)	51.7 (18.6%)	52.79 (19.0%)	49.99 (18.0%)	35.67 (12.8%)	25.21 (8.89%)

1947 to 52.79 km^2 in 1993, then started to decline from 2002, leading to 25.21 km^2 in 2016, less than half of that of 1993 (Table 2). However, Zones 2 and 3 have experienced distinct trends, as Zone 3's decline of industrial land came much later than that of Zone 2. Zone 2 experienced an increase of industrial land by 50%, from 9.23 km^2 in 1947 to 15.81 km^2 in 1984, and then started to decline in 1993 and shrank to 3.28 km^2 in 2016, about 20% of its figure in 1984. Initially only occupied 4.76 km^2 in 1947, industrial land in Zone 3 experienced a dramatic expansion of 9 times and reached 40.93 km^2 in 2002. Its decline started in 2009, resulting in 21.93 km^2 in 2016, about half of its figure in 2002.

Visually, we observed that Shanghai's urban industrial lands have transformed from scattered small industrial land pieces interspersed with other types of urban land concentrated along the Huangpu River and the Suzhou Creek within the urban core to a polycentric pattern of large patches with greater distances between patches, which here we describe it as transforming from a hybrid mono-centric form to a specialized polycentric one (Fig. 3). Until 1958, most industrial land appeared to be located on both sides of the Huangpu River and the Suzhou Creek, although the north-south axis (Huangpu River) was clearly dominant and the east-west axis (Suzhou Creek) was secondary. Most of the industrial land was located in Zone 2 (within the Inner Ring Road) except for industrial land along the Huangpu River along both the north and south ends. Since 1964, we witnessed a much faster growth of the industrial land in Zone 3 (outside of the Inner Ring Road) in addition to the original two axes.

3.2. Major determinants of industrial land conversion

We have identified several spatial variables that significantly influenced the conversion of industrial land (Table 3). They are: land price (L_PRICE), existing industrial land (IND), and industrial land planning (POLICY) for both periods of 2002–2009 and 2009–2016 and additionally distance to main transport station (D_Station) and economic development level (GDP) for 2009–2016. We measured the performance of our models by the values of relative operating characteristic statistic (ROC) (Pontius & Schneider, 2001; Swets, 1986). We consider our models successful as the values of ROC range from 0.64 to 0.88 (Tables 3, 4a, 4b, 4c) for the eight models (4 models for 2002–2009, 4 models for 2009–2016), comparable to other studies on spatial determinants of land use changes (e.g., Braimoh & Onishi, 2007; Liu et al., 2011; Verburg et al., 2004). Also, when the p-values are <0.001, we consider those spatial determinants significant.

For the general model (Table 3), first, land price (L_PRICE) has a negative impact on industrial land conversion. The increase in land price by 1000 RMB/m^2 decreases the odds of industrial land conversion by 9% for 2002–2009 and by 1% for 2009–2016. Second, the high percentage of the existing industrial land in the neighborhood (IND) encourages industrial land conversion, as an increase in the density of the existing industrial land by 1% increases the odds of industrial land development by 4% for 2002–2009 and 8% for 2009–2016. Finally, the policy dummy variable (POLICY) has a positive effect on industrial land conversion as areas in planned industrial zones are 1.87 times for 2002–2009 and 1.18 times for 2009–2016 more likely to be converted from non-industrial land to industrial land. The ROC value is 0.72 and 0.79, respectively, for the two periods, indicating a reasonable fit while at the same time also indicating that the variables used only explain part of the spatial variation in industrial land conversion.

3.3. Spatial determinants for different size of patches

Conversion of urban industrial land conversion affiliated with different sizes of industrial land was driven by slightly different sets of spatial determinants (Tables 4a–4c). Corresponding to the overall model, land price (L_PRICE) and the percentage of existing industrial land in the neighborhood (IND) are significant for all converting patches affiliated with different sizes of industrial land, confirming the importance of these determinants. However, the policy dummy variable (POLICY) has different effects on patches affiliated with different sizes of industrial land for 2002–2009 while it has significant impact on patches of different sizes for 2009–2016. For the period of 2009–2016, while POLICY encourages industrial conversion of patches affiliated with large-size industrial land, it discourages the industrial land development

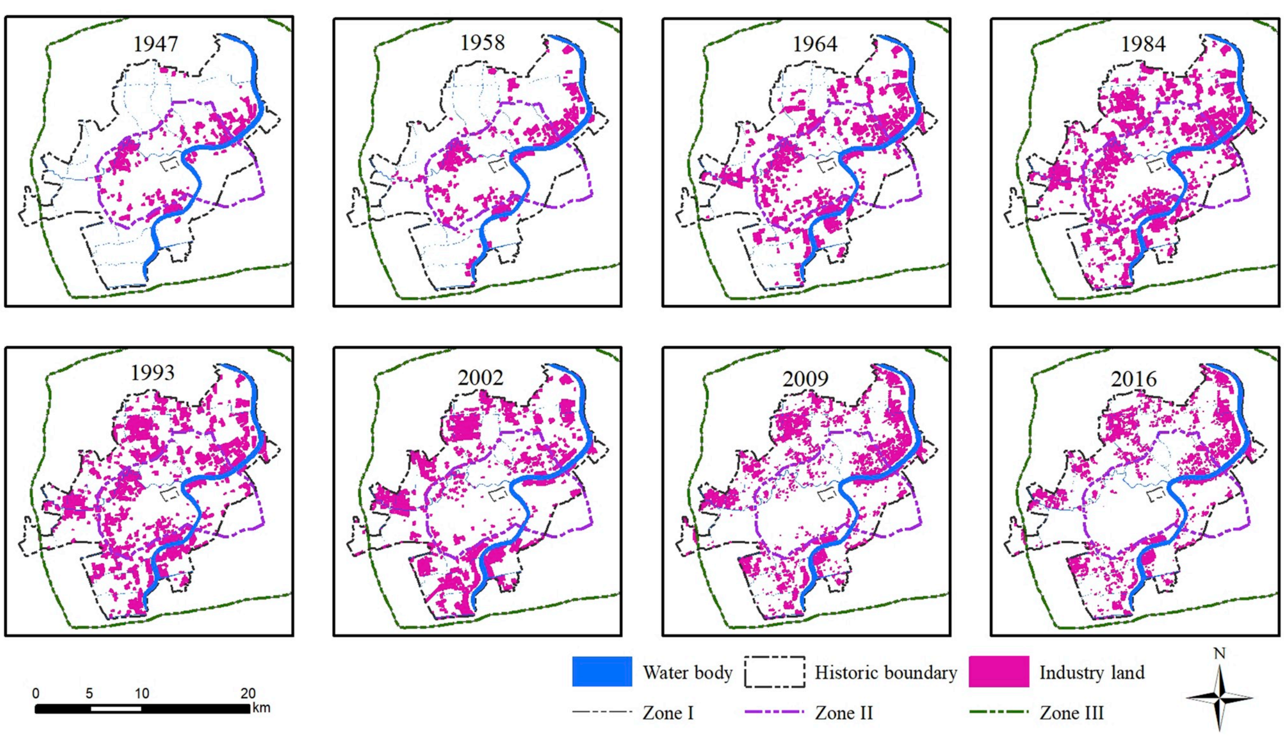

Fig. 3. Industrial land use of Shanghai (1947–2016). Shanghai's industrial land in our study area increased rapidly from 1947 until 1993 then the industrial land decreased from 2002 to 2016. Its spatial pattern was transformed from a hybrid mono-centric one in early years to a specialized polycentric one in the 2000s.

Table 3
Estimation results of the logistic regression model for urban industrial land conversion in Shanghai (2002–2009 and 2009–2016).

Variables	Coefficient (β)		Standard Deviation		P-value		Exp(β)		z-Scores	
	02–09	09–16	02–09	09–16	02–09	09–16	02–09	09–16	02–09	09–16
D_MRD	−0.05	−0.02	0.03	0.05	0.131	0.699	0.95	1.05	−1.51	−0.39
D_Station	0.00	0.03	0.01	0.01	0.811	<0.001**	1.00	1.01	0.24	4.46
GDP	0.00	0.04	0.01	0.01	0.914	0.004**	1.00	1.01	−0.11	2.89
L_PRICE	−0.09	−0.01	0.01	0.00	<0.001**	<0.001**	0.91	1.00	−13.86	−3.55
IND	0.04	0.08	0.00	0.00	<0.001**	<0.001**	1.04	1.00	19.18	31.60
POLICY	0.62	0.60	0.12	0.16	<0.001**	<0.001**	1.87	1.18	5.06	3.70
Constant	0.96	−1.43	0.13	0.15	<0.001**	<0.001**				
Likelihood-ratio statistic	−3967.43	−3729.05								
ROC value	0.72	0.79								
Numbers of sample	8000	8000								

Note: 1. 'β' means coefficient. 'SD' is standard deviation. 'Exp(β)' is factor change in odds for unit increase in variables.
2* Significant at 5%; ** Significant at 1%.

Table 4
Estimation results of the logistic regression model for urban industrial land conversion with different size patches in Shanghai (2002–2009 and 2009–2016).

a. Large-size patches

Variables	Coefficient (β)		Standard Deviation		P-value		Exp(β)		z-Scores	
	02–09	09–16	02–09	09–16	02–09	09–16	02–09	09–16	02–09	09–16
D_MRD	−0.14	0.15	0.05	0.06	0.008**	0.018*	0.87	1.16	−2.64	2.36
D_Station	−0.07	0.06	0.01	0.01	<0.001**	<0.001**	0.93	1.06	−6.73	6.21
GDP	0.00	0.20	0.02	0.02	0.993	<0.001**	1.00	1.22	0.01	10.20
L_PRICE	−0.22	−0.01	0.01	0.00	<0.001**	0.004**	0.80	0.99	−15.10	−2.84
IND	0.05	0.12	0.00	0.00	<0.001**	<0.001**	1.05	1.13	21.94	32.45
POLICY	1.39	0.65	0.13	0.20	<0.001**	0.001**	4.01	1.91	10.47	3.28
Constant	0.77	−5.01	0.20	0.23	<0.001**	<0.001**				
Likelihood-ratio statistic	−2090.48	−2004.75								
ROC value	0.83	0.88								
Numbers of sample	4192	4557								

b. Medium-size patches

Variables	Coefficient (β)		Standard Deviation		P-value		Exp(β)		z-Scores	
	02–09	09–16	02–09	09–16	02–09	09–16	02–09	09–16	02–09	09–16
D_MRD	−0.13	0.18	0.04	0.06	0.001**	0.018*	0.88	1.20	−3.18	2.59
D_Station	0.01	0.00	0.01	0.01	0.125	<0.001**	1.01	1.00	1.53	0.08
GDP	−0.03	−0.01	0.01	0.02	0.048*	<0.001**	0.97	0.99	−1.98	−0.35
L_PRICE	−0.07	0.00	0.01	0.00	<0.001**	0.004**	0.93	1.00	−9.50	−1.55
IND	0.03	0.08	0.00	0.00	<0.001**	<0.001**	1.03	1.08	15.02	22.98
POLICY	−0.22	0.68	0.15	0.20	0.155	0.001**	0.81	1.98	−1.42	3.37
Constant	0.28	−2.23	0.14	0.23	0.052	<0.001**				
Likelihood-ratio statistic	−2967.47	−1856.97								
ROC value	0.68	0.80								
Numbers of sample	4706	3415								

c. Small-size patches

Variables	Coefficient (β)		Standard Deviation		P-value		Exp(β)		z-Scores	
	02–09	09–16	02–09	09–16	02–09	09–16	02–09	09–16	02–09	09–16
D_MRD	0.10	−0.19	0.04	0.06	0.018*	0.002**	1.10	0.83	2.38	−3.14
D_Station	0.03	0.03	0.01	0.01	0.002**	<0.001**	1.03	1.03	3.04	4.05
GDP	0.06	−0.02	0.02	0.02	<0.001**	0.213	1.07	0.98	3.49	−1.24
L_PRICE	−0.07	−0.01	0.01	0.00	<0.001**	0.006**	0.93	0.99	−6.41	−2.76
IND	0.01	0.05	0.00	0.00	0.046*	<0.001**	1.01	1.05	2.00	16.65
POLICY	−0.55	0.50	0.23	0.19	0.018*	0.009**	0.58	1.65	−2.37	2.62
Constant	−0.96	−0.99	0.19	0.18	<0.001**	<0.001**				
Likelihood-ratio statistic	−1836.27	−2562.74								
ROC value	0.64	0.70								
Numbers of sample	2958	4048								

Note: 1. 'β' means coefficient. 'SD' is standard deviation. 'Exp(β)' is factor change in odds for unit increase in variables.
2.* Significant at 5%; ** Significant at 1%.

for patches affiliated with small-size industrial land, and is not significant for patches affiliated with medium-size industrial land. In addition, although accessibility reflected by the distance to major roads (D_MRD) and the distance to major stations (D_STATION) do not seem to be significant in the overall model, they are significant determinants for patches affiliated with different sizes of industrial areas. While distance to major road (D_MRD) discourages the industrial land development for patches affiliated with large- and medium-size industrial areas in 2002–2009, it encourages industrial land conversion of patches affiliated with small-size industrial areas 2002–2009. But this pattern switched for 2009–2016, i.e., distance to major road (D_MRD) encourages the industrial land development for patches affiliated with large- and medium-size industrial areas in 2009–2016, but discourages industrial land conversion of patches affiliated with small-size industrial areas 2009–2016. Similarly, while distance to stations (D_Station) discourages the industrial land development for patches affiliated with large industrial areas for 2002–2009, it encourages industrial land conversion for patches affiliated with small industrial areas for both 2009–2009 and 2009–2016. It is interesting to note that while GDP encourages industrial land conversion of patches affiliated with small-size industrial areas, it discourages industrial land conversion of patches affiliated with medium-size industrial areas, and is not a significant determinant for industrial land conversion of patches affiliated with large-size industrial areas for 2002–2009. However for the period of 2009–2006, GDP encourages industrial land conversion of patches affiliated with large-size industrial areas.

Overall, large-size patches seem to be very sensitive to almost all spatial determinants (except GDP for 2002–2009). For medium-size patches, while easy access to major roads as well as low GDP encourages industrial land conversion for 2002–2009, easy access to major roads, low land price, existing industrial land, and industrial planning policy encourage industrial land conversion for 2009–2016. For small-size patches, all spatial determinants have an effect for both periods except GDP for 2009–2016. We also notice that the ROC values indicate a relatively better fit of the model of large-size patch but a poorer fit for the models of medium- and small-size patches, as compared to the fit for all sizes together for both 2002–2009 and 2009–2016.

4. Discussion

Our findings on industrial land evolution and spatial determinants can contribute to the understanding Shanghai's industrial land evolution as well as its industrialization. In this section, we first present a comprehensive summary of our empirical results and their direct implications, first on the evolution pattern of industrial land, then on spatial determinants. In particular, we analyze how market and planning policy have influenced industrial land conversion in recent years. We then further reflect on our findings in the historic context of Shanghai's industrialization, emphasizing the role of planning in shaping Shanghai's industrial landscape since the 1950s. Following that, we analyze the current conditions and the prospect of the industrial sector in Shanghai. We end the discussion with thoughts on limitations of our research.

4.1. Evolution of industrial land and implications

We have found that while Shanghai's industrial land expanded until the early 1990s, it started to decline afterwards, with a spatial pattern transformed from scattered small industrial land areas interspersed with other types of urban land concentrated within the urban core to a polycentric pattern of large patches with further distances between patches mainly located in suburbs in recent years. As Fig. 3 illustrates, small patches of industrial land have gradually disappeared in the central part of the city. Although our study area is smaller than Xu et al. (2007), the spatial evolution pattern is consistent with their finding on Shanghai's overall industrial land pattern from 1979 to 2002.

Our results suggested that different parts of Shanghai have followed distinct paths for industrial land evolution. Some parts of Shanghai experienced industrialization while others went through de-industrialization or industrial restructuring. While districts in Shanghai's outer suburb, such as Jiading, Baoshan, and Jinshan, have significantly increased their industrialization in terms of industrial output, employment in the industrial sector, districts in Shanghai's urban core, such as Yangpu, suffered declines and the relocation of most of their manufacturing enterprises. Meanwhile, districts in transition, such as Pudong, present a more complicated case. Although Pudong increased in industrial output and land use, some industries were forced to move out of the district such as the Shanghai Shipyard and Shanghai No. 3 Steel, to make room for Pudong's producer services and rising high-tech industrial sites, e.g., Zhangjiang High-tech Park. We echo Kabisch, Haase, and Haase (2010) that urban land transformation has been influenced by the differing supply and situation of locally available social, economic, and other infrastructures. Thus, treating a city homogeneously is inappropriate and there is a great need to examine the land evolution at the sub unit, such as the district level, and at a specific land use function, such as industrial land.

4.2. Spatial determinants: market logic, clustering effect, and planning policies

Our spatial determinant analysis indicated that land price, existing industrial land, and industrial land planning are the main significant spatial determinants for the industrial land conversion from 2002 to 2009 and from 2009 to 2106. These results further corroborated the importance of both market logic and planning policies as spatial determinants for urban industrial land use. First, the negative impact of land price on industrial land conversion implied that cost is an important determinant in acquiring land for industrial purpose. Land of high cost, usually due to advantageous locations, attracts many different uses. Therefore, only those that have the highest returns dominate. Since industrial activities usually cannot produce returns per unit as high as commercial activities or high-density residential living, they tend to stay away from high-cost urban land. The significance of the land price in industrial land conversion implied that the recently established urban land market in China may have been in fact played an essential role in guiding the urban development process (Ma and Wu, 2005). With the implementation of land markets in urban China, urban expansion and restructuring activities within Chinese cities have increased. Industries seek low cost locations with good accessibility, which usually can be found at the urban periphery with easy access to railways, ports, etc. For instance, according to Shanghai Real Estate and Land Bureau's land price statistics, the price of industrial land in city core is 5 times that of the suburbs (Zeng, 2001). Our logistic regression for both periods found that the lower land cost encourages industrial land conversion whereas the increasing distance to major roads and stations discourages large-size industrial land development. Looking back into Shanghai's history of industrial development, the city's earliest factories and industrial land were clustered around Huangpu River in Yangpu District, a low cost land at the time yet with good water transportation.

Second, the significance of the existing industrial land in the neighborhood affirmed the neighborhood effect (Braimoh & Onishi, 2007; Liu et al., 2011; Verburg et al., 2004) and the industrial clustering effect that have populated the literature, which basically articulates that the clustering of industries/firms achieves economies of scale (Arthur, 1987; Krugman, 1991; Marshall, 1920; Porter, 1990).

Third, the positive effect of the policy dummy variable on industrial land conversion indicates the effectiveness of the government policy in guiding the industrial land development process in Shanghai for the study period (2002–2009). Our findings provided evidence to the claim that spatial planning affected Shanghai's urban spatial restructuring and industrial land evolution (Ning, 2006; Zeng, 2001). It also confirmed that urban spatial structure has been heavily influenced by spatial policies in Chinese cities, such as in Wuhan, Hangzhou, and Guangzhou (Cheng & Masser, 2003; Liu et al., 2011; Wu, 1998). We would like to emphasize that it is clear that planning policy has influenced the industrial land development both during the socialist planning period and in the market reform period. We will further entail how two industrial waves in the period of 1949–1978 dramatically changed the industrial landscape of Shanghai through the creation of five satellite towns, ten industrial zones, and two industrial cities in the next subsection.

After the economic reform, to better accommodate the development for both industrial and service sectors, the municipal government rearranged the spatial distribution of industrial and service sectors and mandated that industrial activities be gradually concentrated in the large existing or newly established industrial development zones with modern infrastructure, most located in suburban areas (Ma, 2009). At the same time industrial activities located in the urban core, mostly in small industrial land, were relocated or shuttered (Ma, 2009). Our findings on the different effects of planning on patches affiliated with different sizes of industrial land reflected the effectiveness of these policies on concentrating industrial activities in large patches. For instance, Shanghai's suburb has 97.6% of the total land area for industrial zones, whereas the urban core has a mere of 2.4% land area devoted to industrial zones (Wang & Lin, 2009).

Finally, the findings on the various effects of economic development level (measured by GDP per capita) on industrial land conversions of patches affiliated with different-size industrial areas suggested that large-scale industrial land conversion is less sensitive to the local socio-economic situation but rather to the physical conditions of the localities (accessibility) or policy and price. For instance, the significances of distance to major road and distance to stations indicated that accessing transportation nodes for industrial activities of large-size patches and moving large numbers of workers. In contrast, areas of high economic development level may be particularly attractive to certain small-scale high-tech industries that are sensitive to local economic conditions, but are not attractive to medium-scale industries probably due to the intense competition from other types of land uses. It would be interesting to verify these through further classifying the industrial land according to their sectors. It is worth mentioning that Han et al. (2009) found that economics (measured by GDP) is one of the primary determinants for urban growth in Shanghai.

4.3. Evolution of the industrial land and Shanghai's industrialization

Two waves of industrialization have facilitated the expansion of the industrial land in the socialist planning period in Shanghai, forming the base map of today's industrial land distribution (Fig. 4). The first wave is related to Shanghai's significant expansion of its administrative area and its industrial strategy to establish 10 industrial zones and 5 industrial satellite towns. After 1949, Shanghai experienced significant changes of boundaries of the city and its various districts. Its land area had two substantial increases, gaining most from lands originally part of the Jiangsu and Zhejiang provinces. In 1958, Shanghai's land increased from 638.18 km^2 to 5910.01 km^2 as the central government allowed Shanghai to annex10 counties of Jiangsu Province. In 1970, Shanghai's land area further increased to 6185.48 km^2. Shanghai's industrialization

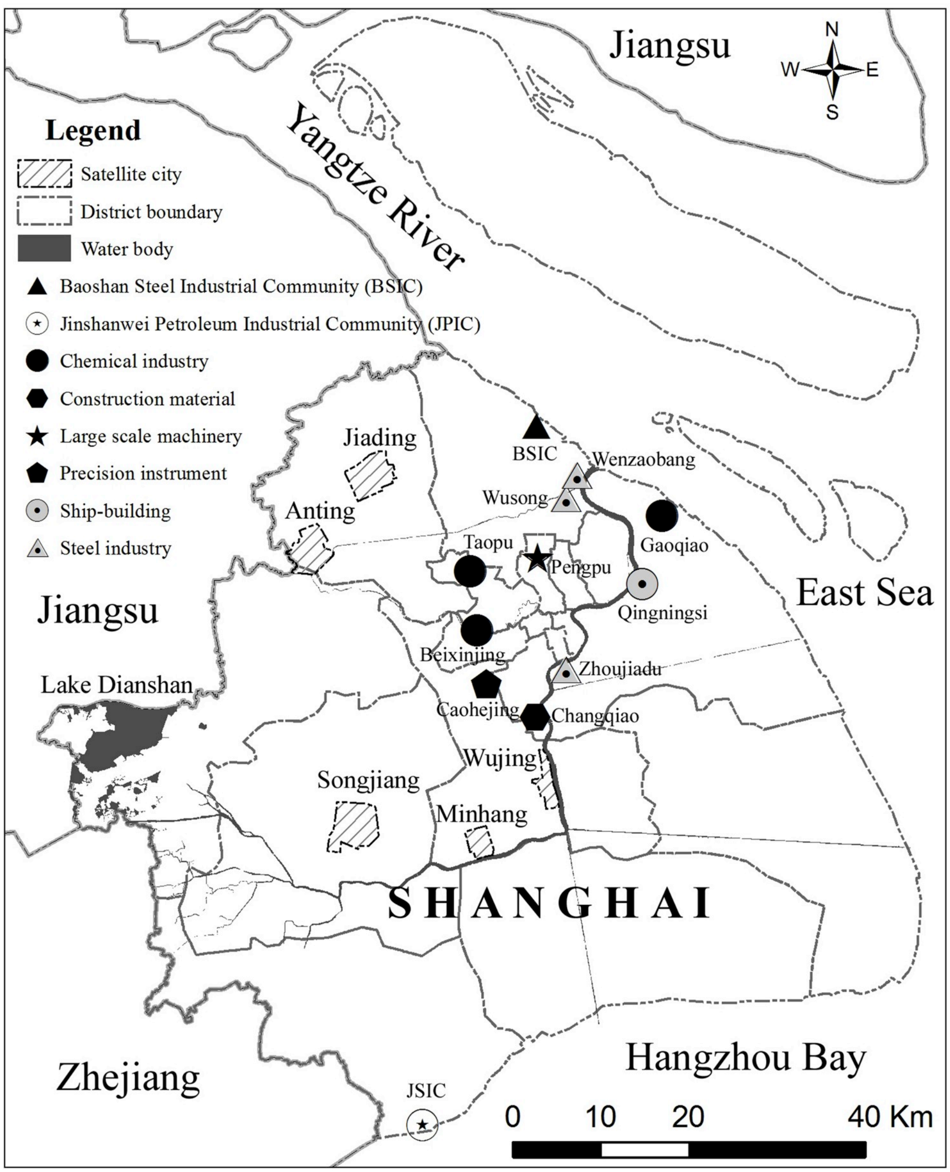

Fig. 4. Suburban industrial zones and industrial communities in Shanghai established in the pre-reform era. Shanghai established 10 industrial zones and 5 industrial satellite towns in the 1950s and 1960s. In the 1970s, Baoshan Steel Industrial Community (BSIC) and Jingshan Petroleum Industrial Community (JPIC), two massive industrial complexes, each of a size of a small to medium sized industrial city, are established.

was the underlying driving force for this land gain. During the Great Leap Forward and the Adjustment Period in the 1950s and 1960s, Shanghai decided that it was necessary to build satellite towns around the urban core to decongest the city center; large scale industries that demand large areas of land, generate high levels of pollution, and with high demands in transportation were to be relocated to these satellite towns. The central government approved Shanghai's industrial plan and allocated land in Jiangsu province to Shanghai to achieve its industrial planning goal. From 1958, Shanghai planned five satellite towns in Minhang, Wujing, Songjiang, Jiading, and Anting for electrical, chemical, light industrial and machinery, scientific research, and auto industries, respectively (Gong, 2007). From 1959 to 1966, another 10 suburban industrial zones were established (Fig. 4). In the satellite towns and new industrial zones, all necessary infrastructures were pre-constructed. For instance, from 1958 to 1960, 445 km of roads, two-thirds of Shanghai's road construction, were associated with the satellite towns and suburban industrial zones. However, since most of the ten suburban zones are close to the city core, when the city expanded, these industrial areas soon became part of the city.

Shanghai experienced a second wave of industrialization with a specific focus on the steel and petro-chemical industries. Starting from the 1970s, the central government made a strategic decision to enhance steel and petrochemical industries in Shanghai and committed large amounts of resources to that end. Under this initiative, massive industrial complexes such as Baoshan Steel Industrial Community (BSIC) and Jingshan Petroleum Industrial Community (JPIC), each resembling a small to medium sized industrial city were established (Fig. 4). BSIC is located in Baoshan District south of Yangtze River whereas JPIC is located in Jinshan District along the Hangzhou Bay. Both have good connections to the central city. While many workers live in these cities, a significant number commute daily between BSIC/JPIC and their homes in the urban core area.

The maps on historical industrial land use captured the first wave of Shanghai's industrialization and part of the second wave since only a very small portion of BSIC and none of JPIC fall in our historical study area. Figs. 3 and 4 show that the industrial land evolution occurred most intensively at or around the 10 suburban industrial zones from the 1950s to the 1990s. Our figures from 2002, 2009, and 2016 cover a relatively larger study area and illustrate most of the BSIC. It should also be noted that after the 1990s, as the Pudong New Area was established to attract foreign direct investment (FDI), new Shanghai industrial zones were rapidly established for export-oriented industries, such as the industrial parks in Minhang and Caohejing.

4.4. Economic restructuring and the decline of the industrial sector

As most industrialized countries experienced some level of industrial restructuring during the 1980s and 1990s, cities of these countries, such as Paris, London, and New York have transformed themselves to post-industrial forms where traditional industrial activities retreated from dominance and advanced service sectors arose to become the growth engines of these post-industrial urban economies (Bell, 1973; Ley, 1996; Savitch, 1988). As substantial decrease in industrial land occurred in Shanghai, it may lead to the conclusion that industrial sector also declined in Shanghai. Nevertheless, we consider industrial sector a vital part of the economy of Shanghai and industrial land will remain to be an important part of the urban development of Shanghai that warrants proper management and planning in the foreseeable future for the following three reasons.

First, although the industrial land has decreased significantly from 1993, the evolution of Shanghai's industrial land is a spatially uneven process. Although the industrial land decreased almost to nothing in the central part of the city, it increased in the periphery and formed large-scale clustered industrial land use patterns (Fig. 3). The formation of a polycentric pattern of industrial land of Shanghai and the respective industrial clusters demonstrate that Shanghai's spatial transformation, partly fueled by industrial land evolution, has been closely related to its on-going industrial restructuring. And the spatial pattern may not be considered as a simple decline but as a restructuring to a more efficient form, proactively facilitated by the government.

Second, although its relative contribution to GDP declined, unlike most post-industrial cities, Shanghai's industrial sector continued to grow. The industrial and service sectors contributed to 77% and 18% to Shanghai's GDP in the 1978, respectively. However, their respective contributions have changed to 31% and 69% in 2017. While industrial sector has maintained an average annual growth rate of 10% from 1978 to 2017, the service sector grew at an even faster rate of 17%. The faster expansion of the service sector may be due to the relatively weak service sector Shanghai had before the economic reform in 1978 as the city during the Maoist period (1949–1978) focused only on industrialization (Yusuf & Wu, 1997).

Third, Shanghai's strategic plan has always identified the industrial sector as an important economic engine for the city and through industrial restructuring and upgrading, to promote technological and capital intensive industrial sectors. In the 1990s, the Shanghai municipal government decided that the city's economic development would rely on both the industrial and service sectors (Ma, 2009). Despite being the largest industrial base in China, Shanghai's service sector was extremely underdeveloped as late as the 1980s. The municipal government emphasized that the development of the service sector could not be at the expense of the growth of industrial sector. Nevertheless, significant industrial restructuring has occurred in recent years to promote the growth of technological- and capital-intensive industrial sectors. Certain sectors, such as textiles, have relinquished their historically dominant positions in Shanghai's industrial structure, while other sectors, such as electronics and telecommunication equipment, transportation equipment, and petro-chemical production, have quickly arisen to become major industries. For instance, from 1996 to 2000, electronics and telecommunication equipment, transportation equipment, and petro-chemicals grew at such a rapid pace that they combined to contribute 70% of Shanghai's industrial economic growth during the period (Gong, 2003).

4.5. Limitations of the research and future research directions

We should be aware that there are several limitations of this study despite its usefulness in understanding the pattern and driving forces of industrial land change in Shanghai. The first limitation lies in the limitation of data. As the industrial land data from 1947 to 1990s are only available for the urban core with an area of 284 km^2, we were not able to capture the industrial land evolution for the entire Shanghai, especially the rapid expansion of industrial areas into the outer suburbs. Our findings are also affected by the diverse datasets with different spatial resolutions that we used. We have used vector data, raster data, digitized paper maps, as well as statistical data at census tract and district levels. Further, the dataset has a variety of spatial and temporal resolutions, from 15m-resolution for the ASTER image, to demographic data at the census tract level, to economic indicators at the administrative district level. It is difficult to import diverse data types into geographically co-registered databases, accurately integrate vector-format data with raster-format data, and merge data of different resolutions. Nevertheless, despite the incompleteness of the data and uncertainty that may be introduced through the integration of the diverse datasets, our work, as a first step, revealed the overall evolutionary patterns and identified important driving factors, making it useful for understanding the spatial dynamics of industrial land.

The second limitation comes from the spatial unit of our analysis. We have identified the uneven pattern of the industrial land evolution in Shanghai and mentioned briefly distinct industrial land conversion process in different parts of Shanghai, such as Yangpu district in the urban core or Pudong and Jiading districts in inner and outer suburbs. However, it would be ideal to examine the heterogeneous industrial land conversion processes using the more detailed district level scale. This obviously goes beyond the scope of this paper. We plan to follow up with detailed case analysis at the district level in our future research.

The third limitation is our current treatment of industrial land. We did not distinguish industrial land according to their particular sectors. However, different industrial sectors tend to have different location and clustering patterns; while petrochemical, auto, and steel industries tend to have large land requirement and therefore are associated with locations in the outer suburbs, certain high-tech industries such as biotech and information technology can be accommodated in smaller parcels of industrial land within or close to the urban core that are more attractive to their highly educated labor forces. It would be interesting to further classify the industrial land into different types of industries, as different patch sizes are likely associated with different types of industries. Other limitations include not being able to use more explanatory variables, such as land users and environmental policies. For example, when land users are powerful state owned enterprises, conversion of industrial land, usually large in size, may be difficult, leading to a very different land use conversion spatial determinants from the middle or small-size patches that may have more private enterprises as land users. Environmental policy is also an important policy variable that may have affected industrial land conversion due to constraint on land uses when an area is designated as the environmental protection zone or specific environmental policies are implemented. In future research, we can consider to incorporate these variables in our analysis.

5. Conclusion

This paper studies the evolution of the industrial land in Shanghai since the beginning of 1947, with a specific focus on the period after the economic reform. Relying on land use data extracted from satellite images, air photos, and historic land use maps produced by local experts, we find that industrial land in the central area of Shanghai increased from 1947 to 1993 but declined from 2002 to 2016. The spatial form was transformed from scattered small industrial land pieces interspersed with other types of urban land within the urban core to a polycentric pattern of large patches with greater distances between patches. Using a binary spatial logistic regression on data from 2002 to 2009 and 2009–2016 for an extended area beyond Shanghai's central city, we found that major spatial determinants contributing to the recent conversion of Shanghai's industrial land include land price, the existing industrial land, and the planning policies for both periods and additionally distance to main transport station and economic development level for the period of 2009–2016. Moreover, patches affiliated with different sizes of industrial areas were driven by different sets of spatial determinants. Both large-size patches (>0.1 km^2) and small-size patches (<0.05 km^2) seem to be very sensitive to all spatial determinants, i.e., distances to major roads, to major station, economic development level, existing industrial land, land price, and planning policy, except economic development level for large patches for 2002–2009 and for small-size patches for 2009–2016.

As many Chinese cities have experienced industrial restructuring in parallel with rapid urban expansion, we expect that they may follow Shanghai's path in industrial land conversion. We hope this study can offer insights to planners and policy makers of cities experiencing industrialization and post-industrialization. For instance, planners can focus on improving accessibility to major roads and stations, especially for large industrial land areas, if industrial land conversions are desired. Furthermore, providing low-cost land through land banking, a common practice of local governments in contemporary urban China, may be useful to attract targeted industries. Appropriate land planning that encourages the clustering of the industries might be an effective strategy for policy makers to promote local industrialization via a positive feedback system.

Finally, more research should be conducted to assess the evolution of different kinds of urban land uses, such as residential lands, park lands, and public/commercial lands, particularly analyzing the driving forces, thus providing insights for urban planning and decision-making. We may also investigate if different sets of determinants have driven different types of industrial land conversions by further classifying the industrial lands according to their respective industries. Our study offers an example on how we can examine industrial land conversion facing most Chinese cities by utilizing different sources of land use data and applying a variety of methods in land modeling.

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Appendix A. Supplementary data

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