



# Driving forces of impervious surface in a world metropolitan area, Shanghai: threshold and scale effect

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**Abstract** Shanghai is one of the largest metropolitan areas in the world, during the rapid urbanization of the past decades, impervious surface expanded dramatically and became a main factor influencing surface water quality. Thus, exploring the driving forces of impervious surface has great implications in such metropolitan area. In this study, an impervious surface coefficient method (ISC) was used to measure the percentage of total impervious area (PTIA) of Shanghai; regression analysis was conducted to define the relationship between PTIA and three socio-economic factors, population density,

unit area gross domestic product, and unit area industrial output at the city and district scale. Results showed that the industrial land use generated the highest ISC value, followed by high-density residential. Strong correlations were showed between PTIA and socio-economic indicators, in which population density was the most significant. Threshold effect was presented that when population density was higher than 15000 per/km<sup>2</sup>, this relationship would become less significant and PTIA remained stable. Similar effects were found when unit area gross domestic product exceeded 125 million yuan/km<sup>2</sup>. Scale effect was also discussed that the relationship was more significant at city scale than district. An improved understanding of the threshold effect and scale effect will help guide future urban planning and design new urban ecosystem policies.

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## Introduction

During processes of urban expansion, a large proportion of pervious surfaces transform into impervious (Chaudhuri et al. 2017; Sekertekin et al. 2018). Impervious surfaces are often defined as roads, parking lots, rooftops, etc. (Ma et al. 2018; Xian et al. 2007), and the percentage of total impervious area (PTIA) has been identified as a reliable indicator of environment quality (Xian and Crane 2005; Yan et al. 2019). Relationships between impervious surfaces and related socio-economic driving forces may explain why

impervious surfaces expand, and guide urban and environmental planners in designing policies related to PTIA control. Previous researches on impervious surfaces have mainly focused on estimation and mapping techniques, spatial distributions, and relationships between PTIA and environmental indicators (Wu and Murray 2003; Jat et al. 2008; Xian 2008; Yue 2009; Jacobson 2011; Nagy et al. 2012; Uygun and Albek 2015; Hafsi et al. 2016; Tahmina et al. 2018).

However, few studies have discussed on whether there is a linear relationship between PTIA and the socio-economic indicators, and whether the relationship has a scale effect. The threshold and scale effects are essential for planning the future of urban development, particularly for the studies of typical rapid-urbanization megacities. The objective of this study is to quantify the relationship between socio-economic indicators and PTIA to test the capability of socio-economic indicators for predicting the trends of impervious surface expansion, while examining whether this relationship shows threshold and scale effects.

There are three methods that have been employed to estimate and map PTIA: manual extraction, GIS-based model, and impervious surface coefficient method (ISC). The first one, which involves manually digitizing impervious surfaces from aerial photographs or satellite images, is generally the most accurate but cost effective for small areas. However, it is too expensive and time-consuming to employ when examining larger-scale applications (Weng 2012). The second, which involves extracting impervious surface bases via GIS, spectral mixture analysis (SMA), and classic vegetation-impervious surface-soil (V-I-S) models, must be conducted by researchers with professional background in geography and remote sensing, and typically used in specific cases of impervious surface extraction (Rashed et al. 2001; Wu and Murray 2003; Guo and Huang 2013; Henits et al. 2017). The third method involves applying field survey-derived ISC to specific land uses in order to measure PTIA; land uses can typically be divided into industrial, commercial, residential, forest, agriculture, public, road, and water area (Sleavin et al. 2000; Lu and Weng 2006; Barbara et al. 2010; Beck et al. 2016).

Taking Shanghai as a case, we developed an impervious surface coefficient (ISC) set for land uses in this metropolitan area; the PTIA and its spatial distribution were displayed; it is also discussed whether socio-economic indicators such as population density (PD), unit area gross domestic product (UAGDP), and unit

area industrial output (UAIO) played as driving forces in impervious surface expansion, and the threshold and scale effects were then displayed. An improved understanding of the relationships and its threshold effects will help guide future planning efforts aimed at urban ecosystem management.

## Study area and method

### Study area

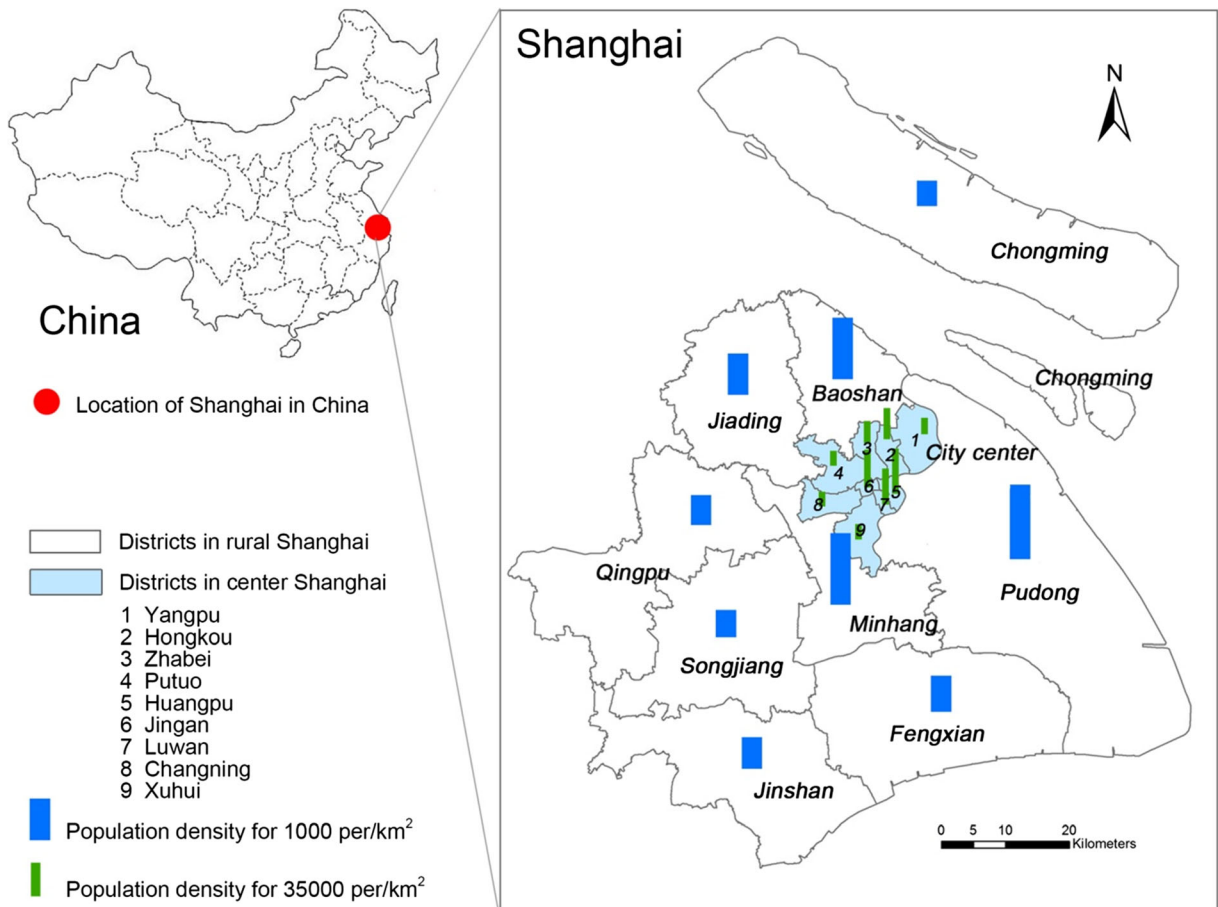
Shanghai is a metropolitan area composed of 18 districts (nine urban and nine suburban districts) with a total area of 6340.5 km<sup>2</sup>, making it one of the largest metropolises in the world. In the past three decades, Shanghai has experienced rapid urbanization, growing from a population of 11.46 million in the 1980s to 24.15 million in 2010; the city's GDP has also increased from RMB 33.7 billion Yuan to 2496.5 billion Yuan. Although the process of rapid urbanization has brought prosperity to the city, it also caused environmental problems. Figure 1 illustrates Shanghai's location in China and population density histograms of each district.

### Data

The imagery data of sampling sites is from ZY-3 satellite and provided by the China National Platform for Common Geospatial Information Services, and the image resolution is 0.6 m, while the land use data of Shanghai were originated from STOP-5 satellite remote sensing image and interpreted by the Key Laboratory of Geographic Information Science of the Education Ministry of East China Normal University; the image resolution is 1.4 m.

It should be stressed that in the land use data of Shanghai, land uses dominated by impervious area, such as residential and industrial, were interpreted as entirely impervious, for example, the permeable surfaces like the green spaces in residential were ignored. Moreover, the green spaces and parks were interpreted as entirely pervious, and the impervious elements like roads and buildings embedded in the pervious areas were interpreted as impervious. Therefore, the land use data is not suitable to measure the impervious surface coefficients in Shanghai.

The data of socio-economic indicators of Shanghai were drawn from Shanghai statistical yearbook (2007)



**Fig. 1** Location of Shanghai and population density of each district

(Table 1), while the PD, UAGDP, and UAIO for all 18 districts were derived from statistical yearbook (2007) of each district. Statistical Yearbook of Shanghai and each district contain economic and social statistical data (e.g., population, GDP, total industrial output, acreage) collected by Shanghai Municipal Bureau of Statistics and China National Bureau of Statistics.

**Methods**

The imagery data can be used to map the impervious surfaces such as roofs, roads, and parking lots in various land uses (e.g., residential, industrial, and green space). Therefore, this paper combined the land use data with imagery data to assess the impervious surface coefficients of sampling sites in Shanghai (Fig. 2). Based on the land use data, a total of 240 samples were selected for six land uses (50 high-density residential, 50 middle-density residential, 50 low-density residential, 30

public, 30 industrial, and 30 green space) (Fig. 3). With imagery data, the impervious surfaces were interpreted in ArcGIS vectorization module. First, the roof, road, parking lot, and square were mapped for each sampling site, and the ISC for each sampling site was then calculated. Finally, the ISC value of each land use was assigned as an average of sampling sites; furthermore, when mapping the PTIA for Shanghai and its districts/towns, the ISC of each land use would be applied to all corresponding land uses.

Two regression analyses were conducted to define the relationship between PTIA and three socio-economic indicators at the city and district scale, which would display the threshold effect and scale effect. At city scale, this paper takes Shanghai as the research subject and 18 districts or 136 towns as samples. In terms of district scale, the study took nine suburban districts as the research subjects and towns/sub-districts in each district as samples.

**Table 1** Social and economic conditions of each district in Shanghai (2006)

Districts in center Shanghai	Area (km <sup>2</sup> )	Population (thousands)	PD (per/km <sup>2</sup> )	UAGDP (millions yuan/km <sup>2</sup> )	UAIO (millions yuan/km <sup>2</sup> )
Huangpu	12.4	599.7	48324.6	570.3	1021.7
Luwan	8.0	316.6	39326.8	277.5	497.2
Xuhui	54.7	883.9	16141.1	520.9	933.3
Changning	38.3	633.9	16551.4	137.5	246.4
Jingan	7.6	309.9	40666.5	214.4	384.2
Putuo	54.8	857.5	15638.3	220.2	394.5
Zhabei	29.2	719.1	24576.6	292.8	524.6
Hongkou	23.4	791.9	33727.3	146.3	262.1
Yangpu	60.7	1028.4	16934.0	444.6	796.6
Average	32.1	682.3	27987.4	313.8	562.3
Districts in suburban Shanghai	Area (km <sup>2</sup> )	Population (thousands)	PD (per/km <sup>2</sup> )	UAGDP (millions yuan/km <sup>2</sup> )	UAIO (millions yuan/km <sup>2</sup> )
Pudong	1210.4	2562.0	2116.7	111.5	229.9
Baoshan	270.9	759.6	2802.9	101.8	240.1
Minhang	370.7	853.6	2302.3	126.9	815.2
Jiading	464.2	541.1	1165.7	104.7	342.8
Jinshan	586.0	552.5	942.8	33.0	131.2
Songjiang	605.6	531.9	878.2	85.6	417.7
Qingpu	670.1	495.9	740.0	58.1	161.8
Fengxian	687.3	508.4	739.5	28.0	107.9
Chongming	1185.4	705.1	594.8	5.7	9.5
Average	597.0	834.5	1364.8	72.8	272.9

*PD* population density, *UAGDP* unit area gross domestic product, *UAIO* unit area industrial output

It should be noted that the area of each urban district (city center) in Shanghai is too small, and even the total area of urban districts may be smaller than that of any suburb district. Furthermore, the level of urbanization in the urban district is usually higher, and there were no differences between towns and sub-districts in city center. For suburb districts, they cover a larger area and the urbanization level is unevenly distributed in towns and sub-districts. Therefore, the urban districts were no longer subdivided into sub-districts and towns in our analysis, but the suburbs were further subdivided into towns and sub-districts.

## Results

### Impervious surface coefficients of land uses

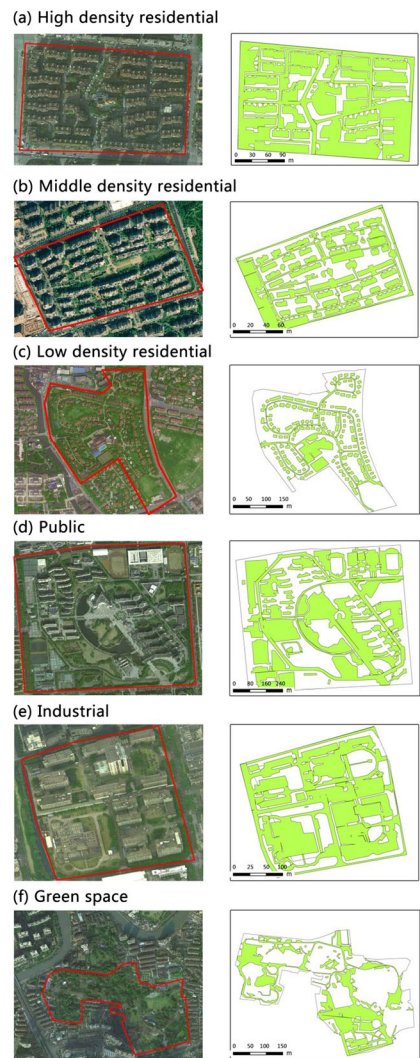
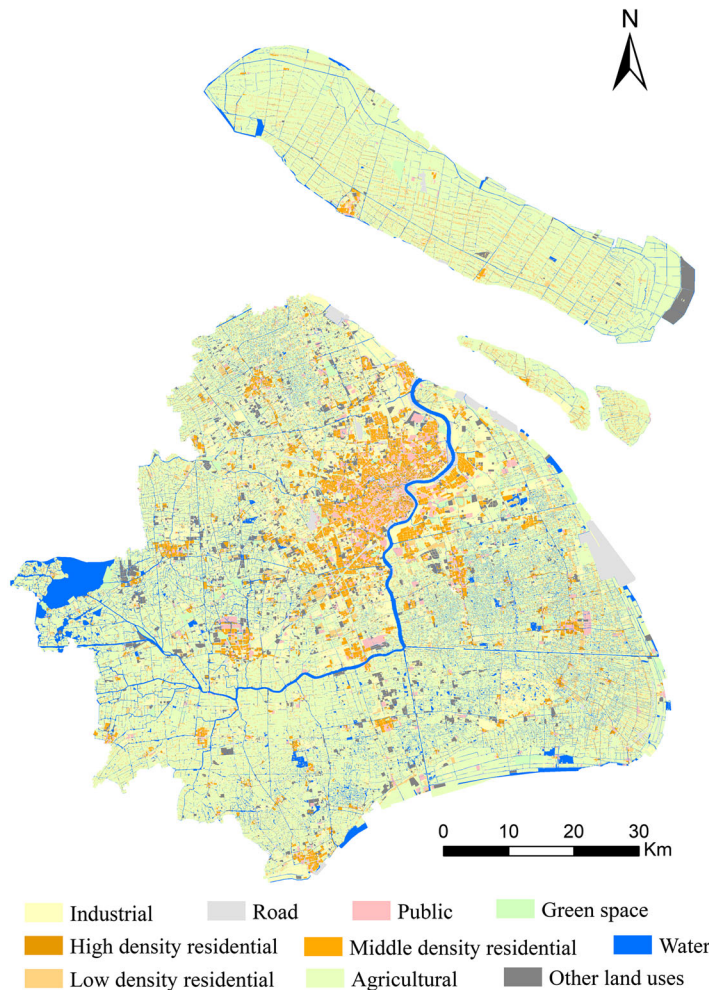
Industrial land uses generate the highest ISC with a value of 0.75 and are followed by high-density residential and public areas with ISC values of 0.73 and 0.64,

respectively, and green spaces generate the lowest value of 0.33 (Table 2).

### Spatial variations of impervious surfaces

Figure 4 illustrates spatial variations of PTIA for Shanghai; it shows that PTIA levels in the city center were higher than those of suburban areas. The average PTIA value for the city center (nine urban districts) was recorded as 64.9% and the average PTIA value for the nine suburban districts was 19.24%. Chongming district, an island isolated from mainland Shanghai, generated the lowest PTIA of 3.69%. Overall, PTIA levels in the city center and in the center of suburban district were found to be higher due to the presence of impervious structures such as buildings, roads, and parking lots. However, PTIA levels were found to be lower in less-developed suburban area and water resource protection area composed of agricultural land and suburban residents.

Land use in Shanghai



**Fig. 2** Land uses in Shanghai (2006) and sampling imagery data of each land use type

Relationship between PTIA and population density

*Relationships at the city scale*

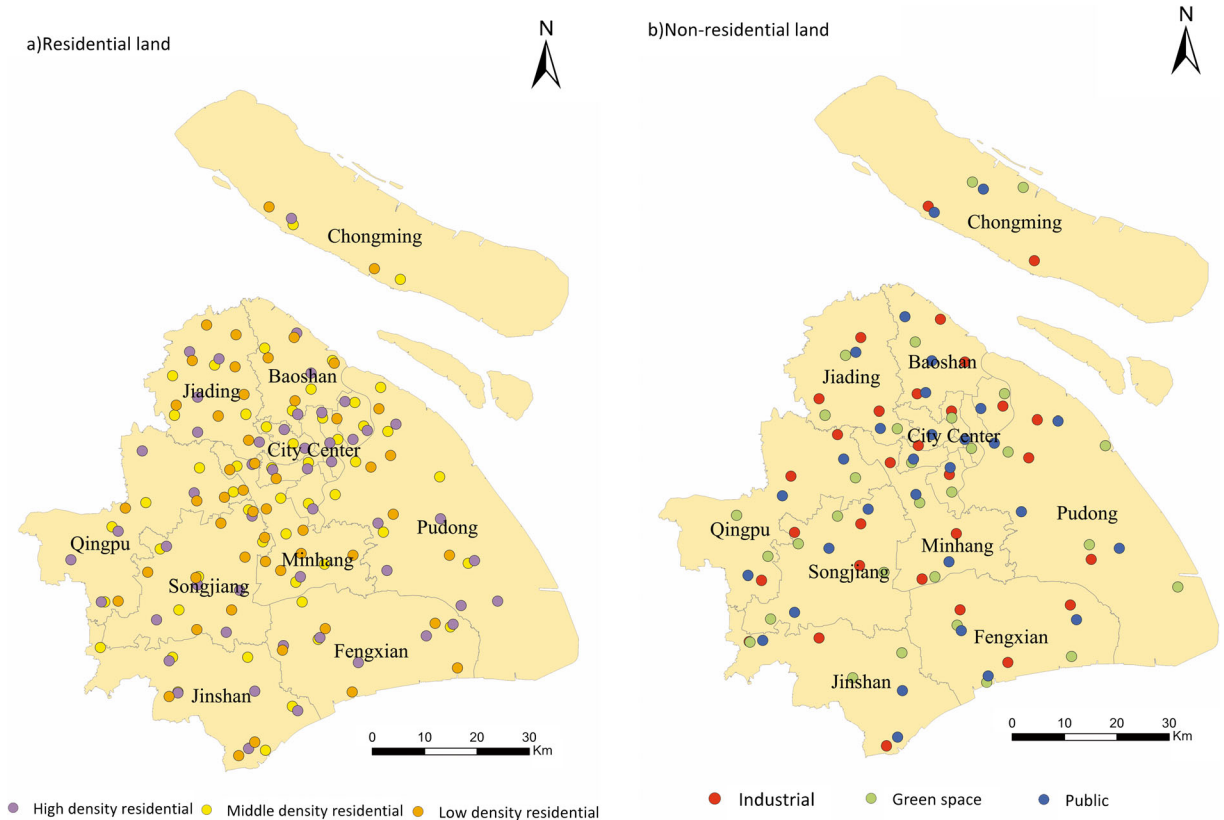
Figure 5 shows regression results for the relationship between PTIA and population density (PD) at the city scale. When a total of 18 districts in Shanghai were examined, strong correlations were found between PTIA and PD ( $R^2 = 0.922$ ). From Fig. 5, we could deduce that when PD increase five times, PTIA of corresponding areas increase by 20%. However, when PD reached 15,000 per/km<sup>2</sup>, PTIA would remain stable.

In order to verify the above conclusions, 136 towns and sub-districts were also examined; a strong correlation was also found between PTIA and PD ( $R^2 = 0.670$ ).

Figure 5 also shows a threshold effect wherein the relationship between PTIA and PD becomes insignificant when PD levels exceed 15,000 per/km<sup>2</sup>. At the same time, it can be found that the results of the study using 18 districts as samples were significant than those for towns.

*Relationships at the district scale*

Relationships between PTIA and PD for nine suburban districts were examined. Table 3 shows regression models for the relationship between PTIA and PD in suburban districts. The Jiading, Jinshan, and Minhang districts generated higher  $R^2$  values of 0.682, 0.661, and 0.634, respectively, while the Qingpu district showed the lowest  $R^2$  with a value of 0.108. Generally, districts



**Fig. 3** Sampling map of six land uses in Shanghai

with higher PD ( $> 1000$  per/km<sup>2</sup>) presented better relationship ( $R^2 > 0.5$ ), and districts with lower PD ( $< 750$  per/km<sup>2</sup>) expressed unclear relationship. An average  $R^2$  value of 0.473 was found at the district scale, which is much lower than that found at the city scale. The analyses suggested that the relationship between PTIA and PD is more significant at city scale (the whole Shanghai) than district scale (each suburban district).

**Table 2** ISC value of each land use in Shanghai

Land uses	Detailed description	Samples	ISC	Standard deviation (%)
Industrial	Factories gathered industrial parks	30	0.75	11.95
Public	Schools, hospitals, libraries	30	0.64	11.03
High-density residential	Multi-family residential, built before year 2000	50	0.73	10.36
Middle-density residential	Multi-family residential, built after year 2000	50	0.55	9.64
Low-density residential	Single-family residential	50	0.49	10.82
Green space	City greenbelts, parks	30	0.33	14.12
Roads	Railway land, aviation land, port land	-	1.00	-
Agricultural	Cultivated land, garden, woodland	-	0.00	-
Water areas	River, lake, ponds	-	0.00	-

Since there are no impervious surfaces in agricultural and water area, the ISC of agricultural and water area is zero

Relationships between PTIA and economic variables

*Relationships at the city scale*

Figure 6 shows regression models of the relationships between PTIA and economic factors at the city scale. When a total of 18 districts in Shanghai were examined, a stronger positive correlation between PTIA and

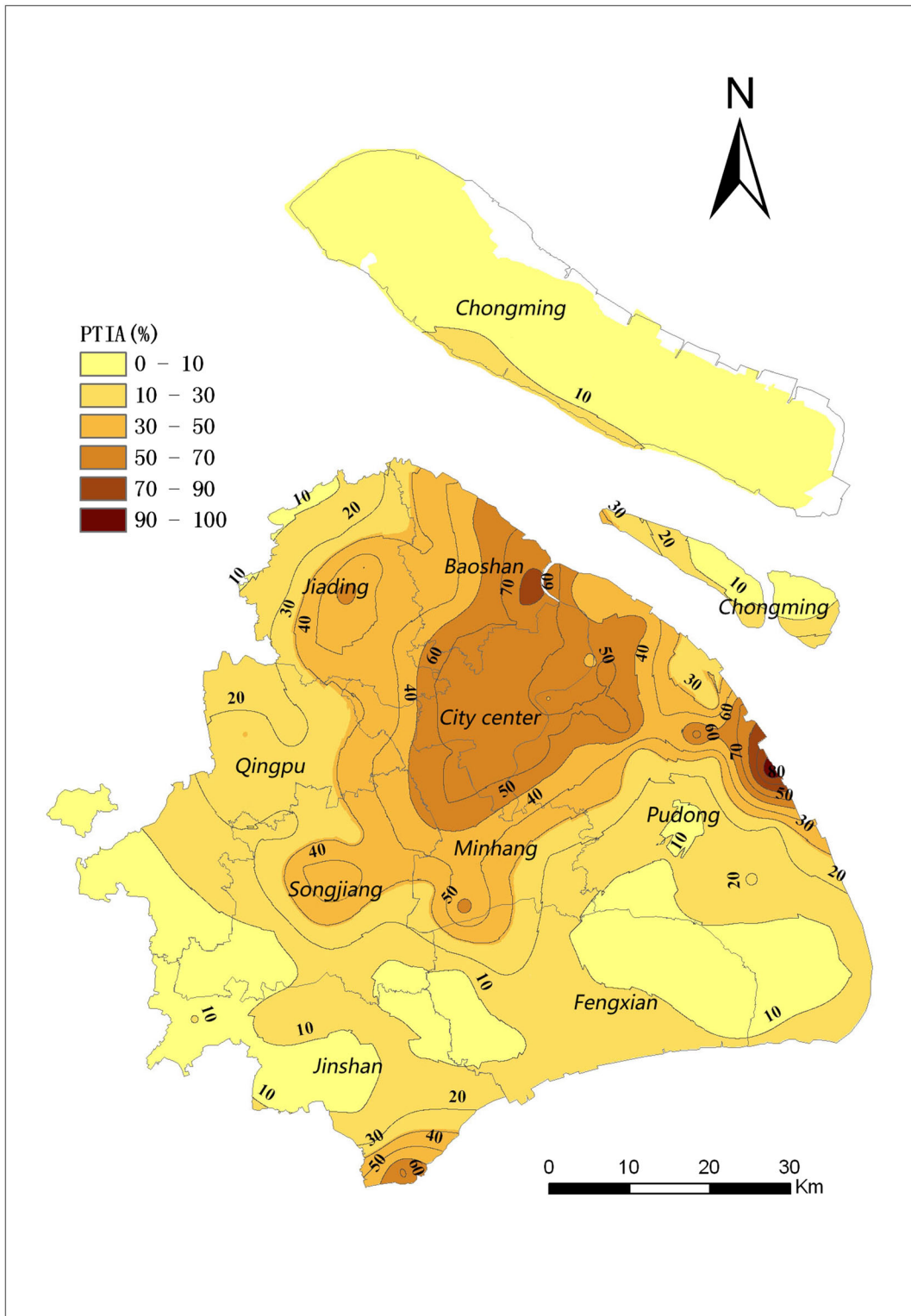
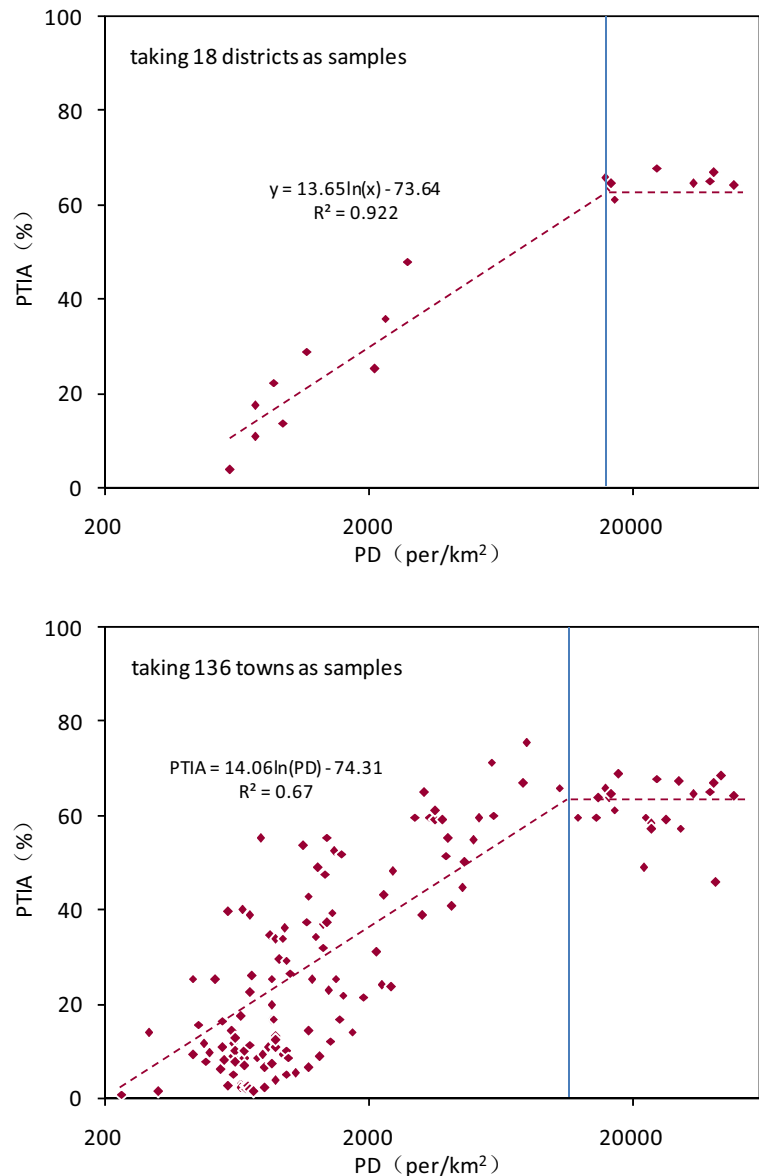


Fig. 4 Spatial variation of PTIA in Shanghai

**Fig. 5** Relationships between PTIA and PD at city scale



UAGDP ( $R^2 = 0.739$ ) was found that between PTIA and UAIO ( $R^2 = 0.463$ ). This implies that PTIA was affected more by UAGDP. Figure 6 also shows a threshold effect of the relationship between PTIA and economic indicators. Also, an interesting finding was displayed, namely, when UAGDP increased five times, the PTIA increased by 20%, and this relationship was less significant when UAGDP was higher than 125 million yuan/km<sup>2</sup>. Similar results were found for the relationship between PTIA and UAIO. Rather, when

UAIO was higher than 250 million yuan/km<sup>2</sup>, PTIA remained stable.

In order to verify the above conclusions, 136 towns and sub-districts were also examined; positive correlations were found between PTIA and economic factors. The relationship between PTIA and UAGDP was calculated as  $R^2 = 0.520$ , and  $R^2 = 0.355$  was found for the relationship between PTIA and UAIO. Thus, UAGDP represents a more significant factor when analyzing relationships between PTIA and economic factors.



**Table 3** Relationships between PTIA and socio-economic indicators at district scale

District	PD		UAGDP		UAIO	
	per/km <sup>2</sup>	Regression equations	million yuan/km <sup>2</sup>	Regression equations	million yuan/km <sup>2</sup>	Regression equations
Baoshan	2802.9	PTIA = 9.735ln(PD) - 24.65	101.8	PTIA = 10.93ln(UAGDP) - 47.61	240.1	PTIA = - 6.65ln(UAIO) + 120.7
Fengxian	739.5	PTIA = 5.369ln(PD) - 23.70	28.0	PTIA = 9.656ln(UAGDP) - 65.02	107.9	PTIA = 8.854ln(UAIO) - 69.93
Jiading	1165.7	PTIA = 15.25ln(PD) - 76.46	104.7	PTIA = - 4.90ln(UAGDP) + 76.21	342.8	PTIA = - 4.90ln(UAIO) + 82.03
Jinshan	942.8	PTIA = 24.15ln(PD) - 149.5	33.0	PTIA = 5.751ln(UAGDP) - 34.42	131.2	PTIA = 4.992ln(UAIO) - 35.17
Minhang	2302.3	PTIA = 11.72ln(PD) - 48.28	126.9	PTIA = 26.58ln(UAGDP) - 210.4	815.2	PTIA = - 3.33ln(UAIO) + 81.78
Pudong	2116.7	PTIA = 12.28ln(PD) - 61.84	111.5	PTIA = 7.477ln(UAGDP) - 30.77	229.9	PTIA = 8.854ln(UAIO) - 69.97
Qingpu	740.0	PTIA = 7.513ln(PD) - 29.32	58.1	PTIA = 6.840ln(UAGDP) - 36.92	161.8	PTIA = 6.807ln(UAIO) - 43.54
Songjiang	878.2	PTIA = 15.67ln(PD) - 78.93	85.6	PTIA = 15.41ln(UAGDP) - 110.5	417.7	PTIA = 4.953ln(UAIO) - 21.19
Chongming	594.8	PTIA = 4.372ln(PD) - 24.92	5.7	PTIA = 4.716ln(UAGDP) - 27.16	9.5	PTIA = 0.596ln(UAIO) - 0.463
Average						
		$R^2$		$R^2$		$R^2$
		0.528		0.473		0.392
		0.361		0.473		0.321
		0.682		0.473		0.368
		0.661		0.473		0.188
		0.634		0.473		0.034
		0.583		0.473		0.321
		0.108		0.473		0.368
		0.340		0.473		0.188
		0.360		0.473		0.034
		0.473		0.473		0.257

*Relationships at the district scale*

Table 3 presents regression models of the relationship between PTIA and economic factors at the district scale. Positive correlations were observed for the relationships between PTIA and UAGDP (average  $R^2 = 0.392$ ), and PTIA and UAIO (average  $R^2 = 0.257$ ). Minhang district showed the highest UAGDP correlation while Fengxian district generated the highest UAIO correlation ( $R^2 = 0.912$ ). It should be noted that Jiading district generated the lowest UAGDP value while Chongming district generated the lowest UAIO values.

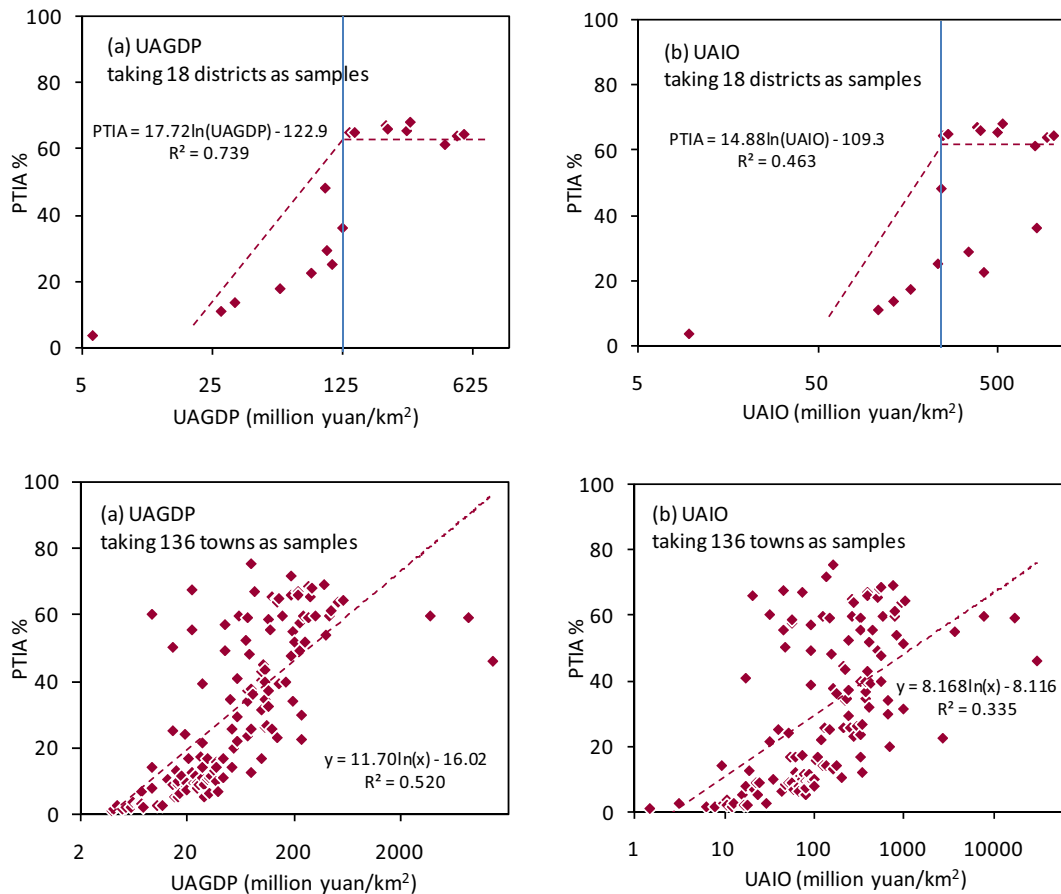
When all regression models for the relationship between PTIA and socio-economic indicators are considered together, relationships between PTIA and PD were superior for all of the socio-economic indicators at the district scale ( $R^2 = 0.473$ ), which was inferior to relationships between PTIA and PD at the city scale ( $R^2 = 0.922$ ). The analyses suggested that PD serves as the most significant factor; additionally, larger scale cases show better relationships.

**Discussion**

ISC and impervious surface estimations

ISC values for six land uses were compared with previous studies. Several differences were found, and especially in relation to residential, industrial, green spaces, and public land uses.

- (1) We examined residential areas based on three categories (high, middle, and low density) following Choi and Ball (2002) and found ISC levels of 0.73, 0.55, and 0.49, respectively. Chen et al. (2006) showed ISC values for middle- and high-density residential areas of between 0.55 and 0.95 for Nanjing, another Chinese city, consisting with our results. Carlson (2001) found the values of ISC range from 0.30 to 0.75, echoing with our results. Prisloe et al. (2001) found an ISC value of 0.36 for mixed residential and commercial areas, while the ISC value is 0.12 for suburban residential areas. Sleavin et al. (2000) found ISC values for residential areas ranged from 0.08 to 0.39. However, our average ISC for residential areas are 50–100% higher than those of previous studies (Lu and Weng 2006; French 2009). This is attributable to



**Fig. 6** Relationships between PTIA and UAGDP (a) and UAIO (b) at the city scale

the fact that percentage of low density residential land in China, a huge population country, is quite lower than those of developed countries.

- (2) An ISC value of 0.75 was found for industrial areas. Previous studies have found ISC values for such areas range between 0.5 and 0.9 (Sleavin et al. 2000; French 2009; Barbara et al. 2010). Reporting on California, Barbara et al. (2010) found an ISC value of 0.91 for heavy industry areas and an ISC value of 0.81 for light industry areas, exceeding our results by 15%. While American industrial sites include little vegetation and bare soils (Chen et al. 2006), industrial sites in Shanghai include more green spaces in accordance with municipal regulations, thus explaining our lower ISC results for industrial areas.
- (3) ISC value of green spaces is 0.33 in Shanghai. Chabaeva et al. (2009) found ISC values of 0.13,

0.046, and 0.049 for turf and grass, deciduous forest, and coniferous forest areas, respectively. Prisloe et al. (2001) found ISC values of 0.09 for turf and grass areas and ISC values of 0.045 for forested areas. Green spaces in this study refer to man-made parks and grass areas with few paved surfaces and buildings, while forested areas examined in previous studies were natural with virtually no impervious features, and thus, our results for green spaces are much higher.

- (4) ISC value of public areas is 0.64 in Shanghai. Barbara et al. (2010) found an ISC value of 0.44 for public/quasi-public areas, while Chen et al. (2006) displayed a value of 0.83 for public areas. These results showed the highest degree of variance of the results for land uses considered, as designations were based on ownership rather than on types of use (Barbara et al. 2010). Hence, ISC values for public areas were more variable.

## Driving forces of impervious surface

Several researchers have showed positive correlations between PTIA and socio-economic factors (Dhorde et al. 2012; Ma et al. 2016; Liao et al. 2017; Chen et al. 2018; Li et al. 2018; Cao et al. 2019). Azar et al. (2010) conducted a regression analysis to determine the relationship between impervious surfaces and PD levels at three administrative levels.  $R^2$  values of 0.94, 0.81, and 0.85 were found for department (1st level), commune (2nd level), and section scales (3rd level), respectively. The same result was found by Dhorde et al. (2012). Our study finds a similar result that at the city scale, PD levels correlate strongly with PTIA. However, at the district scale, several districts (e.g., Fengxian, Songjiang, and Qingpu) showed very low  $R^2$  values (0.10–0.35).

Cao et al. (2019) indicated that the growths of population and gross domestic product (GDP) are regarded as the key drivers for urban expansion associated with an increase of ISC. The same result was showed by Liao et al. (2017) and Li et al. (2018). Chen et al. (2018) thought that tertiary industry product, GDP, secondary industry product, total population, and urban population were driving factors of urban land sprawl in Northeast China from 1990 to 2015.

We also made clear that positive relationships were showed between PTIA and economic forces, and UAGDP may be having a more significant effect than UAIO. As a world-famous developing country, China's industrialization is the most important driving force of urbanization (Ma 2002; Eng. 2010). As one of the most developed city in China, Shanghai had entered the post-industrialization stage after the 1990s. In this stage, the development of cities no longer depended solely on industry, and technological innovation and service industry have become primary factors leading urbanization. For example, according to our study (Zhao 2008), the percent of industrial land in center Shanghai increased from 4.86% in 1947 to 22.07% in 1989, but decreased to 13.05% in 2006. It can be speculated that the urbanization of Shanghai was dependent on industrialization before 1989, and then the industrial land has transmitted to the suburbs and concentrated in industrial parks. At the same time, the percentage of residential and public land is rising. As the best indicator of a country's economic, UAGDP shows more significant relationship between PTIA than UAIO.

As to population, when a city was at its preliminary stage, low population density areas have more impervious surface per resident because of roads and non-residential land use. When the city is in the stage of rapid development, the population increases rapidly, the living facilities continue to increase due to the increase of population, and high population density areas have less impervious surface per resident. Thus, the relationship between PD and PTIA is more significant in the case of high population density.

It should be stressed that China's urban population includes the local population, permanent immigrants, and floating population, and the floating population is the main source of urban population growth. With the continuous development of the economy, labor productivity has increased and labor demand has begun to decrease, which slowed down the increase in the floating population. Furthermore, the inflow of young labor and the outflow of mature labor have formed a cycle in the internal structure of population mobility. With some arbitrary, we hold that floating population had no influence on this research.

In addition, since the actual population of some highly migrated areas is difficult to count, the PTIA can also be used to estimate the actual population. This paper can provide a way of estimating internal migration, for regions that have a high level of unofficial movement to cities.

## Threshold effect and scale effect

A clear threshold effect was indicated. When PD levels exceeded 15,000 per/km<sup>2</sup>, the relationship with PTIA was less significant. Similar results were found when UAGDP exceeded 125 million yuan/km<sup>2</sup>. Since the city's land is limited, we argue that processes of impervious surface expansion have limits, and eventually, PTIA must reach the summit and remain stable.

The relationship between PTIA and socio-economic factors was more significant at city scale than district scale, which means that the relationship was more significant on a larger scale. At the same time, the results in the case of 18 districts as samples were more significant than those of 136 towns.

## Limitations

The results of this study are limited by the following factors. First, our ISC of land use calculations were less

specific, as ISC levels were regarded as 1 for roads and as 0 for agricultural and water areas. Second, only 240 samples were examined and our use of fewer samples may have introduced sampling bias. Third, while our explanations of threshold phenomena and scale effects found are empirical to a degree, more quantitative analyses should be conducted such as the piecewise regression method, such as R software.

## Conclusion

Taking Shanghai, a world metropolitan area, as a case, this paper examined coefficients for all land uses, and it is found that industrial land use generates the highest impervious surface coefficient (ISC) with a value of 0.75, followed by high-density residential. A regression analysis was also conducted to define the relationship between PTIA and three socio-economic factors at city scale and district scale. The results suggest that there is a significant positive correlation between PTIA and socio-economic indicators, in which PD was the most significant one. Threshold effect and scale effect were also presented. When PD exceeded 15,000 per/km<sup>2</sup>, the relationship between PTIA and socio-economic indicators would be less significant. Similar results were found for UAGDP, which exceeded 125 million yuan/km<sup>2</sup>. Moreover, the relationship became more significant at larger scale. The results of this paper would give suggestions for urban planning and environmental management.

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