Land Use Policy 59 (2016) 434–445

Contents lists available at ScienceDirect

Land Use Policy

journal homepage: www.elsevier.com/locate/landusepol

Behind the rapid expansion of urban impervious surfaces in China: Major influencing factors revealed by a hierarchical multiscale analysis

Qun Ma[a], Chunyang He[a,*], Jianguo Wu[a,b]

[a] Center for Human-Environment System Sustainability (CHESS), State Key Laboratory of Earth Surface Processes and Resource Ecology (ESPRE), Beijing Normal University, Beijing 100875, China
[b] School of Life Sciences and School of Sustainability, Arizona State University, Tempe, AZ 85287, USA

ARTICLE INFO

Article history:
Received 12 December 2015
Received in revised form 8 September 2016
Accepted 18 September 2016

Keywords:
Urban impervious surfaces (UIS)
Socioeconomic factors
Urbanization
Hierarchical analysis
China

ABSTRACT

Urban impervious surfaces (UIS) are well known to have negative impacts on the environment. Studies that consider multiple UIS-influencing factors at multiple administrative levels and spatial scales are still lacking. The main goal of this study was to determine the major socioeconomic factors that shaped the spatiotemporal patterns of UIS in China from the county to provincial levels over the most recent decades. Specifically, remote sensing and statistical data from 1992 to 2009 were used to examine the relationship of UIS to a suite of socioeconomic factors across hierarchical administrative levels from small (county), medium (prefectural) to large (provincial) levels. Our results show that the key influencing factors of UIS varied substantially across hierarchical administrative levels: economic factors dominated the provincial level, demographic factors were most significant at the county level, and a mixed group of economic, demographic and traffic factors were important at the prefectural level. This suggests that, for determining major influencing factors for UIS, a hierarchical or multiscale approach is preferred to any single-scale analysis. Our findings from such a hierarchical perspective provide useful information for formulating mitigation strategies for excessive UIS expansions and for designing more sustainable cities. It is recommended that policies to control rampant expansion of UIS in China need to combine macro-scale economic regulations with micro-scale demographic planning measures.

1. Introduction

The world has become increasingly urban and this trend is likely to continue (Grimm et al., 2008; Wu, 2008, 2014). The percentage of global human population living in urban areas was 54% in 2014, and is projected to be 66% in 2050 (United Nations, 2014). Almost the entire global population is projected to live in urban areas by 2092 (Batty, 2011). As urbanization unfolds, more and more natural land covers have been converted into urban impervious surfaces (UIS), which are human-made land covers in urban areas through which water cannot penetrate, including rooftops, parking lots, roads, and driveways (Arnold and Gibbons, 1996; Weng, 2012). UIS replace natural vegetation and soils, resulting in myriad ecological and environmental impacts from local to global scales, such as modifying near surface energy budgets (Oke, 1982; Buyantuyev and Wu, 2010), increasing urban runoff (Brun and Band, 2000; Weng, 2001), reducing water quality (Brabec, 2002), and decreasing aquatic biodiversity (Goetz and Fiske, 2008). Therefore, UIS have been widely regarded as a crucial indicator of urban environmental quality and has attracted much attention during the past decade (Elvidge et al., 2007; Weng, 2012; Liu et al., 2014; Ma et al., 2014; Wu, 2014).

The rapid urbanization of China since the 1980s is unprecedented in human history, resulting in enormous increases in UIS (Liu et al., 2012a; He et al., 2013; Ma et al., 2014; Wu et al., 2014). From 1992 to 2009, the total UIS area of China increased at an annual rate of 6.54%, which was nearly 2 times the annual increase of urban population (Ma et al., 2014). As the UIS expansion unfolds, a growing number of pressing environmental problems have emerged or worsened throughout the nation, including urban heat islands (Zhou et al., 2014a; Ma et al., 2016), urban flooding (Qin et al., 2013), air and water pollution (Shao et al., 2006), and

* Corresponding author.
E-mail addresses: mq-0127@163.com (Q. Ma), hcy@bnu.edu.cn (C. He), Jingle.Wu@asu.edu (J. Wu).

http://dx.doi.org/10.1016/j.landusepol.2016.09.012
0264-8377/

biodiversity loss (He et al., 2014b; Zhou et al., 2014a). To assess and mitigate the negative environmental impacts of UIS in China, it is necessary to identify the major influencing factors underlying spatiotemporal patterns of UIS (Wu, 2008, 2014; Kuang et al., 2014; Wu et al., 2014).

Several recent studies have been carried out to analyze the relationship between UIS and socioeconomic factors (Lu et al., 2006; Michishita et al., 2012; Kuang et al., 2014; Zhu et al., 2015), but most of these studies focused on single factors (e.g., population or GDP) at individual scales (e.g., provinces or counties). Studies that simultaneously consider multiple influencing factors of UIS across multiple administrative levels or spatial scales are scarce. Urban systems are multi-scaled and spatially heterogeneous systems, exhibiting a hierarchy of different centers or clusters across spatial scales. For such multi-scaled systems, the scale of analysis often affects the results of statistical analyses, such as correlation and regression analyses with landscape and socioeconomic data, and thus single-scale analyses are inadequate or even misleading (Wu et al., 1997; Buyantuyev et al., 2010). Instead, multiscale or multilevel methods are necessary (Wu, 1999; Blaschke, 2006; Li et al., 2013; Ma et al., 2016).

In this study, therefore, we used a hierarchical multiscale approach to determine the key influencing factors of UIS dynamics in China, with explicit consideration of three administrative levels: provinces, prefectures, and counties. Our main goal was to address the following two specific research questions: (1) What are the major socioeconomic factors influencing the spatiotemporal patterns of UIS in China? (2) How do these factors compare and contrast across hierarchical administrative levels with different spatial scales?

2. Methods

2.1. Study area and data acquisition

Our study area was mainland China, focusing on three levels of the administrative hierarchy: (1) provinces (also including autonomous regions and municipalities which are province-equivalent divisions), (2) prefectures, and (3) counties (Fig. 1). The boundaries of administrative units of all the three levels were based on the National Geomatics Center of China at the scale of 1: 4,000,000.

Five types of remote sensing data were used in this study: the Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS) nighttime light (NTL) data (http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html), the Moderate Resolution Imaging Spectroradiometer (MODIS) 16-day Normalized Difference Vegetation Index (NDVI) composite data (http://ladsweb.nascom.nasa.gov/data/search.html), the Advanced Very High Resolution Radiometer (AVHRR) 10-day NDVI composite data (http://earthexplorer.usgs.gov/), high-resolution images available on Google Earth, and land use/cover data (http://www.geodata.cn/). Socioeconomic data were obtained from China Statistical Yearbooks (see Table 1 for details).

2.2. Selecting hierarchical levels for analysis

Our multiscale approach was adapted from the hierarchical patch dynamics paradigm (Wu and Loucks, 1995; Wu, 1999), which requires different hierarchical levels of landscape to be explicitly identified. As per Li et al. (2013), we selected three administrative levels: provinces, prefectures, and counties. Each province is a spatially nested landscape hierarchy as each county belongs exclusively to a prefecture which in turn is part of a province (Chan, 2010; Li et al., 2013) (Fig. 1). We chose the three hierarchical levels because they were the primary levels of the Chinese administrative hierarchy, with relatively complete statistical data over the past several decades.

2.3. Quantifying urban impervious surfaces

Numerous remote sensing approaches have been used to extract UIS (Weng, 2012; Lu et al., 2014). In our study, we used a recently improved nighttime light-based method (Ma et al., 2014, 2016) to estimate the spatiotemporal patterns of UIS in China for the years of 1992, 2000, and 2009 (Fig. 2). This improved method has been demonstrated to have a substantially higher accuracy than previous methods using the NTL data (Ma et al., 2014, 2016). Here we briefly describe the key procedures of the method, whose details can be found in Ma et al. (2014).

Five steps were carried out to estimate the percent UIS values for each urban pixel from 1992 to 2009. First, the thresholding technique was applied to extract urban areas, using the methods developed by Liu et al. (2012b). The optimal threshold was determined when the urban areas extracted from the NTL data could best match the urban areas acquired from land use/cover data in terms of the spatial extent. Second, Vegetation Adjusted NTL Urban Index (VANUI) in urban areas was calculated using the following formula (Zhang et al., 2013):

$$VANUI = (1 - NDVI) * NTL_{nor}, \tag{1}$$

where $NDVI$ is the annual mean NDVI derived from MODIS or AVHRR, and NTL_{nor} is the normalized value of the preprocessed NTL data (Liu et al., 2012b). NTL_{nor} was computed as:

$$NTL_{nor} = \frac{NTL - NTL_{\min}}{NTL_{\max} - NTL_{\min}}, \tag{2}$$

where $NTL_{\min}$ and $NTL_{\max}$ are the minimum and maximum values in the NTL data (0 and 63, respectively). Third, samples with a window size of 1 × 1 km were randomly generated in urban areas with no major land use and land cover changes during 1992–2009, and their actual percent UIS values were obtained using Google Earth images. Fourth, a linear regression model was developed using the VANUI values of samples as the independent variable and the actual percent UIS values of samples as the dependent variable. Fifth, the linear regression model and the VANUI values acquired from step 2 were used to quantify the dynamics of UIS in China.

To recognize regional differences in geography and socioeconomic conditions, we divided China into eight regions, and all the steps mentioned above were performed for each region (Ma et al., 2014). Our earlier accuracy assessment showed that the average root-mean-square error (RMSE) for the entire mainland China from 1992 to 2009 was 0.136, with mean absolute error (MAE) of 0.108, systematic error (SE) of −0.018, and correlation coefficient (R) of 0.852 (see Ma et al., 2014 for details).

2.4. Selecting potentially important socioeconomic factors

Previous studies have shown that demography, economy, and transportation are important factors influencing urban land expansion (Berling-Wolff and Wu, 2004; Liu et al., 2005, 2008; Long et al., 2007; Deng et al., 2008; Han et al., 2009; Aljoufie et al., 2013). Here, we hypothesized that the three kinds of driving forces would also be key to the spatiotemporal patterns of UIS. Specifically, we selected 12 variables covering the three kinds of factors to examine how they would be related to UIS and how that relationship would change across different hierarchical levels. The 12 socioeconomic variables are: total population (i.e., the sum of urban population and rural population), urban population, rural population, non-agricultural population, gross GDP, GDP in primary industry, GDP in secondary

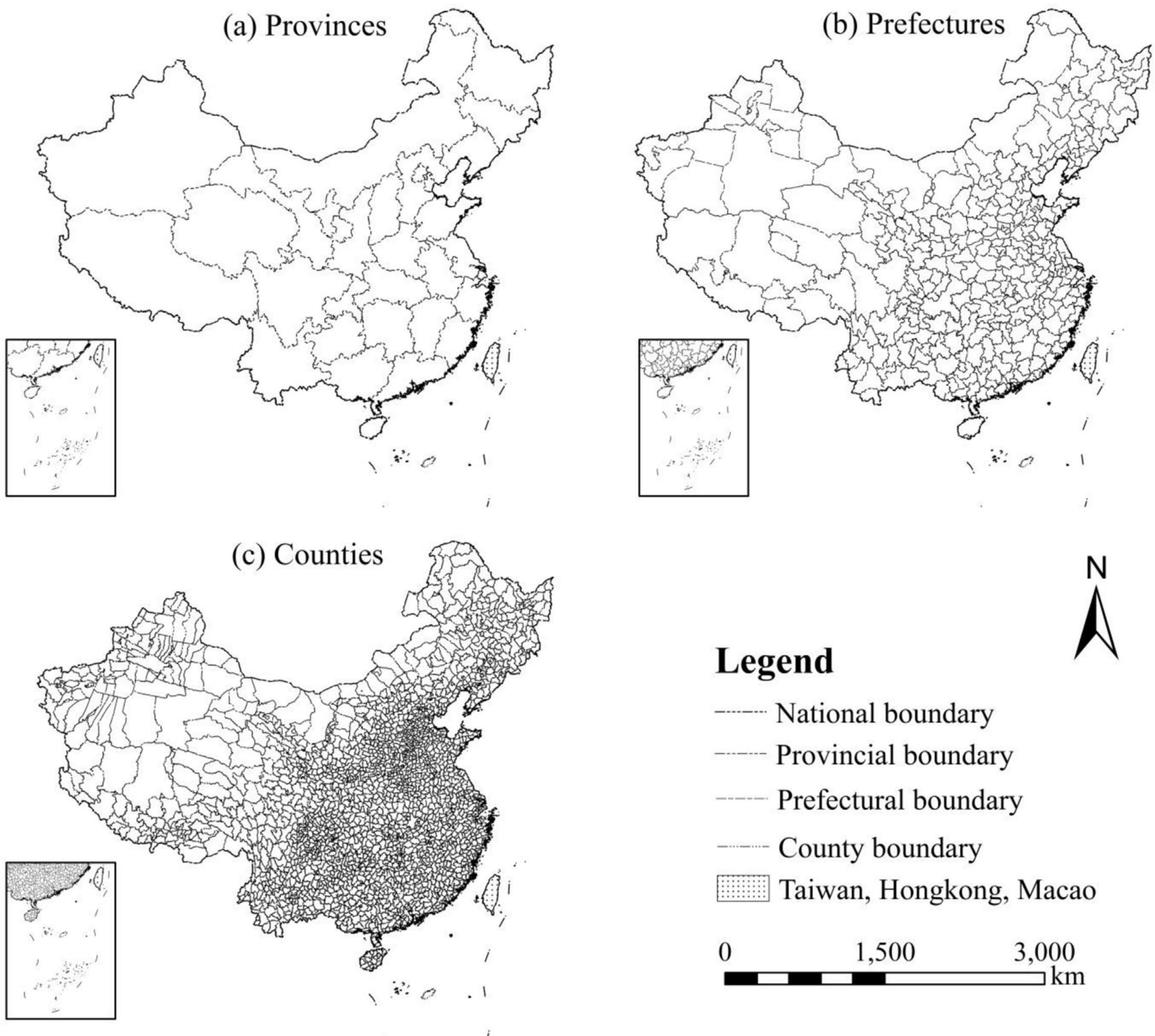

Fig. 1. Maps of the study area, mainland China, showing three administrative levels: provinces (a), prefectures (b), and counties (c).

industry, GDP in tertiary industry, investment in fixed assets, revenue of local governments, per capita disposable income of urban households, and the number of civil vehicles (including private and public vehicles and taxis) (Table 1).

2.5. Statistical analysis

Both Pearson correlation and stepwise multiple linear regression have been widely used in UIS-related studies (Buyantuyev and Wu, 2010; Buyantuyev et al., 2010; Zhou et al., 2014a, 2014b). In this study, we conducted Pearson correlation analysis to determine whether the 12 socioeconomic variables were individually correlated with UIS in 1992, 2000, and 2009 and which ones had stronger correlations. In order to know whether each of these socioeconomic factors would still be significantly correlated with UIS when others were held constant, we also performed stepwise multiple linear regressions at each hierarchical level. Three of the 12 socioeconomic variables were excluded from stepwise multiple regression analysis because of rather low values of the Pearson correlation coefficient (rural population, GDP in primary industry, and per capita disposable income of urban households).

We also computed standardized regression coefficients to compare the significant socioeconomic factors and determine which ones were more important statistically in stepwise multiple linear regression. The standardized regression coefficients represent the amount of change in the dependent variable in response to a change of one standard deviation in an independent variable. Thus, the larger the absolute value of the standardized regression coefficient, the more important that independent variable.

All our statistical analyses were done with SPSS for Windows (version 16.0).

3. Results

As mentioned earlier, we used both Pearson correlation and stepwise multiple linear regression in our analysis so as to help identify UIS-influencing factors through comparing and contrasting the results from the two methods. In this section, we organized our results first by the three hierarchical levels (provinces, prefectures, and counties) and then the two methods. In general, the Pearson correlation analysis showed that essentially all the selected socioeconomic variables were significantly correlated with UIS at least at one or more of the three hierarchical levels, but a much smaller set of them were statistically significant in the stepwise multiple lin-

Table 1
Socioeconomic variables considered in this study and their associated metadata.

Factors		Level	Acquisition date	Data source
Demographic factors	Total population Urban population Rural population[a]	Provinces Prefectures Counties	1992[b], 2000, 2009[b] 1992[b], 2000, 2009[b] 1992[b], 2000, 2009[b]	Tabulation on the 1990/2000/2010 Population Census of China (Population Census Office under the State Council and Department of Population and Employment Statistics of National Bureau of Statistics of China, 1993, 2002, 2013)
	Non-agricultural population[c]	Provinces Prefectures Counties	1992, 2000, 2009 1992, 2000, 2009 1992, 2000, 2009	Tabulation on the 1992/2000/2009 Population Statistics of China by County (Ministry of Public Security of China, 1993, 2001, 2010)
Economic factors	Gross GDP GDP in primary industry GDP in secondary industry GDP in tertiary industry	Provinces Prefectures Counties	1992, 2000, 2009 2000, 2009 2009	China Statistical Yearbook for Regional Economy 2000/2009 (Department of Comprehensive Statistics and Department of Rural Survey of National Bureau of Statistics of China, 2003, 2010);
	Investment in fixed assets Revenue of local governments	Provinces	1992, 2000, 2009	China Statistical Yearbook 1992/2000/2009 (National Bureau of Statistics of China, 1993, 2001, 2010);
		Prefectures Counties	1992, 2000, 2009 2009	
	Per capital disposable income of urban households	Provinces	1992, 2000, 2009	China City Statistical Yearbook 1992/2000/2009 (Department of Urban Surveys of National Bureau of Statistics of China, 1995, 2002, 2011)
		Prefectures Counties	2000, 2009 2009	
Traffic factor	Number of civil vehicles (including private and public vehicles and taxis)	Provinces	2000, 2009	
		Prefectures Counties	2000, 2009 No data	

[a] Urban population/Rural population refer to the population living in urban areas or rural areas of a city for more than half a year.
[b] Total population/Urban population/Rural population for 1992 and 2009 were calculated, respectively, using the corresponding population in 1990 and 2000, and in 2000 and 2010, based on the exponential growth equation (Malthus, 1798).
[c] Non-agricultural population refer to the registered permanent urban residents in a city, which are generally smaller than urban population (Bai et al., 2014).

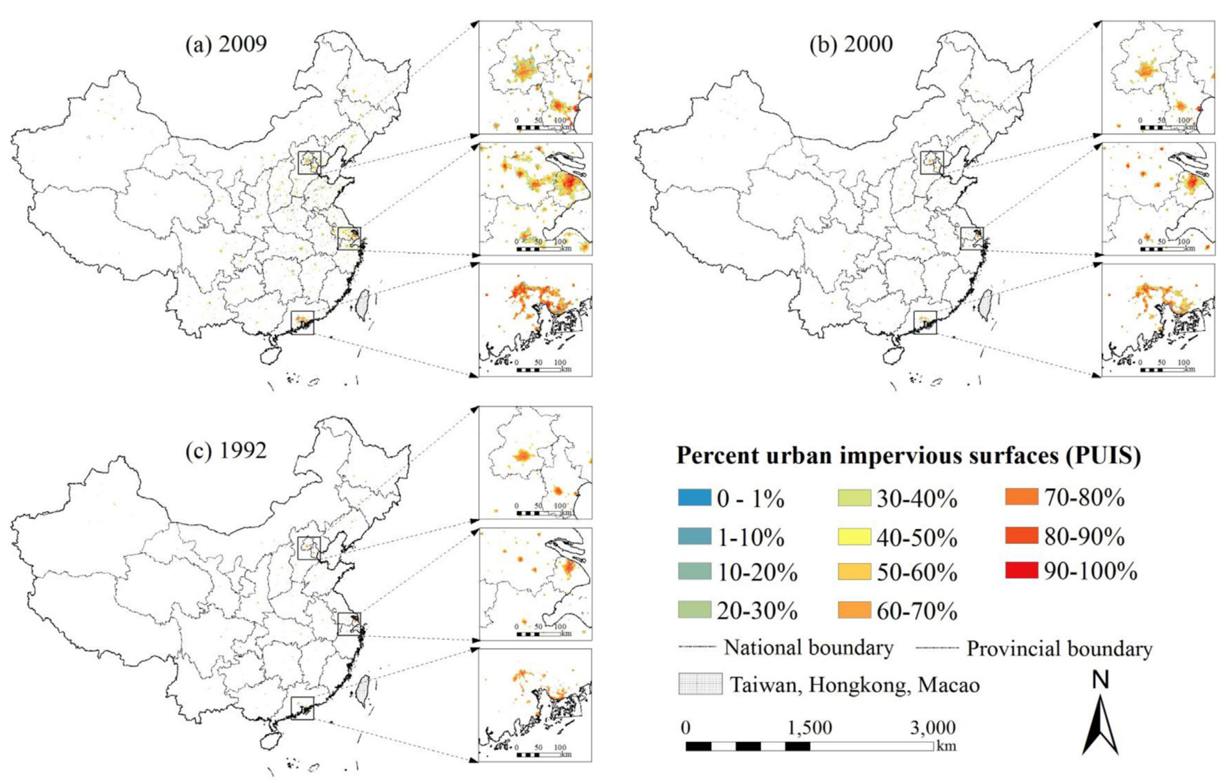

Fig. 2. Spatial distributions of UIS in mainland China in 2009 (a), 2000 (b) and 1992 (c). Non-urban areas are all in white.

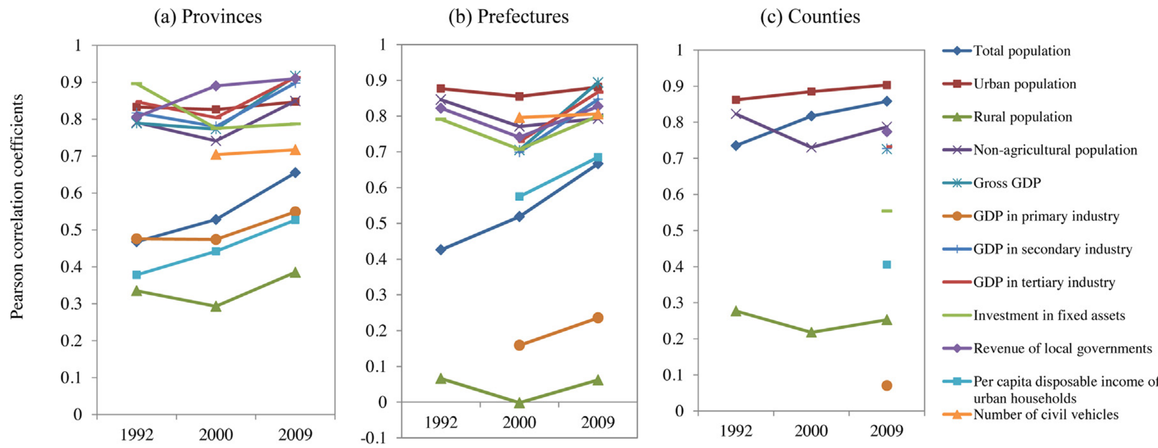

Fig. 3. Pearson correlation coefficients between UIS and socioeconomic factors from 1992 to 2009 at three hierarchical levels: the provincial level (a), the prefectural level (b), and the county level (c). Due to unavailable data, some values of Pearson correlation coefficients are absent.

ear regression analysis because, as expected, many of these factors were correlated with each other.

3.1. Relationship between UIS and socioeconomic factors at the provincial level

3.1.1. Pearson correlation analysis

Our correlation analysis showed that all the 12 selected socioeconomic variables were significantly correlated with UIS at the provincial level, although the values of their Pearson correlation coefficients varied substantially. Eight of them had Pearson correlation coefficients of larger than 0.70, and three (rural population, GDP in primary industry, and per capita disposable income of urban households) had Pearson correlation coefficients of about 0.5 or smaller (Fig. 3a). The highest Pearson correlation coefficient was found between UIS and gross GDP in 2009 with the value of 0.92, more than 2 times the lowest value of 0.39 between UIS and rural population in the same year.

From 1992 to 2009, the strength of the relationship between UIS and socioeconomic variables changed between years, but the order of the variables in terms of their values of the Pearson correlation coefficient remained relatively consistent. Largest temporal variations were associated with total population, gross GDP, and per capita disposable income of urban households (Fig. 3a). For example, the Pearson correlation coefficient between UIS and total population increased from 0.47 in 1992 to 0.66 in 2009. On the other hand, the Pearson correlation coefficient between UIS and urban population varied little during 1992–2009 (Fig. 3a).

3.1.2. Stepwise multiple linear regression analysis

Different from the results of Pearson correlation analysis, our stepwise multiple linear regression analysis showed that not all the selected socioeconomic factors were statistically significant. Specifically, at the provincial level, economic factors (i.e., gross GDP, revenue of local governments, and investment in fixed assets) were the major influencing factors (Fig. 4; Table 2). In 2009, more than 86% of the variability in UIS was explained jointly by gross GDP and revenue of local governments (Table 2). Gross GDP was slightly more important than revenue of local governments as indicated by their standardized regression coefficients (Table 2). In contrast, revenue of local governments in 2000 and investment in fixed assets in 1992 explained nearly 80% of the variability in UIS for the corresponding years, respectively (Table 2).

3.2. Relationship between UIS and socioeconomic factors at the prefectural level

3.2.1. Pearson correlation analysis

At the prefectural level, all the 12 socioeconomic factors, but rural population, were significantly positively related to UIS (Fig. 3b). Except for GDP in primary industry whose Pearson correlation coefficient was <0.30, all other variables had Pearson correlation coefficients of larger than 0.67 in 2009, with the highest Pearson correlation coefficient of 0.89 between UIS and gross GDP. The general patterns of temporal changes in the Pearson correlation coefficients from 1992 to 2009 were similar to those at the provincial level (Fig. 3b). The Pearson correlation coefficients changed relatively small between years for most variables (<0.10), with the exception of total population (a change of about 0.30) (Fig. 3b).

3.2.2. Stepwise multiple linear regression analysis

At the prefectural level, economic factors (gross GDP, GDP in secondary industry, GDP in tertiary industry, investment in fixed assets, and revenue of local governments), demographic factors (total population and urban population), and a traffic factor (the number of civil vehicles) were all statistically significant influencing factors (Fig. 4; Table 2). In 2009, nearly 87% of the variability in UIS was explained by the above-mentioned variables excluding investment in fixed assets and revenue of local governments (Table 2). Among these variables, gross GDP was the most important one with the absolute value of the standardized regression coefficient reaching 2.40 (Table 2).

In 2000, a combination of urban population, economic factors (i.e., gross GDP, GDP in secondary industry, and revenue of local governments), and the number of civil vehicles explained 81.10% of the variability in UIS (Table 2). Gross GDP was again found to be the most important one among the explanatory variables of UIS. In 1992, about 75% of the variability in UIS was explained jointly by total population, urban population, investment in fixed assets, and revenue of local governments (Table 2). Urban population was among the most important one with its standardized regression coefficient of about 0.35.

3.3. Relationship between UIS and socioeconomic factors at the county level

3.3.1. Pearson correlation analysis

All the selected socioeconomic variables were again found significantly positively correlated with UIS in 2009, as well as in 1992

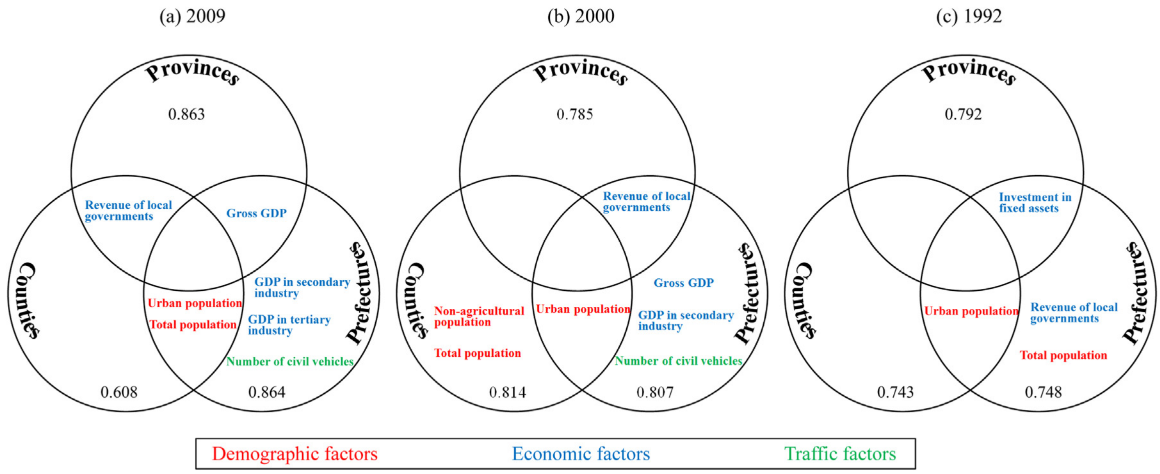

Fig. 4. Venn diagrams of the major influencing factors of UIS at three hierarchical levels (provinces, prefectures, and counties) in 2009 (a), 2000 (b), and 1992 (c). Different colors represent different kinds of factors: red for demographic factors, blue for economic factors, and green for traffic factors. The number in each circle is the combined adjusted R^2. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

Table 2
Standardized regression coefficients and coefficients of determination (R^2) at provincial, prefectural, and county levels for 1992, 2000, and 2009.

Level	Year	Standardized regression coefficients									R^2 (adjusted)
		Total population	Urban population	Non-agricultural population	Gross GDP	GDP in secondary industry	GDP in tertiary industry	Investment in fixed assets	Revenue of local governments	Number of civil vehicles	Combined
Provinces	2009				0.518**				0.437*		0.873 (0.863)
	2000								0.890**		0.792 (0.785)
	1992							0.894**		–	0.799 (0.792)
Prefectures	2009	−0.166*	0.324**		−2.403**	1.597**	1.494**			0.246*	0.867 (0.864)
	2000		0.504**		−1.424**	1.076**			0.514**	0.334**	0.811 (0.807)
	1992	−0.086*	0.347**		–	–	–	0.335**	0.295**	–	0.752 (0.748)
Counties	2009	−0.207**	0.198**						0.728**	–	0.609 (0.608)
	2000	−0.087*	1.340**	−0.413**	–	–	–	–	–	–	0.814 (0.814)
	1992		0.862**		–	–	–	–	–	–	0.744 (0.743)

– No data.
* Significant at the 0.05 level.
** Significant at the 0.01 level.

and 2000 when data were available (Fig. 3c). The differences in the Pearson correlation coefficients among the different variables for each year were similar to those at the prefectural level but larger than those at the provincial level (Fig. 3c). Except for rural population, GDP in primary industry, and per capita disposable income of urban households, all other variables had relatively strong correlation with UIS, with the Pearson correlation coefficients of larger than 0.50. Urban population had the highest Pearson correlation coefficient (0.90), followed by total population (0.86) and non-agricultural population (0.79) in 2009 (Fig. 3c).

For the four socioeconomic variables that had data for all the three years, the general pattern of their temporal variations in the Pearson correlation coefficients was similar to that found at the prefectural and provincial levels. The Pearson correlation coefficient between UIS and total population had the largest temporal change, increasing monotonically by 0.12 from 1992 to 2009 (Fig. 3c). Other three variables had much smaller between-year variations (<0.09).

3.3.2. Stepwise multiple linear regression analysis

Demographic factors (total population, urban population, and non-agricultural population) and an economic factor (revenue of local governments) were the major influencing factors at the county level (Fig. 4; Table 2). In 2009, total population, urban population, and revenue of local governments together explained 61% of the variability in UIS (Table 2). Revenue of local governments was more important than the other two factors in terms of their standardized regression coefficients. In 2000, more than 80% of the variability in UIS was explained jointly by total population, urban population, and non-agricultural population (Table 2). Urban population was among the most important variable to explain the variability in UIS with its standardized regression coefficient of 1.34. In 1992, urban population alone explained 74.40% of the variability in UIS (Table 2).

4. Discussion

4.1. What are the major influencing factors for the rapid expansion of UIS in China?

Our study has demonstrated that the answer to this question depends on the statistical methods used (i.e., the Pearson correlation analysis vs. stepwise multiple linear regression analysis in this case), as well as the levels of administrative hierarchy and associated spatial scales. The results of the Pearson correlation analysis indicated that all the selected socioeconomic factors were significantly correlated with UIS individually on at least one hierarchical level in one of the three study years (Fig. 3). This suggests that each of the factors could contribute to the expansion of UIS through promoting the constructions of industrial development zones, res-

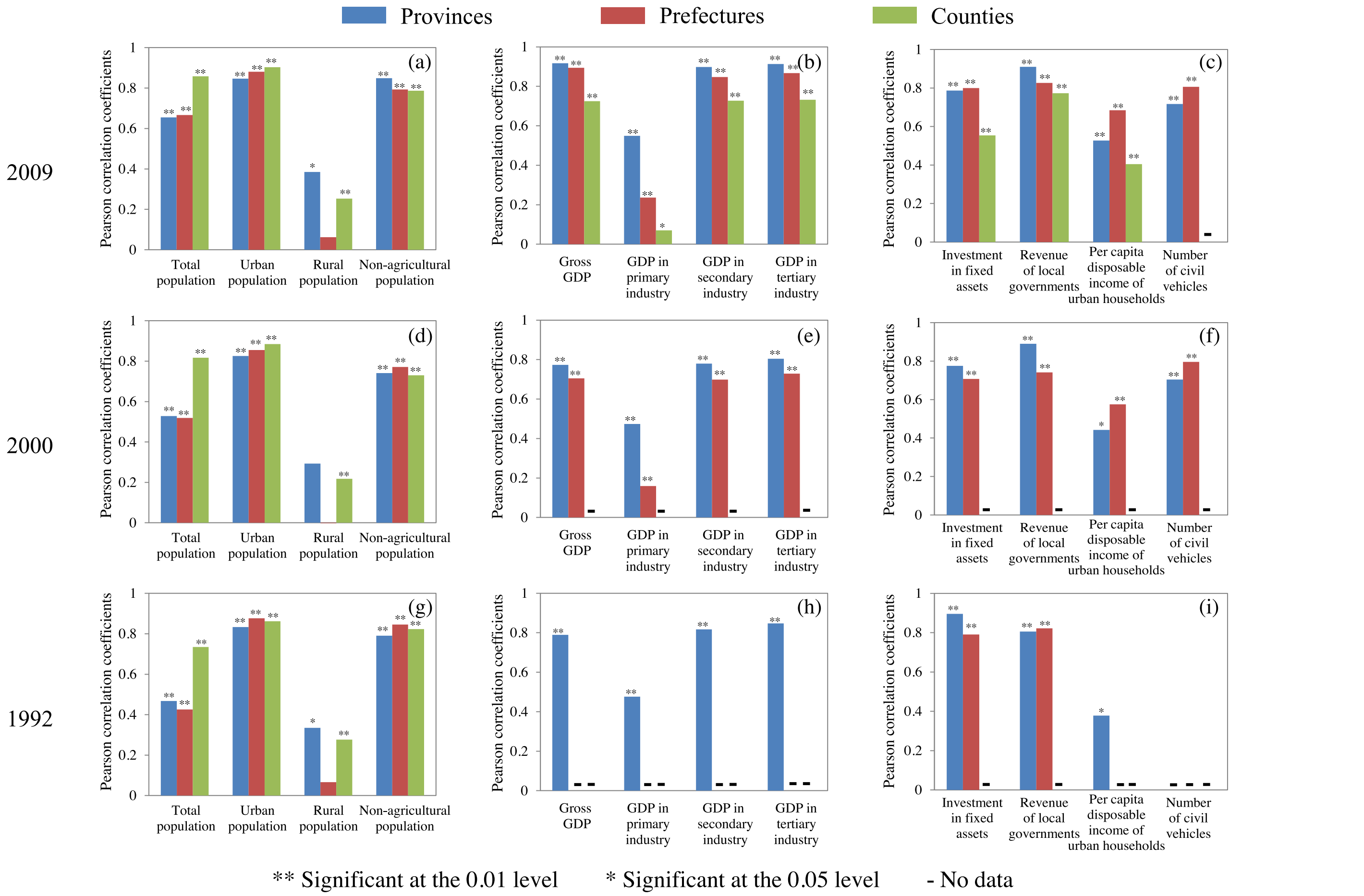

Fig. 5. Comparison of Pearson correlation coefficients between UIS and socioeconomic factors at the provincial, prefectural, and county levels in 2009 (a-c), 2000 (d-f), and 1992 (g-i).

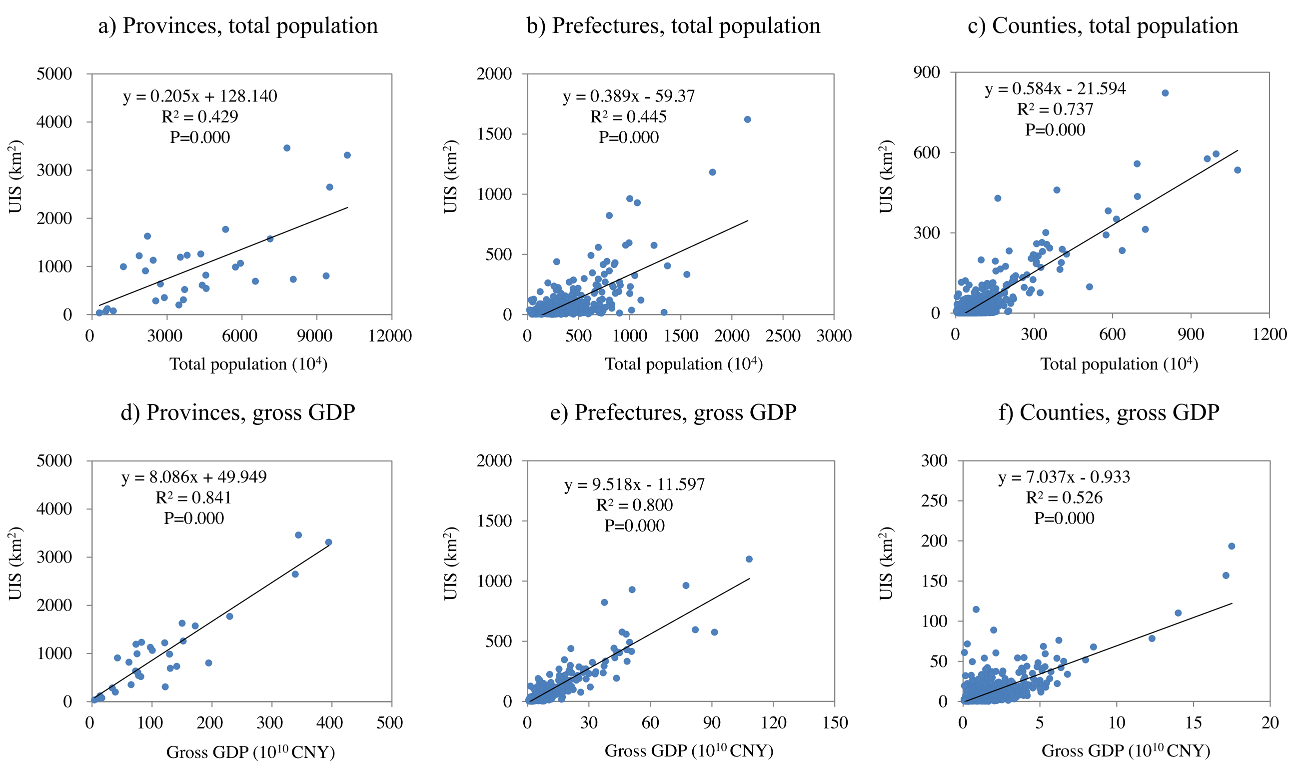

Fig. 6. Examples of linear regressions between UIS (km^2) and total population (10^4) and gross GDP (10^{10} CNY) in 2009 at the provincial, prefectural, and county levels.

idential and shopping areas, or infrastructure projects in order to meet the increasing needs of work, living, and leisure spaces (Yue et al., 2013; Kuang et al., 2016). Particularly, urban population tended to have the strongest positive correlation with UIS at all three hierarchical levels, with small temporal variations from 1992 to 2009 (Fig. 3). This implies that urban population is likely to be a good predictor of UIS dynamics across different levels of administrative hierarchy or spatial scales.

The stepwise multiple linear regression analysis provided the best parsimonious prediction model of UIS using only the socioeconomic variables with independent information. Those variables that provided only redundant information were excluded from the list of major influencing factors. Our results show that only a few socioeconomic factors were significantly correlated with UIS when other factors were kept constant (Table 2), and the major influencing factors from the stepwise multiple linear regression analysis varied considerably across the three hierarchical levels (more details discussed in the next section).

4.2. How do major influencing factors change across hierarchical levels?

From the Pearson correlation analysis, the strength of the relationship between UIS and the major influencing factors varied from the county to prefectural and provincial levels with increasing spatial scales (Fig. 5). Total population, urban population, and the number of civil vehicles were more strongly correlated with UIS at the county level than at the two higher levels (Fig. 5). For example, the coefficient of determination (R^2) value of the relationship between UIS and total population increased from 0.43 at the provincial level to 0.74 at the county level in 2009 (Fig. 6a–c). The slope of the linear regression between UIS and total population for counties was nearly 1.5 times the slope for prefectures, and 3 times the slope for provinces, respectively (Fig. 6a–c). This means that the relationship between UIS and socioeconomic factors is sensitive to the hierarchical administrative level in focus or the scale of analysis.

Previous studies have shown that rural-urban migration and transportation accessibility were the main drivers of urban growth in China, with geographic distance as a key factor in both (Zhang and Shunfeng, 2003; Ding and Zhao, 2011; Chen et al., 2014; He et al., 2014a, 2014b). Long distance increases the cost of migration and commuting time, and thus migration and commute within counties tend to be much easier and more efficient than those across prefectures or provinces. For example, Ye and Huang (2004) showed that the inter-county migration accounted for 45.5% of the total migration in China in 2000. Thus, the effects of population and transportation factors on UIS were stronger at the county level than at the prefectural and provincial levels.

By contrast, the strength of the correlation between UIS and economic factors (except for per capita disposable income of urban households) decreased from the provincial level to the prefectural and county levels (Fig. 5). For example, more than 80% of the variability in UIS was explained by gross GDP at the provincial level in 2009, while only half of the change in UIS was explained by gross GDP at the county level (Fig. 6d–f). Meanwhile, as gross GDP increased by 1 billion CNY, UIS expanded by 0.81 km^2 at the level of provinces and 0.70 km^2 at the level of counties, respectively (Fig. 6d–f). This may be because higher administrative units in the Chinese administrative system usually correspond to greater administrative, institutional, and financial powers (Ma, 2005; Li et al., 2015). In comparison with the two lower levels, provinces have larger administrative territory for land conversion and can attract more central, local, and foreign investments for real-estate development and industrial and transportation projects. Thus, economic factors tend to have larger effects on UIS at the provincial level than at the two lower levels.

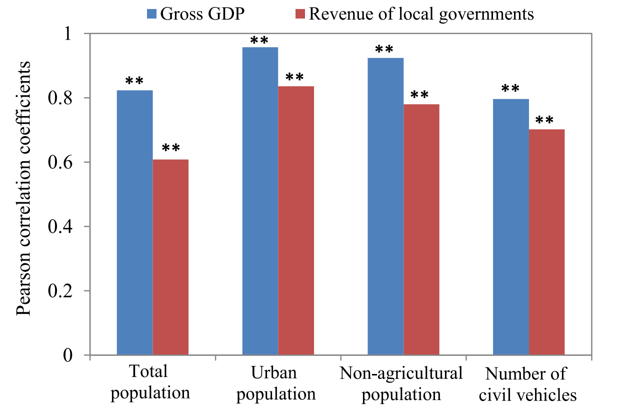

Fig. 7. Pearson correlation coefficients between demographic and traffic factors and economic factors of gross GDP and revenue of local governments in 2009 at the provincial level.

Our stepwise multiple linear regression analysis also revealed that the major influencing factors of UIS differed greatly with hierarchical levels (Fig. 4; Table 2). Spatiotemporal patterns of UIS were mainly affected by economic factors at the provincial level during 1992–2009, although most of demographic and traffic factors were highly correlated with UIS when considering them separately (Figs. 3 and 4). For example, if gross GDP and revenue of local governments were controlled, all demographic and traffic factors had no significant relationship with UIS, with partial correlation coefficients of smaller than 0.24 and P-value of larger than 0.20 (Table 3), despite the fact that all the socioeconomic factors were significantly correlated with UIS individually at the provincial level in 2009 (Fig. 3a). We also found that both demographic and traffic factors were positively correlated with gross GDP and revenue of local governments, with the Pearson correlation coefficients of larger than 0.6 and the P-value equal to 0 (Fig. 7). Thus, only using gross GDP and revenue of local governments could explain nearly 90% of the variance in UIS in 2009 at the provincial level (Table 2).

Similarly, Brueckner and Fansler (1983) and Deng et al. (2008) also found that economic factors (e.g., income growth) played more important role in urban land expansion than other factors (e.g., population and transportation costs). At the provincial level, there is a positive feedback between landscape urbanization and economic growth in China (Bai et al., 2012). On the one hand, local (provincial) governments reap more GDP and revenues through expropriating rural land from farmers at a low price and then selling the land to real-estate developers at a high price (Yue et al., 2013; Liu et al., 2014b; Zhang et al., 2014). Bai et al. (2014) indicated that land release/resale deals accounted for as much as 70% of the total revenues of local governments in China during the recent decades. On the other hand, more GDP and revenues of local governments promote further development of urban infrastructures, including roads, airports, and energy structures, which contribute to the expansion of UIS (Bai et al., 2012; Kuang et al., 2016). At the provincial level, therefore, economic factors were the most fundamental factors influencing UIS dynamics, although population and transportation factors were all significantly related to UIS individually.

At the prefectural and county levels, demographic and traffic, other than economic, variables became increasingly dominant (Fig. 4; Table 2). Apart from economic factors, several demographic and traffic factors (total population, urban population, and the number of civil vehicles) were also important at the prefectural level (Fig. 4). Fast growth of population and civil vehicles usually leads to more buildings, roads, and parking lots, all increasing the amount of UIS (Elvidge et al., 2007). At the county level, the

Table 3
Partial correlation coefficients[a] of demographic and traffic factors against urban impervious surfaces in 2009 at the provincial level.

Controlling factors	Factors		Partial correlation coefficients	P-value
Gross GDP and revenue of local governments	Demographic factors	Total population	−0.230	0.231
		Urban population	−0.143	0.461
		Non-agricultural population	0.239	0.212
	Traffic factor	Number of civil vehicles	−0.009	0.963

[a] Partial correlation coefficient estimates the degree of relationship between two variables by removing the effect of a set of controlling variables.

number of significant influencing factors was reduced to a few demographic variables (total population, urban population, and non-agricultural population) and one economic variable (revenue of local governments) (Fig. 4). This further suggests that population factors strongly affected UIS at the county level, and that relationship between population and UIS was tighter at the local scale than broader scales.

4.3. Methodological implications

Most complex systems, be they biophysical or socioeconomic, are hierarchical and multi-scaled (Simon, 1962; O'Neill et al., 1986; Wu and Loucks, 1995; Wu 1999). The hierarchical structure of administrative systems is apparent everywhere, and particularly evident in China where an administrative level only interacts directly with the next level immediately above and below it in most cases (Ma, 2005). The hierarchical administrative levels differ in their ability to exercise power (Ma, 2005). A higher administrative level generally has stronger administrative, economic, and fiscal powers, consequently resulting in differential impacts on urbanization in terms of both scale and scope. Consequently, urbanization may have different spatiotemporal patterns and associated socioeconomic drivers across hierarchical administrative levels and spatial scales (Wu, 1999; Li et al., 2013, 2015; Ma et al., 2016), which can be regarded as an example of the Modifiable Area Unit Problem (MAUP) (Openshaw and Openshaw, 1984; Jelinski and Wu, 1996). Our study demonstrates that a hierarchical or multiscale approach is needed to adequately quantify complex urban landscape dynamics because any single-level or single-scale study is likely to misrepresent the patterns and drivers on other levels. Only by explicitly considering the hierarchical structure and scale multiplicity of the urban administrative hierarchy, can we capture the generalities and idiosyncrasies of complex urban landscape dynamics (Wu, 1999, 2014; Li et al., 2013; Ma et al., 2016).

In addition, although Pearson correlation and stepwise multiple linear regression have been commonly used to investigate the relationship of UIS to a suite of socioeconomic factors, a better understanding of how they compare and contrast is lacking. Our results show that the two methods can produce disparate and even conflicting results, thus leading to quite different conclusions on the key influencing factors of UIS. Pearson correlation may be used to scope potentially important factors and seek the best simple predictive models with only one independent variable, given that different factors may be correlated or interact with each other. In contrast, stepwise multiple linear regression is more appropriate for identifying the key UIS-influencing factors because multicollinearity between different factors is removed (as indicated by standardized regression coefficients). Using stepwise multiple linear regression, one may obtain a parsimonious predictive model with multiple independent variables and higher accuracy/explanatory power. Thus, the two methods, when used properly together, can provide complementary and comprehensive information that should not be considered contradictory or redundant. Of course, as shown in our study, both methods should be used across different hierarchical levels or spatial scales.

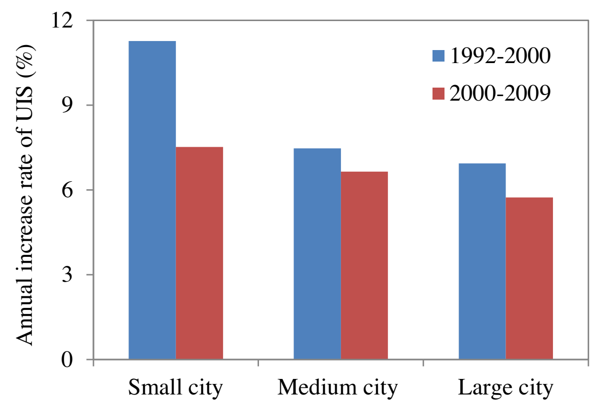

Fig. 8. The average annual increase rates of UIS for cities of different sizes in two periods. The cities were classified as small, medium, and large cities according to the criteria proposed by Gao et al. (2016).

4.4. Policy influences and implications

Land use policies have played an important role in shaping urbanization patterns in China during the past several decades (Fang, 2009, 2015; Liu et al., 2014a; Long, 2014; Wu et al., 2014; Zhang et al., 2014; Huang et al., 2015). Particularly, some policies containing urban development guidelines have had large effects on UIS dynamics in China since the early 1990s. For example, China's urban development policies during the 1990s focused mainly on promoting small and medium cities and controlling the size of large cities (Table 4). As a result, the average annual growth rate of UIS in small and medium cities was nearly twice that in large cities between 1992 and 2000 (Fig. 8). Since 2000, China's urban development policies began to emphasize the coordinated development of large, medium, and small cities as well as the development of urban agglomerations (Table 4). Consequently, the differences in the average annual increase rate of UIS among small, medium, and large cities substantially decreased for the period of 2000–2009 (Fig. 8). Urban agglomerations in China experienced a rapid expansion of UIS between 2000 and 2009: the 23 urban agglomerations (Fang, 2011) accounted for about 20% of China's total land area but more than 70% of the total area of UIS expansion during that period. The most recent governmental policies on urban development, such as National New-Style Urbanization Plan and China's 13th Five-Year Plan (Table 4), are expected to have major influences on the patterns of UIS over the next several years.

Our findings have several implications for policy implementation and UIS management in China. First, to achieve the intended outcomes of the new urban development policies, implementation actions should involve multiple administrative levels to curtail the excessive expansion of UIS as different influencing forces exist or dominate on different scales. Second, at the provincial level, focusing on economic policies is key to effective management of UIS in China. To control rampant profit-driven expansion of UIS and improve land use efficiency, the increase in UIS per unit of GDP should be considered explicitly and compensated ecologically through properly designed regulations. Third, at the prefectural

Table 4
Major governmental policies that have had important influences on urban development in China from the 1980s to 2010s.

Year	Policy/decree	Main contents
1989	City Planning Law of China	Strictly control the size of large cities and properly develop small and medium cities in order to achieve a more geographically balanced distribution of productive forces and urban populations.
1994	China's Agenda 21	Appropriately control the momentum of rapid population growth in large cities and develop satellite towns around large cities, actively and appropriately develop small and medium cities, and vigorously develop small towns.
2001	China's 10th Five-Year Plan (2001–2005)	Selectively develop small towns, actively develop small and medium cities, improve the function of regional core cities, bring the radiation effects of large cities into play, and guide the areas concentrated by cities and towns towards orderly development.
2006	China's 11th Five-Year Plan (2006–2010)	Focus on urban agglomerations as the main backbones for promoting urbanization, continue coordinated development of small towns and large, medium, and small cities, and improve the integrative carrying capacity of cities and towns.
2011	China's 12th Five-Year Plan (2011–2015)	Follow the principles of urban development, form urban agglomerations with large radiation effects by relying on large cities and focusing on small and medium cities, and promote the coordinated development of small towns and cities of different sizes.
2014	National New-type Urbanization Plan (2014–2020)	Comprehensively improve the quality of urbanization, speed up the transformation of the path of urbanization, emphasize the people-centered urbanization, gradually transfer agricultural immigrants to citizens, and take urban agglomerations as the main backbone for accelerating the coordinated development of small towns and large, medium, and small cities.
2016	China's 13th Five-Year Plan (2016–2020)	Optimize the layout of urbanization, promote the development of urban agglomerations, strengthen the radiation effects of core cities, and accelerate the development of small and medium cities as well as some select towns.

level, UIS management should pay more attention to concerted development of demographic, economic, and transportation sectors to optimize the spatial patterns of UIS. Fourth, at the county level, population policies (e.g., some restrictions on migration) may help better control excessive UIS expansion. Implementing urban development policies also need increases public scrutiny and stakeholder governance to minimize malpractices of local governments and to promote people-centered sustainable cities (Bai et al., 2014; Wu et al., 2014).

5. Conclusions

To improve the ecology and sustainability of our cities, it is necessary to curb the expansion of impervious surfaces because of their myriad negative environmental impacts (Grimm et al., 2008; Wu, 2008, 2014). This is especially important for developing countries, such as China, where rampant urbanization is fuelled by rapid economic growth. Our study offers several important findings of the relationship between UIS and its key influencing factors. First, UIS-influencing factors differ across hierarchical administrative levels and spatial scales. Thus, for determining major influencing factors for UIS, a hierarchical multiscale approach, as illustrated here, is preferable to any single-scale analysis. Second, during the period of 1992–2009 the expansion of UIS in China was influenced mainly by a few economic factors at the provincial level, a few demographic factors at the county level, and a mixed group of economic, demographic, and traffic factors at the prefectural level. Third, our study demonstrates that Pearson correlation and stepwise multiple linear regression can be used together to provide complementary information that helps better understand the major influencing factors of UIS across different hierarchical levels or spatial scales.

It is important to note that correlation is not causation, and our study only examines the statistical relationship between UIS and socioeconomic factors, without doing any direct causality analysis. Nevertheless, the findings of our current study suggest that both the design and implementation of policies to curb disorderly expansion of UIS in China need to explicitly consider macro-scale economic regulations and micro-scale demographic planning measures. Our study is an important, but only a first step toward adequately understanding the processes of UIS dynamics across administrative levels and spatial scales in order to achieve urban sustainability. Further studies are needed to test these findings and reveal the underlying mechanisms.

Acknowledgments

We would like to thank the anonymous reviewers and the editor for their valuable comments which led to substantial improvements of the paper. We also thank Dr. Qingxu Huang for his assistance with collecting urban development policies. Our research was supported in part by the National Basic Research Programs of China (Grant No. 2014CB954302 & 2014CB954303) and the National Natural Science Foundation of China (Grant No. 41321001).

References

Aljoufie, M., Zuidgeest, M., Brussel, M., van Maarseveen, M., 2013. Spatial–temporal analysis of urban growth and transportation in Jeddah City, Saudi Arabia. Cities 31, 57–68.
Arnold, C.L., Gibbons, C.J., 1996. Impervious surface coverage—the emergence of a key environmental indicator. J. Am. Plann. Assoc. 62, 243–258.
Bai, X., Chen, J., Shi, P., 2012. Landscape urbanization and economic growth in China: positive feedbacks and sustainability dilemmas. Environ. Sci. Technol. 46, 132–139.
Bai, X., Shi, P., Liu, Y., 2014. Society: realizing China's urban dream. Nature 509, 158.
Batty, M., 2011. When all the world's a city. Environ. Plann. A 43, 765–772.
Berling-Wolff, S., Wu, J., 2004. Modeling urban landscape dynamics: a case study in Phoenix, USA. Urban Ecosyst. 7, 215–240.

Blaschke, T., 2006. The role of the spatial dimension within the framework of sustainable landscapes and natural capital. Landscape Urban Plann. 75, 198–226.
Brabec, E., 2002. Impervious surfaces and water quality: a review of current literature and its implications for watershed planning. J. Plann. Lit. 16, 499–514.
Brueckner, J.K., Fansler, D.A., 1983. The economics of urban sprawl: theory and evidence on the spatial sizes of cities. Rev. Econ. Stat., 479–482.
Brun, S., Band, L., 2000. Simulating runoff behavior in an urbanizing watershed. Comput. Environ. Urban Syst. 24, 5–22.
Buyantuyev, A., Wu, J., 2010. Urban heat islands and landscape heterogeneity: linking spatiotemporal variations in surface temperatures to land-cover and socioeconomic patterns. Landscape Ecol. 25, 17–33.
Buyantuyev, A., Wu, J., Gries, C., 2010. Multiscale analysis of the urbanization pattern of the Phoenix metropolitan landscape of USA: time, space and thematic resolution. Landscape Urban Plann. 94, 206–217.
Chan, K.W., 2010. Fundamentals of China's urbanization and policy. China Rev., 63–93.
Chen, R., Ye, C., Cai, Y., Xing, X., Chen, Q., 2014. The impact of rural out-migration on land use transition in China: past, present and trend. Land Use Policy 40, 101–110.
Deng, X., Huang, J., Rozelle, S., Uchida, E., 2008. Growth, population and industrialization, and urban land expansion of China. J. Urban Econ. 63, 96–115.
Department of Comprehensive Statistics, Department of Rural Survey of National Bureau of Statistics of China, 2003. China Statistical Yearbook for Regional Economy 2000. China Statistics Press, Beijing (in Chinese).
Department of Comprehensive Statistics, Department of Rural Survey of National Bureau of Statistics of China, 2010. China Statistical Yearbook for Regional Economy 2009. China Statistics Press, Beijing (in Chinese).
Department of Urban Surveys of National Bureau of Statistics of China, 1995. China City Statistics Yearbook 1992. China Statistics Press, Beijing (in Chinese).
Department of Urban Surveys of National Bureau of Statistics of China, 2002. China City Statistics Yearbook 2000. China Statistics Press, Beijing (in Chinese).
Department of Urban Surveys of National Bureau of Statistics of China, 2011. China City Statistics Yearbook 2009. China Statistics Press, Beijing (in Chinese).
Ding, C., Zhao, X., 2011. Assessment of urban spatial-growth patterns in China during rapid urbanization. Chin. Econ. 44, 46–71.
Elvidge, C.D., Tuttle, B.T., Sutton, P.S., Baugh, K.E., Howard, A.T., Milesi, C., Bhaduri, B.L., Nemani, R., 2007. Global distribution and density of constructed impervious surfaces. Sensors, 1962–1979.
Fang, C., 2009. The urbanization and urban development in China after the reform and opening-up. Econ. Geogr. 29, 19–25 (in Chinese).
Fang, C., 2011. New structure and new trend of formation and development of urban agglomerations in China. Sci. Geogr. Sin. 31, 1025–1034.
Fang, C., 2015. Important progress and future direction of studies on China's urban agglomerations. J. Geog. Sci. 25, 1003–1024.
Gao, B., Huang, Q., He, C., Sun, Z., Zhang, D., 2016. How does sprawl differ across cities in China? A multi-scale investigation using nighttime light and census data. Landscape Urban Plann. 148, 89–98.
Goetz, S., Fiske, G., 2008. Linking the diversity and abundance of stream biota to landscapes in the mid-Atlantic USA. Remote Sens. Environ. 112, 4075–4085.
Grimm, N.B., Faeth, S.H., Golubiewski, N.E., Redman, C.L., Wu, J., Bai, X., Briggs, J.M., 2008. Global change and the ecology of cities. Science 319, 756–760.
Han, J., Hayashi, Y., Cao, X., Imura, H., 2009. Evaluating land-use change in rapidly urbanizing China: case study of Shanghai. J. Urban Plann. Dev. 135, 166–171.
He, C., Zhao, Y., Tian, J., Shi, P., 2013. Modeling the urban landscape dynamics in a megalopolitan cluster area by incorporating a gravitational field model with cellular automata. Landscape Urban Plann. 113, 78–89.
He, C., Huang, Z., Wang, R., 2014a. Land use change and economic growth in urban China: a structural equation analysis. Urban Stud. 51, 2880–2898.
He, C., Liu, Z., Tian, J., Ma, Q., 2014b. Urban expansion dynamics and natural habitat loss in China: a multiscale landscape perspective. Global Change Biol. 20, 2886–2902.
Huang, Q., He, C., Gao, B., Yang, Y., Liu, Z., Zhao, Y., Dou, Y., 2015. Detecting the 20 year city-size dynamics in China with a rank clock approach and DMSP/OLS nighttime data. Landscape Urban Plann. 137, 138–148.
Jelinski, D.E., Wu, J., 1996. The modifiable areal unit problem and implications for landscape ecology. Landscape Ecol. 11, 129–140.
Kuang, W., Chi, W., Lu, D., Dou, Y., 2014. A comparative analysis of megacity expansions in China and the US: Patterns, rates and driving forces. Landscape Urban Plann. 132, 121–135.
Kuang, W., Liu, J., Dong, J., Chi, W., Zhang, C., 2016. The rapid and massive urban and industrial land expansions in China between 1990 and 2010: a CLUD-based analysis of their trajectories, patterns, and drivers. Landscape Urban Plann. 145, 21–33.
Li, C., Li, J., Wu, J., 2013. Quantifying the speed, growth modes, and landscape pattern changes of urbanization: a hierarchical patch dynamics approach. Landscape Ecol. 28, 1875–1888.
Li, H., Wei, Y.D., Liao, F.H., Huang, Z., 2015. Administrative hierarchy and urban land expansion in transitional China. Appl. Geogr. 56, 177–186.
Liu, J., Zhan, J., Deng, X., 2005. Spatio-temporal patterns and driving forces of urban land expansion in China during the economic reform era. AMBIO: J. Hum. Environ. 34, 450–455.
Liu, Y., Wang, L., Long, H., 2008. Spatio-temporal analysis of land-use conversion in the eastern coastal China during 1996–2005. J. Geog. Sci. 18, 274–282.
Liu, J., Zhang, Q., Hu, Y., 2012a. Regional differences of China's urban expansion from late 20th to early 21 st century based on remote sensing information. Chin. Geog. Sci. 22, 1–14.
Liu, Z., He, C., Zhang, Q., Huang, Q., Yang, Y., 2012b. Extracting the dynamics of urban expansion in China using DMSP-OLS nighttime light data from 1992 to 2008. Landscape Urban Plann. 106, 62–72.
Liu, Z., He, C., Zhou, Y., Wu, J., 2014. How much of the world's land has been urbanized, really? A hierarchical framework for avoiding confusion. Landscape Ecol. 29, 763–771.
Liu, Y., Fang, F., Li, Y., 2014a. Key issues of land use in China and implications for policy making. Land Use Policy 40, 6–12.
Liu, Y., Yang, R., Long, H., Gao, J., Wang, J., 2014b. Implications of land-use change in rural China: a case study of Yucheng, Shandong province. Land Use Policy 40, 111–118.
Long, H., Tang, G., Li, X., Heilig, G.K., 2007. Socio-economic driving forces of land-use change in Kunshan, the Yangtze River Delta economic area of China. J. Environ. Manage. 83, 351–364.
Long, H., 2014. Land use policy in China: introduction. Land Use Policy 40, 1–5.
Lu, D., Weng, Q., Li, G., 2006. Residential population estimation using a remote sensing derived impervious surface approach. Int. J. Remote Sens. 27, 3553–3570.
Lu, D., Li, G., Kuang, W.H., Moran, E., 2014. Methods to extract impervious surface areas from satellite images. Int. J. Digit. Earth 7, 93–112.
Ma, Q., He, C., Wu, J., Liu, Z., Zhang, Q., Sun, Z., 2014. Quantifying spatiotemporal patterns of urban impervious surfaces in China: an improved assessment using nighttime light data. Landscape Urban Plann. 130, 36–49.
Ma, Q., Wu, J., He, C., 2016. A hierarchical analysis of the relationship between urban impervious surfaces and land surface temperatures: spatial scale dependence, temporal variations, and bioclimatic modulation. Landscape Ecol. 31, 1139–1153.
Ma, L.J., 2005. Urban administrative restructuring, changing scale relations and local economic development in China. Political Geogr. 24, 477–497.
Malthus, T., 1798. An Essay on the Principle of Population. Printed for J. Johnson, in St. Paul's Church-Yard, London.
Michishita, R., Jiang, Z., Xu, B., 2012. Monitoring two decades of urbanization in the Poyang Lake area, China through spectral unmixing. Remote Sens. Environ. 117, 3–18.
Ministry of Public Security of China, 1993. Tabulation on the 1992 Population Statistics of China by County. The Masses Press, Beijing (in Chinese).
Ministry of Public Security of China, 2001. Tabulation on the 2000 Population Statistics of China by County. The Masses Press, Beijing (in Chinese).
Ministry of Public Security of China, 2010. Tabulation on the 2009 Population Statistics of China by County. The Masses Press, Beijing (in Chinese).
National Bureau of Statistics of China, 1993. China Statistics Yearbook 1992. China Statistics Press, Beijing (in Chinese).
National Bureau of Statistics of China, 2001. China Statistics Yearbook 2000. China Statistics Press, Beijing (in Chinese).
National Bureau of Statistics of China, 2010. China Statistics Yearbook 2009. China Statistics Press, Beijing (in Chinese).
O'Neill, R.V., DeAngelis, D.L., Waide, J.B., Allen, T.F.H., 1986. A Hierarchical Concept of Ecosystems. Princeton University Press, Princeton.
Oke, T.R., 1982. The energetic basis of the urban heat island. Q. J. R. Meteorolog. Soc. 108, 1–24.
Openshaw, S., Openshaw, S., 1984. The Modifiable Areal Unit Problem. Geo Abstracts University of East Anglia.
Population Census Office under the State Council & Department of Population, Employment Statistics of National Bureau of Statistics of China, 1993. Tabulation on the 1990 Population Census of China. China Statistics Press, Beijing (in Chinese).
Population Census Office under the State Council & Department of Population, Employment Statistics of National Bureau of Statistics of China, 2002. Tabulation on the 2000 Population Census of China. China Statistics Press, Beijing (in Chinese).
Population Census Office under the State Council & Department of Population, Employment Statistics of National Bureau of Statistics of China, 2013. Tabulation on the 2010 Population Census of China. China Statistics Press, Beijing (in Chinese).
Qin, H., Li, Z., Fu, G., 2013. The effects of low impact development on urban flooding under different rainfall characteristics. J. Environ. Manage. 129, 577–585.
Shao, M., Tang, X., Zhang, Y., Li, W., 2006. City clusters in China: air and surface water pollution. Front. Ecol. Environ. 4, 353–361.
Simon, H.A., 1962. The architecture of complexity. Proc. Am. Philos. Soc. 106, 467–482.
United Nations, 2014. World Urbanization Prospects −the 2014 Version Highlights. Department of Economic and Social Affairs, New York.
Weng, Q., 2001. Modeling urban growth effects on surface runoff with the integration of remote sensing and GIS. Environ. Manage. 28, 737–748.
Weng, Q., 2012. Remote sensing of impervious surfaces in the urban areas: requirements, methods, and trends. Remote Sens. Environ. 117, 34–49.
Wu, J., Loucks, O.L., 1995. From balance of nature to hierarchical patch dynamics: a paradigm shift in ecology. Q. Rev. Biol., 439–466.
Wu, J., Gao, W., Tueller, P.T., 1997. Effects of changing spatial scale on the results of statistical analysis with landscape data: a case study. Geogr. Inf. Sci. 3, 30–41.
Wu, J., Xiang, W.-N., Zhao, J., 2014. Urban ecology in China: historical developments and future directions. Landscape Urban Plann. 125, 222–233.

Wu, J., 1999. Hierarchy and scaling: extrapolating information along a scaling ladder. Can. J. Remote Sens. 25, 367–380.
Wu, J., 2008. Making the case for landscape ecology an effective approach to urban sustainability. Landscape J.l 27, 41–50.
Wu, J., 2014. Urban ecology and sustainability: the state-of-the-science and future directions. Landscape Urban Plann. 125, 209–221.
Ye, Y., Huang, R., 2004. The features of floating population and urbanization policy in China. J. Renmin Univ. China, 75–81 (in Chinese).
Yue, W., Liu, Y., Fan, P., 2013. Measuring urban sprawl and its drivers in large Chinese cities: the case of Hangzhou. Land Use Policy 31, 358–370.
Zhang, K.H., Shunfeng, S., 2003. Rural–urban migration and urbanization in China: evidence from time-series and cross-section analyses. China Econ. Rev. 14, 386–400.
Zhang, Q., Schaaf, C., Seto, K.C., 2013. The vegetation adjusted NTL Urban Index: a new approach to reduce saturation and increase variation in nighttime luminosity. Remote Sens. Environ. 129, 32–41.
Zhang, Q., Wallace, J., Deng, X., Seto, K.C., 2014. Central versus local states: which matters more in affecting China's urban growth? Land Use Policy 38, 487–496.
Zhou, D., Zhao, S., Liu, S., Zhang, L., Zhu, C., 2014a. Surface urban heat island in China's 32 major cities: spatial patterns and drivers. Remote Sens. Environ. 152, 51–61.
Zhou, W., Qian, Y., Li, X., Li, W., Han, L., 2014b. Relationships between land cover and the surface urban heat island: seasonal variability and effects of spatial and thematic resolution of land cover data on predicting land surface temperatures. Landscape Ecol. 29, 153–167.
Zhu, H., Li, Y., Liu, Z., Fu, B., 2015. Estimating the population distribution in a county area in China based on impervious surfaces. Photogramm. Eng. Remote Sens. 81, 155–163.