



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
Available online 29 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.

© 2016 Elsevier Ltd. All rights reserved.

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).

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):

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

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:

$$NTL_{nor} = \frac{NTL - NTL_{min}}{NTL_{max} - NTL_{min}}, \quad (2)$$

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

Download English Version:

<https://daneshyari.com/en/article/6461579>

Download Persian Version:

<https://daneshyari.com/article/6461579>

[Daneshyari.com](https://daneshyari.com)