Chin. Geogra. Sci. 2014 Vol. 24 No. 2 pp. 231–244
doi: 10.1007/s11769-013-0645-2

Springer Science Press
www.springerlink.com/content/1002-0063

Assessment of Human Impacts on Vegetation in Built-up Areas in China Based on AVHRR, MODIS and DMSP_OLS Nighttime Light Data, 1992–2010

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Abstract: Since the reform and opening-up program started in 1978, the level of urbanization has increased rapidly in China. Rapid urban expansion and restructuring have had significant impacts on the ecological environment especially within built-up areas. In this study, ArcGIS 10, ENVI 4.5, and Visual FoxPro 6.0 were used to analyze the human impacts on vegetation in the built-up areas of 656 Chinese cities from 1992 to 2010. Firstly, an existing algorithm was refined to extract the boundaries of the built-up areas based on the Defense Meteorological Satellite Program Operational Linescan System (DMSP_OLS) nighttime light data. This improved algorithm has the advantages of high accuracy and speed. Secondly, a mathematical model (Human impacts (HI)) was constructed to measure the impacts of human factors on vegetation during rapid urbanization based on Advanced Very High Resolution Radiometer (AVHRR) Normalized Difference Vegetation Index (NDVI) and Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI. HI values greater than zero indicate relatively beneficial effects while values less than zero indicate proportionally adverse effects. The results were analyzed from four aspects: the size of cities (metropolises, large cities, medium-sized cities, and small cities), large regions (the eastern, central, western, and northeastern China), administrative divisions of China (provinces, autonomous regions, and municipalities) and vegetation zones (humid and semi-humid forest zone, semi-arid steppe zone, and arid desert zone). Finally, we discussed how human factors impacted on vegetation changes in the built-up areas. We found that urban planning policies and developmental stages impacted on vegetation changes in the built-up areas. The negative human impacts followed an inverted 'U' shape, first rising and then falling with increase of urban scales. China's national policies, social and economic development affected vegetation changes in the built-up areas. The findings can provide a scientific basis for municipal planning departments, a decision-making reference for government, and scientific guidance for sustainable development in China.

Keywords: vegetation change; human impact; urbanization; built-up areas; nighttime light data; Normalized Difference Vegetation Index (NDVI)

Citation: Liu Qinping, Yang Yongchun, Tian Hongzhen, Zhang Bo, Gu Lei, 2014. Assessment of human impacts on vegetation in built-up areas in China based on AVHRR, MODIS and DMSP_OLS nighttime light data, 1992–2010. *Chinese Geographical Science*, 24(2): 231–244. doi: 10.1007/s11769-013-0645-2

1 Introduction

Over the past decades, urbanization has taken place at an unprecedented rate around the world. In 1950, as an example, only 29% of the world population resided in urban areas, and this number rose to 52% by 2011

Received date: 2013-02-05; accepted date: 2013-06-03
Foundation item: Under the auspices of National Natural Science Foundation of China (No. 41171143, 40771064), Program for New Century Excellent Talents in University (No. NCET-07-0398), Fundamental Research Funds for the Central Universities (No. lzujbky-2012-k35)
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(United Nations, Department of Economic and Social Affairs, Population Division, 2012). Moreover, this trend is projected to continue in the future decades (Deng and Wu, 2012; Liu J Y *et al.*, 2012; United Nations, Department of Economic and Social Affairs, Population Division, 2012). Since its reform and opening up, China has also experienced a rapid urbanization as a developing country. The level of urbanization has increased greatly in China. Particularly, since approximately 1990, there was a dramatic shift in urbanization in China. As a large number of people migrated to cities, the expanding population put unprecedented pressure on cities (Zhang and Song, 2003; Sato and Yamamoto, 2005; Roy, 2009; Chen *et al.*, 2011), particularly in built-up areas. Rapid urbanization has led to a number of ecological and environmental problems (e.g. damage to vegetation, water quality degradation, air pollution, loss of biodiversity, and urban heat island effect). In particular, environmental changes within built-up areas were the strongest during the Chinese transition period.

Increasing urbanization has significant impacts on vegetation coverage. In order to accommodate ever-increasing population from rural to urban, there are a large of urban construction and expansion, resulting in more damages to vegetation (Zhang *et al.*, 2011; Byomkesh *et al.*, 2012; Zhou *et al.*, 2012; Liu L *et al.*, 2012; Jia, 2013). It is consistently blamed for the conversion of a great deal of green spaces into impermeable surfaces around the world, which has many detrimental effects on the environment (Kong and Nakagoshi, 2006; Phan and Nakagoshi, 2007). On the other hand, with urban economic development and social development, there are more investments in urban greening resulting in urban vegetation improvements. Greater emphasis was placed on improving the quality of life after the basic needs of the people were met. In addition, there was a shift in the ideas of urban planning and management. More attention was paid to the ecological environment and construction of urban green space, resulting in the vegetation cover or biomass increased (Xia and Gong, 2006; Wang *et al.*, 2012).

Urban vegetation is an important indicator of urban ecological environments. It makes important contributions to improving urban ecological environments. Urban vegetation can provide favorable living environments for residents, while enhancing the naturalness of urban landscapes and promoting harmonious symbiosis with nature (Xia, 2010). The causes of urban vegetation change can be divided into two categories: those that are due to natural causes and those that are created by man. Natural factors include temperature, precipitation, *etc*. There are a number of human factors responsible for vegetation change in built-up areas. Some of the more prominent ones are urban expansion, construction, governmental policies, the concepts guiding urban planning during urbanization, *etc*. Many experts and scholars have attached great importance to vegetation change, and provided valuable research data (Yu *et al.*, 2003; Weiss *et al.*, 2004a; Xu and Liu, 2007; Huang and Wang, 2010; Hu *et al.*, 2011; Jing *et al.*, 2011; Zhao *et al.*, 2011; Jiang *et al.*, 2013). However, the scales of these studies are large, and they mainly analyzed the relationship between vegetation change and natural factors. Very few studies have quantitatively examined the impacts of human factors, and studies on built-up areas are considerably less. Furthermore, during the process of urbanization, the impacts on vegetation caused by human factors are the strongest in the built-up areas. On one hand, the impacts on urban vegetation caused by human factors could be adverse, e.g. damage to vegetation caused by a rapid and large-scale process of urban expansion. On the other hand, the impacts on urban vegetation caused by human factors could be beneficial, e.g. there was a shift in the ideas of urban planning and management, from Howard′s Garden City, Wright′s Broadacre City, Perry′s neighborhood unit, or Geddes′s eco-town (Han and Qin, 2004) to that of eco-city or landscape city, compact city (Jenks *et al.*, 1996; Breheny, 1997; Chen *et al.*, 2008), livable city (Dong and Yang, 2008; Meng *et al.*, 2009), and low-carbon city (Feliciano and Prosperi, 2011; Liu *et al.*, 2011; Yung and Chan, 2012), which practitioners and theorists widely advocated. The present study examines how human factors affected urban vegetation during rapid urbanization periods in China. Objective measurement of human impacts on vegetation in the built-up areas will not only provide a scientific basis for municipal planning departments, but also provide a decision-making reference for government departments.

The Operational Linescan System (OLS) sensor from the Defense Meteorological Satellite Program (DMSP) provides a useful data source for urban study at a large spatial scale (He *et al.*, 2006). Many researchers have studied extraction methods of urban areas based on

DMSP_OLS nighttime light data (Croft, 1978; Imhoff *et al.*, 1997; Henderson *et al.*, 2003; He *et al.*, 2006; Shu *et al.*, 2011). Especially, Shu *et al.* (2011) made a comprehensive assessment of four methods of extracting urban areas based on DMSP_OLS nighttime light data, and showed that the method based on statistical data had two advantages: greater accuracy and convenience. Consequently, in this study, the method based on statistical data was chosen to extract the built-up areas of 656 cities in China.

Many studies have used remote sensing images to examine vegetation at different scales, ranging from the global to the regional. Normalized Difference Vegetation Index (NDVI) has been effectively used in vegetation dynamics monitoring (Al-Bakri and Taylor, 2003; Weiss *et al.*, 2004b; Anyamba and Tucker, 2005; Beck *et al.*, 2006; Martínez and Gilabert, 2009). Various NDVI datasets are available now: Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI, Advanced Very High Resolution Radiometer (AVHRR) NDVI, Satellite pour l'observation de la Terre Vegetation (SPOT VGT) NDVI, and Thematic Mapper (TM) NDVI. In this study, AVHRR NDVI and MODIS NDVI were used to investigate vegetation changes in built-up areas.

The purposes of this study are: 1) to extract the boundaries of the built-up areas in China in 1992, 2000 and 2010; 2) to build a model to measure the human impacts on vegetation in the built-up areas based on AVHRR NDVI and MODIS NDVI; 3) to quantitatively analyze the human impacts on vegetation in the built-up areas during rapid urbanization periods; 4) to discuss how human factors impacted on vegetation in the built-up areas.

2 Data and Methods

2.1 Data sources

(1) Statistical data. This study included 656 cities (four municipalities, 15 sub-provincial cities, 267 prefecture-level cities and 370 county-level cities, except Lhasa and cities in Chinese Taiwan, Hong Kong and Macau due to the lack of data) according to the *China City Statistical Yearbook* (National Bureau of Statistics of China, Department of Urban Social and Economic Survey, 2011). Statistical data were taken from the *China City Statistical Yearbooks* (National Bureau of Statistics of China, Department of Urban Social and Economic Survey, 1993; 2001; 2011).

(2) Nighttime light data. Nighttime light data (1 km resolution) were from the US National Geophysical Data Center website (http://www.ngdc. noaa.gov/dmsp/downloadV4composites.html) and include the years 1992 (DMSP F10 satellite), 2000 (DMSP F15 satellite), and 2010 (DMSP F18 satellite). In the annual composites, the Digital Number (DN) value of each pixel was the average of the visible-band DN values of lights from cities, towns, and other sites with persistent lighting. Background noise was identified and replaced with values of zero. Sunlight, glare, moonlight, clouds, and lighting features from auroras were excluded through a number of constraints. Ephemeral events such as fires were also excluded. The range of data values for lit pixels was 1–63 (Liu Z F *et al.*, 2012).

(3) Vegetation data. Vegetation data for 1992 (1 km resolution) were obtained from the website of the US geological survey (http://edc2.usgs.gov/1KM/comp10d.php). Vegetation data for the years 2000 and 2010 (MODIS data: 1 km monthly vegetation index) were from the International Scientific Data Service platform (http://datamirror.csdb.cn/search.mod?proShortName=MOD13A3).

(4) Other data. Digital Elevation Model (DEM) data at a resolution of 90 m were from the International Scientific Data Service platform website (http://datamirror.csdb.cn/dem/search.jsp). The administrative boundaries of county-level cities and urban point location data are from the 1∶4 000 000 data set of the National Fundamental Geographic Information System (http://nfgis.nsdi.gov.cn/).

2.2 A model to measure human impacts on vegetation in built-up areas

The response of vegetation in remote sensing imagery is determined from the difference and dynamic change in the spectral characteristics of green plant leaves, while near-infrared and visible red bands contain more than 90% vegetation information (Baret and Guyot, 1991). Near-infrared and visible red bands are used to calculate the vegetation index (Chen and Zhao, 1990). Many studies reported that the vegetation index shows good correlation with vegetation cover and biomass (Asrar *et al.*, 1985; Sellers, 1987; Rhew *et al.*, 2011). NDVI is a common vegetation index. The value of NDVI on a pixel reflects vegetation area and growth. Mean NDVI refers to the sum of all NDVI values divided by the number of all pixels added in a built-up area. Therefore, mean NDVI can reflect two aspects of vegetation in built-up area: vegetation cover and vegetation biomass.

Urban vegetation is influenced by both human and natural factors. In this study, we created a model to analyze the human impacts on vegetation in the built-up areas. This model assumed that human factors had little influence on vegetation on the regions at some distance from the built-up areas. In order to identify a suitable background region (Fig. 1), the following method was used. A buffer of 5–10 km surrounding a built-up area was selected to minimize the impacts of urban effects (e.g. urban heat island) (Han *et al.*, 2008). In order to minimize the impacts of terrain, a region was selected from the buffer with similar terrain, where the elevation of the region was within a ± 100 m range of the corresponding urban area (Fig. 1) (Chen, 1993). The mean NDVI of the background region was used as a reference value. A mathematical model (Equation (1)) was constructed to measure the impacts of human factors on vegetation within a built-up area. A HI value greater than zero indicates a beneficial effect, i.e., increase in vegetation cover or vegetation biomass, with a higher value indicating an improving effect. A HI value less than zero indicates an adverse effect, i.e., decrease in vegetation cover or vegetation biomass, with a lower value indicating worsening effect.

$$HI_{ij} = \frac{C_{NDVI_{ij}}}{B_{NDVI_{ij}}} - 1 \quad (1)$$

where HI_{ij} is the human impacts of built-up area j in year i; $C_{NDVI_{ij}}$ is the mean NDVI of built-up area j in year i; $B_{NDVI_{ij}}$ is the mean NDVI of the background region to built-up area j in year i.

2.3 Data processing

Prior to processing, vegetation data, light data, and DEM data were merged and extracted with ENVI software. The Asia North Albers Equal Area Conic projection was selected. The DEM data were resampled to 1 km × 1 km resolution using ArcGIS.

2.3.1 Data modification and consistency check

(1) Data modification from different remote sensors

AVHRR NDVI and MODIS NDVI were obtained from different remote sensors and exhibited certain spectrum variance in response to vegetation. Thus, in analysis of long-term NDVI time-series based on AVHRR NDVI and MODIS NDVI, modifying the two datasets and checking consistency of the two datasets are necessary. Many scholars have studied data integration from different remote sensors (Gitelson and Kaufman, 1998; Gallo *et al.*, 2005; Brown *et al.*, 2008; Fensholt and Proud, 2012; Mao *et al.*, 2012). Especially, Mao *et al.* (2012) integrated AVHRR and MODIS data using the per-pixel unary linear regression model, and studied NDVI changes and their relationships with climatic parameters in Northeast China. In this paper, we selected the per-pixel unary linear regression model to modify the two datasets. The per-pixel unary linear regression model can acquire the most appropriate regression equation for each pixel. The elementary structure form of the model for different data is: Y = a + bX + c. Parameters a and b are estimated by the Method of Least Squares, and c is random error.

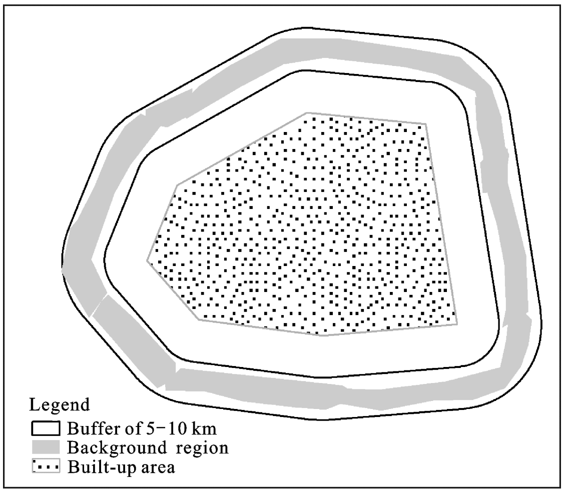

Fig. 1 Schematic diagram of a built-up area and its background region

In this study, AVHRR NDVI spanned from 1992 to 1996, and MODIS NDVI spanned from 2000 to 2010. Because the two datasets did not overlap over any time period, Global Inventory Modeling and Mapping Studies (GIMMS) dataset (1981–2006) was chosen as reference data. To match the AVHRR NDVI and MODIS NDVI, GIMMS at 8 km × 8 km resolution was resampled to 1 km × 1 km. First, based on AVHRR NDVI and GIMMS from 1992 to 1996, one per-pixel unary linear regression model was computed to modify AVHRR

NDVI to GIMMS. Secondly, based on GIMMS and MODIS NDVI, another per-pixel unary linear regression model was computed to modify GIMMS to MODIS NDVI. Finally, using the two per-pixel unary linear regression models, AVHRR NDVI in 1992 was modified to fit MODIS NDVI.

(2) Consistency check

We randomly selected 600 points in China, and extracted the NDVI values from modified AVHRR NDVI and GIMMS for 1992 at 1 km × 1 km resolution, modified GIMMS and MODIS NDVI for 2000 at 1 km × 1 km resolution. The correlation coefficient of modified AVHRR NDVI and GIMMS was 0.97 ($p < 0.001$) (Fig. 2a); the difference value between ± 0.1 in all pixels was 98%; the relative deviation of all pixels was within 9%. The correlation coefficient of modified GIMMS and MODIS NDVI was 0.89 ($p < 0.001$) (Fig. 2b); the difference value between ± 0.1 in all pixels was 91%; the relative deviation of all pixels was within 10%.

2.3.2 Extraction of boundaries of built-up areas

He *et al.* (2006) used statistical data to extract urban land within every Chinese province, based on DMSP_OLS nighttime light data. In their methods, urban land area was computed according to the light threshold of every province. In this study, the algorithm was refined. The new algorithm has two main advantages: first, computation according to urban administrative boundaries can enhance spatial accuracy; second, the computation of nighttime light threshold through numerical calculation can greatly reduce the computational time requirement. The calculation process (Fig. 3) is as follows.

(1) Extracting of light data within the urban administrative boundaries. Light data for each city was individually extracted within its urban administrative boundary. Then, the attribute tables of light data of the 656 cities were converted to database files (*.dbf*).

(2) Computing light thresholds of the built-up areas. A program in Python was written to read the database

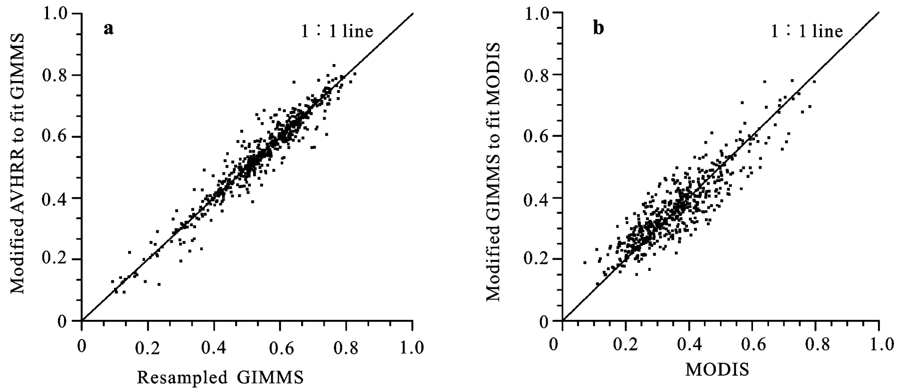

Fig. 2 Results of consistency check

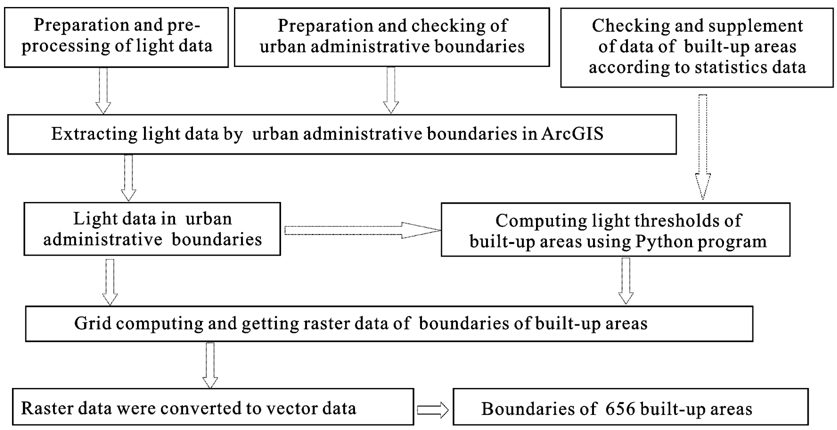

Fig. 3 Flow chart of extracting boundaries of built-up areas

files. Through an iterative process, areas were computed according to the values (from 1 to 63) for lit pixels of light data. The looping algorithm was stopped when the area with the value for lit pixels was most similar to the statistical datum. The value of lit pixels was the light threshold of the city in the period. This gave light thresholds of the 656 built-up areas for the three periods.

(3) Extracting the boundaries of the built-up areas. Using the light thresholds, raster data of the boundaries of the built-up areas were extracted in ArcGIS 10. Then, the raster data of the built-up areas were converted to vector data. After regions with an area less than 1 km^2 were excluded, the final vector boundaries of all 656 built-up areas in the three periods were obtained (Fig. 4).

(4) Accuracy assessment

Because the spatial resolution of Landsat TM/ETM+ data (30 m) is much finer than that of light data (1 km), evaluation of results using Landsat TM/ETM+ data is feasible and accepted (Small *et al.*, 2005; Liu Z F., 2012). In consideration of different urban scales, regions and periods, we selected fifteen cities including five metropolises, two large cities, two medium-sized cities, and six small cities (Table 1). Landsat TM/ETM+ images of fifteen cities for the years 1992, 2000 and 2010 with basic geometric and radiometric corrections were used to extract the built-up areas through the techniques of visual interpretation and supervised classification. The built-up areas extracted using Landsat TM/ETM+ data were used to evaluate the results extracted using light data (Table 1). The values of overall accuracy (OA) and Kappa of each city in different periods were computed. The evaluation results revealed that urban boundaries extracted using light data were consistent with those extracted using Landsat TM/ETM+ data, with an average OA of 83% and an average Kappa of 0.63.

Liu Z F *et al.* (2012) analyzed the dynamics of urban expansion in China using DMSP_OLS nighttime light data from 1992 to 2008, and checked the results through Landsat TM/ETM+ images. The average overall accuracy was 86.27% and the average Kappa was 0.60. The results of this paper were consistent with the results obtained by Liu Z F *et al.* (2012).

2.3.3 Computation of HI in 656 built-up areas

The computation of HI includes two components: mean NDVI of the built-up area and mean NDVI of the background region. Using the boundaries of the 656 built-up areas and NDVI data in the three sampling periods, we computed the mean NDVI values of the built-up areas and the background regions in ArcGIS. According to Equation (1), the HI values of the 656 built-up areas in the three sampling periods were computed.

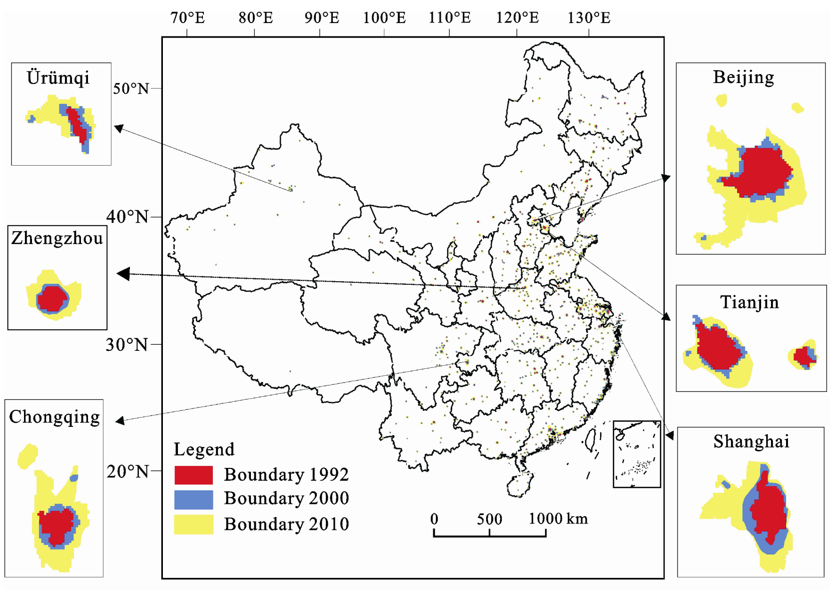

Fig. 4 Boundaries of built-up areas in China from 1992 to 2010. The six insets are large-scale maps of built-up areas

Table 1 Validation results of 15 sample cities

Urban scale	Cities	TM/ETM+ code	2010		2000		1992	
			kappa	OA (%)	kappa	OA (%)	kappa	OA (%)
Metropolises	Zhengzhou	124/36	0.65	82.1	0.64	83.4	0.57	86.7
	Chengdu	129/39	0.6	81.5	0.72	90.7	0.79	96.4
	Xi′an	127/36	0.67	83.2	0.77	90.2	0.73	91.9
	Lanzhou	131/35	0.65	85.8	0.77	91.3	0.66	87.5
	Ürümqi	142/30	0.48	73.6	0.70	91.5	0.73	95.8
large cities	Rizhao	120/35	0.51	75.9				
	Siping	119/30	0.55	77.1				
Medium-sized cities	Yiyang	124/40	0.56	77.9				
	Yulin	124/44	0.71	86.2				
Small cities	Wudalianchi	119/26	0.44	69.4				
	Danjiangkou	125/37	0.53	59.8				
	Pingliang	129/35	0.5	75.7				
	Zhangjiajie	125/40	0.42	70.9				
	Qinyang	124/36	0.69	84.5				
	Jinggangshan	122/41	0.66	83.2				

3 Results

The HI values of the 656 built-up areas in the three sampling periods were analyzed from four aspects which include urban scales, large regions, administrative divisions and vegetation zones.

3.1 Statistics based on urban scales

According to the urban non-agricultural population (National Bureau of Statistics of China, Department of Urban Social and Economic Survey, 2011), 656 cities were classified into four categories: metropolises (greater than 1 000 000), large cities (500 000 to 1 000 000), medium-sized cities (200 000 to 500 000), and small cities (less than 200 000). The averages and changes in HI were calculated for these four categories of built-up areas (Table 2).

As shown in Table 2, all the averages of HI were less than zero, indicating the human impacts on vegetation were adverse. In the same year, the averages of HI in medium-sized and small cities generally were greater than those in metropolises and large cities, indicating the negative impacts of human factors on vegetation were greater at larger urban scales. During 1992–2000 and 1992–2010, in all cities except small cities, the averages of HI of the built-up areas increased. During the period 2000–2010, the averages of HI of built-up areas increased in metropolises and large cities and decreased in medium-sized and small cities. These observations indicated that during almost twenty years, the negative impacts of human factors on vegetation became less in metropolises and large cities, and it was almost unchanged in medium-sized cities and became greater in small cities.

3.2 Statistics based on large regions

China is divided into four regions: the eastern, central, western, and northeastern China. The eastern China includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central China covers Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western China includes Inner

Table 2 Averages and changes of HI in four urban categories of built-up areas (1992 to 2010)

Urban scale	Average for 1992	Average for 2000	Average for 2010	Change in 1992–2000	Change in 2000–2010	Change in 1992–2010
Metropolis	–0.3597	–0.3255	–0.2775	0.0342	0.0480	0.0822
Large city	–0.3628	–0.3170	–0.3114	0.0458	0.0056	0.0514
Medium-sized city	–0.3005	–0.2898	–0.2946	0.0108	–0.0049	0.0059
Small city	–0.2139	–0.2168	–0.2568	–0.0030	–0.0400	–0.0430

Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. The northeastern China includes Liaoning, Jilin, and Heilongjiang. The averages and changes of HI were calculated in the built-up areas of these four regions (Table 3).

As shown in Table 3, all the averages of HI were less than zero, indicating the human impacts on vegetation were adverse. During the same year, the average of HI was relatively large in the western China, indicating that the adverse effect on vegetation was relatively small. During 1992–2000, in all regions except the northeastern China, the averages of HI increased. During 2000–2010 and 1992–2010, an increase was observed in the eastern China, and a decrease was observed in the other three regions, which implied that more attention was paid to the ecological environment and the construction of urban green space during the rapid development in the eastern China, with less attention in the central, western, and northeastern China.

3.3 Statistics based on administrative divisions

According to administrative divisions, the study area comprises four municipalities, 22 provinces (not including Chinese Taiwan, Hong Kong and Macau due to the lack of data) and five autonomous regions. The averages and changes in HI were calculated for the built-up areas of 31 administrative divisions (Fig. 5).

In 1992 and 2000, the impacts on vegetation caused by human factors were beneficial in Xinjiang, Tibet, Gansu and Qinghai, but in 2010, those were beneficial only in Tibet and Qinghai. From 1992 to 2000, the averages of HI of the built-up areas decreased, and the adverse effect on vegetation caused by human factors increased in Beijing, Fujian, Jilin, Xinjiang, Heilongjiang, Guizhou, Hainan, Jiangsu, Gansu, Henan, Guangxi and Guangdong. The opposite occurred in the other administrative divisions. During 2000–2010, the averages of HI of the built-up areas increased, and the adverse effect on vegetation caused by human factors decreased in Beijing, Shanghai, Chongqing, Tianjin, Fujian, Jiangsu, Zhejiang, Guangdong, Shandong, and Heilongjiang. The opposite occurred in the other administrative divisions. During 1992–2010, the averages of HI decreased and the adverse effect on vegetation caused by human factors increased in the built-up areas in Shanxi, Xinjiang, Gansu, Hainan, Shaanxi, Jilin, Guizhou, Inner Mongolia, Heilongjiang, Jiangxi, Henan, Guangxi, Hunan, Hebei and Hubei (Fig. 5).

3.4 Statistics based on vegetation zones

Chinese vegetation regionalization comprises three zones: humid and semi-humid forest zone, semi-arid steppe zone, and arid desert zone (Sun, 1998). The averages and changes in HI were calculated in the built-up areas for the three zones (Fig. 6).

In the same year, the average of HI in the built-up areas in humid and semi-humid forest zone was lower than in semi-arid steppe zone, and which in turn was lower than in arid desert zone. Especially, it was greater than zero in arid desert zone, indicating that the impact on vegetation caused by human factors was beneficial. During 1992–2010, except in humid and semi-humid forest zone, the averages of HI decreased in the built-up areas of the other two zones, indicating that the adverse effect on vegetation caused by human factors was increasing. During the period 1992–2000, except in arid desert zone, the averages of HI increased in the built-up areas of the other two zones. During 2000–2010, the averages of HI decreased in the built-up areas of all three zones.

4 Discussion

4.1 Analysis of factors impacting vegetation change in built-up areas

Urban vegetation includes natural or man-made vegetation but is present in built-up areas. The causes of urban vegetation change can be divided into two categories: those that are due to natural causes and those that are

Table 3 Averages and changes of HI in built-up areas of four regions (1992 to 2010)

Region	Average for 1992	Average for 2000	Average for 2010	Change in 1992–2000	Change in 2000–2010	Change in 1992–2010
Western China	–0.1911	–0.1683	–0.2118	0.0228	–0.0434	–0.0206
Central China	–0.2753	–0.2560	–0.2991	0.0193	–0.0431	–0.0238
Eastern China	–0.3200	–0.3148	–0.2819	0.0051	0.0330	0.0381
Northeastern China	–0.3472	–0.3491	–0.3668	–0.0019	–0.0177	–0.0196

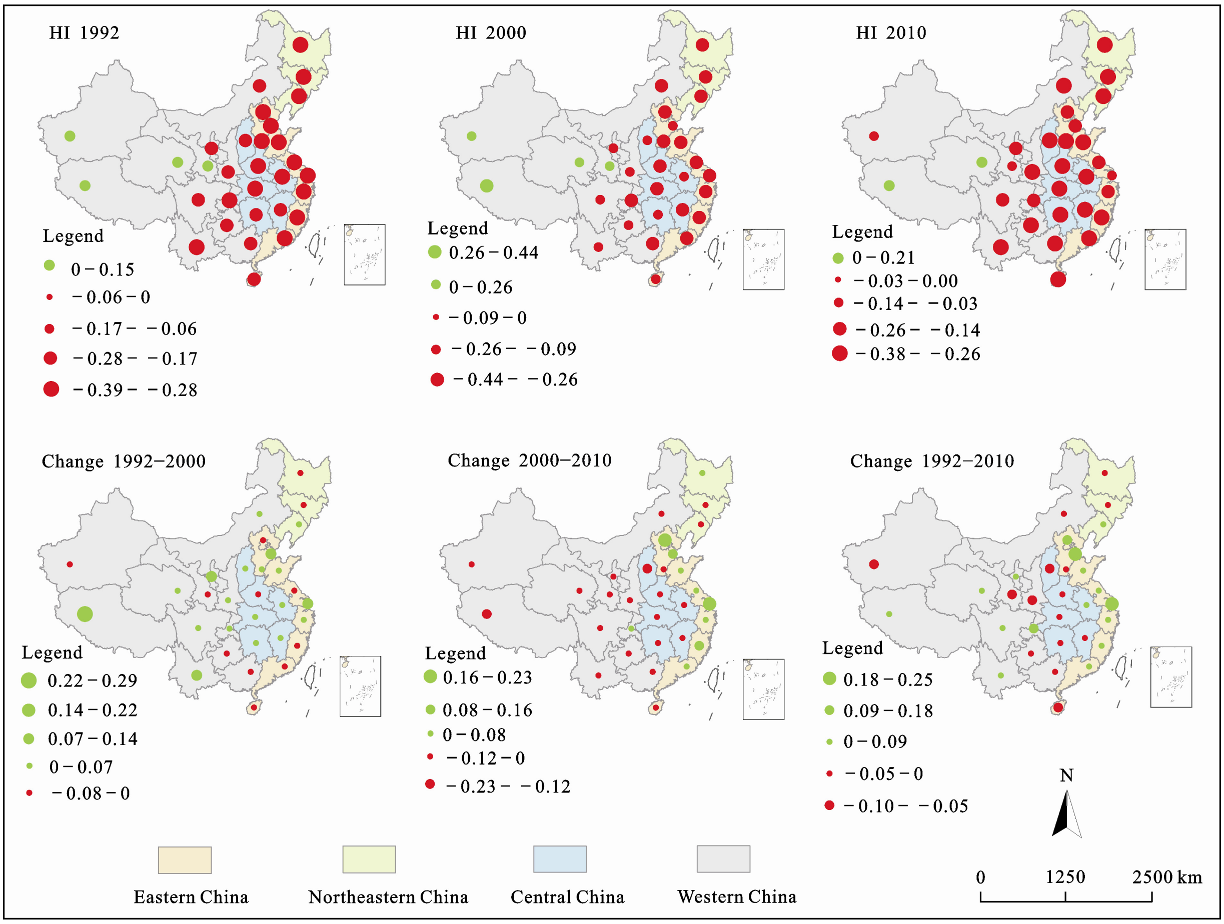

Fig. 5 Averages and changes of human impacts (HI) in built-up areas of 31 administrative divisions from 1992 to 2010. Based on the HI, green points indicated that the impact on vegetation caused by human factors was beneficial, and red points indicated that it was adverse. Based on the changes of HI, green points indicated that the adverse impact decreased, and red points indicated that it increased

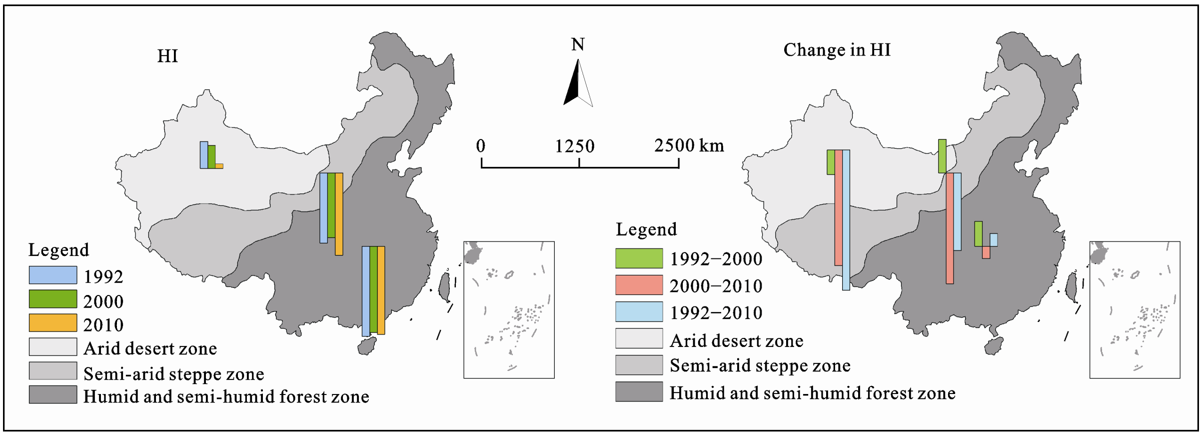

Fig. 6 Averages and changes in human impacts (HI) in built-up areas of three vegetation zones from 1992 to 2010

created by man (Fig. 7). Natural factors include temperature, precipitation, *etc*. There are a number of human factors responsible for vegetation change in built-up areas. Some of the more prominent ones are urban development (e.g. urban population and urban GDP), ideas of urban planning, requirements of residents, urban construction (e.g. urban green space and building), investments in urban environment, governmental policies, *etc*.

Human activities are the most strong in built-up areas during urbanization. In addition, some measures of urban greening (irrigation for lawns and trees, greenhouse practices for plants in winter, *etc.*) reduce the impacts from natural factors. Consequently, human factors are the major driving forces for vegetation changes in built-up areas.

In the early stages of urban development, its economy grows extensively. In order to gain more economic benefits and accommodate ever-increasing population mainly from rural areas, both public and private sectors are continuously developing natural lands within and on the outskirts of the city, without considering the environmental costs of this action. These negative effects (e.g. outdated ideas of urban planning, increasing urban expansion, building density and height) are stronger than positive effects. As a result, urban vegetation has deteriorated. In the advanced stages of urban development, both the national and local governments pay more attention to the urban ecological environments. For example, extensive economic growth has converted to intensive economic growth, a series of environmental protection measures can be developed (e.g. increasing the proportion of urban green spaces, more investments in urban greening). Meanwhile, with the continuous improvement of the socio-economic and cultural levels, residents put more and more emphasis on the quality of their lives, and their environmental awareness is enhancing in their daily lives after basic needs of life are met. All these positive effects made urban vegetation becoming better (Fig. 8).

4.2 Impacts on urban vegetation from policy of urban planning and stage of urban development

In the same year, the negative impact of human factors on vegetation was greater at larger urban scales generally. The reason may be that there are greater agglomeration effects in capital and population with increasing urban scales. In order to meet the needs of the population growth, urban planning programs were created to accommodate the increased habitation, roads and public squares, resulting in an increase in building density and a decrease in vegetation cover or biomass. Consequently, the negative impact of human factors on vegetation became larger.

From 1992 to 2010, the negative impact of human factors on vegetation became less in metropolises and large cities, and it was almost unchanged in medium-sized cities and became greater in small cities. What were the principal causes of these changes? With economic and social development, the investments in urban greening were greater at larger urban scales. Greater emphasis was placed on improving the quality of life after the basic needs of the people were met. In addition, there was a shift in the ideas of urban planning and management, from Howard′s Garden City, Wright′s Broadacre City, Perry′s neighborhood unit, or Geddes′s eco-town to that of eco-city or landscape city, compact city, livable city and low-carbon city, which practitioners and theorists widely advocated (Han and Qin, 2004; Chen *et al.*, 2008; Meng *et al.*, 2009; Feliciano and Prosperi, 2011). More attention was paid to the ecological environment and construction of urban green

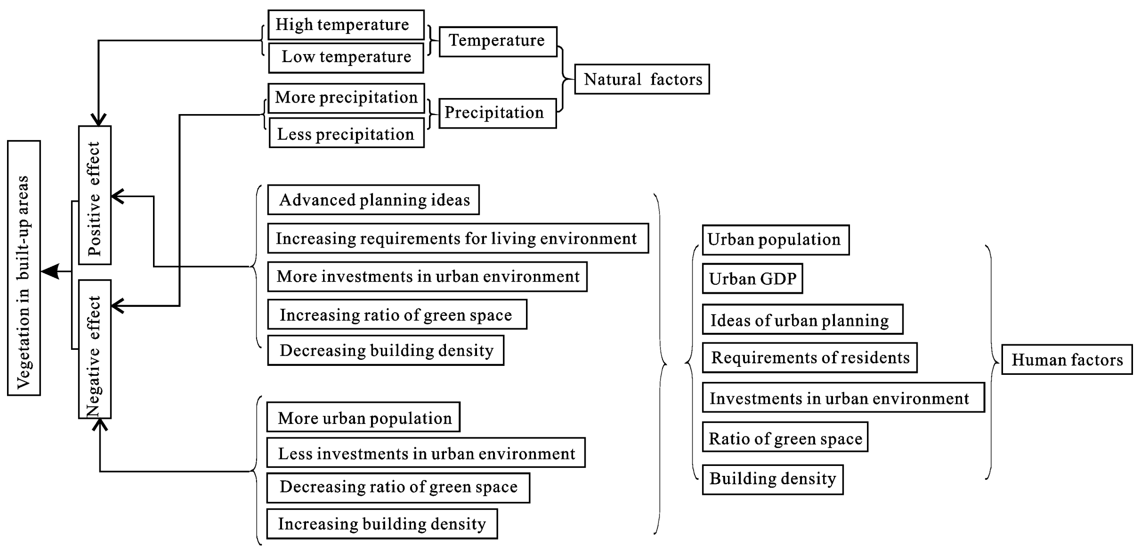

Fig. 7 Factors affecting vegetation change in built-up areas

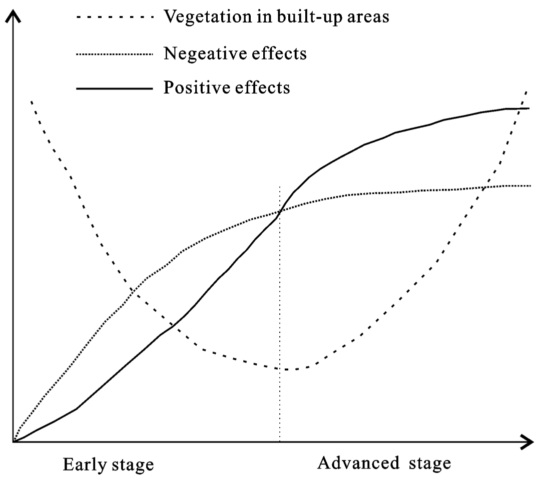

Fig. 8 Mechanism model of vegetation change in built-up areas

space, resulting in the vegetation cover or biomass increased. In consequence, the negative impact of human factors on vegetation became less.

In the same year, the negative impact of human factors on vegetation increased progressively but this trend reversed generally from smaller to larger cities. These negative impacts follow an inverted 'U' shape, first rising and then falling with urban development as described in the Environmental Kuznets Curve (EKC) (Shafik, 1994). The principal causes may be that the negative impact of human factors on vegetation varies in different stages of urban development. Early stages include large construction and expansion, resulting in more damages to vegetation. The negative impact of human factors on vegetation increased. With continuous urban development, there was a shift in the ideas of urban planning and management, and the requirements of the higher environmental quality were needed. More attention was paid to the ecological environment, and the construction of urban green space. At the same time, the Chinese government increased investment in urban greening mainly due to economic growth and the progress of science and technology. Consequently, the negative impact of human factors on vegetation became less. From 1992 to 2010, it increased in small cities due to being in the early stages of urban development.

4.3 Impacts on urban vegetation from China's socio-economic development and policies

During 2000–2010 and 1992–2010, the negative impact of human factors on vegetation increased in the western, central and northeastern China, and a decrease was observed in the eastern China. Since 2000, a series of developmental strategies were launched by the Chinese government. They include strategies for 'the development campaign of the western regions', 'revitalizing the old northeastern industrial bases' and 'the rise of central China'. These strategies were launched in 2000, 2003 and 2006 respectively. The three regions shifted to the accelerative development periods (Liu J Y *et al.*, 2012). As a result, large numbers of people migrated to cities, and urban space was rapidly expanding, resulting in less attention being paid to the ecological environment and to construction of urban green space. Consequently, the negative impact of human factors on vegetation became greater. However, during 2000–2010, the development of the eastern coastal areas was in a new stage. Through industrial restructuring, upgrading and functional remodeling, more attention was paid to the construction of living environment. Additionally, the ideas of urban planning and management were adjusted, e.g. increasing the proportion of urban green. Evidently, the negative impact of human factors on vegetation became less.

4.4 Human impacts on urban vegetation in different vegetation zones

The impact on vegetation caused by human factors was beneficial in arid desert zone, but was adverse in humid and semi-humid forest zone, and semi-arid steppe zone in China. This indicates that human activities can improve the ecological environment in built-up areas which are located in a poorer environment (e.g. arid desert zone), and vice versa.

5 Conclusions

In this paper, 1992, 2000, 2010 DMSP_OLS nighttime light data were selected to extract the boundaries of the built-up areas of 656 cities in China. MODIS NDVI and AVHRR NDVI were chosen to build a model for measuring the human impacts on urban vegetation during rapid urbanization periods. The results were analyzed from four aspects of the size of cities, large regions, administrative divisions and vegetation zones in China. The findings are as follows: 1) the policy of urban planning and the stage of urban development had a great impact on the vegetation in different scale cities. In the same year, the negative impact of human factors would follow an inverted 'U' shape as it rises and then falls again with the increase of urban scales. From 1992 to

2010, the negative impact of human factors on vegetation became less in metropolises and large cities, and it was almost unchanged in medium-sized cities and became greater in small cities. 2) The level of China′s social and economic development and the policies distinctly affected vegetation changes in built-up areas. During 1992–2010, the negative impact of human factors on vegetation increased in the western, central and northeastern China, and a decrease was observed in the eastern China. 3) Human activities can improve the ecological environment in built-up areas which are located in a poorer environment (e.g. arid desert zone), and vice versa. In the same year, the negative impact of human factors on vegetation in the built-up areas in humid and semi-humid forest zone was larger than in semi-arid steppe zone, and which in turn was larger than in arid desert zone. Especially, it was beneficial in arid desert zone.

This study gave a preliminary model to measure the human impacts on urban vegetation. The findings can provide a scientific basis for municipal planning departments and a decision-making reference for government, and also provide scientific guidance for sustainable development in China. Although the results provide additional knowledge on human factors affecting vegetation in the built-up areas, the concrete mechanisms and detail factors that drive urban vegetation change should be investigated in subsequent research.

Acknowledgments

The authors would like to thank the anonymous reviewers for their valuable comments and suggestions to improve the quality of the paper. We are also grateful to Gilbert R. Bossé for his language help.

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