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Spatiotemporal trends of terrestrial vegetation activity along the urban development intensity gradient in China's 32 major cities

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HIGHLIGHTS

- Spatiotemporal trends of the EVI were analyzed in 32 major Chinese cities.
- Urbanization impacts varied across cities and UDI zones within a city.
- EVI trends along UDI gradient demonstrated linear, concave, and convex forms.
- Urbanization posed negative effects on overall vegetation condition.
- Importance of the positive effects generated by the urban environment.

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ABSTRACT

Terrestrial vegetation plays many pivotal roles in urban systems. However, the impacts of urbanization on vegetation are poorly understood. Here we examined the spatiotemporal trends of the vegetation activity measured by MODIS Enhanced Vegetation Index (EVI) along Urban Development Intensity (UDI) gradient in 32 major Chinese cities from 2000 to 2012. We also proposed to use a new set of concepts (i.e., actual, theoretical, and positive urbanization effects) to better understand and quantify the impacts of urbanization on vegetation activities. Results showed that the EVI decreased significantly along a rising UDI for 28 of 32 cities ($p < 0.05$) in linear, convex or concave form, signifying the urbanization impacts on vegetation varied across cities and UDI zones within a city. Further, the actual urbanization effects were much weaker than the theoretical estimates because of the offsetting positive effects generated by multiple urban environmental and anthropogenic factors. Examining the relative changes of EVI in various UDI zones against that in the rural area (ΔEVI), which effectively removed the effects of climate variability, demonstrated that ΔEVI decreased markedly from 2000 to 2012 for about three-quarters of the cities in the exurban ($0.05 < UDI \leq 0.25$) and suburban ($0.25 < UDI \leq 0.5$), and only half of the cities in the urban ($0.5 < UDI \leq 0.75$) and urban core ($0.75 < UDI \leq 1$). The stable or even increasing tendencies of ΔEVI in the urban and urban core of many cities could primarily be attributed to the importance of positive effects derived from the urban environment and the improvement of management and maintenance of urban green space. More work is needed to quantify mechanistically the detailed negative and positive effects of urban environmental factors and management practices on vegetation activities.

1. Introduction

Human activities are now altering Earth's biosphere at a rate unseen in recorded history (Vitousek et al., 1997; Foley et al., 2005). Among these activities, urbanization, physically transforming vegetated surface into impervious surface, is one of the most evident modifications on Earth system (Grimm et al., 2008). Today, more than half of world's population living in urban areas, and this number are projected to be 67% by 2030 (United Nations, 2012). Accompanying with the soaring city dwellers, the global urban area is now expanding at twice their population growth rate (Angel et al., 2011). If the current trend continues, the urban land area in 2030, is expected to nearly triple the area in circa 2000 (Seto et al., 2012).

Urbanization can pose many effects on Earth environments (Grimm et al., 2008). Among these, its impact on vegetation has received considerable interest among scientists and urban planners, since vegetation plays many pivotal roles in urban systems (Grimm et al., 2008; Jim and Chen, 2009; Dallimer et al., 2011). Vegetation can reduce atmospheric CO_2 through assimilation (Imhoff et al., 2004; Myeong et al., 2006;

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Davies et al., 2011), air pollution through uptake via leaf stomata and plant surface (Nowak et al., 2006; Salmond et al., 2013), noise pollution through absorption by leaves, and dispersion, reflection and diffraction by stems (Pathak et al., 2008), and storm water run-off through retention of rainwater (Oldfield et al., 2013). Additionally, it can regulate the microclimate by altering local exchanges of heat, water vapor, and CO_2 (Peters and McFadden, 2010). In particular, it can mitigate heat island effects through transpiration, which could reduce energy consumption and thus the CO_2 emissions from the power plants (Myeong et al., 2006; Park et al., 2012). These ecosystem services of urban vegetation are closely related to the environmental quality, human heath, and sustainable urban development (Kuo and Sullivan, 2001; Jim and Chen, 2009; Lee and Maheswaran, 2011; Gong et al., 2012).

The urban area can be considered as a composite of both "built-up" (i.e., impervious surface) and "non-built-up" (i.e., vegetated or bare land) surfaces, and the vegetation activity (refers to the ability of vegetation to interact with surrounding environments per unit urban area) in urban areas could undergo changes during development mainly in two opposite ways. On one hand, the increasing proportion of built-up land for living and infrastructure would reduce the vegetated areas directly, which was expected to pose negative effects on the overall vegetation activity, resulting in many environmental changes such as the reduction in net primary production (Imhoff et al., 2004; Lu et al., 2010) and the urban heat island (Arnfield, 2003). On the other hand, several urban environmental and anthropogenic factors likely enhance urban vegetation activity. For example, urban areas tend to have warmer temperatures, greater tropospheric CO_2 concentrations, and higher atmospheric nitrogen deposition compared with rural areas, which can promote the plant growth in urban areas (Gregg et al., 2003; Zhang et al., 2004; Searle et al., 2012). Meanwhile, the management of agricultural and/or urban green space such as fertilization, irrigation, and green space creation can largely offset the negative effects associated with raising built-up intensities on vegetation activity (Yu and Padua, 2007; Manninen et al., 2010).

However, a systematic evaluation on the spatiotemporal trends of vegetation activities along an urban development intensity gradient across multiple cities over large areas is still lacking. Relatively limited studies on the urban vegetation focused on the temporal trends or were site-scale observations. For instance, Sun et al. (2011) showed that the average urban Normalized Difference Vegetation Index (NDVI) decreased significantly during the last three decades ($p < 0.01$) in China. Salvati and Zitti (2012) found that the vegetation quality increased slightly between 1975 and 2010 with a diverging trend between urban and rural areas in a Mediterranean region. Jenerette et al. (2013) suggested that the cumulative Enhanced Vegetation Index (EVI) in low-density built-up areas were higher than grass, herb, and shrub land covers of seven metropolitan regions in the southwestern United States. Several key questions related to urban vegetation remain unanswered to date: 1) what's the urbanization effects on the overall vegetation condition in a city? 2) what's the magnitude of the positive urbanization effects on urban vegetation conditions? and 3) how these urbanization effects vary over time and space?

As the world's most populous country, China has experienced the rapidest urbanization in past decades and this trend is expected to continue in upcoming decades (Seto et al., 2011, 2012; United Nations, 2012). About half of China's population lives in urban areas now, and this proportion is predicted to be 73% by 2050 (with an urban population amounting to 1.04 billion) (United Nations, 2012). Meanwhile, China covers a wide climate range, from the tropical to subarctic/alpine and from rain forest to desert (Wu et al., 2005). These together make China an ideal area to investigate the vegetation changes induced by urbanization. Using a Moderate Resolution Imaging Spectoradiometer (MODIS) EVI in conjunction with Landsat TM/ETM + images, we analyzed the spatiotemporal trends of vegetation activities (as reflected by EVI) from 2000 to 2012 in 32 major cities across China. The main objectives of this study were to (1) investigate the EVI trends along a rising urban development intensity gradient, (2) explore new ideas to better quantify the impacts of urbanization on vegetation conditions, and (3) examine the temporal trends of EVI in parallel with rapid urbanization over the past 13 years across cities in China.

2. Materials and methods

2.1. Remotely sensed vegetation activity and urban development intensity

We focused on 32 major cities in China in this study. Distributed across all climatic zones of China, all these cities are municipalities or provincial capitals except Shenzhen, which is China's first special economic zone established in 1978 and is now considered as one of the global fastest growing cities (Fig. 1). Most cities are mainly surrounded by cultivated land except a few southern and northwestern sites that were primarily surrounded by forests (e.g., Hangzhou and Fuzhou) or grassland (Lhasa).

The boundaries of these 32 major cities were defined as follows. First, the maximal areas were defined by China's official administrative areas (i.e., city, *shi*) (Chan, 2010). Second, pixels within the administrative boundaries that were water body or with elevation more than 50 m higher than the highest point in the urban and urban core zones (see definition below) were excluded from this analysis (Figs. 1 and 2) because these pixels may overshadow the urbanization effects on terrestrial vegetation activity (e.g., Imhoff et al., 2010).

We examined the vegetation activity across all cities from 2000 to 2012 using the version-5 MODIS/Terra EVI (MOD13A2) data (1×1 km^2 spatial resolution and 16-day interval). Compared with NDVI, the EVI minimizes canopy background variations while remains sensitive to dense vegetation conditions (Huete et al., 2002). Moreover, it removes residual atmosphere contamination caused by smoke and sub-pixel thin clouds using the blue band. EVI provides a continuous measure and hence responds to small changes in vegetation activities (Dallimer et al., 2011), and its accuracy has been assessed over a widely range of locations and time periods (Huete et al., 2002). Thus the EVI is more appropriate for monitoring vegetation dynamics in urban areas that are usually covered by sparse vegetation (Zhang et al., 2004; Dallimer et al., 2011). Noises caused by cloud contamination, atmospheric variability and bi-directional effects (Chen et al., 2004) were further removed in this analysis using an adaptive Savitzky–Golay filtering method (Jönsson and Eklundh, 2004; Chen et al., 2004). To avoid spurious EVI trends due to winter snow, we used EVI of growing season (defined as April to October) to analyze vegetation activity (e.g., Zhou et al., 2001; Piao et al., 2003) in this study.

Land cover maps within the administrative boundary of each city for the year 2000, 2005, and 2010 were derived from Landsat TM/ETM + images (downloaded from http://www.usgs.gov/ and http://datamirror.csdb.cn/) with a spatial resolution of 30×30 m^2. First, the Landsat images were preprocessed (e.g., re-projection, mosaic, histogram equalization) using ERDAS Imagine version 9.2. Second, the land covers were classified into three broad types (i.e., built-up land, water body, and other land) using the maximum likelihood classification approach (Strahler, 1980). The built-up land consisted of impervious surfaces. Water body included reservoirs, ponds, and rivers. Other land covered all other land covers such as cropland, forest, shrub, grass, and unused land. Finally, the accuracies of the classified products were assessed for 1) the products in 2010 and 2) the unchanged land covers between 2000 and 2010, using the high-resolution images and pictures incorporated in Google Earth Pro® (GE) (Zhou et al., 2012). The accuracy requirement for classification has been met since the Kappa coefficients, measuring classification accuracy (Foody, 2002), ranged from 0.77 to 0.93 for the 32 cities with most of them larger than 0.80.

The Urban Development Intensity (UDI), defined as the proportion of built-up areas in each 1×1 km^2 grid based on the 30×30 m^2 urban land cover maps, was mapped using a 1×1 km^2 moving window (in order to keep accordance with the size of the MODIS EVI pixels) for

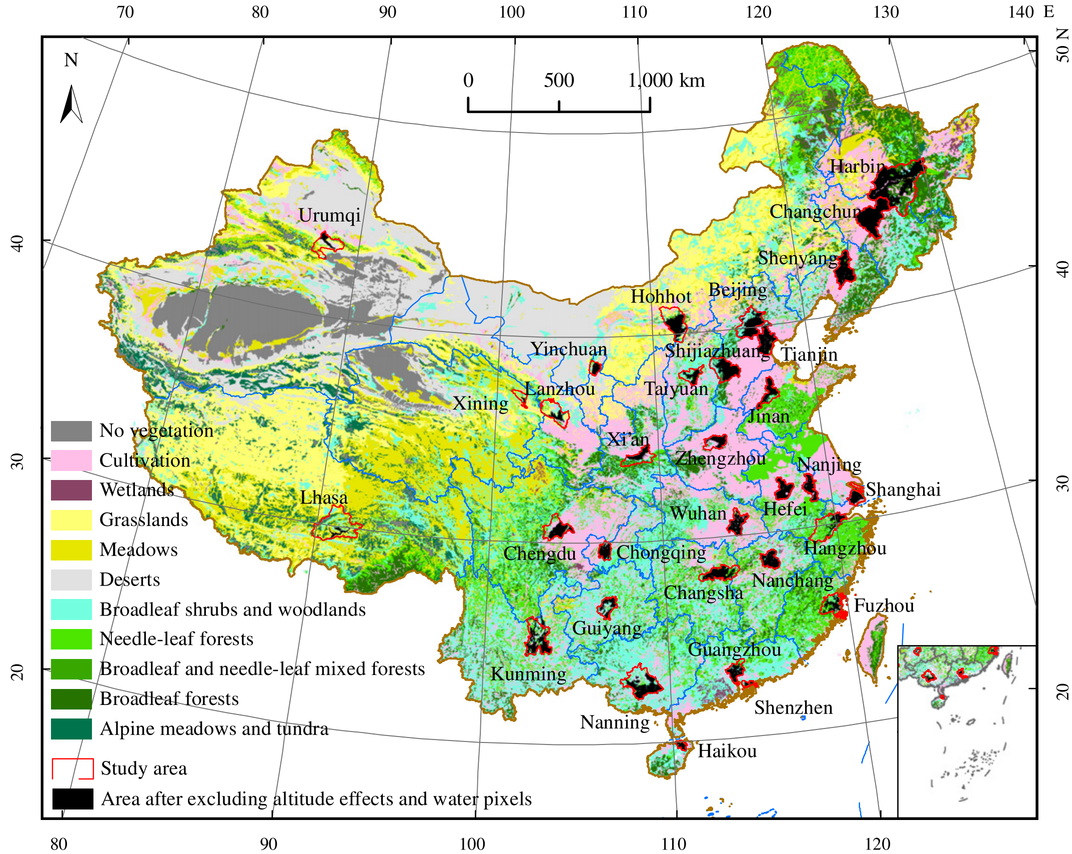

Fig. 1. Vegetation map of China (this data set is provided by "Environmental & Ecological Science Data Center for West China, National Natural Science Foundation of China" (http://westdc.westgis.ac.cn)) and the cities including in this study. All the sites are provincial capitals or provincial/autonomous regional capitals except Shenzhen, which is China's first special economic zone and is now considered one of the fastest growing cities in the world. The boundaries of these 32 major cities (study areas) were defined according to China's official definitions of their administrative areas (i.e., city, *shi*). The black areas on the map were included in this analysis, which excluded the altitude effects and water pixels.

the year 2000, 2005, and 2010. We further stratified the landscape into five zones based on the UDI. Emanating inward from the lowest to the highest UDI in a city (Fig. 2), these five zones were rural ($UDI \leq 0.05$) and four urban zones (exurban [$0.05 < UDI \leq 0.25$], suburban [$0.25 < UDI \leq 0.5$], urban [$0.5 < UDI \leq 0.75$], and urban core [$0.75 < UDI \leq 1$]). The rural area was usually covered by both cultivated and natural vegetation, while the exurban and suburban areas were mainly covered by cultivated vegetation besides built-up land (Fig. 2).

2.2. EVI trends along UDI gradients

The zonal mean growing season EVIs in the five UDI zones (rural, exurban, suburban, urban, and urban core) were calculated over the period 2000–2012 for all the 32 cities. For the years without UDI maps, we assumed that the UDI maps in 2000, 2005, and 2010 can be applied to 2001–2004, 2006–2009, and 2011–2012, respectively. Linear regression analysis was performed to examine the decaying rate of EVI with increasing UDI for each city. The impacts of background vegetation condition (reflected by rural EVI) on the EVI decaying rate was also assessed with the hypothesis that the city with a better background EVI should have a greater decaying rate. We also explored the climatic effects (mean annual precipitation [MAP] and temperature [MAT]) on the spatial variability of the EVI decaying rates across cities. Annual climate data of precipitation and temperature from 2000 to 2012 for each city was obtained from Chinese Meteorological Observations (http://cdc.cma.gov.cn/). The Pearson's correlation and general linear regression analyses were performed in SPSS PASW Statistics 18 (SPSS Inc.).

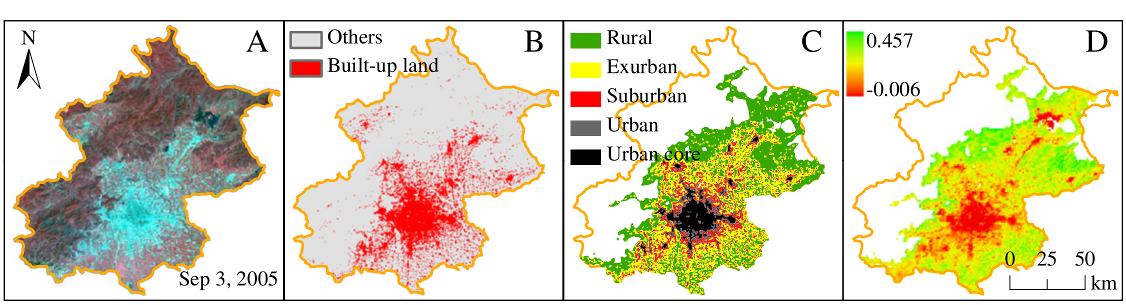

Fig. 2. Beijing area maps of (A) Landsat TM false color image acquired on Sept 3, 2005 with a spatial resolution of 30 m × 30 m, (B) urban land cover map derived from Landsat TM images, (C) regions with different urban development intensity (UDI) that was derived from urban land cover map (i.e., rural, $UDI < 0.05$; exurban, $UDI = 0.05$–0.25; suburban, $UDI = 0.25$–0.5; urban, $UDI = 0.5$–0.75; urban core, $UDI > 0.75$–1), and (D) averaged growing season (April to October, 2005) Enhanced Vegetation Index (EVI). The blank areas on the map were not included in the analysis, which were either water bodies or areas excluded by elevation consideration.

Since the EVI in urban core (the most urbanized area) would impossibly exceed that in its corresponding rural area due to the transformation of vegetated surface into impervious surface by urbanization, the vegetation activity should decrease along the UDI gradients. Moreover, the EVI decline patterns (refers to "EVI–UDI" thereafter) may differ by city (Yuan and Bauer, 2007; Luck et al., 2009). With this in mind, we used three possible forms (i.e., "Linear", "Convex", and "Concave") to differentiate the significant decline patterns (when $p < 0.05$) among cities (Fig. 3). "Linear" means that the EVI decreased linearly with rising UDI. "Convex" indicates that the EVI decreased significantly with UDI, but was in a relatively lower decaying rate or even slight upward trend first, followed by a faster decrease with increasing UDI. This trend is possible for the cities with relatively higher EVI per vegetated pixel in the exurban or suburban compared with rural zones. In contrast to "Convex", "Concave" suggests a sharp decrease of EVI first, then followed by a relatively low declining rate, which is likely to occur in a city with high rural EVI.

In parallel with linear regression analysis, quadratic regression analysis was performed for each city to detect the presence of the "Concave" or "Convex" trend:

$$y = b_2x^2 + b_1x + b_0 \tag{1}$$

where b_2 indicates whether the EVI was in "Convex" ($b_2 < 0$) or "Concave" ($b_2 > 0$) downward trends as well as the convexity or concavity. The larger $|b_2|$ indicates the greater convexity or concavity.

Since the five EVI data points along the UDI gradient in each city (i.e., rural, exurban, suburban, urban, and urban core) are not enough for us to distinguish these three EVI–UDI forms statistically, we calculated the mean zonal EVIs using ten UDI bins from 0 to 1 with an interval of 0.1. The goodness of the fit of the linear and quadratic regression models was evaluated by the corrected Akaike Information Criterion (AICc) (Motulsky, 2004; Symonds and Moussalli, 2011):

$$AIC_c = N* \ln\left(\frac{RSS}{N}\right) + 2K + \frac{2K(k+1)}{N-K-1} \tag{2}$$

where N is the number of data points, K is the number of parameters fit by the regression plus 1, and RSS is the residual sum of squares of the model. When comparing two models, the model with the lower AIC_c score is considered the better one. In addition, the significance of the difference between the linear and quadratic regression models for each city was also tested using ANOVA. All regression analyses, AICc calculation, and ANOVA analysis were performed using R (R Development Core Team, 2013).

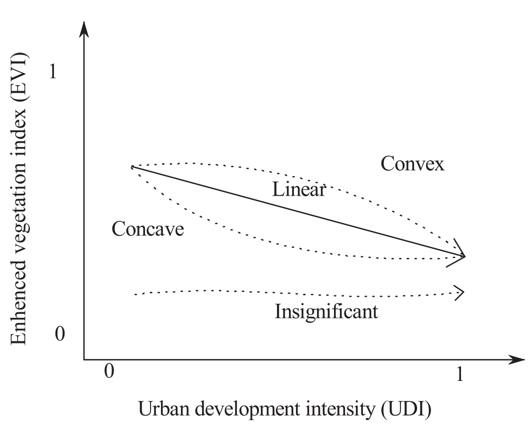

Fig. 3. Conceptual models describe the changes of vegetation index with urban development intensity.

2.3. Methods to quantify the AUE, TUE, and PUE

To our knowledge, no study had ever been conducted to quantify the actual urbanization effects (AUE), theoretical urbanization effects (TUE, provided without positive effects associated with the urban environment), and the positive urban effects (PUE, facilitated by urban environmental and anthropogenic factors) on the overall vegetation conditions. Specifically, we defined the AUE, TUE, and PUE as the percent relative changes of the actual to background, theoretical to background, and actual to theoretical vegetation conditions, respectively. Those effects were then quantified in the following steps:

a) We hypothesized that the background EVI for each city can be represented by its rural EVI (Fig. 4).
b) We assumed that the theoretical EVI for built-up land was 0.05, and that for non-built-up pixels equaled to the background EVI in the city. The value of 0.05 was selected for the built-up land because there was no vegetation activity under this threshold (Huete et al., 2002).
c) The theoretical EVI of certain urban zone for a particular city was then estimated as the area-weighted mean EVI of both built-up (i.e., 0.05) and non-built-up (i.e., rural EVI) pixels. For example, the theoretical EVI for suburban (the mid-value of the UDI range is 0.375) was estimated as: [rural EVI] × (1–0.375) + 0.05 × 0.375.
d) We defined the background vegetation condition (VEG_{back}) as the area of the rectangle of the rural EVI over the UDI range (i.e., 1) ([rural EVI] × 1]), and the actual vegetation condition (VEG_{actual}) as the integral of the actual EVI over the UDI range ([rural EVI] × 0.05 + [Exurban EVI] × 0.20 + [Suburban EVI] × 0.25 + [Urban EVI] × 0.25 + [Urban core EVI] × 0.25), respectively. Similarly, the theoretical vegetation condition (VEG_{theory}) was defined as the integral of theoretical EVI over the UDI range (Fig. 4).
e) The AUE, TUE, and PUE were then calculated as follows:

$$AUE = (VEG_{actual} - VEG_{back})/VEG_{back} \times 100\% \tag{3}$$

$$TUE = \left(VEG_{theory} - VEG_{back}\right)/VEG_{back} \times 100\% \tag{4}$$

$$PUE = \left(VEG_{actual} - VEG_{theory}\right)/VEG_{theory} \times 100\%. \tag{5}$$

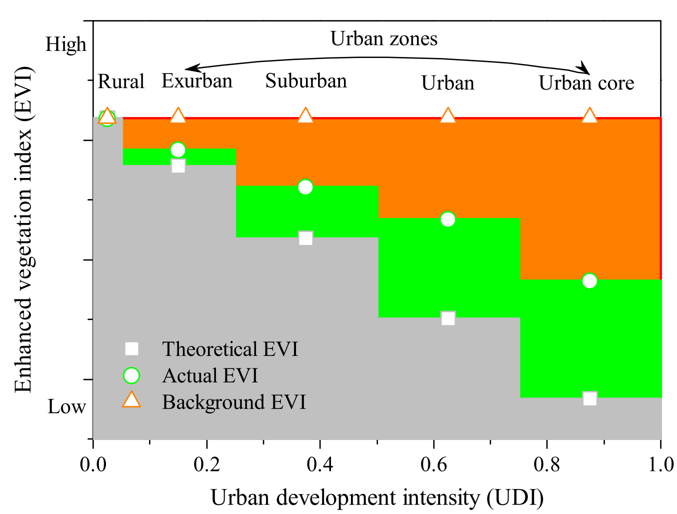

Fig. 4. Conceptual map shows the background, theoretical (assuming no positive urban effect), and actual vegetation activities along an urban development intensity (UDI) gradient.

2.3.1. Temporal trends of EVI in different urban zones

In order to examine the EVI trends over time induced by rapid urbanization from 2000 to 2012, the annual mean growing season EVI was estimated for the period 2000–2012 using the UDI zones of the year 2000. To remove the possible effects of inter-annual climate variability on the EVI fluctuations, we used rural EVI as a base EVI condition assuming that urbanization has little impact on rural EVI, and analyzed the temporal trends of EVI over urban zones (i.e., exurban, suburban, urban, and urban core) for each city by calculating the EVI differences between them and their corresponding rural areas (ΔEVI) (e.g., Dallimer et al., 2011). The vegetation activity in an urban zone was assumed constant if an insignificant ΔEVI trend over time was observed. Linear regression models were used to test for temporal patterns of ΔEVI for each city separately. We also evaluated the temporal trends of rural EVI using linear regression to examine the possible trend as a result of climate variability or/and human activities (e.g., tree planting or deforestation, and cropland management). Finally, we calculated the Pearson's correlation coefficients between the background EVI, MAP, or MAT and the annual change rates of ΔEVI across cities. The general linear regression analysis was conducted to examine the overall explanation rate of these drivers to the observed change of ΔEVI. Latitudinal and longitudinal information were not used in the analysis as they are closely related to climate variables in China (Wu et al., 2005).

3. Results

3.1. Spatial trends of average growing season EVI with rising UDI

The area-weighted growing season EVI averaged from 2000 to 2012 decreased significantly ($p < 0.05$) with elevating UDI for 28 of 32 cities (Fig. 5A). The EVI–UDI trends in three arid cities (Lanzhou, Urumqi, and Lhasa) and the country's most developed city (Shanghai) were not statistically significant. The significant EVI decaying rates along the rising UDI gradient (reflected by the linear regression slope) varied with geographic locations from −0.322 in Haikou to −0.070 in Taiyuan (Fig. 5A). Overall, cities with humid-hot climates (e.g., Haikou, Guangzhou, and Fuzhou) had larger decaying rates than those with dry-cold climates (e.g., Xining, Yinchuan, and Taiyuan). As expected, the EVI decaying rates were negatively related to the background vegetation conditions ($r = -0.85$, $p < 0.01$) (Table 1). Moreover, MAT and MAP related closely and negatively to EVI decaying rates ($r = -0.60$ and -0.59, respectively, and $p < 0.01$). Together, they contributed 72.6% of the total variance in EVI decaying rates across cities (Table 1).

Table 1
Pearson's correlation coefficients between the linear decaying rates of Enhanced Vegetation Index (EVI) along the Urban Development Intensity (UDI) gradients (EVI–UDI) or the annual change rates of the EVI in urban zones relative to the base condition in the rural area (ΔEVI) from 2000 to 2012 and the potential drivers across cities. ΔUDI indicates the UDI changes between 2000 and 2010. MAT and MAP represent the mean annual temperature and precipitation, respectively. The combined explanation rates of all factors are estimated using general linear regression analysis.

Spatiotemporal trends of EVI		Pearson's correlations ($N = 32$)				Explanation rate (%)
		ΔUDI	Rural EVI	MAT	MAP	
EVI–UDI		–	−0.85[a]	−0.60[a]	−0.59[a]	72.6[a]
ΔEVI 2000-2012	Exurban	−0.49[a]	−0.31	−0.51[a]	−0.27	46.8[a]
	Suburban	−0.41[*]	−0.35	−0.42[*]	−0.31	32.6[*]
	Urban	−0.44[*]	−0.28	−0.26	−0.26	28.6
	Urban core	−0.14	−0.14	−0.00	−0.09	11.7

[a] Significant at the 0.01 level; [*]significant at the 0.05 level.

In addition, we found that the significant EVI decline trends can be further grouped into three types ("Linear", "Convex", and "Concave") with evident geographic clusters (Fig. 5B). The "Linear" decrease occurred in various geographic zones of China (15 cities), the "Convex" pattern mainly happened in the north and northeastern (e.g., Changchun, Hohhot, and Tianjin) parts of China (11 cities), and the "Concave" appeared in two southwestern cities (Kunming and Nanning).

3.2. The AUE, TUE, and PUE on vegetation conditions

As shown in Fig. 6A, urbanization actually (i.e., AUE) posed negative effects on vegetation conditions in all the cities except two arid cities (Urumqi and Lanzhou) and Shanghai where positive effects were observed. The positive value in Shanghai should be mainly attributed to our underestimation of its background EVI using its rural one because the impacts of urbanization in Shanghai, country's largest and most modern city, extend far beyond its urban zones (Zhao et al., 2006). This can also be seen from the fact that the rural EVI in Shanghai is notably lower than those of its neighbors (e.g., Hangzhou and Nanjing) (Fig. 6). We thus excluded Shanghai from the following general analysis. The AUE ranged from −40% in Haikou to 17% in Urumqi, and correlated significantly and negatively to the background EVI ($r = -0.83$,

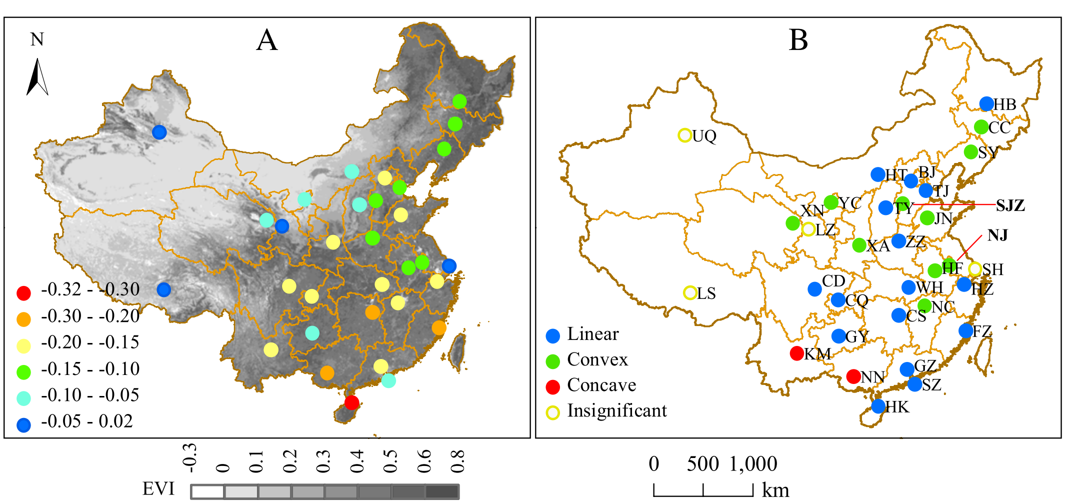

Fig. 5. Spatial distribution of the EVI decaying rates (A) and the EVI–UDI modes (B) in China's 32 major cities, with background color indicating the mean growing season EVI averaged over the period 2000–2012. We excluded Shanghai from the general correlation analysis because of our possible underestimation of its background vegetation condition (as reflected by rural EVI). BJ: Beijing; CC: Changchun; CS: Changsha; CD: Chengdu; CQ: Chongqing; FZ: Fuzhou; GZ: Guangzhou; GY: Guiyang; HK: Haikou; HZ: Hangzhou; HB: Harbin; HF: Hefei; HT: Hohhot; JN: Jinan; KM: Kunming; LZ: Lanzhou; LS: Lhasa; NC: Nanchang; NJ: Nanjing; NN: Nanning; SH: Shanghai; SY: Shenyang; SZ: Shenzhen; SJZ: Shijiazhuang; TY: Taiyuan; TJ: Tianjin; UQ: Urumqi; WH: Wuhan; XA: Xi'an; XN: Xining; YC: Yinchuan; ZZ: Zhengzhou.

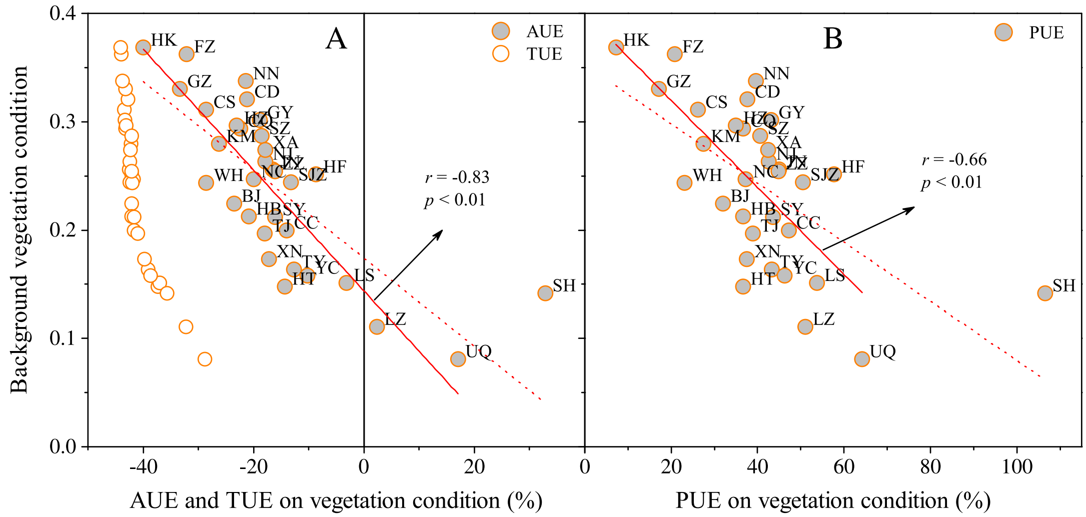

Fig. 6. The actual urbanization effects (AUE), theoretical urbanization effects (TUE), and positive urban effects (PUE) on the overall vegetation conditions in 32 major Chinese cities, and their relationships with city's background vegetation conditions as reflected by rural EVI. The PUE means the positive effects facilitated by multiple urban environmental and anthropogenic factors on vegetation activity.

$p < 0.01$). However, the AUE were much lower than the theoretical urbanization effects (i.e., TUE) for all the cities (Fig. 6A), mainly due to the positive urban effects (i.e., PUE) facilitated by multiple urban environmental and anthropogenic factors (Fig. 6B). Specifically, the PUE, indicated by the percent relative changes of the actual to theoretical vegetation conditions, were all positive, ranging from 7% in Haikou to as much as 64% in Urumqi. The PUE related tightly and negatively to the background EVI across cities in China ($r = -0.66$, $p < 0.01$) (Fig. 6B).

3.3. Temporal trends of the mean growing season EVIs in different urban zones

The temporal trends of vegetation activities differed greatly across urban zones and cities from 2000 to 2012 (Fig. 7, Table 2). Relative to the rural base condition (i.e., ΔEVI), the ΔEVI declined significantly for most cities in the exurban (24 of 32) and suburban (25 of 32), but only around half cities in the urban (17 of 32) and urban core (16 of 32). The maximal decreasing rate of -0.006 yr^{-1} occurred in Hefei in its urban zone. Three cities (i.e., Beijing, Kunming, and Shenzhen) presented a significant decrease of ΔEVI in the exurban only, one city (Hangzhou) exhibited no apparent change of ΔEVI in all urban zones, and three cities (i.e., Nanjing, Shanghai, and Urumqi) even showed an obvious increase of ΔEVI in the urban core over the whole study period. In addition, ΔEVI in the urban zones of many cities showed evident increases or remained stable (e.g., Changsha, Chengdu, Chongqing, Kunming, and Nanjing) in the later of the study period.

The background EVI, MAT, and MAP had weaker correlations with the temporal trends of ΔEVI in urban areas than those on decaying rates of EVI along the UDI gradient (Table 1). The correlation was only evident for MAT in the exurban and suburban areas ($p < 0.05$). In contrast, the UDI changes between 2000 and 2010 related significantly and negatively to the annual rates of ΔEVI in all urban zones except in the urban core. In general, the four factors together explained less than half of the total variations in ΔEVI trends across cities and their explanatory powers declined with increasing UDI levels (i.e., 46.8%, 32.6%, 28.6%, and 11.5% for exurban, suburban, urban, and urban core, respectively).

4. Discussion

Vegetation, an integral component of the urban environment, plays many key roles in urban systems (Grimm et al., 2008; Jim and Chen, 2009). However, vegetation dynamics induced by urbanization remained poorly understood over large areas because they were hardly inventoried by traditional ground surveys due to highly complicated urban landscape configuration and rapid changes of urban vegetation (Sudha and Ravindranath, 2000; Myeong et al., 2006; Liu and Yang, 2013). The use of the MODIS EVI (1×1 km^2) in combination with high resolution Landsat TM/ETM + (30×30 m^2) data provides us a cost-effective approach to quantify urban vegetation activity in a timely and spatial-explicitly manner (Stefanov and Netzband, 2005). We explored not only the temporal trends of EVI like the most previously efforts did (e.g., Sun et al., 2011; Salvati and Zitti, 2012), but also the trends of EVI along urban development intensity (i.e., UDI) gradient. Since China is characterized by complex climate conditions and large geographical extent (Piao et al., 2003; Wu et al., 2005), the results derived from this analysis might help enhance our understanding of vegetation dynamics caused by urbanization both regionally and globally. The quantitative methods originated from this study (e.g., the evaluations of AUE, TUE, and PUE) might also provide new insights for future efforts to evaluate the urbanization effects on vegetation over large areas.

Our results showed that the EVI reduced significantly with raising UDI for most of the cities except an insignificant change occurred in few arid cities (Figs. 5A), which was in accordance with the previous knowledge (Imhoff et al., 2000; Sun et al., 2011). We found that the EVI decaying rates across cities correlated negatively with rural EVI (Table 1) because urbanization likely poses more strong negative effects on vegetation in the cities with better background vegetation conditions (reflected as rural EVI) (Imhoff et al., 2000). The EVI decaying rates also linked tightly to climate factors (mean annual temperature and precipitation) because the large-scale variability of the background vegetation conditions was strongly influenced by climate (Nemani et al., 2003; Zhang et al., 2004). We also found that not all EVI–UDI relationships were linear in cities. "Convex" and "Concave" patterns can be formed under certain natural and anthropogenic influences. For example, two southwestern cities (Kunming and Nanning) presented a "Concave" trend mainly because of the strong vegetation activity in the rural zones owing to their humid-hot climates (Piao et al., 2003; Wu et al., 2005). In contrast, some northern and eastern cities (11 cities) showed a "Convex" decrease primarily due to intensive land use activities (e.g., agricultural practices and urban green land management) in the exurban or/and suburban, which led to higher vegetation activity per vegetated surface compared with its rural counterpart (e.g., Allen, 2003; Piao et al., 2003). Notably, human activities can alter the shape of EVI–UDI relationship. For instance, the EVI–UDI relationship in Shanghai was not significant even though it was located in a humid-hot region. This might be attributed to (1) the relatively high vegetation activities in the

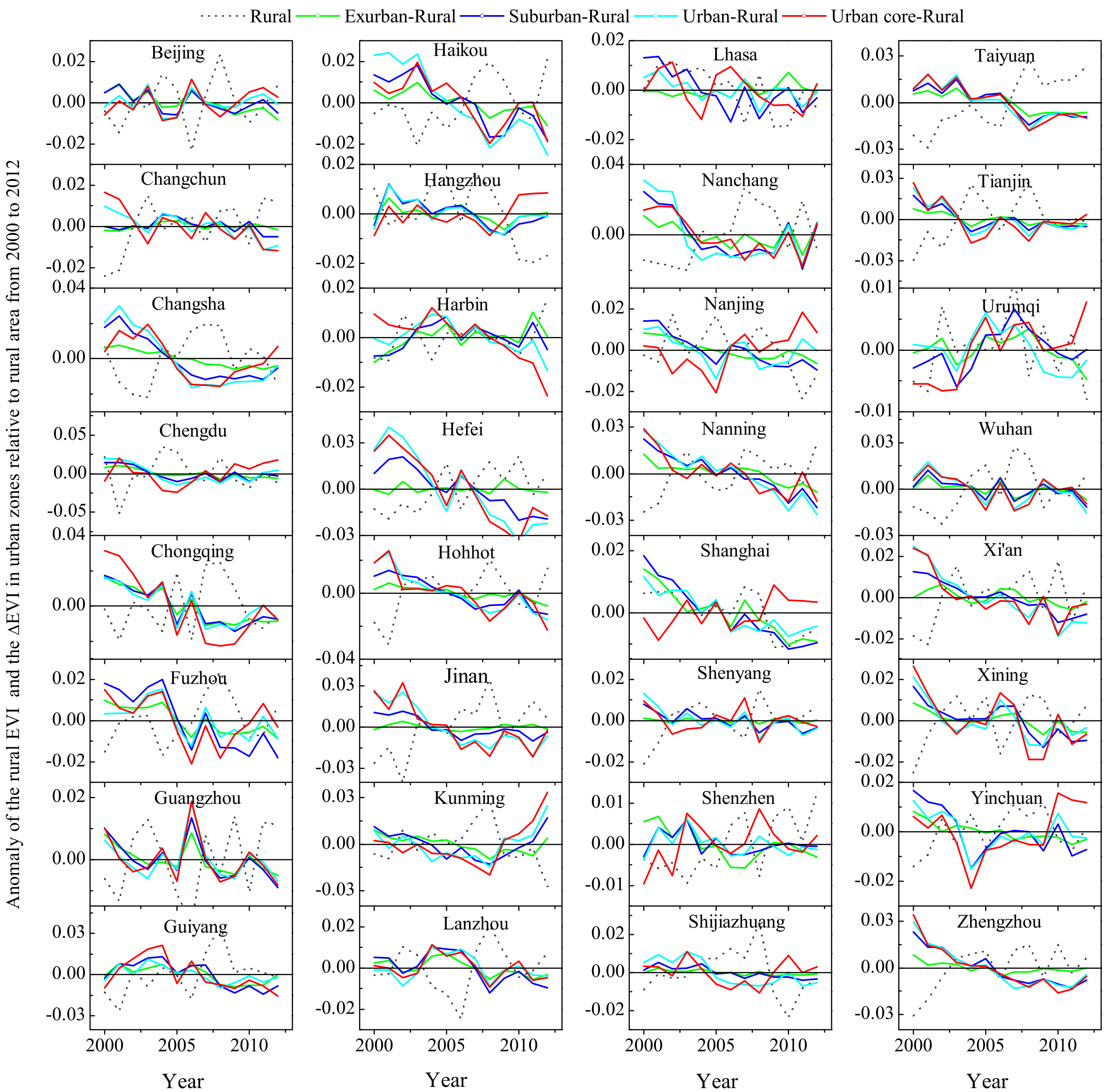

Fig. 7. Anomalies of the area-weighted mean growing season EVI in rural area and the EVI differences between urban zones (i.e., exurban, suburban, urban, and urban core) and corresponding rural area (i.e., ΔEVI) from 2000 to 2012 for China's 32 major cities.

urban zones resulted from urban green land management activities in the city, and (2) our possible underestimation of its background vegetation condition, which can be seen from the better background EVIs in its neighboring cities such as Hangzhou and Nanjing.

Urbanization posed negative effects on the overall vegetation conditions in most of the cities (Fig. 6). The actual urbanization effects (i.e., AUE) were much weaker than the potential theoretical effects (i.e., TUE) because of the positive effects generated by the urban environment (i.e., PUE) such as the favorable plant growth conditions (Gregg et al., 2003; Zhang et al., 2004; Searle et al., 2012) and green land management (Yu and Padua, 2007; Manninen et al., 2010). The negative urbanization effect was observed more evident in the city with better background vegetation condition and the opposite occurred for the PUE, suggesting that it's relatively easier to conserve vegetation activities in cities with poor background vegetation conditions during urban development. Particularly, urbanization even improved the vegetation conditions in two arid cities (i.e., Urumqi and Lanzhou) thanks to the large PUE effects (Fig. 6), which agreed well with the findings from seven arid cities in the United States (Jenerette et al., 2013).

Temporally, we found that the vegetation activity was more likely to decrease in the exurban and suburban (over more than three-quarters of cities) than that in the urban and urban core (only around half of the cities) (Fig. 7, Table 2). These can be attributed to three possible reasons: (1) relatively better vegetation condition in the exurban and suburban than that in the urban and urban core, (2) more urban built-up expansion occurred inside the exurban and suburban over time, and (3) more intensive management and maintenance of urban green space in the urban and urban core. Similar findings were observed from a study on the correlations of changes in vegetation quality and the distribution and density of urban settlement in two Mediterranean cities (Athens and Rome) (Salvati and Ferrara, 2013). Notably, some cities in our study even witnessed an evident recovery following a decrease in vegetation conditions in the urban or/and urban core possibly owing to the improvement of management and maintenance of urban green space in recent years.

Table 2
Linear regression examining the temporal trends of rural EVI and the ΔEVI in urban zones (i.e., exurban, suburban, urban, and urban core) relative to the base rural condition (unit: 10^{-3}) for China's 32 major cities from 2000 to 2012.

City	Rural EVI (N = 13)		EVI difference between urban zones and rural area (N = 13)							
			Exurban		Suburban		Urban		Urban core	
	Slope	R^2	Slope	R^2	Slope	R^2	Slope	R^2	Slope	R^2
Beijing	0.68	0.05	−1.02	0.62[b]	−0.71	0.30	0.10	0.01	0.56	0.11
Changchun	1.89	0.34[a]	0.07	0.03	−0.30	0.13	−1.32	0.64[b]	−1.64	0.53[b]
Changsha	0.79	0.05	−1.17	0.89[c]	−2.84	0.75[c]	−3.47	0.67[b]	−1.54	0.25
Chengdu	−0.42	0.01	−1.21	0.72[c]	−1.49	0.42[a]	−1.67	0.30	1.32	0.13
Chongqing	0.56	0.02	−2.32	0.79[c]	−2.36	0.68[b]	−1.89	0.47[a]	−3.54	0.55[b]
Fuzhou	1.03	0.12	−1.50	0.73[c]	−3.18	0.73[c]	−1.23	0.30	−1.30	0.20
Guangzhou	0.93	0.09	−0.71	0.38[a]	−0.93	0.32[a]	−0.44	0.06	−0.66	0.11
Guiyang	1.77	0.20	−0.98	0.39[a]	−1.72	0.49[b]	−0.79	0.26	−1.67	0.30
Haikou	1.57	0.24	−1.18	0.66[b]	−2.66	0.74[c]	−4.15	0.85[c]	−2.09	0.49[b]
Hangzhou	−1.69	0.27	−0.31	0.15	−0.80	0.30	−0.60	0.17	0.78	0.27
Harbin	0.73	0.15	0.75	0.34[a]	0.327	0.06	−0.80	0.26	−2.018	0.68[b]
Hefei	2.36	0.45*	0.02	0.00	−3.31	0.85[c]	−5.66	0.82[c]	−5.03	0.77[c]
Hohhot	1.52	0.18	−0.84	0.72[c]	−2.08	0.78[c]	−2.82	0.82[c]	−2.70	0.67[b]
Jinan	3.26	0.43[a]	−0.04	0.01	−1.49	0.62[b]	−3.36	0.72[c]	−3.22	0.57[b]
Kunming	−0.65	0.03	−0.95	0.47[a]	−0.42	0.03	0.73	0.08	1.53	0.19
Lanzhou	0.53	0.03	−0.61	0.36[a]	−1.20	0.41[a]	−0.14	0.01	−0.42	0.08
Lhasa	−1.16	0.44[a]	0.29	0.16	−1.54	0.50[b]	−0.68	0.30	−0.76	0.15
Nanchang	2.33	0.33[a]	−0.75	0.18	−2.13	0.37[a]	−2.41	0.31	−1.87	0.41[a]
Nanjing	−1.27	0.19	−1.08	0.79[c]	−1.82	0.78[c]	−0.84	0.20	1.43	0.31[a]
Nanning	2.01	0.32[a]	−1.52	0.77[c]	−3.14	0.91[c]	−3.92	0.91[c]	−2.76	0.64[b]
Shanghai	−1.22	0.49[b]	−1.78	0.83[c]	−2.32	0.89[c]	−1.44	0.76[c]	0.73	0.32[a]
Shenyang	1.14	0.23	−0.05	0.04	−0.807	0.56[b]	−0.99	0.43[a]	−0.27	0.03
Shenzhen	1.29	0.49[b]	−0.68	0.43[a]	−0.19	0.08	−0.23	0.10	0.48	0.13
Shijiazhuang	−0.39	0.02	−0.21	0.42[a]	−0.65	0.72[c]	−1.35	0.60[b]	−0.18	0.01
Taiyuan	4.01	0.76[c]	−1.43	0.75[c]	−2.06	0.71[c]	−2.40	0.71[c]	−2.44	0.71[c]
Tianjin	1.60	0.15	−0.84	0.61[b]	−1.47	0.53[b]	−1.80	0.46[a]	−1.47	0.22
Urumqi	0.00	0.00	−0.16	0.08	0.31	0.14	−0.35	0.17	0.91	0.55[b]
Wuhan	1.62	0.17	−0.67	0.35[a]	−0.98	0.35[a]	−1.60	0.44[a]	−1.20	0.26
Xi'an	1.32	0.17	−0.55	0.34[a]	−1.89	0.90[c]	−2.93	0.82[c]	−2.19	0.55[a]
Xining	1.03	0.12	−0.89	0.63[b]	−1.78	0.67[b]	−1.43	0.35[a]	−2.08	0.39[a]
Yinchuan	0.73	0.12	−0.84	0.78[c]	−1.54	0.42[a]	−0.68	0.13	0.89	0.11
Zhengzhou	2.04	0.32[a]	−0.56	0.40[a]	−2.70	0.85[c]	−2.86	0.73[c]	−3.11	0.75[c]

[a] Significant at 0.05 level.
[b] Significant at 0.01 level.
[c] Significant at 0.001 level.

The temporal trends of EVI, relative to the base condition in the rural area (ΔEVI), related strongly to human activities. For example, the UDI changes, induced primarily by human activities, related significantly and negatively to the temporal changes of ΔEVI in the exurban, suburban, and urban zones across cities ($p < 0.05$) because UDI increase directly reduced the vegetated surface. As illustrated in Fig. 8, the area-weighted mean UDI increased most rapidly in the suburban over the recent decade, followed by the urban and exurban, with much lower increase rate in the urban core for nearly all the cities. This in part explained the phenomenon that the number of cities that experienced significant ΔEVI decrease over time in the urban core was much less than that in the exurban and suburban. At the same time, Chinese municipal governments have put in efforts in creating new green areas or preserving existing green spaces in conjunction with rapid urbanization in recent years (Yu and Padua, 2007; Zhao et al., 2013), and that might mainly contribute to the stable or even increasing tendencies of ΔEVI in urban areas of many cities experiencing simultaneous urbanization intensification.

The major concern of the urbanization effects on vegetation is its influences on both eco-environments and human well beings. Many studies indicated that the rapid urbanization in China decreased net

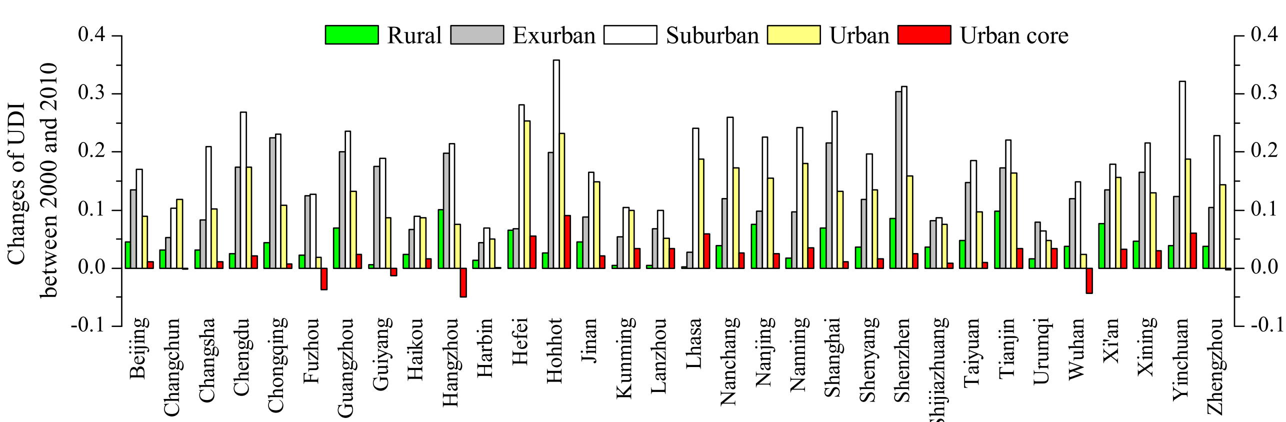

Fig. 8. Changes of the area-weighted mean UDI in different UDI zones from 2000 to 2010.

primary production significantly in the past two decades (Piao et al., 2005; Lu et al., 2010; Wu et al., 2014). The negative urbanization effects on vegetation conditions observed in this analysis further corroborated this finding as EVI is a surrogate of ecosystem production (Sjöström et al., 2011; Wu et al., 2011). The reduction in vegetation activity would intensify urban heat island, which might not only amplify the energy consumption directly but also pose a major public health threat (Patz et al., 2005; O'Loughlin et al., 2012; Gong et al., 2012). As China's urbanization is likely to continue in upcoming decades (United Nations, 2012; Seto et al., 2012), it's urgent to adopt a sustainable urban plan to minimize vegetation losses and to enhance the vegetation activity over urban areas to maximize the multiple benefits associated with urban vegetation. Our detailed study on the spatiotemporal trends of vegetation activity with urban development across China provides useful information for future urban planning.

Uncertainties remain in the results from this analysis. First, large area differences existed among UDI zones for a particular city and across cities, which may affect the area-weighted mean vegetation indexes. Second, we used the empirical value of the rural EVI to represent city's background vegetation condition, which may introduce uncertainty. Third, we assumed that there were no urbanization effects in rural areas when studying the impacts of urbanization on vegetation. Actually, our results showed that the UDI in the rural zone increased over time for all the cities albeit with a small magnitude, suggesting that the EVI difference between urban and their corresponding rural areas (i.e., ΔEVI) might be overestimated. Fourth, we did not conduct a detailed attribution analysis on the phenomena that urban areas had higher EVI than in rural areas. Although the possible driving forces include intensified vegetation management (e.g., irrigation, fertilization, choice of species) and/or some other urban characteristic (e.g., higher temperature, CO_2, nitrogen deposition, and lower O_3), other alternative explanations are equally possible. For example, the rural areas, largely cultivated, do not exhibit the full EVI that would be expected if they were vegetated with the same species as urban areas. Despite these uncertainties, our findings showed large reduction of vegetation activities with urban development in space and time, and at the same time, highlighted the importance of positive effects generated in urban areas. More work is needed to quantify the detailed negative and positive effects of urban environmental factors (such as CO_2, temperature, nitrogen deposition and O_3) and management practices on vegetation activities, and to understand other potential driving forces on the modification of EVI in urban environments.

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