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Long-term satellite observations show continuous increase of vegetation growth enhancement in urban environment

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Highlights

Proposed a long-term framework to quantify urbanization impacts on vegetation.

Urbanization decreased regional EVI due to direct surface-replacement impact.

Urban environment stimulated an enhancement of vegetation growth over time.

Growth enhancement offset about 28% to 44% of direct EVI loss.

1. Abstract

Urbanization shows continuous expansion and development, ushering in the co-evolution of urban environments and vegetation over time. Recent remote sensing-based studies have discovered prevalent vegetation growth enhancement in urban environments. However, whether there is a temporal evolution of the growth enhancement remains unknown and unexplored. Here we expanded the existing framework for assessing the long-term impact of urbanization on vegetation greenness (enhanced vegetation index, EVI) using long time series of remote sensing images and applied it in Changsha, the capital city of Hunan province in China. Results showed that vegetation growth experienced widespread enhancement from 2000 to 2017, and increased 1.8 times from 2000 to 2017, suggesting strong continuous adaptive capability of vegetation to urban conditions. Although the overall impact of urbanization was negative due to the replacement of vegetated surfaces, the growth enhancement nevertheless offset or compensated the direct loss of vegetated cover during urbanization in the magnitude of 28% in 2000 to 44% in 2017. Our study also revealed large spatial heterogeneity in vegetation growth response among various districts at different

urbanization levels and found an emergent trend under the observed spatial heterogeneity toward an asymptotic maximum with urbanization, showing EVI converges to 0.22 in highly urbanized areas. We further found that the positive effect of urbanization on vegetation growth is a function of urbanization intensity and time, which implies that the effect of the urban environment on vegetation can be simulated and predicted, and can be verified in more cities in the future. Our study is the first to successfully quantify long-term spatial patterns on the co-evolution of urbanization and vegetation, providing a new understanding of the continuous adaptive responses of vegetation growth to urbanization and shedding light on predicting biological responses to future environmental change.

Keywords: urbanization, vegetation growth, temporal evolution, regional disparity, indirect effect, time-series analysis

2. Introduction

Urbanization represents the process of urban landscape transformation and urban environment intensification, with significant modification to the vegetation cover and growth, to entail both changes in urban environments and vegetated structures that co-evolve over time (Hutyra et al., 2011; Li et al., 2013; Shi et al., 2021). The changes in urban environments can be regarded as a baseline trajectory (e.g., localized warming, or increasing CO_2 enrichment), serving as a “harbinger” for future global change (Grimm et al., 2008). Thus, the adaptation of urban vegetation to these environmental changes can serve as a natural experiment for projected responses to future climate change (Youngsteadt et al., 2015). Remote sensing-based approaches have provided opportunities to monitor the spatial and temporal dynamics of vegetation growth in urbanization-affected environments (Jia et al., 2018; Zhao et al., 2016). However, long time-series analyses of the co-evolution of urban environments and vegetation have been rarely reported, which hinders us from further understanding and inferring about the future impact of urbanization on vegetation. Thus, it is necessary to explore the long-term vegetation responses to urbanization, to provide empirical evidence and theoretical basis to better understand the biological responses to future urbanization processes and climate change.

A few remote sensing-based studies have found a prevalent vegetation growth enhancement in urban environments (Jia et al., 2018; Zhang et al., 2022; Zhao et al., 2016;

Zhong et al., 2019). However, whether there is temporal evolution of growth enhancement remains unknown and unexplored. Most existing studies only compared differences in vegetation growth between limited years and may not capture long-term interannual changes in growth enhancement (Jia et al., 2018; Zhao et al., 2016; Zhong et al., 2019). Because the observed variations in vegetation responses may be transient and pulsating over limited periods, analysis without long-term observations might not reveal the gradual responses and adaptation of vegetation to altered environmental conditions (Tang et al., 2021). The need to quantify and understand the long-term aggregated effects of urbanization (including changing land cover, various atmospheric conditions, human management conditions, etc.) on vegetation growth has motivated us to expand the existing framework for analyzing the temporal dynamic evolution of vegetation growth in cities.

Accurate characterization of the urbanization impact on vegetation is complicated by significant regional differences in land cover and land use history, plant species assemblage, human behavior, and microclimate change. Previous studies usually relied on a rural-urban gradient or urbanization intensity (i.e., the percentage of developed imperviousness) to describe the regional differences (Li et al., 2020; Zhou et al., 2014). Because cities are often divided into districts and each district has its urban core and fringe areas, and the different development levels for each district also increase the regional disparity and possible vegetation consequences (de Jong et al., 2016; Liu et al., 2020). Such variability in the developmental stage exhibits more subtle spatial differences over time, leading to a more pronounced heterogeneity in vegetated cover and annual variation (Zhang et al., 2023). Therefore, analyzing the vegetation responses to urbanization at the district level would more accurately depict the process of urbanization, including development, redevelopment, and renewal of each district, and might shed new light on the response of vegetation growth to urbanization.

The overall goal of this study was to examine the long-term evolution of the impacts of urbanization on holistic urban vegetation greenness (quantified by enhanced vegetation index, EVI) by expanding the Zhao and colleagues' framework, which developed a general conceptual framework for quantifying the direct and indirect effects of urbanization on vegetation growth (Zhao et al., 2016). The work is applied in Changsha, the capital city of Hunan province, China with many city-subordinated districts showing obvious spatial and temporal variations in regional and urban development. Specifically, we aimed to (1) quantify temporal evolution patterns of urbanization impacts on vegetation growth; (2) investigate regional disparity of EVI trends along urbanization intensity; (3) investigate processes and temporal evolutions of EVI in rural and highly urbanized areas of all districts.

2. Methods

2.1. Study Area

Changsha (27°51′N to 28°41′N, 111°53′E to 114°15′E) is the capital city of Hunan province, south-central of China, with a total area of 11,819 km^2 (Fig. 1). It is in the hilly area in the south of the Yangtze River, and the terrain is undulating with an elevation difference of 1586.3 meters. The city is dominated by a typical subtropical monsoon climate with four distinct seasons. The annual mean temperature is about 17.2℃, and annual mean precipitation is approximately 1451.4 mm, and the annual mean rainy days are 152 days, mainly in spring and summer (the climate data was provided by the China Meteorological Data Network (http://data.cma.gov.cn/site/index.html, accessed date: 10 August 2021) and based on 1987-2015 normal). The potential vegetation in Changsha is mainly subtropical evergreen broad-leaved forest.

Changsha is divided into nine administrative districts, namely Furong District (FR, 43 km^2), Tianxin District (TX, 141 km^2), Kaifu District (KF, 188 km^2), Yuhua District (YH, 287 km^2), Yuelu District (YL, 545 km^2), Wangcheng district (WC, 947 km^2), Ningxiang city (NX, 2,906 km^2), Liuyang city (LY, 5,006 km^2), and Changsha county (CSC, 1,756 km^2) (Fig. 1c). The nine administrative districts show obvious variations in regional development, manifesting a coexistence of developing and highly developed regions. There was a development priority sequence among districts from 2000 to 2017 with the main urban area (the districts of FR, TX, KF, YH, and YL) first prioritized for development in the early years and then WC, NX, LY, and CSC in recent years (Fig.1c) (Liu et al., 2020).

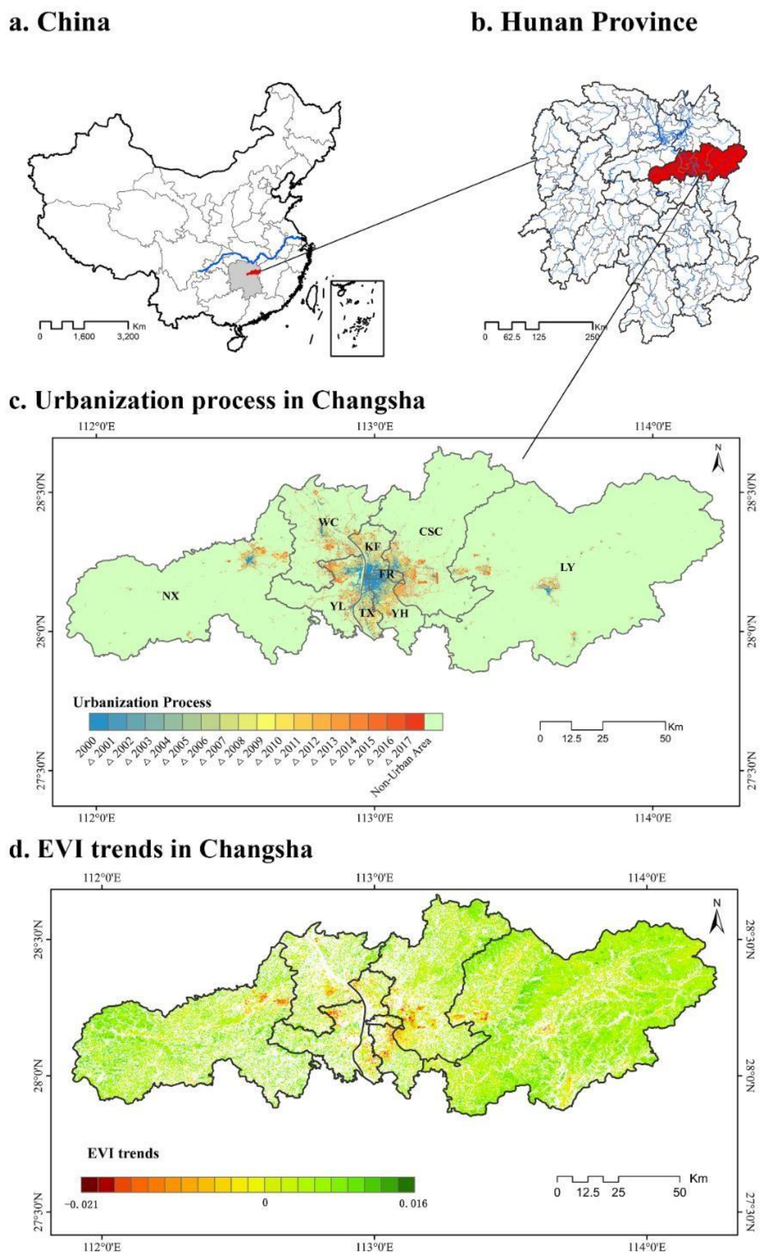

Fig.1 Spatial and temporal distribution of urbanization process and EVI trends from 2000 to 2017 in Changsha (c,d), the capital city of Hunan province (b) in China (a). (c) The dark blue of "2000" represents the urban areas in 2000, the "△" means the increase of urban areas compared with the previous year, and the abbreviations represent nine districts of Changsha. (d) EVI trends indicate the slope of the linear regression between EVI and time (year) for each pixel from 2000 to 2017, greater than 0 means that EVI was increasing with the years and less than 0 means decreasing with the years.

2.2. Time series of EVI during the growing season

EVI can be used to measure vegetation performance or growth, and it shows higher performance than the Normalized Difference Vegetation Index (NDVI) in capturing vegetation conditions in impervious areas (Yu et al., 2017). The EVI product (MOD13Q1) from the MODIS satellite, with a spatial resolution of 250 m and a temporal resolution of 16 days, was used in this study. To further eliminate the influence of atmospheric conditions, the maximum-value-composite (MVC) technique (Fang, 2004) was used to obtain monthly time-series EVI data. The time series of EVI in each year were calculated by averaging the monthly values of EVI in the growing season (Zhao et al., 2018).

2.3. Calculation of the urbanization intensity

The urbanization intensity (β) of a MODIS pixel was defined as the percentage of impervious surfaces within the pixel, ranging from 0 (completely covered by vegetation) to 1 (urban cover with no vegetation) (Zhao et al., 2016). The impervious surface data spanning 2000-2017 at 30 m ×30 m resolution from the Finer Resolution Observation and Monitoring – Global Land Cover system of Tsinghua University (http://data.ess.tsinghua.edu.cn/, accessed date: 14th August 2020) (Chen et al., 2019; Gong et al., 2019) were used to calculate β of each MODIS pixel (i.e., the proportion of land cover map pixels belonging to the built-up area within the pixel).

2.4. Analysis of EVI trends

EVI trend was defined as the slope of the linear regression between EVI and time (year) for each pixel from 2000 to 2017 (Yu et al., 2017). EVI trends were determined for each pixel using Sen’s slope estimator (Sen, 1968), which has the advantage of dealing well with the presence of missing data and the ability to resist outliers and keep unbiased and accurate for skew and heteroscedastic data (Liu et al., 2015a). For these reasons, this robust non-parametric method has been used widely in vegetation time-series change studies (He et al., 2015). The change of the EVI trends along the urbanization intensity gradient from 0 to 1 was investigated using boxplots in Changsha and its nine administrative regions, and 50% quantile regression analyses (i.e., median regression) were used to explore the change of EVI trend along the urbanization intensity gradient.

2.5. Quantification of the Impacts of Urbanization on EVI

According to the conceptual framework defined by Zhao et al. (2016), the impact of urbanization on vegetation growth can be systematically quantified as direct impact and indirect impact (Zhao et al., 2016). The direct impact refers to the EVI reduction caused by direct area loss of vegetated surfaces during urban development, and the indirect impact is the effects imposed on vegetation by the altered urban environment (e.g., warming, increased CO_2 and nitrogen deposition, pollution, and improved management practices) (Jia et al., 2018; Zhao et al., 2016). Conceptually, the vegetation index of an urban pixel is composed of contributions from vegetation and non-vegetated areas, which can be expressed by the following formulae (Zhao et al., 2016):

$$V_{obs} = (1 + \omega)(1 - \beta)V_v + \beta V_{nv} \tag{1}$$

where β is urbanization intensity, V_{obs} is the observed VI of the pixels (EVI in this study), V_v is the background vegetation index not affected by urbanization (i.e., β =0, VI = V_v), ω is the overall impact of urbanization produced, and V_{nv} is the VI of impervious surfaces (i.e., β =1, VI= V_{nv}).

A set of quantitative measures are defined in Zhao and colleagues' framework to evaluate the impacts of urbanization. The zero-impact line, the relative indirect influence, and the growth offset rate were calculated by Zhao et al. (2016). The zero-impact line, representing the conditions that vegetation growth was not indirectly affected by urbanization, can be defined as follows:

$$V_{zi} = (1 - \beta)V_v + \beta V_{nv} \tag{2}$$

where Vzi was the theoretical VI of a 250-m resolution pixel, defined by Vv (β =0, VI = Vv) and Vnv (β =1, VI= Vnv).

The relative indirect influence is expressed as:

$$\omega_\tau = \frac{V_{obs} - V_{zi}}{V_{zi}} \tag{3}$$

The growth offset rate (τ) between indirect and direct effects can be defined as:

$$\tau = \frac{V_{obs} - V_{zi}}{V_v - V_{zi}} \tag{4}$$

τ represents how much the growth change of remaining vegetation caused by the indirect impact can compensate (if τ was positive) or exacerbate (if τ was negative) the loss of vegetated productive surface owing to direct built-up replacement.

A cubic polynomial model was used to fit the EVI~β relationship of each year: $y = a_0 + a_1x + a_2x^2 + a_3x^3$, where y is the mean observed EVI for a given β (i.e., x). The intercept (a_0) was fixed to be the empirical background EVI value observed, as it depended on the trend of EVI change and greatly reduced the influence of EVI outliers (Jia et al., 2018; Zhao et al., 2016; Zhong et al., 2019).

This study determined Vnv (β =1, VI= Vnv) by the mean EVI value of fully urbanized pixels (β = 1) in years from 2000 to 2017. To ensure that the value of Vnv was obtained without interference from vegetation activities, we used a high-resolution Google Earth image visual inspection of β= 1 pixel to avoid uncertainties from the imperviousness data. The resultant average Vnv was 0.066.

We used linear regression analyses to explore the relationships between the indirect effects, the growth offset, and β of each year at 250-m resolution in Changsha from 2000 to 2017. The growth offset was calculated as the average within each urbanization intensity β bin, defined at 0.01 intervals along the gradient. Then, the inter-annual variation and trends in the indirect effects during 2000-2017 at 250-m resolution were calculated and analyzed using Ordinary Least Square regression.

3. Results

3.1 EVI trends along urbanization intensity (β) gradients

The spatial and temporal patterns of EVI trends from 2000 to 2017 showed a large spatial heterogeneity of vegetation growth response across nine districts of Changsha and were associated with urbanization intensity (Fig. 1, Fig.S2). The EVI trends ranged from -0.02 to 0.016, where positive values showed an increase in EVI over the years and negative values vice versa. Regions with high urbanization levels usually showed a decreasing EVI trend over the years (Table S1). For example, 64% of areas showed significant decreasing trends of EVI in the district with the highest average urbanization intensity (i.e., FR), while only 6.2% of areas had EVI declined over years in the district with the lowest average urbanization intensity (i.e., LY, Fig. S1, S2). We further quantified the EVI trends from 2000 to 2017 along urbanization intensity based on regional disparity analysis (Fig. 2). EVI trends showed a decrease from positive to negative values with urbanization intensity, which means, there was a turning point of EVI temporal changes from increasing to decreasing along β gradient in every district (Fig. 2, Fig. S3). The corresponding β values of the turning point of EVI trends varied across regions at different urbanization levels. For example, the turning point β values were lower in districts with higher levels of urbanization (i.e., FR, TX, KF, and YH, at β = 0.15-0.25) than in districts with lower levels of urbanization (i.e., YL, WC, CSC, NX, and LY, at β = 0.4-0.5).

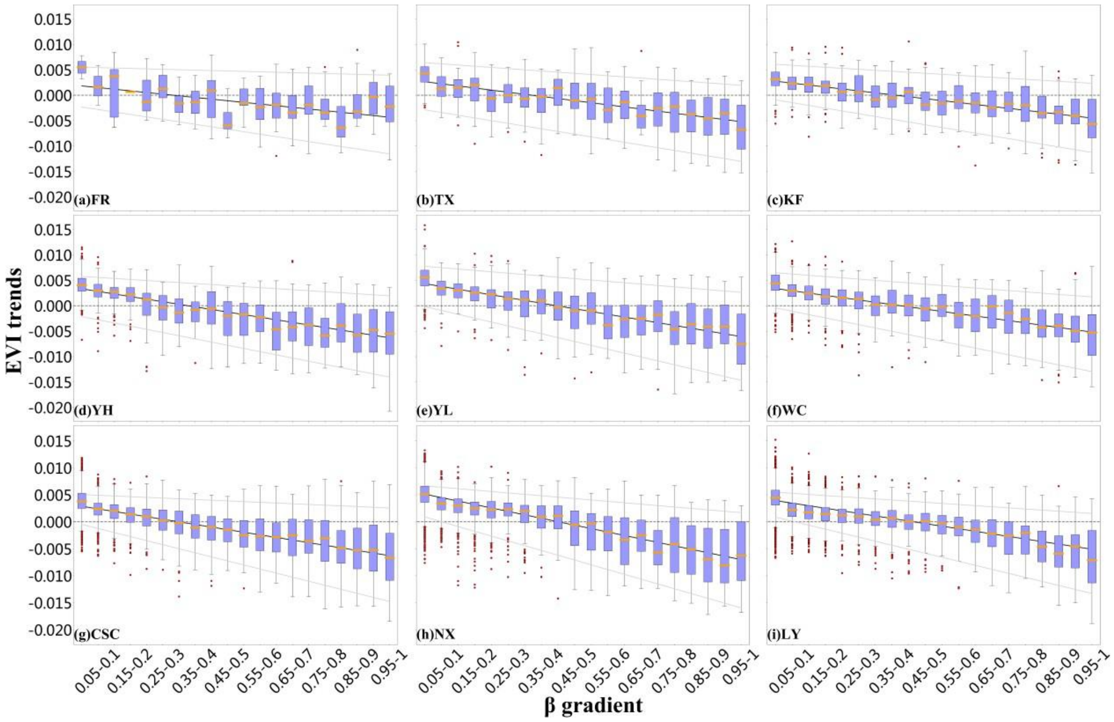

Fig. 2. Bin-wise (0.05 intervals) boxplots showing changes in vegetation EVI trends from 2000 to 2017 in nine administrative districts of Changsha along the urbanization intensity (β) gradient. The horizontal line in the center of each box is the median, the edges of each box are the 25th and 75th percentiles, and the whiskers extend to 1.5 times the interquartile range. Red points outside the whiskers are potential outliers. Black lines represent median fitted lines and gray lines show the 5% and 95% quantile regression fits. The Gray dotted line shows the zero-line of EVI trends.

3.2 Vegetation responses to urbanization

The EVI~β Relationship and its Variability in 2000, 2009, and 2017. We used the relationships in 2000, 2009 and 2017, respectively, to initially examine the details of the temporal variation of the EVI~β relationship (Fig. S4). Overall, the relationships were all statistically significant with cubic regression fits, and EVI all decreased with urbanization intensity. However, there were differences in the shape of the relationship over the three years, showing significant temporal variation. The y-intercept of the EVI~β relationship was higher in 2017 compared with that in 2000, representing a temporal increase of maximum EVI in natural areas without urbanization impacts. The positive enhancement by urbanization on EVI was indicated by the differences between EVI values and the zero-impact line (also called indirect EVI change) from the shape of the EVI~β relationship. Importantly, about 77%, 81% and 94% of the urban intensity bins recorded EVI enhancement in 2000, 2009 and 2017 respectively, representing a potential temporal evolution of the impacts of urbanization on vegetation growth along urban intensity gradient across years.

Temporal Enhancement of EVI~β Relationships. We extracted EVI-related parameters from the EVI~β relationships and overlaid the annual relationships between the parameters and β gradient from 2000 to 2017, whereby the temporal evolution of the impacts of urbanization on EVI was quantified, resulting in the most important results that can be presented from three perspectives (Fig. 3).

First, from the perspective of indirect EVI change~β gradient relationship, indirect EVI change caused by urbanization showed an increasing trend with β gradient in all years (Fig. 3a1). In addition, the lines of the relationships became steeper over the years, as shown by the slopes of the relationships exhibiting a linear enhancement with time (Fig. 3a2), and a 1.8-fold increase in slopes from 2000 (0.09) to 2017 (0.17). The results clearly show positive enhancement of vegetation growth by urbanization was not only increasing with urban intensity but also intensifying with time.

Second, the relative impact of urbanization on EVI (ω, quantified by the ratio of indirect EVI change to EVI without urbanization impacts) showed a superlinearly increase along the β gradient in all years (Fig. 3b1). Similarly, the superlinear growth scaling exponent of the relationship also showed a linear increase in time, varying from 2.99 in 2000 to 3.33 in 2017 (Fig. 3b2). Such superlinear growth relationships suggested that vegetation in high urban intensity regions ($\beta>0.6$) was much more positively sensitive to urbanization than vegetation in lower urban intensity regions, suggesting temporal indirect enhancement was more pronounced in high urban intensity areas. For example, the relative impact of urbanization on vegetation can be doubled from 2000 (90%) to 2017 (180%) in the highest urban intensity areas (β close to 1).

Third, the EVI compensation effect by urbanization positive impact increased sublinearly along urbanization intensity, showing maximum effects at $\beta > 0.8$, implying a potential compensation threshold in urban environments (Fig. 3c1). The maximum compensation effect also showed a linear increasing trend with the year (Fig. 3c2), and the vegetation growth enhancement offset about 28% of the direct surface-replacement impact in 2000 rising to 44% in 2017.

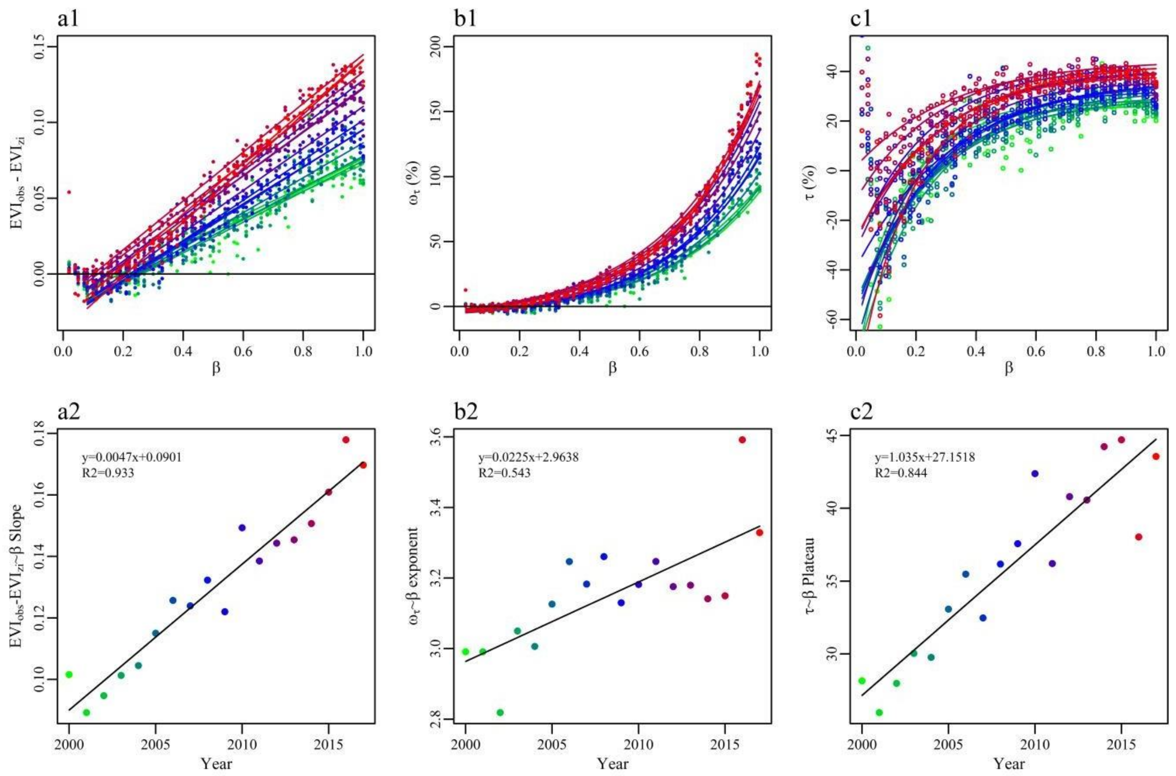

Fig. 3. Temporal dynamics of relationships between EVI-related parameters and urbanization intensity (β) during 2000-2017: β-dependent growth enhancement (i.e., EVI change caused by urbanization or indirect effect) (a1); change of the linear dependence of growth enhancement on β (i.e., yearly slopes in a1) with time (a2); β-dependent relative growth enhancement (ω) of urbanization (b1); regression exponent (in b1) change with time (b2); β-dependent EVI compensation (τ) by growth enhancement (c1); and temporal change of the maximum compensation effects (asymptotes in c1) (c2). The color gradient (from green to blue to red) represents the change in time from 2000 to 2017.

Differences in the β Dependence of EVI~Time Relationships. We established the linear relationships between key EVI-related parameters (i.e., growth enhancement EVI_{obs}-EVI_{zi}, relative growth enhancement ω, and offset τ) and time, and found the slopes of the relationships increased with urbanization intensity, suggesting the temporal evolution of urbanization impacts on vegetation growth (Fig. 4). Both the direct and the relative impact of urbanization on EVI (ω) increased linearly with year in all β gradients (from 0 to 1), and the relationships steepened with urbanization intensity, as shown by the slopes increasing with β (Fig4. a1, a2, b1, b2). Particularly, the superlinear growth relationship of the slopes of the ω~year relationship along the β gradient indicated that the relative growth enhancement of vegetation responded superlinearly to urbanization intensity (i.e., the more intense the urbanization, the faster the increase of the ω~year slope) (Fig. 4b2).

Furthermore, the EVI compensation effect also increased linearly with years, however, the growth sensitivities (slopes) of such relationships did not show an obvious increasing or decreasing trend along the β gradient (Fig. 4c1, 4c2), manifesting a converged similarity across all districts (Fig. S5).

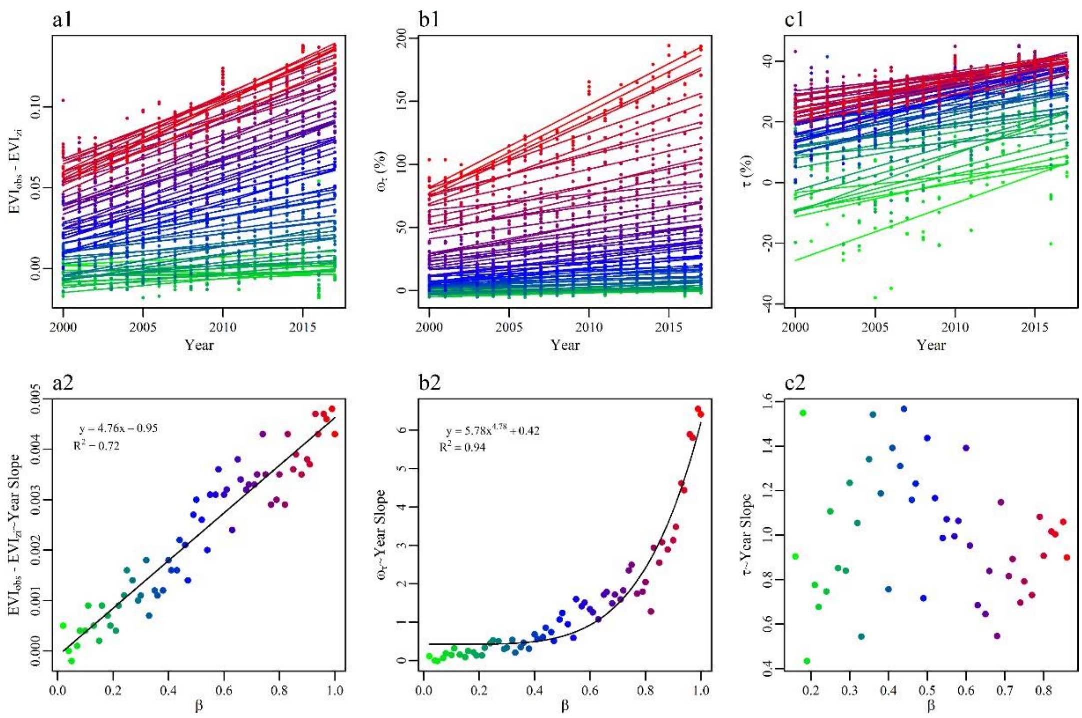

Fig. 4. Relationship between EVI-related parameters and time, and their changes along an urbanization intensity (β) gradient. The gradient colors (from green to blue to red) represent the change in urbanization intensity (from 0 to 1). Plots in the upper row represent the

relationships between times (from 2000 to 2017) and (a1) EVI growth enhancement; (b1) the relative growth enhancement (ω) of urbanization; and (c1) the EVI compensation by growth enhancement (τ). Figures in the lower row (a2, b2, c3) represent the evolution of the regression slopes shown in the upper row (a1, b1, and c1, respectively) along β.

3.3 EVI in rural and highly urbanized areas

Further, EVI in rural and highly urbanized areas showed a generally upward trend over time (Fig. 5). The EVI in rural areas increased from about 0.33 to 0.41 on average during the study period (β=0, Fig 5a), although the magnitude of increase was district-specific and dependent on the initial EVI. The increasing trends of EVI in rural areas were similar among all districts. The annual average EVI in highly urban areas in different districts increased gradually over time and converged towards 0.22 in all districts (Fig. 5b). The increasing trends of EVI in highly urban areas were different among all districts, depending on the urbanization development priority sequence of districts. For instance, districts prioritized for development first (e.g., FR, KF, TX) had a low initial EVI in 2000 (around 0.13), and EVI exhibited an obvious upward convergence to 0.22. While districts with no priority for development (e.g., LY, CSC, WC) had a higher initial EVI (around 0.17-0.22) and showed interannual fluctuations around EVI=0.22 during 2000-2017.

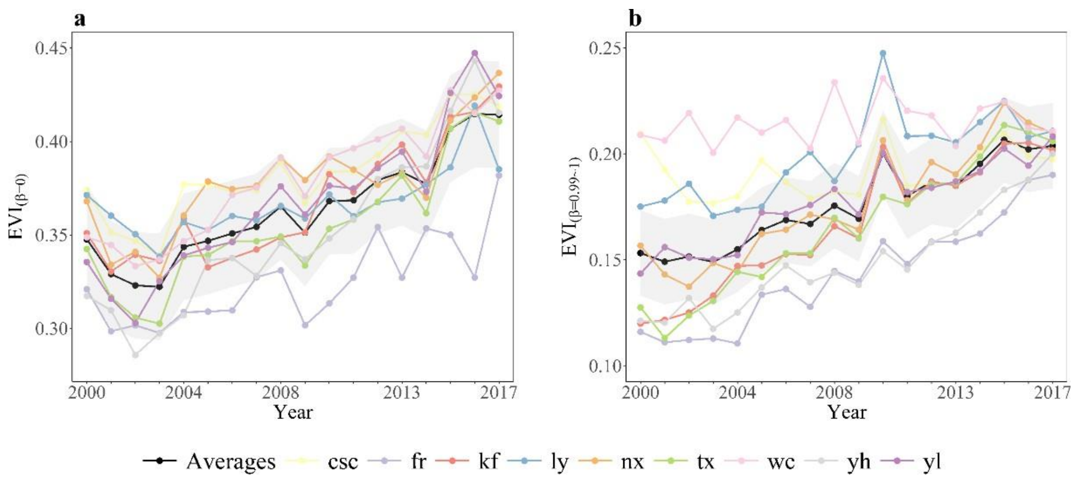

Fig. 5. Comparison of EVI corresponding to (a) fully vegetated (β = 0) and (b) highly urbanized (β =0.99 ~1) areas from 2000 to 2017 in nine administrative regions. The shaded area represents the 95% confidence interval of the average EVI change.

4. Discussion

4.1. Regional disparity of temporal evolution in EVI changes

Our results provided a new insight into the regional disparity of temporal evolution in vegetation growth by urbanization impacts (Fig. 2). A few studies have discovered a prevalent enhancement impact of urbanization on vegetation growth (Jia et al., 2018; Zhao et al., 2016; Zhou et al., 2014). However, they often focused on vegetation growth change with urbanization intensity gradient within cities, or compared vegetation growth between urban core and fringe areas (Guan et al., 2019; Gui et al., 2019; Li et al., 2020; Zhong et al., 2019). Our study further quantified the response of vegetation not only across urbanization intensity but also the spatial heterogeneity among various districts at different urbanization levels, depicting a dynamic trend of EVI changes as urbanization proceeds. Thus, our study emphasized the importance of considering the levels and process of urbanization more accurately to better manifest the spatial heterogeneity of the co-evolution of vegetation growth and urbanization-induced environments, therefore shed new light on the dynamic response of vegetation growth to urbanization at a large scale.

4.2. Temporal vegetation growth in rural and highly urbanized areas

Although EVI temporal changes include both changes in vegetated cover areas and vegetation growth (Yuan et al., 2007), our results have described interannual increasing trends in vegetation growth by focusing on two special β bins (i.e., β=0 completely covered by vegetation and β=0.99~1 highly urbanized areas) to exclude the interference of changing vegetation areas (Fig. 5). Generally, the temporal increase of vegetation growth in natural vegetated areas may be attributed to climate change, whereas in highly urbanized areas may confirm the positive impact of urbanization on vegetation enhancement.

In natural vegetated areas, EVI increase in our study area (Fig. 5a) is consistent with a remote sensing-derived study that reported that China is a vegetation greening hotspot since 2000 (Piao et al., 2019), which might be mainly contributed to CO_2 fertilization and global warming. Given the location of Changsha is in a warm-humid region with sufficient nutrient and water availability, the CO_2 fertilization effect plays a full role in enhancing photosynthesis and water use efficiency leading to vegetation greening (Hickler et al., 2008; Huang et al., 2017; Schimel et al., 2015; Zhu et al., 2016). The temperature increase may also be the reason for EVI increase by enhancing metabolism and extending the growing season (Braswell et al., 1997; Piao et al., 2007; Richardson et al., 2010).

There is an emergent trend in vegetation growth toward an asymptotic maximum response as urbanization proceeds (Fig 5b). In highly urbanized areas, our study reported the annual growth trends of EVI, which further expands the existing understanding of the impact of urbanization on vegetation greening. There is prevalent vegetation greening over time in the urban core (Li et al., 2020; Liu and Gong, 2012; Liu et al., 2015b; Zhong et al., 2019; Zhou et al., 2014), however, most of these results are based on annual maps of greenness indices changes and do not quantify the spatial-temporal dynamics. Our results not only found a dynamic increase in vegetation growth over time, but also made a pathbreaking discovery that there may be an upper limit to this increase (Fig. 5b). The increasing tendency of EVI could be attributed to the positive effects derived from a changing urban environment, such as localized warming, CO2, and nitrogen enrichment, and the improvement of management and maintenance of urban green space (Elmore et al., 2012; Gregg et al., 2003; Imhoff et al., 2004b; Jia et al., 2018; Jia et al., 2021; Pretzsch et al., 2017; Zhao et al., 2016). We further found the average EVI gradually narrowed and converged to 0.22 (Fig. 5b). This means in areas with little vegetation (e.g., β=0.99-1), the promotion effect of urbanization on vegetation growth becomes saturated over time because of vegetation adaptation limit. This case suggests that vegetation growth cannot be simply enhanced through warming urban environments or management measures but by increasing the vegetation cover. Further, that indicates a possible pattern of future vegetation growth if we regard the urban environment as the surrogate of future global change. We speculate that the saturation of urbanization effects on vegetation growth is pervasive in cities, depending on city-specific maximum EVI value determined by climate zone, water availability, growing season length, species types, and composition.

4.3. Positive effects of urbanization on vegetation growth as a function of β and time

The most important finding of this study was the relationship between the positive effects of urbanization and β was not stable across years, but rather demonstrated a clear pattern of temporal evolution showing a 1.8-fold increase in vegetation growth from 2000 to 2017 (Fig. 3 and Fig. 4). The time-variant EVI_{en}~β relationship is different from the findings of Zhao et al. (2016) and Jia et al. (2018), who compared the city-specific regression coefficients between EVI and urbanization intensity in three time periods (2000, 2006 and 2011), and found that the EVI_{en}~β relationship had strong temporal stability (Jia et al., 2018; Zhao et al., 2016). However, the regression coefficient variation they compared may be instantaneous and pulsatile over limited periods, and might not be able to capture the gradual temporal responses of vegetation. We quantified the models to elucidate the relationship between urbanization's positive impacts (EVI_{en}), β, and time as follows.

The dependence of EVI_{en} on β and time can be further revealed by examining the relationship between EVI_{en} and time fitted by β bin (Fig. 3a1, a2). EVI_{en} increased with time (t in the year) linearly for all β bins:

$$EVI_{en} = k \times (t - 2000) + c \quad (5)$$

and the slope (k) increased with β:

$$k = b \times \beta + a \quad (6)$$

and the intercept (c) increased with β:

$$c = d \times \beta + f \quad (7)$$

Combining equations (5), (6) and (7), the EVI_{en} can be calculated as follows:

$$EVI_{en} = b \times \beta \times (t - 2000) + a \times (t - 2000) + d \times \beta + f \quad (8)$$

For Changsha, the coefficients were: b=4.76, a=-0.95, d=0.08, and f=-0.02.

Following the same logic for deriving EVI_{en}, ω can be calculated as follows:

$$\omega = m \times \beta^{g}(t - 2000) + n \times (t - 2000) + p \times \beta + q \quad (9)$$

For Changsha, the coefficients were: m=5.78, g=4.78, n=0.42, p=85.5, and q=-22.2. For convenience, time *t* in some expressions above was subtracted by 2000, the starting year of our analysis.

Our models are the first to successfully quantify and predict vegetation growth and the long-term impact of urbanization on vegetation. One difference that highlights our study from others is that we quantify the impacts of urbanization-induced environments on vegetation growth by exhibiting an interannual EVI enhancement in the same β bins (Fig. 3), which excluded the vegetated area increase through urban maintenance measures. Temporal increase of the impacts of urbanization on vegetation growth is mainly attributed to the temporal intensification of urban environments as urbanization continuously proceeds, and implies the continuous physiological adaptation process of vegetation to urban environments. Based on this, it is understandable why the EVI evolves more strongly over time in regions with high urbanization intensity (β>0.6, Fig. 4b1, 4b2). Urban environment incorporates a myriad of driving forces to plant growth, such as localized warming, CO_2 and nitrogen enrichment, ozone, air pollutants, and traffic volume (Imhoff et al., 2004a; Ning et al., 2022; Ning et al., 2023; Pei et al., 2013; Shu et al., 2022; Takagi and Gyokusen, 2004), which all evolve over time (Liu et al., 2017). Many studies have ever focused on non-urban ecosystems and emphasized the importance of time in considering ecosystem response to intensified climate changes (Dieleman et al., 2012; Luo et al., 2004; Norby et al., 2010; Norby and Zak, 2011;

Reich et al., 2006). Our results demonstrated a continuous adaptation and growth enhancement of vegetation over time in urban ecosystems. Urbanization-induced environments are considered the harbinger of future global change in other ecosystems (Grimm et al., 2008). Our study confirmed a possibility of future vegetation growth response based on the temporal evolution, in addition, our proposed model also demonstrated that future urban vegetation growth could be predicted by the urban intensity and time. Moreover, although we cannot directly translate the EVI enhancement into net carbon gain, owing to the offsetting effect of increased soil carbon decomposition (Zhao et al., 2016), our findings still highlight the importance of considering vegetation in urbanized areas within the terrestrial carbon cycle and predicting plant adaptation under future conditions as cities continue to evolve over time and across the globe.

4.4. The offsetting effect became stronger over time

Our results demonstrated that vegetation growth compensation capacity from urbanization, positive effect minus vegetation loss by urban expansion, reached a peak in regions with high urbanization intensity (e.g., $\beta > 0.8$), which strengthened over the years (from 28% in 2000 to 44% in 2017, Fig. 3, 4). The patterns of the offset effect with urbanization intensity gradient may be related to regional heterogeneity of urban development, background vegetation cover, and city location (Jia et al., 2018; Zhong et al., 2019). For example, the offset effect was generally lower in regions with higher background vegetation cover, lower urbanization levels and better vegetation growth conditions (Jia et al., 2018). It was reported the mode of offset percentage was almost invariant across urbanization intensity gradient in multiple cities (Jia et al., 2018; Zhao et al., 2016), which provides a general pattern but ignored the heterogeneity of individual cities. We emphasized the maximum growth enhancement offset effects become stronger over time, which should be related to the continuous temporal increase of positive enhancement by urbanization shown in this study. Urban areas have been expanding over the years, resulting in continuous loss of vegetation due to land conversion, while our research shows that temporal environmental changes caused by urbanization can promote the enhancement of residual vegetation growth to compensate for vegetation loss caused by urbanization. Further quantification of long-term annual changes in the urbanization intensity-offset effect relationship can support a deeper understanding of urban ecology, which is of great significance for realizing the sustainable development goals of human society in an increasingly urbanized world.

5. Conclusion

Our study quantified the temporal evolution of urbanization impacts on vegetation growth by using annual time-series remote sensing images by expanding Zhao and colleagues' framework. Overall, the EVI temporal trends showed a general increasing trend in less urbanized areas and a decreasing trend in highly urbanized areas in all districts. More importantly, our study revealed the intensification of the vegetation growth enhancement over time across all districts in Changsha. Specifically, we found the indirect growth enhancement effects increased with urbanization intensity and the power of the effects (slope and exponent of the relationships) increased with time as well; moreover, the maximum offsetting effects from growth enhancement effects became stronger over time (from 28% in 2000 to 44% in 2017). We further developed a model to predict the positive effect of urbanization on vegetation growth by using urbanization intensity and time, which can be verified in more cities in the future.

Our study is a successful first attempt to explore the long-term spatial-temporal pattern of urbanization and vegetation co-evolution. Future research is expected to extend our framework to more cities and stress the importance of time. One implication of our results is that EVI enhancement in urban environments over time could be an indicator of increasing productivity globally, leading to changes of carbon sources and sinks at different spatial and temporal scales owing to continuous urban expansion. Understanding the response of vegetation to urbanization based on long-term observations could provide new insight into interactions and co-evolution of multiple global-change drivers and adaptation strategies of plants.

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Declaration of Interest Statement:

All authors disclose any actual or potential conflict of interest including any financial, personal, or other relationships with other people or organizations within three years of beginning the work submitted that might inappropriately influence, or be perceived as influencing, their work.

Data availability statement

All original datasets used in this study are available from the respective references, with most being open access. The generated data that form the results of this study are available from the corresponding author upon reasonable request.

Author Contributions

Xi Peng: Formal analysis, Writing – original draft; Shucheng Jiang: Data curation, Writing – original draft; Shuguang Liu: Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing, Funding acquisition; Yang Zhan, Yi Shi: Formal analysis, Writing – review & editing; Rubén Valbuena, Andy Smith: Validation, Writing – review & editing; Ying Ning, Shuailong Feng, Haiqiang Gao and Zhao Wang: Writing – review & editing.

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