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Effects of climate, socioeconomic development, and greening governance on enhanced greenness under urban densification

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ABSTRACT

Urban vegetation is essential for the quality of life in cities. Despite direct vegetation loss during urban expansion, urbanization can indirectly enhance vegetation greening through various factors. Yet, it remains unclear what conditions promoted these greening trends within cities. We quantified the greenness trends in 294 Chinese cities based on satellite imagery (2001–2018), which we then explained with climate and socioeconomic indicators, particularly considering the National Garden Cities incentive program for urban greening (NGC). Results reveal large potential for enhancing greenness under urban densification, with larger cities leading urban greening development. We further show that the effectiveness of NGC in promoting enhanced urban greenness is context-dependent, particularly depending on aridity, which is not sufficiently considered in current policy. Our findings show that the indirect vegetation growth index is an effective tool to evaluate urban greening governance and highlight the importance of tailoring regional greening strategies to local conditions for sustainable urban vegetation development.

1. Introduction

Urban areas are rapidly expanding worldwide. The United Nations reported approximately 55 % of the world's population live in urban areas (Affairs, 2019), a proportion that is expected to increase to 68 % by 2050 (Grimm et al., 2008; Sun et al., 2020). Urban densification is an important strategy to mitigate urban encroachment into natural areas (He et al., 2023; van Vliet, 2019). Such a process of increasing population density and building utilization within urban areas can be achieved through measures such as infill development, redevelopment of existing areas, or replacing low-density structures with high-rise buildings (Haaland and van den Bosch, 2015; Wicki et al., 2022). However, densification also poses significant environmental challenges, such as urban heat islands (Manoli et al., 2019), biotic homogenization (McKinney, 2006), shifts in biogeochemical cycles (Pataki et al., 2006), and substantial losses in ecosystem services (Cumming et al., 2014), which can have negative impacts on the functioning of urban ecosystems and the well-being of urban residents (Richards et al., 2022). To deal with increasing environmental challenges accompanied by urban expansion, UN-Habitat is calling for policies, strategies, and cities and governments to create resilient and sustainable urban environments (Vaidya and Chatterji, 2020). Urban vegetation plays a pivotal role in sustainable urban development by offering a range of vital ecosystem services (Richards et al., 2022), including the mitigation of heat (Chen et al., 2020; Greene and Kedron, 2018) and air pollution (De Carvalho and Szlafsztein, 2019), maintaining biodiversity (Ali and Wang, 2021), and providing aesthetic values of cities and leisure spaces (Kleinschroth and Kowarik, 2020; Yang et al., 2021). Globally, vegetation covers over 210,000 km^2 of urban areas, but is strongly dispersed by human modifications (Richards and Belcher, 2020). While densifying cities can limit urban sprawl, promoting healthy urban green spaces within dense urban environments remains challenging (Haaland and van den Bosch, 2015).

Within already urbanized areas, an increased potential for vegetation growth has been observed due to the effects of fertilization, urban climate, and atmospheric chemistry (e.g., CO_2) (Bush et al., 2023; Gregg et al., 2003; Huang et al., 2023; Jia et al., 2021). Several studies also showed that regional economic development relates closely to urban vegetation growth (Peng et al., 2014; Zhang et al., 2021). For these

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reasons, Zhao et al. (2016) proposed a conceptual framework to differentiate between the direct loss of vegetation due to urban development and the potential for vegetation growth enhancement resulting from changes in the urban environment. This framework has been applied in global and regional studies (Jia et al., 2018; Zhang et al., 2022; Zhao et al., 2016). While the effects of climate change and socioeconomic development on urban greening have been extensively explored (Wang et al., 2022; Zhang et al., 2021), however, these studies did not differentiate between direct vegetation loss and indirect vegetation growth. There is an urgent need to develop strategies for enhancing urban vegetation (Chen et al., 2022; Kleinschroth et al., 2024; Wu et al., 2023). Urban greening governance and its impact on vegetation growth trends vary due to differences in the objectives of policymakers, investment levels, and the rigor of policies across countries and regions (Liberalesso et al., 2020). The influence of governance on enhancing urban greenness is thus often overlooked (Jia et al., 2018) and not included in studies evaluating trends in urban greenness (Wang et al., 2022; Zhang et al., 2023a). Not considering such governance implementations runs the risk of triggering policy inefficiencies (Ordóñez et al., 2019).

China is currently witnessing the world's largest loss of natural areas due to urban expansion, with 8.8 million hectares lost between 1992 and 2015 (van Vliet, 2019). It is also experiencing substantial increases in urban greening (Haaland and van den Bosch, 2015; Zhou and Wang, 2011), especially in its eastern regions (Zhang et al., 2022). This juxtaposition of rapid urbanization, economic development, and urban greening makes China a unique setting for investigating the dynamics of urban vegetation growth amidst rapid urban densification and sprawl. The National Garden Cities (NGC) policy, initiated by the Chinese central government in 1992, stands out as one of the most enduring and comprehensive urban greening policies globally (Ding et al., 2022; Zhao, 2011). The NGC project employs a nationwide selection process, assessing cities based on their established urban landscape with 18 indicators, including green space coverage, number of parks per capita, and wetland conservation. The top-down authority of the central government and reputation for facilitating tourism ensures broad national participation. Cities consistently prioritize financial and technological investments in enhancing green infrastructure before each selection round. Consequently, being designated as NGC cities signifies a higher level of achievement in creating a livable urban environment with a well-established emphasis on greenery compared to non-awarded cities. Yet, national-scale effectiveness of this policy for enhancing urban vegetation growth in the context of urban densification remains unclear.

Understanding vegetation dynamics in densifying urban areas is grounded in the theories of ecological urbanism (Spirn, 2014) and social-ecological systems (Andersson et al., 2021; Leslie et al., 2015), which both emphasize the importance of integrating social and ecological knowledge and processes to reach sustainable solutions. Our paper adds to these theories by providing large-scale observations on the interactions between urban growth processes and vegetation development to support sustainability in growing urban areas. In this study, we examine the indirect effects of urbanization on urban vegetation in China through a comprehensive analysis of vegetation growth across all major Chinese cities. We also investigate which factors facilitate indirect vegetation growth, with a particular focus on evaluating the effectiveness of the NGC policy in promoting such growth. Specifically, we address the following key questions: (1) How has the enhancement of urban greenness evolved over time and space in China, and to what extent can it compensate for the direct loss of vegetation? (2) How do climatic conditions, socioeconomic factors, and greening governance influence the indirect growth of urban vegetation? (3) What is the effect of NGC policy on indirect vegetation growth? To answer these questions, we measured the direct and indirect vegetation growth in 294 Chinese cities building on a conceptual framework proposed by Zhao et al. (2016). We then assessed the driving effects of climate, socioeconomic development, and NGC policy on indirect vegetation growth with multi-regression models. Further, we evaluated the policy performance for promoting indirect vegetation growth across an urbanization intensity gradient.

2. Methods

2.1. Study area

The focal cities in this study were selected from the municipal districts in China (MDC), which are the officially designated central urban areas of each city (*Shixiaqu* in Chinese). These districts have large contiguous urban areas, high economic development, good transportation connections within the city, and higher urbanization than elsewhere. Administrative information was sourced from the National Administrative Division Information Query Platform of China (http://xzqh.mca.gov.cn/map). To determine the urban boundaries of each city, we used the Global Urban Boundary (GUB) dataset (Li et al., 2020b; Zhao et al., 2023). To ensure each city contains sufficient pixels for further analysis, we set the threshold for urban size as 100 km^2, and 97.9 % of cities have a larger coefficient of determination value (R^2) than 0.6 for simulating the conceptual model with this threshold. Thus, we selected 294 out of 343 cities in China, including four provincial-level cities, 27 provincial capitals, and 263 prefecture-level cities (Fig. 1a).

2.2. Data sources and processing

2.2.1. MODIS EVI data

We used time series of enhanced vegetation index (EVI) from the MOD13Q1 v061 product (16-day composite) with 250 m resolution as indicator to reflect the vegetation status within urban areas (Didan, 2021). The EVI products are atmospherically corrected and exclude low-confidence pixels, for instance, water, clouds, heavy aerosols, and cloud shadows. To avoid the influence of extreme weather in specific years, we used averaged EVI values for six time periods with three-year intervals (i.e., 2001–2003, 2004–2006, 2007–2009, 2010–2012, 2013–2015, 2016–2018) for each pixel to present the vegetation growth state of corresponding period. For these calculations, we utilized the Google Earth Engine platform.

2.2.2. Artificial impervious area and urban boundary dataset

We used the Global Artificial Impervious Area (GAIA) dataset with 30-m resolution to quantify the urbanization intensity (UI, represented by β) in each city. The GAIA dataset was developed in Google Earth Engine to automatically map artificial impervious areas at a 30-m resolution at a global scale annually from 1985 to 2018. Its accuracy is consistently higher than 89 % at the global scale, assessed by randomly selected sample units (Gong et al., 2020). The GUB dataset, which we used to define the urban boundaries (Section 2.1), is also derived from GAIA.

2.2.3. Climate zone and influencing factors

We grouped selected cities based on their climatic characteristics. For this, we used the Köppen-Geiger climate classification map at 1-km resolution (Beck et al., 2018; Zhou et al., 2022), and grouped climate zones into four climatic groups according to the climatic features, which we named temperate dry zone, temperate humid zone, arid zone, and cold zone. Classification rules are described in Table S1.

Previous studies have verified that climatic and anthropogenic factors are influencing urban vegetation growth (Zhang et al., 2022). In urbanized regions, enhanced vegetation growth could be attributed to factors such as climatic context (Li et al., 2020), urban microclimate (Li et al., 2023), and atmospheric chemistry (Kashyap et al., 2023; Zipper et al., 2016), as well as the effects of urban greening practices like irrigation and fertilization (Jia et al., 2018). Additionally, research has shown a close relationship between regional economic development and residential demand with urban vegetation growth (Peng et al., 2014;

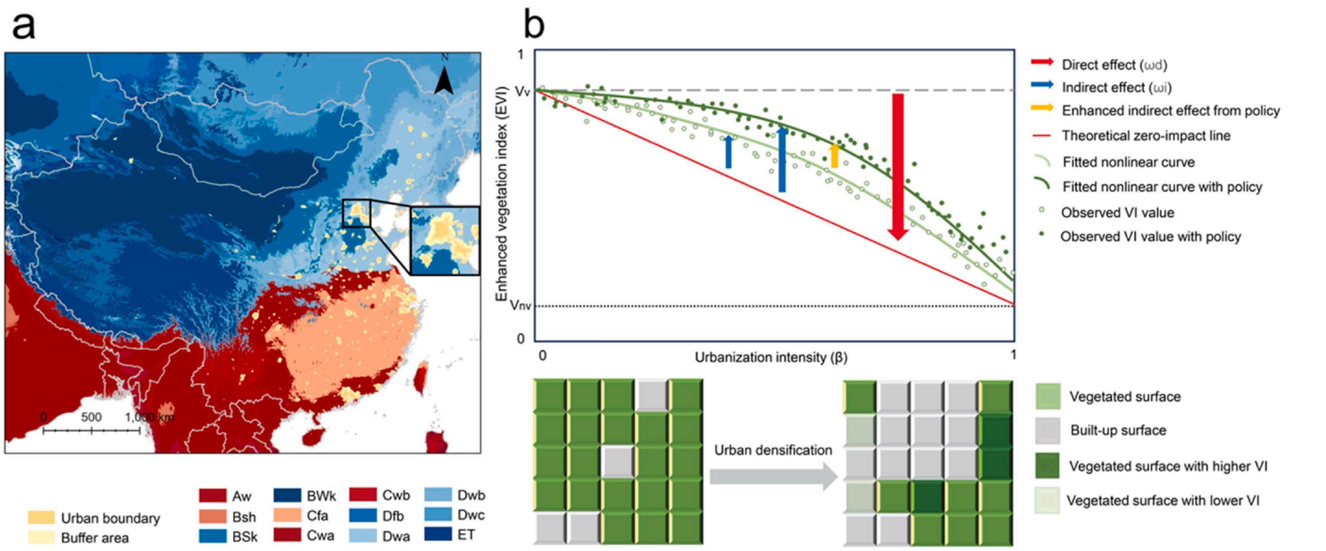

Fig. 1. Research areas and conceptual framework of urbanization impact on vegetation: (a) Cities and their distribution on climate zones with regional zoom in as a schematic for creating buffers, (b) conceptual framework showing the direct and indirect impacts of urbanization on vegetation along the urbanization intensity and the hypothesized policy effect.

Zhang et al., 2021). Based on that, to analyze potential influencing factors of enhanced urban greenness, we quantified 12 variables spanning four categories: natural conditions, urban microenvironment, socioeconomic development, and greening governance (Wang et al., 2022; Zhang et al., 2022; Zhang et al., 2021). To reduce multicollinearity, we calculated the variance inflation factor (VIF) (Table. S2) and removed factors with a VIF above 6 (Li et al., 2023). Nine variables were included in our final selection (Table 1). As the spatial datasets of these variables had varying resolutions, data pre-processing such as reprojection, zonal statistics, and temporal alignment was performed. The detailed description of data processing and workflow (Fig. S1) is shown in Section 3.1 of supplementary materials.

Cities awarded the NGC means they have achieved a high-quality urban environment defined by high greening rates in built-up areas, well-established green infrastructure, landscape aesthetics, and retention of cultural values in green infrastructure (Ding et al., 2022; Feng et al., 2021) (Table. S8). We obtained the list of awarded cities from the Ministry of Housing and Construction of China (https://www.mohurd.gov.cn) in March 2022 (Table. S9). Our final list included all prefecture-level cities and above from the first 20 nomination rounds of NGC between 1992 and 2017.

2.3. Data analysis

2.3.1. Division of urban-rural gradient and urbanization intensity calculation

Following Zhang et al. (2022), we outlined the area with urbanization for each city by creating buffers around the GUB vector file (Fig. 1) to define the urbanized and urban-rural transition zone. The buffer radius was based on the size of each city:

$$D = \left(\sqrt{2} - 1\right)\sqrt{\frac{S}{\pi}} \tag{1}$$

where D is the buffer distance of each city, S presents the size of a city. Under the assumption that larger cities have a larger urban-rural transition zone, a buffer radius determined by the city size better reflects the urban extent highly affected by urbanization.

To quantify the urbanization gradient within cities, urbanization intensity (UI) was calculated as the fractional cover of impervious surface within each 250×250 m pixel (to be consistent with EVI product resolution), ranging from 0 (fully vegetated surfaces) to 1 (fully built-up areas).

Table 1
Description statistics for nine selected factors.

Category	Indicators	Abbreviation	Resolution	Data type	Source
Natural conditions	Temperature	TEMP	0.25°	Raster	European Centre for Medium-Range Weather Forecasts (Hersbach et al., 2020)
	Precipitation	PRE	0.25°	Raster	
Urban microenvironment	Land surface temperature difference between urban and rural areas	LST	1 km	Raster	MOD11A2 V6, reflecting the urban heat island by calculating the LST difference between rural and urban areas (Wan, Z., Hook, S., Hulley, 2015)
	The size of urban green area	UGA	City level	Panel data	China City Statistical Yearbook (2001–2018)
	CO_2 emission density	CED	0.1°	Raster	Monthly anthropogenic CO_2 emissions, excluding short carbon cycle, from the European Copernicus Atmosphere Service (CAMS) data (Kuenen et al., 2022).
Socio-economic development	Population density	POP	1 km	Raster	Resource and Environment Science and Data Center of China (Xu, 2017)
	GDP	GDP	1 km	Raster	
	Urban size (built-up areas)	US	30 m	Vector	GUB dataset (Li et al., 2020b)
Greening governance	Years since the ‘National Garden Cities’ have been awarded	PIY	City level	Panel data	Ministry of Housing and Construction of China (https://www.mohurd.gov.cn/)

2.3.2. Urban vegetation enhancement and mitigatory effects measurement

We quantified the direct and indirect effects of urbanization on urban vegetation following the conceptual framework proposed by Zhao et al. (2016). This framework defines the direct impacts as the conversion of vegetated areas to built-up areas. The indirect vegetation growth (indirect impact) refers to the intensity of vegetation growth in areas that have already been converted to built-up in the past.

Conceptually, the observed EVI could be decomposed into two parts:

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

where V_{obs} is the observed EVI of urban pixel, V_v is the background vegetation index without urbanization, V_{nv} is the EVI of the pixel completely covered by impervious surfaces. We take a conceptual diagram with several pixels as an example (Fig. S1.) with additional explanation for eq.(2) to describe the conceptual framework in more detail.

Without considering indirect impact, the EVI should in theory have a negative linear relationship (i.e., zero-impact line, $\omega = 0$, Fig. 1b) with the gradient of UI. This zero-impact line was determined by linearly connecting two EVI values corresponding to background vegetation ($\beta = 0$, EVI $= V_v$) and fully urbanized pixels ($\beta = 1$, EVI $= V_{nv}$). From this line, a theoretical EVI value, V_{zi}, for if there were only direct impacts can be calculated for every β:

$$V_{zi} = (1-\beta)V_v + \beta V_{nv} \tag{3}$$

Based on eq.(3), the direct impact (ω_d) was calculated as:

$$\omega_d = \frac{V_{zi} - V_v}{V_v} \times 100\% \tag{4}$$

Due to the influence of the complex urban environment and vegetation growth over time, the observed EVI may not coincide well with the zero-impact line (green dots shown in Fig.1b), which means the observed EVI value of the pixel is higher or lower than the theoretical EVI value (V_{zi}) with specific urbanization intensity (β). The difference between the observed values and the zero-impact line is defined as the indirect impact:

$$\omega_i = \frac{V_{obs} - V_{zi}}{V_{zi}} \times 100\% \tag{5}$$

The observed EVI point above the zero-impact line represents a positive indirect impact of urbanization on vegetation, while the points below the zero-impact line indicate vegetation growth with negative impact from urban environment. To characterize correlation between EVI and UI (β), we derived the averaged EVI of each UI bin by setting 0.01 as interval for each city. Following Zhang et al. (2022), we employed a cubic polynomial model to fie the EVI~β curve:

$$y = a_0 + a_1 x + a_2 x^2 + a_3 x^3 \tag{6}$$

where y is the observed EVI, x is the β. This model has been proved to have a good performance for capturing the relationship between EVI and UI (Jia et al., 2018; Zhang et al., 2022; Zhao et al., 2016).

To quantify how much the indirect growth of remaining vegetation caused by urban environment can mitigate the direct vegetation productivity loss from urban sprawl, the mitigatory effect index (τ) is defined as:

$$\tau = \frac{V_{obs} - V_{zi}}{V_v - V_{zi}} \times 100\% \tag{7}$$

2.3.3. Influencing analysis

We assessed the dominant influencing factors on urban vegetation enhancement nationally and temporally using a linear mixed effects model (LMER) and a linear regression model, respectively. The LMER is a widely used statistical method for analyzing data that have both fixed and random effects, which is particularly suitable for studies with hierarchical or clustered data structures, such as our analysis of the effect size of multi-variables on urban vegetation growth across multiple cities (Gelman and Hill, 2006). We set the 'city name' as the random effect to account for individual differences that may arise from specific characteristics of the observational units. We standardized all the dependent and independent variables before regression to make sure all variables had the same scale for comparability of regression coefficients. Depending on the skewed data distribution and statistical tests, green space on built-up areas, population density, GDP, and urban size were logarithmically processed to stabilize variance and make the data more symmetrically distributed. Also, t-test was included in LMER model to test the significance of results. The LMER model is defined as:

$$\begin{aligned}\omega_i = \beta_0 + \beta_1 TEMP_{ct} + \beta_2 PRE_{ct} + \beta_3 LST_{ct} + \beta_4 UGA_{ct} + \beta_5 CED_{ct} + \beta_6 POP_{ct} \\ + \beta_7 GDP_{ct} + \beta_8 US_{ct} + \beta_9 PIY_{ct} + R_c + \varepsilon_{ct}\end{aligned} \tag{8}$$

where $\beta_0 - \beta_9$ are the coefficients from the LMER model; ω_i represents the indirect vegetation growth; the abbreviations of the nine independent variables can be found in Table 1. The labeled ct after each variable refers to the value of specific variables in city c at year t. For example, $TEMP_{ct}$ is the temperature in city c at year t. R_c is the random effect factor, which reflects heterogeneity of influencing mechanism for each city; and the ε_{ct} are the residuals. The LMER was conducted using the lmer function from the lme4 R package (Bates et al., 2015).

To assess how correlations between indirect vegetation growth and certain explanatory variables changes over time, we employed a linear regression model to the observations from a single year. The model was defined as follows:

$$\omega_{ict} = \beta_0 + \beta_1 x_{ct} + \varepsilon_{ct} \tag{9}$$

where ω_{ict} is the urban vegetation enhancement city c at year t; β_0 is the y-intercept, β is the regression coefficient; x_{ct} represents the selected explanatory variable value in city c at year t; and the ε_{ct} is the residual. The lm function in R was utilized for estimating the Eq.(9) above. We explored the temporal variation of each variable's driving effects on ω_i by measuring their correlation at an earlier, middle, and a later point in time. Yet, only a few cities (20 out of 294) were awarded the status as NGC in 2002, and therefore the results of linear regression between implementation years of policy (PIY) and ω_i in 2002 was unreliable due to the small sample size. Also, the size of urban green area (UGA) variable has an incomplete database in 2002. Therefore, we chose 2005 as the earliest year with more comprehensive available data for analysis, with setting 2011 and 2017 as the middle and later timing point, respectively.

In addition, we did analysis of covariance (ANCOVA) for detecting the ω_i and ω_d differences between policy groups by adjusting for covariates. We set ω_i and ω_d as dependent variables, NGC or non-NGC cities as group, and the other eight independent variables as covariate in the model. Here we used F-test to detect the significance of the group difference. Table S6 depicts the interpretation of policy performance alongside the ANCOVA outcomes.

3. Results

3.1. Enhanced urban greenness across MDCs in China

Between 2002 to 2017, there was a notable increase in the average enhancement of urban vegetation in MDCs (Fig. S4-S7), rising from 8.0 % (SE, ±0.31) to 13.7 % (SE, ±0.28). The regions with substantial vegetation enhancement were primarily clustered in East China, with a smaller concentration in Northeast China (Fig. 2a). All four climate zones showed an increase in the EVI along urbanization intensity (β) over time (Fig. 2c), accompanying increasing urban vegetation enhancement. The cold zone exhibited the highest average value (14.5 %) of vegetation enhancement, followed by the temperate humid zone

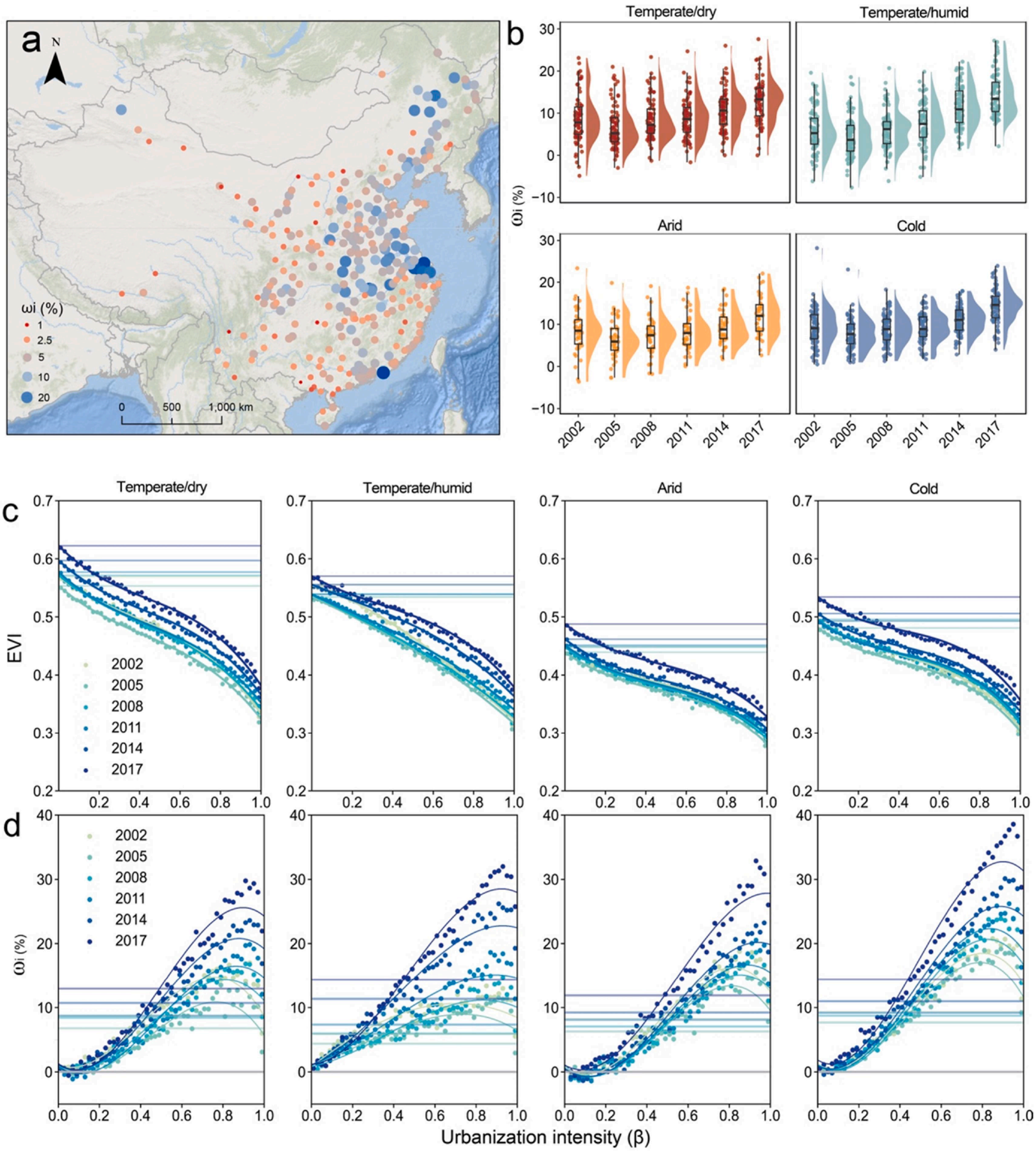

Fig. 2. Spatial-temporal variation of vegetation index and indirect vegetation growth across China: (a) spatial distribution of indirect effect in 2017, (b) temporal change of indirect vegetation growth from 2002 to 2017 across climate zones, (c) vegetation index change, and (d) the indirect vegetation growth change along urbanization intensity.

(14.4 %), the temperate dry zone (13.0 %), and the arid zone (11.9 %) (Fig. 2b). Notably, the temperate humid zone experienced the highest increase in enhancement, with an 8.5 % increase throughout the study period. The arid zone displayed the smallest increase in enhancement of 3.4 %. Highly densified urban areas (β > 0.5) experienced more vegetation enhancement than regions with lower built-up density. This amplified indirect effect was most pronounced in cold zones, particularly in areas where the β exceeded 0.4 (Fig. 2d).

On the city scale, only Chongzuo City, located in the temperate dry zone, exhibited a negative indirect vegetation growth (−0.02 %) in 2017 (Fig. S3a). While Shanwei City in the same zone showcased the highest urban vegetation enhancement in China, reaching 27.6 %. Examining the distribution of cities with indirect vegetation growth (ω_i) greater than the national average, the cold zone exhibited the highest proportion (Fig. S3d), with 63.5 % (54 out of 85) of the cities surpassing the national median. In the temperate humid zone, 47.5 % (41 out of 86) of the cities exceeded the average (Fig. S3b), while in the temperate dry zone and the arid zone, 46.7 % (35 out of 75) and 33.3 % (14 out of 42), respectively, exceeded the national average (Fig. S3c). For the variation in indirect vegetation growth between 2002 and 2017, 63 out of 75 cities in the temperate dry zone experienced increases in ω_i. In the temperate humid zone, all cities showed an increase in ω_i. Within the arid zone, 38 out of 42 cities showed an increase in ω_i from 2002 to 2017, with Longnan City showing the most notable decline at −6.33 %. Of the cold-zone cities, 78 out of 85 showed increases in ω_i, ranging from −11.0 % in Qingyang City to 19.9 % in Yichun City. The additional 6 cities did not show a reliable determination coefficient ($R^2 < 0.6$) in the model, therefore, they were not considered in this result section.

3.2. Urban vegetation enhancement mitigates vegetation loss by urban expansion

We found that ω_i has mitigated 18.1 % of the urbanization-driven decreases in 2002. This mitigatory effect increased to 39.7 % in 2017. The increase in the mitigatory effect (τ) was observed across all climate zones, with more cities showing an increase in mitigatory effects over time (Fig. 3a). By 2017, the temperate humid zone displayed the highest average mitigatory effect value of 49.8 %, followed by the cold zone (45.6 %), the arid zone (33.1 %), and the temperate dry zone (30.5 %). Over the period from 2002 to 2017, the temperate humid zone showed the most substantial increment in mitigation of 19.5 %, while the temperate dry zone exhibited the lowest increases in mitigation of 15.1 % (Fig. 3b & c).

When considering the mitigatory effect of each pixel along urbanization intensity (β), 25th percentile pixels (i.e., dark gray shading in Fig. 3a) predominantly exhibit positive mitigatory effects in the temperate humid zone. This indicates that favorable climatic conditions foster vegetation growth in less urbanized areas, resulting in a positive mitigatory effect on the greenness loss in that region. Compared to other climate zones, pixels with negative mitigatory effects are most prevalent in arid regions. This indicates that in arid areas, especially in peri-urban zones, the direct losses from urbanization far outweigh the limited enhancement in greenness.

3.3. Variables influencing indirect vegetation growth under urban densification

We explored the temporal variation of each variable's driving effects on ω_i by measuring their correlation at an earlier, middle, and later point in time (Fig. 4a). The result of LMER model were presented in Fig. 4b and Table S3. In the LMER model, urban size (US) had the largest effect on ω_i among the nine explanatory variables, followed by GDP and the number of years since NGC awarded (PIY) (Fig. 4b). When classifying the cities by size into five groups (Table S5), the results showed that large cities have a higher indirect urban vegetation growth than small cities (Fig. S12). The urban heat island (LST) showed a significantly negative effect on ω_i in 2005, but not in 2017. The size of urban green space areas (UGA) had no significant effect in 2005 and was positively correlated with ω_i in 2017. Population density (POP) and GDP changed from a non-significant ($P > 0.05$) correlation in 2005 to a significant positive correlation in 2017. Greening governance, represented by the NGC policy (PIY) changed from non-significant effect in 2005 ($P > 0.05$)

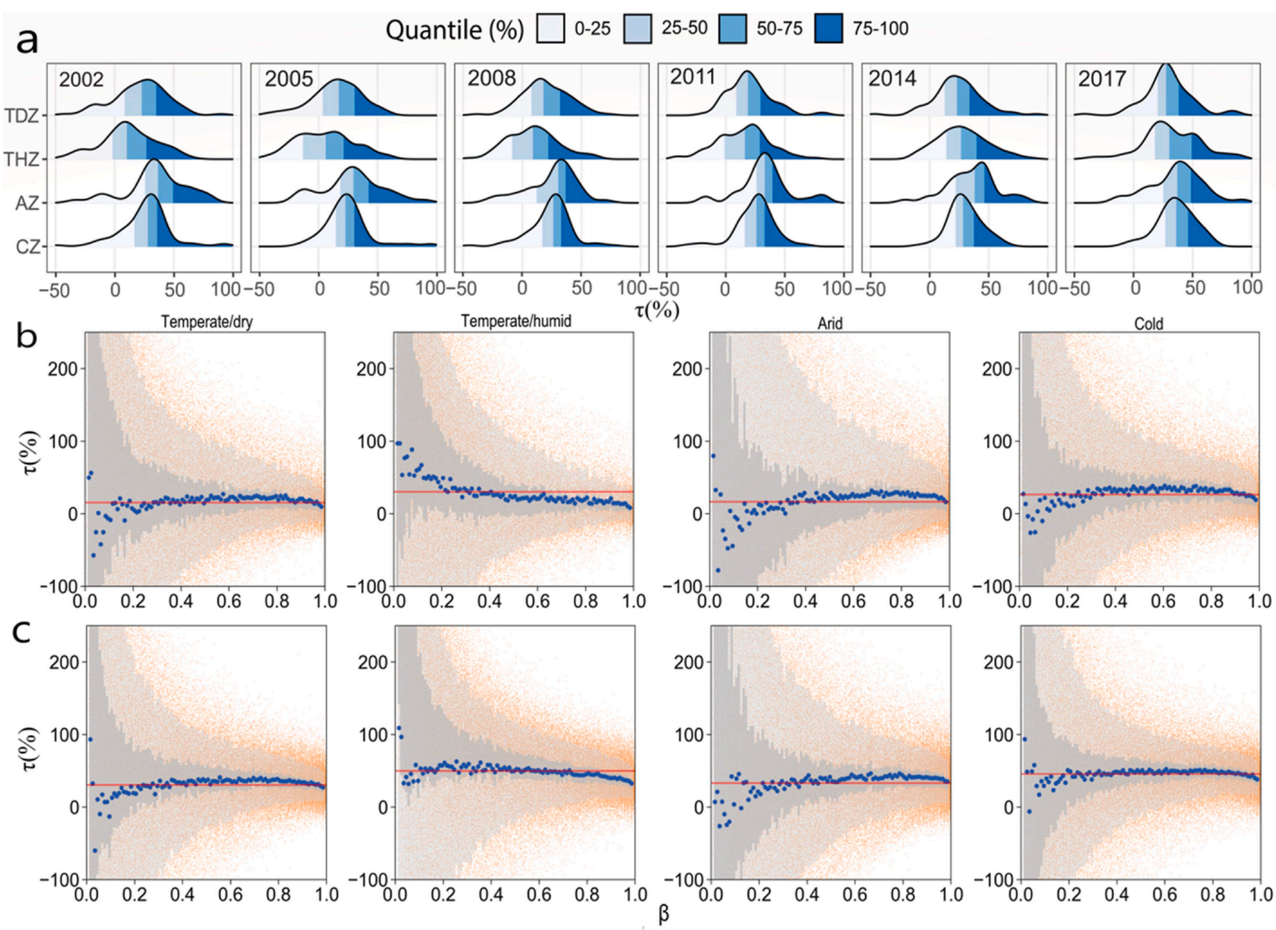

Fig. 3. Mitigatory effects (τ) variation from 2002 to 2017: (a) ridgeline plot for mitigatory effect, the gradient color scale indicates the quantile distribution of the data, TDZ represents temperate dry zone, THZ is temperate humid zone, AZ is arid zone, and CZ refers to cold zone, (b) mitigatory effects along urbanization intensity in 2002, and (c) 2017. The shading shows 25th (dark gray) and 75th (light gray) percentiles of τ dots in each urbanization bin, blue dots represent the mean of each bin, and red lines represent the average of each blue dots.

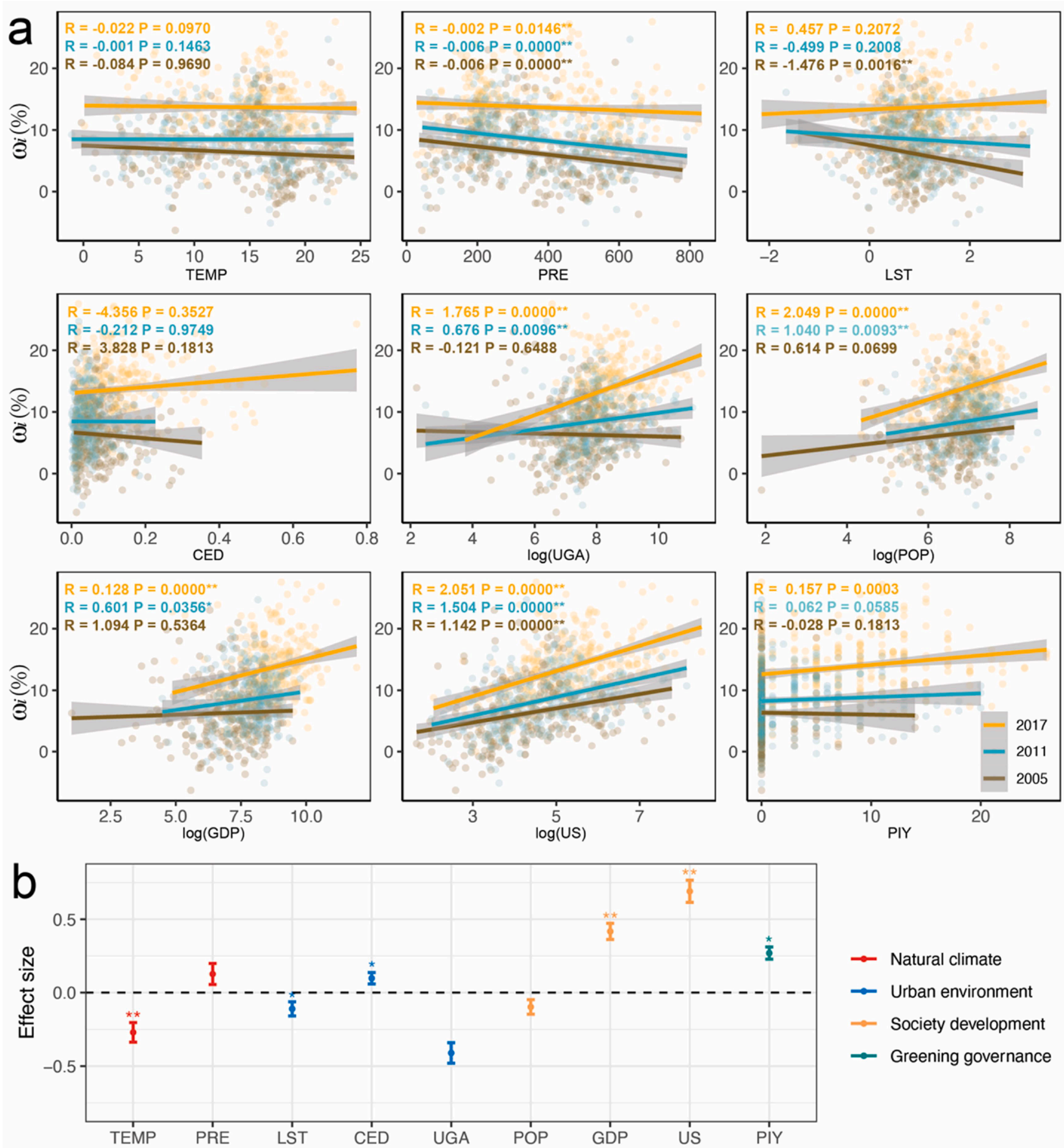

Fig. 4. Relationship between variables and urban vegetation enhancement: (a) correlation between individual variables and ω_i for the year of 2005, 2011, and 2017, representing an early, middle, and a late time step of the analysis, (b) effect sizes of nine variables on indirect urban vegetation growth. Significant effects are indicated by asterisks (* for $P < 0.05$, ** for $P < 0.01$). Error bars represent one standard deviation.

to a positive effect on ω_i in 2017 ($P < 0.001$).

3.4. Spatiotemporal assessment of the impact of urban greening governance on indirect vegetation growth

The effect of the NGC program on ω_i varied across the four climate zones, both at the city level and the pixel level. Accounting for other covariates based on ANCOVA model (summary in Table S7), NGC-policy cities in temperate humid and cold regions showed significantly higher ω_i than the cities which were not awarded, while in temperate dry zone, and arid zone, the differences were not significant (Fig. 5a). The cities with NGC policy showed less direct vegetation loss, ω_d, compared to those without the award, except for arid and humid temperate zone (Fig. 5b).

The variation in ω_i across the urbanization intensity (β) gradient at the pixel level depicts some spatial inefficiencies of the NGC policy (Fig. 5c). We found that there was no obvious difference in ω_i for NGC cities compared to other cities across all bins of β in the temperate dry zone. By contrast, NGC cities had higher ω_i throughout the entire range of β in the temperate humid zone. In the arid zone and cold zone, the role of NGC depended on the degree of urbanization intensity. In the arid zone, NGC cities had lower ω_i in highly urbanized areas ($\beta > 0.5$), suggesting that the policy has negative effects in these regions. In the cold zone, the policy promotes ω_i in highly urbanized areas ($\beta > 0.7$). Furthermore, across the four climate zones, the relationship between ω_i and the number of years since NGC policy was always hump-shaped displaying a positive correlation with cities got the NGC label for 10 to 15 years, followed by a negative correlation or stagnation within the

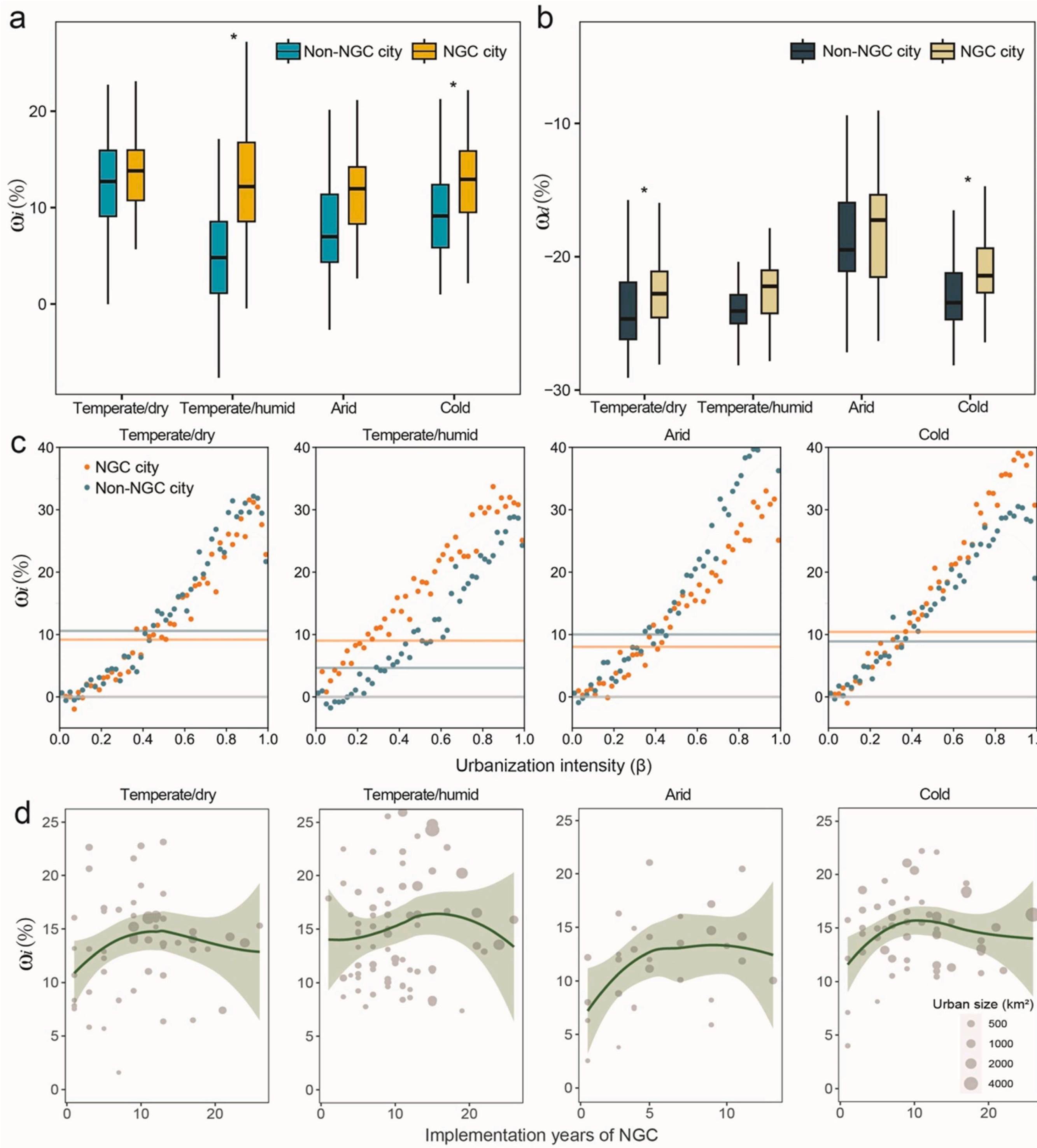

Fig. 5. NGC policy performance assessment. Differences in the indirect ω_i (a) and direct ω_d (b) effects of urbanization on vegetation growth between NGC cities and non-NGC cities across climate zones in 2017. Significant effects are indicated by an asterisk ($P < 0.05$) ($n = 75, 86, 42, 85$, respectively). (c) Enhanced urban greenness variation along urbanization intensity at the pixel level. The orange and blue horizontal lines represent the average ω_i. (d) Locally estimated scatterplot smoothing (LOESS) between the mean of $\omega_i$of each NGC city and the years since NGC has been awarded.

NGC cities holding this label with shorter years (Fig. 5d).

4. Discussion

4.1. Prevalent vegetation enhancement under urban densification in China

While urban expansion continues to encroach upon green spaces in China, our research demonstrates a concurrent trend of increasing urban density and enhanced greening. The vegetation indices in most Chinese municipal districts were higher than theoretically expected, indicating widespread enhanced urban vegetation growth under urban densification. This vegetation enhancement, which ranges from 8.0 % to 13.7 %, is particularly strong in eastern and northeastern China, aligning with previous research (Zhang et al., 2022).

The pursuit of compact cities, a common urban planning objective in Europe and East Asia, often involves infilling inner urban areas at the cost of existing green spaces. However, denser cities simultaneously amplify the demand for ecosystem services from residents and wildlife, which must be met by the remaining vegetation in limited areas (Erlwein et al., 2023; Evans et al., 2022; Haaland and van den Bosch, 2015). This dichotomy between urban densification and green space preservation could potentially be mitigated by the vegetation enhancement, a phenomenon that our study highlights in many Chinese cities. The mitigatory effects we observed in Chinese cities are comparatively lower than those observed in metropolitan areas of the United States (23.3 % in our study vs. 31.0 % in the U.S., 2011). This disparity between China and the U.S. may be attributed in part to differing climatic contexts and variations in the urban population share, which also influence the mitigatory effect (Zhang et al., 2023a).

4.2. Inefficiencies of national garden city policy and governance suggestions

Ongoing urban greening governance should shift its emphasis from preventing green space loss to a nuanced focus on enhancing vegetation growth (Jim, 2013). Our findings indicate certain inefficiencies in this policy. Despite the well-established green contexts in NGC cities within certain climate zones, there was no significant difference in urban vegetation enhancement compared to cities that were not awarded. This could be due to the core selection criterion of the NGC policy, the high ratio of green to urban space (Ding et al., 2022; Feng et al., 2021), which guides cities to prioritize the expansion of green spaces at the expense of maintaining and nurturing existing urban vegetation to achieve this award. In some regions, the NGC policy has led to the planting of monocultures of fast-growing trees to expand urban green coverage (Huang et al., 2021; Li et al., 2022), an approach that can lead to unhealthy urban vegetation in mismatch with the local climate (Churkina et al., 2015; Shah et al., 2022).

Our findings show that the effectiveness of the NGC policy varies across climate zones, with a notable lack of success in arid zones. In these areas, cities with NGC designation were not beneficial for either curbing urban vegetation loss or promoting urban vegetation enhancement when compared to cities without NGC status. NGC cities even displayed notably lower ω_i than their non-NGC counterparts in highly urbanized areas ($\beta > 50$ %). Several factors likely contribute to this policy outcome. First, water scarcity in arid regions hampers urban vegetation growth, and the planting of exotic species, such as *Fraxinus sogdiana* and *Platanus acerifolia*, on non-vegetated surfaces can exacerbate water depletion in arid cities. Additionally, the urban heat island effect is more pronounced in the city centers of arid regions (Peng et al., 2019). This strains the water resources available for newly planted vegetation and limits vegetation growth in arid urban areas. Second, the later designation of most arid cities as NGC compared to their eastern counterparts means that local governments in the arid zone started urban greening projects later than eastern cities, which means newly planted vegetation in these cities is still in a juvenile stage, resulting in a lag in indirect growth effects. Additionally, the initial upward trajectories of urban vegetation enhancement were consistently followed by a decline in vegetation enhancement when we compare the NGC cities with different years since NGC awarded across all four climate zones. The policy's dynamic mechanism for de-listing cities that fail to meet NGC standards is not regularly applied, leading to a lack of sustained maintenance and improvement of urban vegetation post-designation. This highlights the necessity of establishing a more comprehensive monitoring and enforcement mechanism that excludes cities that no longer fulfill the policy requirements (Pediaditi et al., 2010).

Based on our analysis, we advocate the adoption of urban greening policies that consider local climate and resources. This involves selecting autochthonous vegetation that is suitable for the climate and implementing agricultural engineering methods like straw blankets or bark plots to enhance water retention in arid urban green areas during initial restoration phases (Wang et al., 2017). Although not the focus of our study, we additionally suggest that the NGC policy should place more emphasis on multi-stakeholder forums that include public and business sectors in addition to local governments. Such collaborative efforts could better align the supply and demand for urban green spaces (Bush et al., 2023; Goodwin et al., 2023; Yan et al., 2022).

4.3. Larger cities in China witnessed higher urban vegetation enhancement

Our findings reveal that large cities are leading urban vegetation enhancement across China. Zhang et al. (Zhang et al., 2023b) showed that megacities contain a significantly higher percentage of tree coverage (19.4 %) compared to emerging cities (11.8 %), reinforcing that large cities are experiencing increasing vegetation enhancement. Large cities have more resources to prioritize ecological governance in their urban planning strategies by allocating more green spaces within the urban landscape, and adequate public green infrastructure investment budgets that facilitate vegetation growth (Tan et al., 2013). For example, Beijing City implemented the One Million-Mu (666 km^2) Plain Afforestation Project, which has led to over 50 million trees being planted in the city's flat area (Yao et al., 2019). Further, the dense populations in large cities have a high demand for high-quality green space within the urban areas (Yang et al., 2023), which often results in higher urban vegetation enhancement. A prior global study (Zhang et al., 2021) did not identify urban size as a pronounced factor for positive urban vegetation growth trends. This discrepancy is likely attributed to the distinction between the direct and indirect effects of urbanization on vegetation growth. The previous study focused solely on overall greening trends, which are heavily influenced by direct vegetation loss in urban fringes, which tend to be more extensive in larger cities.

4.4. Contributions and limitations

This study provides a comprehensive exploration of indirect vegetation growth along urbanization gradients in China, by distinguishing direct and indirect greening outcomes. It also contributes to a deeper understanding of the effects of socio-economic development on urban vegetation, with a specific focus on urban greening governance, an aspect often overlooked. The innovative introduction of the indirect vegetation growth index as a metric allows for the assessment of urban greening governance across varying urbanization intensities and time series, setting a precedent applicable at regional levels and beyond.

However, certain limitations must be acknowledged. While satellite-based observations consistently identify urban vegetation patterns over time, the 250m-resolution EVI product used here may not fully capture small green spaces or individual trees within cities. Data accuracy limitations persist, especially when conducting statistics at different scales. Furthermore, the focus solely on municipal districts excludes counties awarded NGC, indicating an opportunity for future research to refine the research scale and incorporate ground observations.

Caution is needed in interpreting the mitigatory effects when considering the wealth of ecosystem services provided by urban vegetation. It is crucial not to misinterpret the mitigatory effects as a justification for uncontrolled urban expansion into natural vegetation in urban peripheries. Beyond supporting enhanced vegetation growth, urban ecosystems must also cater to various demands for ecosystem services, including habitat provision for biodiversity, stormwater management, and urban heat island mitigation (McPhearson et al., 2022;

Richards et al., 2022; Yang et al., 2023). Preserving the density and diversity of urban vegetation remains critical for ensuring the healthy development of urban ecosystems within and beyond city boundaries (Bodnaruk et al., 2017; Morani et al., 2011). This holistic perspective is essential for sustainable urban planning that balances development with environmental conservation.

We analyzed the temporal relationships between each independent variable and indirect urban vegetation growth using only three representative time points (2005, 2011, and 2017) for linear regression analysis. While these results provide insights into temporal variation, including data from more years in future studies would enhance result accuracy. The correlation between NGC policy and urban vegetation enhancement should be approached critically due to inherent sampling bias in this official national selection of NGC. The awarded NGC cities are generally larger, have larger urban green spaces, and a higher GDP which favor urban greening compared to those that have not been awarded (Fig. S13). It is therefore potentially misleading if we attribute all vegetations improvements to awarding the NGC label. However, we have controlled the influence of these covariates in the statistical models. Furthermore, we only consider NGC policy as a greening governance indicator in this study, there is a need to include more concurrent policies in further research.

5. Conclusions

Distinguishing between direct and indirect effects of urbanization on urban vegetation development is crucial for the development of sustainable urban strategies that can adapt to the challenges posed by future climate change. Our findings show that Chinese cities, especially large-scale cities, are currently experiencing a prevalent urban vegetation enhancement, which may potentially offset some of the vegetation loss from urban expansion. Socio-economic factors, like urban size and GDP, showed prominent correlation with urban vegetation enhancement, potentially reflecting the necessity of sufficient green spaces and adequate green infrastructure investment budgets for facilitating vegetation growth. However, it is noteworthy that the NGC policy has shown uneven efficacy in promoting urban vegetation enhancement. This shortcoming is particularly evident in arid areas. These findings have significant implications for the prioritization of urban greening governance. They highlight the need for policies that not only ensure sufficient green coverage in cities but also prioritize the nurturing, management, and maintenance of urban vegetation. Policymakers and planners should adopt a region-specific approach to greening governance, taking into consideration local climate, soil quality, and water availability. Furthermore, they should advocate for collaborative and participatory measures that involve multiple stakeholders to achieve the sustainable conservation of urban vegetation resources.

Declaration of generative AI and AI-assisted technologies in the writing process

During the writing process of this work, we used AI-assisted technologies, ChatGPT, to improve the language for clarity and conciseness. After using this tool, we thoroughly reviewed and edited the content and we take full responsibility for the content of the publication.

CRediT authorship contribution statement

Yuyang Chang: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Maarten J. van Strien:** Writing – review & editing, Methodology. **Constantin M. Zohner:** Writing – review & editing, Methodology. **Jaboury Ghazoul:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Fritz Kleinschroth:** Investigation, Conceptualization, Methodology, Resources, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Supplementary materials

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