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Population density regulation may mitigate the imbalance between anthropogenic carbon emissions and vegetation carbon sequestration

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ABSTRACT

The growing imbalance between anthropogenic carbon emissions and vegetation carbon sequestration is impeding cities' sustainability. However, previous research has not reached a consensus on whether population density regulation can mitigate this growing imbalance. In this study, we first used the carbon footprint pressure (CFP) indicator to examine the temporal and spatial characteristics of the imbalance in 370 Chinese cities over the last 20 years. Second, we demonstrated the favorable but limited effect of existing technology on CFP mitigation using the IPAT equation, the Logarithmic Mean Divisia Index decomposition approach, and the Kaya identity. Further, we emphasized the dominant effect of the population on CFP in urban agglomerations and provincial capital cities through Maxwell's triangle. Finally, using a built panel data model, we identified an inverted U-curve relationship between CFP and population density at the middle and low quartiles, whereas population clustering promoted CFP mitigation at the upper quartiles. Given the limited effectiveness of current climate actions, as well as the coexistence of urban diseases and unoccupied buildings, we provided differentiated policy implications in city-scale for population density regulation. This study provides some inspiration for authorities to formulate city-scale population policies to mitigate climate change and achieve sustainable development.

1. Introduction

Climate change mitigation is a critical objective for sustainable development (Krayenhoff et al., 2018; Schmidt-Traub et al., 2017), with cities at the epicenter (Abu Dabous et al., 2022; Franco et al., 2022; Shan et al., 2022; Wiedmann & Allen, 2021). Not only are cities hotspots for emissions and development, but they are also the fundamental unit for implementing the policy of differentiated sustainable development (Shan et al., 2022). Cities are expected to consume more than 60% of the world's energy and produce nearly 75% of carbon emissions (United Nations, 2020). Furthermore, fast building expansion leads to the occupancy of land in the terrestrial ecosystem and reduced vegetation carbon sequestration (Jasper, 2019; Liu et al., 2019). The imbalance between anthropogenic carbon emissions and vegetation carbon sequestration exacerbates climate change (Liu et al., 2019; Piao et al., 2009) and has ramifications for food security, freshwater availability, ecological stability, and human longevity (Chung et al., 2021; Malik et al., 2022; Ribeiro et al., 2021; Zhao et al., 2021). Although countries have made some efforts to mitigate climate change by actively decarbonizing their economies (Guo et al., 2020; Meckling et al., 2022; Semieniuk et al., 2021) and constructing ecological infrastructure (Chen et al., 2019; Cuthbert et al., 2022; Pausata et al., 2017) or passively being affected by the COVID-19 pandemic (Davis et al., 2022; Le Quéré et al., 2020; Shan et al., 2021), it is far from sufficient. More efforts must be made to limit anthropogenic carbon emissions to the carbon sequestration capacity of vegetation, which is an unavoidable

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requirement for sustainable development (Engström et al., 2020; Heck et al., 2018).

Much research has been conducted to identify pathways to mitigate anthropogenic carbon emissions and increase the carbon sequestration capability of terrestrial ecosystems (Bistline & Young, 2022; De Kauwe et al., 2016; Kim et al., 2017; Koch et al., 2022; Lu et al., 2019; Qiu et al., 2022; Wang et al., 2022). However, these studies mostly focused on the pathways of anthropogenic carbon emission reductions or the augmentation of vegetation carbon storage, while disregarding potential climatic and environmental risks. Particularly, vigorously developing the tertiary industry is regarded as a powerful decarbonization measure (Mazzucato, 2022; Nahm et al., 2022), whereas their rapid development is frequently accompanied by the construction and expansion of corresponding sites. For example, the constantly developing amusement parks, hotels, roads, and other supporting facilities weaken the regional vegetation carbon sequestration capacity and increase climate risks (Jasper, 2019; Krayenhoff et al., 2018).

Currently, the carbon footprint pressure (CFP) indicator calculated from the carbon footprint, effectively characterizes the imbalance between anthropogenic carbon emissions and vegetation carbon sequestration. As a crucial indicator in addressing sustainability-related research concerns, it can connect production and consumption patterns to biophysical limits (Liang et al., 2022). In particular, evidence shows that global CFP has increased at a rate of 2.31% in the time 2000–2015 (Chen et al., 2020a). The gradually increased imbalance poses an urgent examination of viable strategies to mitigate it. In this context, many studies have begun to investigate the drivers of CFP to provide policy implications. Given the possible interaction between the elements that drive CFP, the IPAT (Impact = Population × Affluence × Technology) (Ehrlich & Holdren, 1971) equation, Logarithmic Mean Divisia Index (LMDI) decomposition approach (Ang et al., 1998), and the Kaya identity (Kaya, 1990) are commonly employed to examine the drivers of CFP. For example, Chen et al. (2020a) found the favorable influence of technological advancement on CFP mitigation. Further research proposed the strategies of ecological construction (Huang et al., 2021), economic restructuring, energy restructuring (Liang et al., 2022), and urban clustering (Liang et al., 2023) for CFP mitigating. Although the importance of CFP has been reported in many fields, current research on the population effect on CFP still remains scarce. Much evidence has shown that reduced fertility can mitigate climate change (Casey & Galor, 2017), however, this still keeps an open question in nations with aging populations. For example, China has shifted the reproduction policy from constraints to incentives.

Obviously, the existing literature has achieved fruitful results in mitigating the imbalance between anthropogenic carbon emissions and vegetation carbon sequestration, but still has some shortcomings. First, there is no consensus on whether population density regulation can mitigate climate change. Regulating population density can help to mitigate anthropogenic carbon emissions (Jones & Kammen, 2014; Rahman, 2017; Rahman & Alam, 2021; Timmons et al., 2016). Unfortunately, the regulation of population density necessitates a building area consistent with the size of people, and building expansion will result in a loss of carbon sequestration by vegetation (Jasper, 2019; Liu et al., 2019). As a result, it is necessary to consider the negative impact of population density regulation on vegetation carbon sequestration and to thoroughly assess the effect of the regulation in mitigating climate change. Furthermore, distinct population density regulation pathways are required for authorities. For instance, people's geographical distribution is getting increasingly concentrated because of resource endowment and social and economic progress (Piguet, 2012; Timmermann & Friedrich, 2016). The concentrated population distribution generates certain economies of scale and is beneficial to carbon emission reduction (Lin & Zhang, 2016; O'Mahony, 2013). Unfortunately, the ongoing escalation of this process hastens anthropogenic carbon emissions, such as those caused by traffic congestion (Böhm et al., 2022; Zhang & Hanaoka, 2022). In the alternative scenario, over-diluted population density raises people's transit expenses and living carbon emissions (Timmons et al., 2016). As a result, there may be a nonlinear connection between population density and CFP, and over-dense and over-diluted population density necessitates distinct regulatory pathways.

China is an excellent study area. China is not just the world's greatest developing economy and carbon emitter (Shan et al., 2018), but it also boasts a thriving real estate market. In China, urban illnesses and unoccupied buildings have coexisted. Despite being a global greening hotspot (Chen et al., 2019), China has roughly 10 times the global average CFP (Chen et al., 2020a). Previous research has highlighted the drivers of CFP mitigation from nations (Chen et al., 2020a), provinces (Liang et al., 2022), and individual urban agglomerations (Chen et al., 2022b; Liang et al., 2023; Yang et al., 2022), but national city-scale studies are lacking, and resource endowment and development disparities across cities are overlooked. As a result, there is an urgent need to investigate the impact of population density on CFP on the urban scale around China.

The goal of this study is to dissect the drivers of city-scale CFP in China, particularly the effect of population density on CFP, over the last 20 years. Detailed, to analyze the spatial and temporal characteristics of CFP, we first integrate selected remote sensing inversion data to the city-scale using the administrative divisions. Second, the IPAT equation, the LMDI decomposition approach, the Kaya identity, and the Maxwell triangle are used to clarify the effects and spatial patterns of technology, affluence, and population on CFP. Finally, a panel data model is constructed based on the IPAT's stochastic form, i.e., STIRPAT (Dietz & Rosa, 1994), to dissect the effect of population density on CFP by a panel quantile regression approach.

The marginal contributions of this study are as follows: 1) In an attempt to resolve the scientific issue and social concern of whether population density regulation can mitigate climate change, we reveal the effect of population density on CFP. 2) Our STIRPAT-based panel data model is flexible and will inspire future research by taking the interaction of various CFP drivers into account. 3) Our research is focused on the world's largest developing country, and our findings may enlighten and shape the creation of sustainable development strategies in other countries. Currently, population growth has considerably increased anthropogenic carbon emissions, and existing technical pathways make dealing with climate change challenging. This study provides a new perspective to deal with the global climate crisis. We expect that this study will help to complete present sustainable development, urban development, and population policies.

2. Methods and materials

2.1. Methodological overview and data sources

In general, we built the CFP indicator first. The impact of technology, affluence, and population on CFP was then investigated using the IPAT equation, the Kaya identity, and the LMDI decomposition approach, and the spatial pattern of drivers was revealed using the Maxwell triangle. Finally, using STIRPAT, a panel model was built, and a panel quantile approach was used to reveal the potential effect of population density on CFP.

This study's data are entirely high-resolution data acquired through remote sensing, which provides data continuity within the same city, avoids the impact of administrative division adjustment, and is useful for large-scale and long-term analysis. Specifically, anthropogenic carbon emission statistics were derived from Japan's Open-source Data Inventory for Anthropogenic CO_2 (ODIAC), which was built on the Greenhouse Gas Observing SATellite Project (GOSAT). ODIAC2020b (https://db.cger.nies.go.jp/dataset/ODIAC/DL_odiac2020b.html), which we selected, provides global carbon emission data with a 1 km × 1 km granularity from 2000 to 2019. Net primary productivity (NPP) (Running & Zhao, 2015) was used to calculate vegetation's carbon sequestration, and the detailed technique was referenced in the reference (Chen et al., 2020a). After subtracting autotrophic respiration, NPP is the organic dry matter production of green plants per unit area per unit of time. The information came from NASA's Medium Resolution Imaging Spectrometer's NPP product, which had a resolution of 500 m × 500 m. The population statistics were from Open Spatial Demographic Data and Research (https://www.worldpop.org/), and the dataset given the worldwide population density distribution with a 1 km × 1 km resolution. The built-up land/impervious surface data were collected from China's yearly Landsat land cover products (http://doi.org/10.5281/zenodo.4417809), which gave a high-precision land use categorization at 30 m × 30 m spatial resolution from 1990 to 2019 (Yang & Huang, 2021). The gross domestic product (GDP) statistics were chosen from the actual GDP of a 1 km × 1 km grid of the world estimated using the top-down technique from 1992 to 2019 (Chen et al., 2022a). We converted the aforementioned data into panel data before studying it.

2.2. CFP indicator

The CFP indicator is the ratio of anthropogenic carbon emissions to vegetative carbon sequestration (Liang et al., 2022). NPP and net ecosystem productivity (NEP) are the most generally used methodologies for estimating terrestrial ecosystem carbon sequestration potential. The distinction between NPP and NEP is that NPP comprises heterotrophic respiration of terrestrial ecosystems than NEP (Cramer et al., 2001), while NPP is better suited for estimating large-scale carbon sinks (Law et al., 2000). As a result, the CFP developed in this article based on NPP does not reflect net zero carbon emissions, when CFP is equal to 1. The following is the specific calculating method:

$$CFP = \frac{CF}{VCS} \tag{1}$$

where *CFP* is the carbon footprint pressure and is dimensionless, *CF* is the carbon footprint denoted by anthropogenic carbon emissions, and *VCS* is the vegetation carbon sequestration. This indicator can be used to evaluate the relative level of sustainable development among regions, and please refer to (Liang et al., 2022) for information.

2.3. Driver analysis method

2.3.1. IPAT equation and LMDI approach

In terms of CFP drivers, we first looked at the mitigating effect of technology on CFP. The IPAT equation is frequently used to estimate the environmental impact of human activities, and it has gained widespread acceptance in the domains of CFP (Liang et al., 2022), carbon emissions (Danish et al., 2021), air pollution (Wu, Zhou & Xu, 2022), and other related topics. This equation splits the drivers of environmental impact into three categories: technology effect, affluence effect, and population effect (Ehrlich & Holdren, 1971). Based on this, some researchers began to apply the Kaya identity and LMDI decomposition approach to determine the drivers of environmental impact (Cansino et al., 2015; Ortega-Ruiz et al., 2020). The approach's structure is simple, it is unaffected by period, and it can achieve zero residual decomposition for drivers of environmental impact (Ang, 2004). As a result, we used the IPAT equation, Kaya identity, and LMDI decomposition approach to estimate the effect of population size, economic growth, and technology level on CFP change. Furthermore, we used the Maxwell triangle for a spatial display to reveal the spatial distribution pattern of the relative contribution of the three factors on CFP.

First, according to the Kaya identity, the IPAT equation of CFP was built as follows:

$$CFP = P \times \frac{G}{P} \times \frac{CFP}{G} = P \times A \times T \tag{2}$$

where *P* is the population, *G* is the GDP, the ratio of *G* and *P* is the affluence (Liang et al., 2022), and the ratio of *CFP* and *G* reflects the technology (Chen et al., 2020a).

Second, the LMDI decomposition approach was used to calculate the contribution of drivers to CFP change. We set the CFP of the reporting period and the base period as CFP^T and CFP^0, respectively. The change of CFP ($\triangle CFP$) between the reporting period and the base period can be decomposed into three effects, i.e., population effect ($\triangle CFP_P$), affluence effect ($\triangle CFP_A$), and technology effect ($\triangle CFP_T$), as follows:

$$\Delta CFP = CFP^t - CFP^0 = \Delta CFP_P + \Delta CFP_A + \Delta CFP_T \tag{3}$$

$$\Delta CFP_P = \frac{CFP^t - CFP^0}{\ln(CFP^t) - \ln(CFP^0)} \times \ln\left(\frac{P^t}{P^0}\right) \tag{4}$$

$$\Delta CFP_A = \frac{CFP^t - CFP^0}{\ln(CFP^t) - \ln(CFP^0)} \times \ln\left(\frac{A^t}{A^0}\right) \tag{5}$$

$$\Delta CFP_T = \frac{CFP^t - CFP^0}{\ln(CFP^t) - \ln(CFP^0)} \times \ln\left(\frac{T^t}{T^0}\right) \tag{6}$$

Finally, to reveal the relative contribution of three drivers on CFP in space by the Maxwell triangle, the following equation was constructed with reference (Liu et al., 2019):

$$Contr.\ P = \frac{|\Delta CFP_P|}{|\Delta CFP_P| + |\Delta CFP_A| + |\Delta CFP_T|} \times 100\% \tag{7}$$

$$Contr.\ A = \frac{|\Delta CFP_A|}{|\Delta CFP_P| + |\Delta CFP_A| + |\Delta CFP_T|} \times 100\% \tag{8}$$

$$Contr.\ T = \frac{|\Delta CFP_T|}{|\Delta CFP_P| + |\Delta CFP_A| + |\Delta CFP_T|} \times 100\% \tag{9}$$

where *Contr. P, Contr. A*, and *Contr. T* is the percent contributions of CFP change caused by P, A, and T, respectively, were determined as proportions between the $\triangle CFP_P$, $\triangle CFP_A$, $\triangle CFP_T$ and the sum of their absolute values.

2.3.2. Panel model and panel quantile regression method

The IPAT equation is widely used, but it has some limitations. Most importantly, non-monotonic and non-proportional changes in the influencing factors are not permitted (Wu et al., 2021). According to existing research findings, reasonable population density is beneficial to improving production efficiency and promoting carbon mitigation, whereas excessive population density causes urban congestion and other urban diseases, which negatively impact climate change mitigation. Dietz and Rosa (Dietz & Rosa, 1994) created the STIRPAT model by redeveloping the IPAT equation into a stochastic form. The STIRPAT model is expressed as follows:

$$I_{it} = a \cdot P_{it}^b \cdot A_{it}^c \cdot T_{it}^d \cdot e_{it} \tag{10}$$

where *a* denotes the constant coefficient; *b, c*, and *d* reflect the underestimated parameters, and *e* is the error term; when the values of *a, b, c, d, e* are all equal to 1, the STIRPAT model will change to the IPAT identity. After taking log, Eq. (10) can be transformed into:

$$lnI_{it} = lna + blnP_{it} + clnA_{it} + dlnT_{it} + lne_{it} \tag{11}$$

The STIRPAT model not only allows for the estimation of each coefficient as a parameter but also for an appropriate decomposition of each driver, which means that new drivers can be added to the STIRPAT framework based on the characteristics of each study. To meet our research needs, the STIRPAT theoretical model is extended in this study based on previous literature references.

To begin, while population density regulation is an effective technical means of mitigating carbon, urban expansion will have an impact on vegetation carbon sequestration. As a result, we substituted population density for population size, and urban expansion was included as an explanatory variable. Simultaneously, to test the super-linear relationship between population density and CFP, we included the quadratic term of population density in the explanatory variables. We also substituted carbon emission intensity for the technology effect in Eq. (2) as explanatory variables. Carbon emission intensity, as a mandatory index for China to realize the “double carbon strategy” (He, 2015; Normile, 2020; Pan et al., 2022), can more directly reflect China’s economic decarbonization efforts. The model is built as follows:

$$lnCFP_{it} = \beta_1 lnPd_{it} + \beta_2 (lnPd_{it})^2 + \beta_3 lnU_{it} + \beta_4 lnA_{it} + \beta_5 lnCi_{it} + \mu_i + \varepsilon_i \tag{12}$$

where CFP_{it} represents the CFP of the city i in year t, where i denotes the city and t is the year; Pd denotes the population density; U is the urban (or impermeable surfaces) area; Ci stands the carbon emissions intensity, i.e., the ratio of carbon emissions and GDP (Acheampong & Boateng, 2019); β_1-β_5 are estimated parameters; μ_i is unobservable individual effect; ε_i is a random disturbance term.

General panel regression is based on the principle of ordinary least squares (OLS) estimation, and its essence is conditional mean reversion. When the random error terms of the regression conform to the classical econometric assumptions of normal distribution, zero mean, and homogeneous variance, OLS satisfies the unbiased estimation condition of minimum variance. When there is spatiotemporal heterogeneity in variables, the data are prone to peak values, heteroscedasticity, and data at both ends deviate from the large non-normal distribution, which is easily ignored in the process of OLS estimation, resulting in biased estimation. As a result, before tackling the panel model, we ran a descriptive test on the data (see Fig.S1 in Supplementary Materials). First, the results suggest that our data is short panel data. Second, the results of correlation analysis showed that lnCFP was significantly negatively correlated with lnPd, and positively correlated with other explanatory variables. lnCi was negatively correlated with lnA and lnPd, and positively correlated with lnU. lnPd was significantly negatively correlated with its quadratic term and lnU. There is an insignificant collinearity issue among the explanatory variables in Eq. (12), where the mean value of the variance inflation factor (VIF) of explanatory variables is 3.79. Furthermore, most variables in this study do not have a normal distribution.

We choose the panel quantile regression approach to solve Eq. (12). The panel quantile regression tries to quantify the amount to which the primary contributing factors impact CFP in cities at various phases of development and levels of CFP. When the data distribution is non-normal or the regression coefficient varies considerably across quantiles, quantile regression can capture the degree of effect of the explained variable at multiple quantile levels, making the estimation result more robust. This research employed a panel quantile regression with fixed effects. The regression findings are not subject to outliers and can cover individual heterogeneity more fully. The following are the particular expressions:

$$Quant_{y_i}(\theta_k | x_{it}) = \alpha_i + \beta x_{it}^{'} + \left(\delta_i + z_{it}^{'}\gamma\right) q(\theta_k) \tag{13}$$

where y_i is the explained variable, i.e., lnCFP_i; $Quant_{yi}$ (θ_k |x_{it}) is the CFP in θ-th quantile; x_{it} represents the explaining variable; (δ_i+z_{it}’ γ) is the scale coefficient, denotes the fixed effect of quantile “i” over the cross-sectional units “t". In Eq. (13), (δ_i+z_{it}’ γ>)=1, and the (α, β, δ, and γ) should be investigated. (α_i, δ_i), $i = 1, \ldots$ n, denotes the individual fixed effect i, and z is the vector of k element explained by x, differentiates element i explained by:

$$z_i = z_i, \ (x), \ i = 1, \ \ldots, \ k \tag{14}$$

For any fixed i. x_{it} generates a similar and independent distribution and is independent in t. Similarly, $q(\theta_k)$ is independently and identically along t among the units (i) and is unrelated to x_{it}, and more information can be found in Machado et al. (2019).

3. Results

3.1. Spatial and temporal characteristics of CFP

The disparity in growth rates between CF and VCS is depicted in Fig. 1, and the growth rates of CF and VCS are depicted in Fig.S2 and Fig. S3 in Supplementary Materials. VCS in 370 cities has grown at a 15% average rate over the last 20 years, much slower than CF (358%). Overall, the western part of the Hu-Line has seen rapid growth in CF and VCS, primarily in North China (Fig. 1e) and Northwest China (Fig. 1f). The northeast region experienced relatively high VCS improvement but low CF growth. Southwest China (Fig. 1g), East China (Fig. 1h), and South China (Fig. 1i) are all exhibiting high CF growth but low VCS improvement.

The ecological construction of “two barriers and three belts” in China has yielded some achievements. Fig. 1b depicts rapid VCS improvement in the ecological belt of Northeast Forest, the ecological belt of Northern Desert, northeast of the ecological barrier of Qinghai-Tibet Plateau, northern of the ecological barrier of Sichuan-Yunnan - Loess Plateau, and west of the ecological belt of Southern Hill and Mountain. The VCS in the ecological belt of the Northern Desert has a reasonably high growth rate of more than 15% (Fig.S3). The ecological belt of Southern Hill and Mountain is growing at a slower rate, less than 15%.

The growth rates of CF and CVS in urban agglomeration are heterogeneous (Fig. 1c). With the rapid growth of CF in the northern urban agglomerations, CVS has also greatly improved, i.e., the northern part of Beijing-Tianjin-Hebei, Hohhot-Baotou-Ordos-Yulin, Ningxia along the Yellow River, and Lanzhou-Xining. The urban agglomerations of the Yangtze River Delta, middle reaches of the Yangtze River, Central Yunnan, and the Beibu Gulf have higher CF growth and lower CVS improvement, which is mainly distributed in the south of China.

Fig. 2 depicts the CFP characteristic in 370 cities over cross past 20 years. The CFP of all cities increased with time. In 2005 and 2010, the CFP increased dramatically. Under the strain of economic growth during the transitional era of the two Five-year Plans, CF climbed dramatically, as did the CFP. A similar occurrence did not occur in 2015 because, in 2014, under the effect of environmental quality being included in the assessment system for government officials, local governments began to execute green and high-quality development. Cities with higher CFP are mostly located in eastern China, whereas CFP in northeast, southwest, and northwest China is comparatively low. Spatially, more than 30% of cities have a CFP greater than 0.6 in the year 2000, with the majority of them concentrated in northern China. This percentage rises to 50% in the year 2019 and is mostly distributed in China’s urban agglomerations. This suggests that the imbalance between regional anthropogenic carbon emissions and vegetation carbon sequestration is being exacerbated by China’s development in urban agglomerations.

The above results revealed the spatial and temporal characteristics of CFP and emphasized China’s efforts in ecological construction to mitigate climate change. However, in comparison to the rise in anthropogenic carbon emissions, the increase in vegetation carbon absorption supplied by ecological construction is insufficient. As a result, it is critical to further reveal the drivers causing CFP variations and to emphasize regional disparities.

3.2. Reveal the technological negative effect on CFP rise

The IPAT equation, Kaya identity, and LMDI decomposition approach were utilized to further reveal the drivers of CFP variations from 2000 to 2019, and the findings are displayed in Fig. 3. Overall, technological progress has helped to mitigate the rise in CFP induced by affluence and population development. Technological progress has mitigated the growth of CFP induced by affluence by more than 21%, 17%, 0.2%, 2%, 18%, 41%, and 55% in North China, Northeast China, East China, Middle China, Southwest China, Northwest China, and Hong Kong, Macao, and Taiwan, respectively. Population-induced CFP

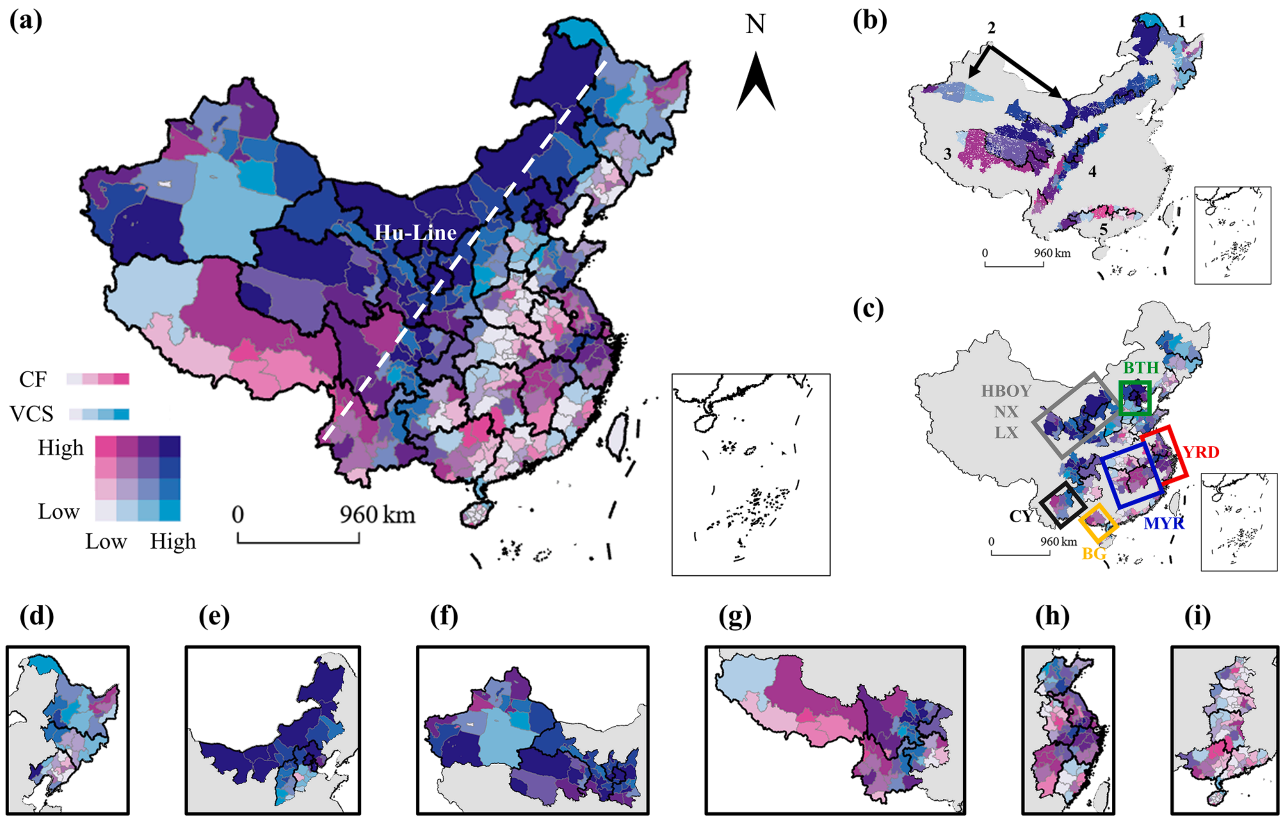

Fig. 1. Growth rates of carbon footprint (CF) and vegetation carbon sequestration (VCS) around Chinese 370 cities from 2000 to 2019. This figure reflects the growth rates of anthropogenic carbon emissions and vegetation carbon sequestration. **(a)**, as shown in the legend: the light color in the lower-left corner to the dark color in the upper-right corner reflects the growth rate of CF and VCS from low to high; the color in the upper-left corner reflects high CF growth and low VCS growth; the color in the lower-right corner reflects low CF growth and high VCS growth. The white dashed line symbolizes the Hu-Line. **(b)** depicts the growth rates of CF and VCS in China's "two barriers and three belts" ecological construction zone: 1 represents the ecological belt of Northeast Forest; 2 represents the ecological belt of Northern Desert; 3 represents the ecological barrier of Qinghai-Tibet Plateau; 4 represents the ecological barrier of Sichuan-Yunnan - Loess Plateau; 5 represents the ecological belt of Southern Hill and Mountain. **(c)** depicts the growth rates of CF and VCS in major urban agglomerations in China, while the urban agglomerations we focus on are marked with rectangular borders: BTH is the Beijing-Tianjin-Hebei; HBOY is the Hohhot-Baotou-Ordos-Yulin; NX is the Ningxia along the Yellow River; LX is the Lanzhou-Xining; YRD is the Yangtze River Delta; MYR is the middle reaches of Yangtze River; CY is the Central Yunnan; BG is the Beibu Gulf. **(d)**—**(i)** represent the growth rates of CF and VCS in Northeast China, North China, Northwest China, Southwest China, Eastern China, and Middle China, respectively. Considering the small area of Hong Kong and Macao and the lack of implementation of national policies in Taiwan, these three regions were not focused on in this study.

increases were suppressed by technological progress by more than 48%, 175%, 0.6%, 4%, 2690%, 92%, and 146%, respectively. It can be seen that the impact of technology on East and Middle China is minimal. In total, technological effect prevents 28% of the positive effect of affluence on CFP rising or 75% of the positive effect of population, implying that advancing technology to improve efficiency remains China's main current pathway to mitigate climate change.

Spatially, the Maxwell triangle reflects the respective contributions in space of these three drivers to the impact of CFP (Fig. 4). According to the finding, thriving affluence has the greatest impact on CFP in most cities in eastern China. Population effect is the primary engine of cities such as Beijing, Tianjin, the Yangtze River Delta, and the Pearl River Delta, and some provincial capitals, e.g., Taiyuan, Zhengzhou, Xi'an, Chengdu, Wuhan, Nanchang, and Guiyang. The CFP in the western region is more driven by technological effects. Because human activities are banned in three cities in western Qinghai, where the National Nature Reserve of three river source regions is located, the CFP is very vulnerable to fluctuations in population size. In general, the effects of technology, affluence, and population on CFP exhibit obvious regional variability, emphasizing that distinct policy responses are required to mitigate environmental burdens and ensure sustainable development.

The above findings emphasized the critical role of technological effects in mitigating the rise in CFP and highlight spatial differences in drivers across 370 Chinese cities. The prominent contribution of population clustering to the rise in CFP in provincial capitals, particularly in urban agglomerations, emphasizes the importance of understanding the impact of population on CFP and investigating the potential impact of population density regulation on CFP.

3.3. Reveal the effect of population density on CFP

In this section, considering the potential interaction between drivers, a unified framework is constructed for a panel data model, including carbon intensity, population density, affluence, and building area, to reveal the potential impact of population density on CFP, and the results are shown in Table 1. The specific cities and spatial distribution of each quantile are shown in Supplementary Materials Fig. S6, and the cities with higher quantiles are mainly concentrated in China's eastern coastal areas and urban agglomerations as well as provincial capitals.

First, at the 1% confidence level, the elasticity coefficient of the influence of population density on CFP is positive and substantial, showing that population clustering plays a role in supporting CFP rise. The positive impact of population density on CFP is more pronounced in low-quantile cities than in intermediate and high-quantile cities. This means that as the population clustering, so will change energy usage and transportation mode, lowering the marginal emission reduction cost through the scale effect and mitigating CFP (Krausmann et al., 2008; Rahman, 2017; Timmons et al., 2016).

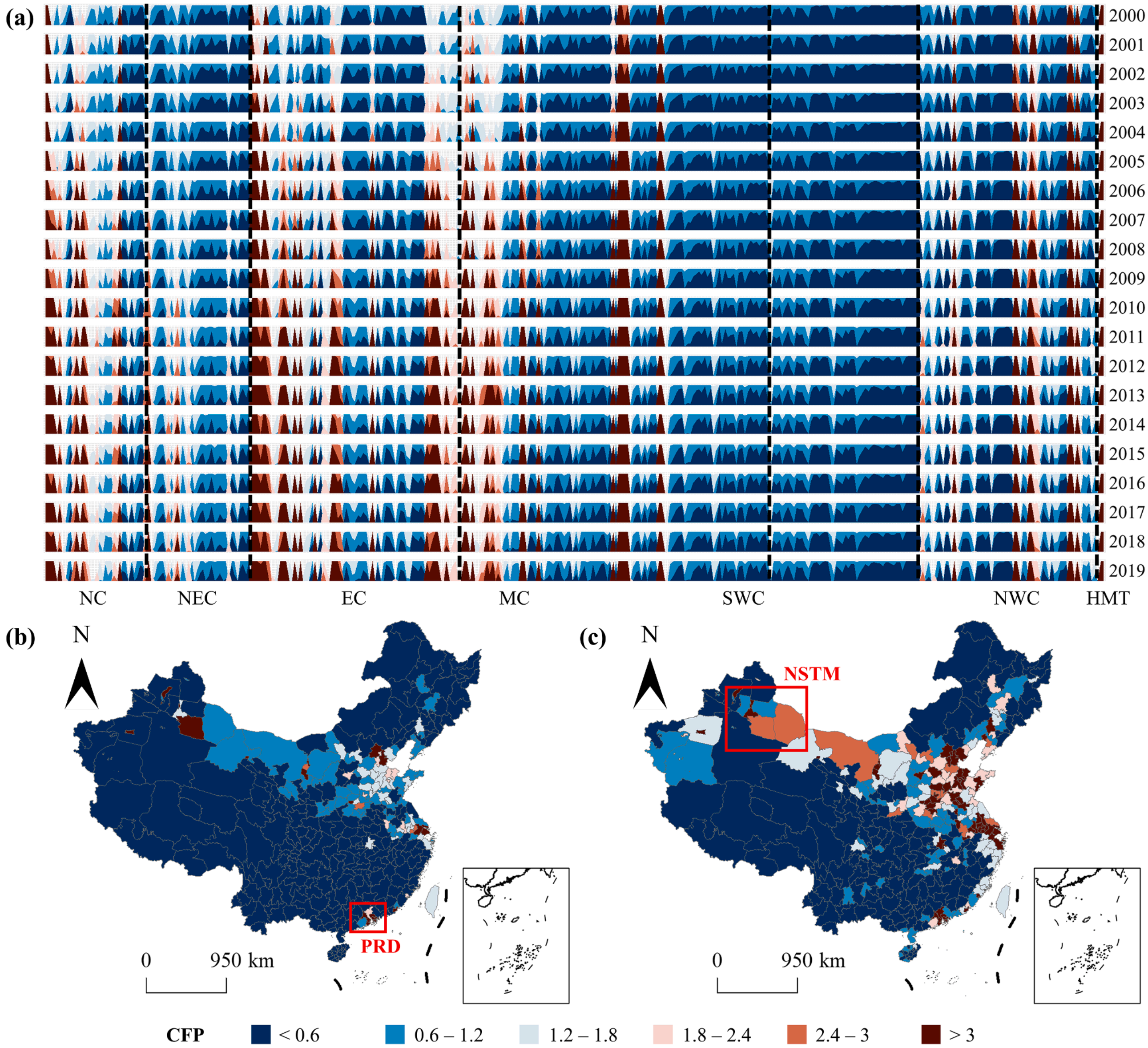

Fig. 2. Temporal (a) and spatial (b and c) characteristics of CFP in Chinese 370 cities from 2000 to 2019. **(a)**, the abscissa of the figure is the cities included in North China (NC), Northeast China (NEC), Eastern China (EC), Middle China (MC), Southwest China (SWC), Northwest China (NWC), and Hong Kong. Macao and Taiwan (HMT) (see Supplementary Materials Table S1), and the ordinate is from 2000 to 2019 from top to bottom. Each peak represents a city whose color reflects its CFP, corresponding to the legend at the bottom. Peak height represents the relative size of its CFP in legend classification, and peaks higher than 0.75 times the mean CFP (2.35) are cut off. (b) and (c) are the spatial characteristics of CFP in Chinese 370 cities in 2000 and 2019, respectively. PRD and NSTM are the urban agglomerations of the Pearl River Delta and the northern slope of the Tianshan Mountains, respectively, which are not highlighted in Fig. 1c.

Second, CFP and population density have a nonlinear connection. The quadratic term of population density is negative and substantial between 0.1 to 0.6 quantiles. In the middle and bottom quintile cities, the data reveal a classic inverted "U" curve connection between population density and CFP. When population density exceeds a certain level, the population size scale effect can significantly mitigate CFP. However, the elasticity coefficient of the quadratic component of population density is not significant in the high-quantile cities, indicating that an "N" -shaped curve connection may exist. Excessive human density encourages industrial growth, urban expansion, and urban congestion, increases carbon emissions, diminishes carbon storage by plants, and supports the rise of CFP.

Third, as a mechanism of managing population density, it directly erodes vegetative carbon sequestration while encouraging urban expansion, resulting in a positive influence on CFP increase that is significant at the 1% confidence level for all quantiles. The elasticity coefficient of urban expansion is relatively small in the high-quantile cities because cities with high CFP tend to have high impervious land coverage, and in recent years, urban greening has been in full swing, which mitigates the growth of CFP to some extent (Brilli et al., 2022).

Fourth, the growth in carbon intensity drives the rise in CFP and has a greater influence than other social determinants, as previously found (Brizga et al., 2013; Liang et al., 2022). It suggests that, in addition to managing population density, it is vital to enhance production efficiency to decrease carbon emission intensity. The positive effect of affluence on the rise of CFP is second only to carbon emission intensity at the quantiles from 0.1 to 0.8, and as the quantile increases, the elasticity coefficient gradually decreases, indicating that the scale economy effect generated by economic activity clustering can effectively mitigate carbon, and thus mitigating CFP (Ahmad et al., 2021). Unfortunately, at the 0.9 quantiles, the elasticity coefficient of urban expansion is greater than that of affluence, suggesting that there may be a nonlinear link between

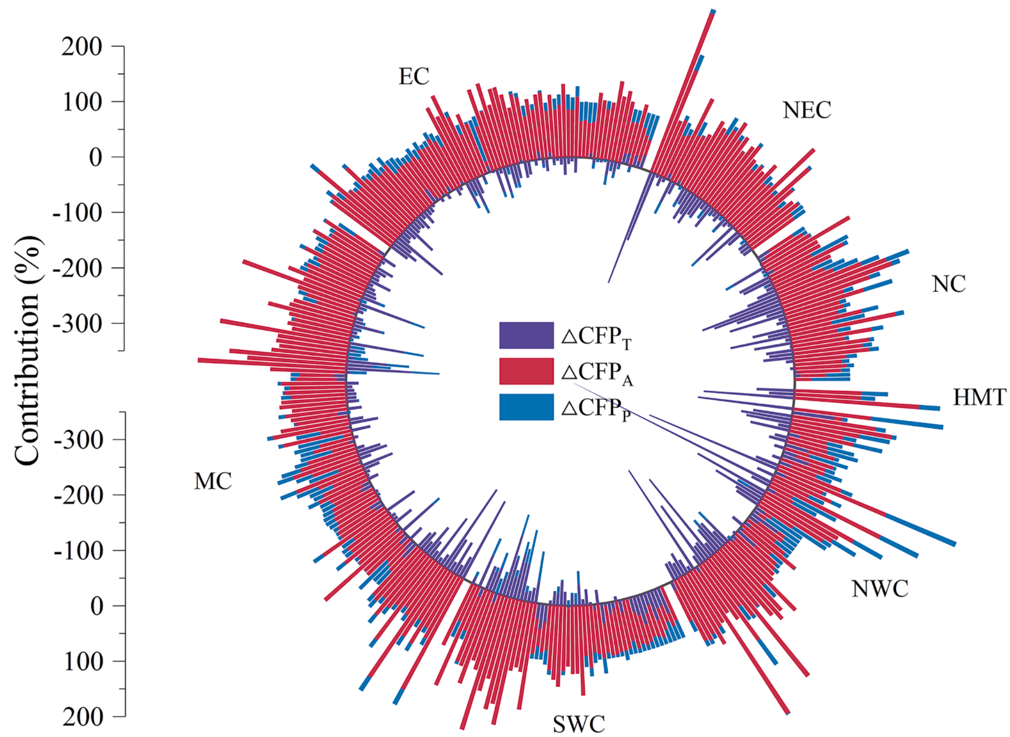

Fig. 3. Contributions of technological effect (△CFP$_T$), affluence effect (△CFP$_A$), and population effect (△CFP$_P$) on CFP change in Chinese 370 cities from 2000 to 2019.

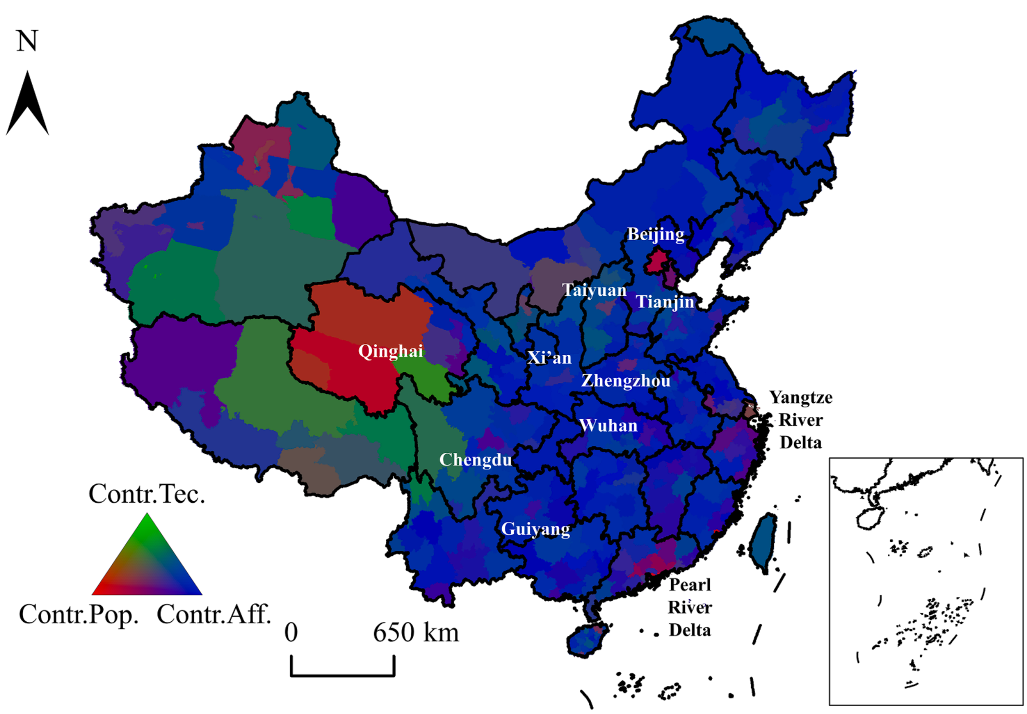

Fig. 4. Spatial distribution of contributions of technology (Contr. Tec.), affluence (Contr. Aff.), and population (Contr. Pop.) to change in CFP from 2000 to 2019 (see Eq. (7)-(9)).

affluence and CFP, which has been validated in the research of affluence and carbon emissions (Liddle, 2015; Salman et al., 2019). Meanwhile, high-quantile cities have promoted urban expansion in recent years by building infrastructure to regulate population density, which has become the second major factor driving the rise of CFP after carbon emission intensity.

Finally, panel quantile regression coefficients are comparable to individual fixed effect regression results. The difference is that the quadratic term of population density is significant at the 1% confidence level, which might be attributed to the data's non-normal distribution. However, the result verifies the super-linear relationship between population density and CFP, emphasizing that the influence of population

Table 1
Panel quantile regression results: Full sample cities.

Variables	Individual fixed effect	Panel quantile regression								
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
lnPd	0.874***	0.932***	0.916***	0.903***	0.891***	0.880***	0.868***	0.856***	0.840***	0.819***
	(0.018)	(0.035)	(0.028)	(0.024)	(0.021)	(0.021)	(0.023)	(0.026)	(0.033)	(0.043)
$(\ln Pd)^2$	−0.004***	−0.005*	−0.005**	−0.004**	−0.004**	−0.004**	−0.003*	−0.003	−0.002	−0.002
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
lnU	0.865***	0.894***	0.886***	0.880***	0.875***	0.869***	0.864***	0.858***	0.851***	0.842***
	(0.015)	(0.031)	(0.025)	(0.021)	(0.019)	(0.018)	(0.020)	(0.023)	(0.029)	(0.038)
lnCi	0.980***	1.006***	0.998***	0.992***	0.986***	0.981***	0.975***	0.969***	0.962***	0.952***
	(0.007)	(0.015)	(0.012)	(0.010)	(0.009)	(0.009)	(0.010)	(0.011)	(0.014)	(0.019)
lnA	0.900***	0.946***	0.930***	0.918***	0.907***	0.895***	0.884***	0.872***	0.858***	0.837***
	(0.006)	(0.012)	(0.009)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)	(0.011)	(0.015)

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. lnPd, lnU, lnTc, and lnA are the logarithm of population density, building area, carbon emission intensity, and affluence, respectively.

density on CFP has a threshold.

The above results emphasize that regulating population density through urban expansion can mitigate the rise of CFP in the middle and high quintiles, and confirm the super-linear relationship between population density and CFP in the middle and low quintiles. While regulating population density to mitigate CFP, it is more important to improve production efficiency and reduce carbon emission intensity.

4. Discussion

4.1. Drivers toward mitigating CFP

This study revealed for the first time the temporal and spatial dynamics and drivers of urban-scale CFP in China, and the positive effect of population density regulation on mitigating the imbalance between anthropogenic carbon emissions and vegetation carbon sequestration. The imbalance is widening across Chinese 370 cities during the past 20 years (see Fig. 2). In terms of the drivers of CFP, we first confirmed the positive role of ecological construction in the two screens and three belts in mitigating climate change (see Fig. 1), but it appeared insignificant in the face of large anthropogenic carbon emissions. In particular, urban agglomerations had a CFP greater than 2.4, indicating an unsustainable state of regional development (Liang et al., 2022). Although China is widely recognized as a worldwide greening hotspot (Chen et al., 2019; Xue et al., 2021), this is insufficient to mitigate climate change. This necessitates an awareness that addressing climate change necessitates structural changes in society and the economy (Mazzucato, 2022; Nahm et al., 2022); otherwise, limiting global warming to 1.5 °C would become a pipe dream (Dvorak et al., 2022; Iyer et al., 2022).

Second, in response to rising CFP, we examined the drivers of CFP change from 2000 to 2019 across 370 Chinese cities using the IPAT equation, the Kaya identity, and the LMDI decomposition approach (see Fig. 3). As previously stated (Rosa & Dietz, 2012), rising affluence is the primary driver of the rise in most urban CFP. We discovered that in most cities, population growth drives the increase in CFP, which is also consistent with previous findings (Chen et al., 2020a; Gilbert, 2009; Liang et al., 2022b). Surprisingly, population emigration keeps CFP from deteriorating in some cities. Reduced population size reduces carbon emissions while also lessening environmental impact (Zhang et al., 2022). If cultivated land is abandoned, it is replaced by grassland, shrubland, or woodland that has a higher capacity for carbon sequestration (Davidson et al., 2007; Segura et al., 2020). Regrettably, current technological levels are insufficient to mitigate climate change; the technology effect offset only 28% of the affluence effect or three-quarters of the population effect, implying that more technologies must be disclosed.

Third, high population growth in urban agglomerations and provincial capitals becomes the dominant driver in the rise in CFP. Taking into account population spatial clustering in urban agglomerations can effectively relieve the CFP around core cities and help create a scale effect to reduce carbon emissions (Lin & Zhang, 2016; O'Mahony, 2013). However, infinite population clustering is not feasible, and building expansion to avoid urban diseases will reduce regional vegetation carbon sequestration and increase climate risk. As a result, in Section 3.3, we revealed the potential effect of population density on CFP and the super-linear relationship between the two at the middle and low quantiles. The super-linear relationship between population density and carbon emission has been confirmed in the previous study (Ribeiro et al., 2019; Wang & Li, 2021). This could be because the damage to vegetation carbon sequestration caused by population density regulation is far less than the carbon reduction benefits provided by regulation. Given the limits of present technology options, we believe that differentiated population density regulation can help to further reduce anthropogenic carbon emissions while also contributing to human sustainability.

In general, our study revealed an effect of population density on CFP, which is related to but also distinct from previous research. Based on previous studies (Chen et al., 2020a; Huang et al., 2021; Liang et al., 2022, 2023), we further revealed the potential effect of population density on CFP, providing a new perspective for further mitigating the imbalance between anthropogenic carbon emissions and vegetation carbon sequestration. In contrast to prior research on the effect of population density regulation on carbon emissions (Rahman & Alam, 2021; Timmons et al., 2016), we considered the potential negative effect of population density regulation on carbon sequestration by vegetation in the framework of analysis. Specifically, we built a panel data model, using CFP as the explained variable, to reveal the potential effect of population density on the imbalance between anthropogenic carbon emissions and vegetation carbon sequestration (see Eq. (12)). We conclude that population density regulation can mitigate the imbalance, which strengthens the scientific nature of the regulation in mitigating climate change, compensates for gaps in existing literature, and addresses social concerns. More importantly, based on the panel quantile regression method (Machado et al., 2019), we provided a theoretical foundation for differentiated population density regulation strategies, which not only contributed to the formation of scale effects but also promoted carbon emissions reduction. Furthermore, we detected the beneficial effect of population increase on the degradation of CFP, which suggested that reducing population growth can ameliorate the deterioration trend of environmental impact to some extent. This coincides with previous research (Gilbert, 2009; O'Neill et al., 2012). However, we would not urge China to do so since severe aging and a low birth rate are extremely urgencies that the government must address (Han et al., 2022).

4.2. Policy implication

This study indicated that regulating population density can help to mitigate climate change, however, the panel quantile regression findings showed that population density regulation cannot be one-size-fits-all across 370 Chinese cities. Differential population density regulation is especially important in light of the present nationwide loose fertility policy. Preventing overly fast urban expansion in low-quantile cities should be a vital measure for mitigating CFP and avoiding excessive loss of vegetation carbon sequestration. Rapid population expansion in cities in high quantile should be avoided to avoid urban illnesses such as urban congestion, which contributes to increased carbon emissions (Asensio et al., 2022; Gurney et al., 2015). Currently, we are aware of certain prospective population density regulation actions in cities with high CFP that are mostly impacted by industrial transfers. For example, the movement of approximately 7000 firms out of Beijing from 2014 to 2020 greatly dilutes Beijing's population density and supplements the population of low-density cities, similar to the industrial transfers in the Yangtze River Delta and Pearl River Delta urban agglomerations. Similarly, we see several substantial population recruitment measures in low CFP cities, such as the provision of talent subsidies and lower housing costs.

In addition to population density regulation, all cities should work on carbon intensity reduction and ecological construction, which are the effective pathway to cope with severe CFP. The decrease in carbon intensity is increasingly dependent on energy and economic structural adjustments, which will shift the economy's reliance on fossil energy (Basheer et al., 2022; Fouquet, 2016; Meckling et al., 2022). For example, although the growth of the high-tech industry is dependent on electric power supplies, the consumption of fossil energy to generate electricity may be lowered further by creating clean energy such as solar energy, hydro energy, and wind energy. Although ecological construction can mitigate the increasingly severe CFP, it is insufficient when contrasted with the quicker rise of carbon emissions. The future potential of this pathway is limited by limited land area (Bastin et al., 2019). As a result, it is critical to construct an ecosystem with greater carbon sequestration capability to alleviate the pressures of economic decarbonization (Kicklighter et al., 2019; Tong et al., 2020; Wang et al., 2019), while the stability, diversity, and sustainability of the ecosystem should pay more attention to in the construction process.

4.3. Limitation

Although this study has achieved considerable advances over prior investigations, it still has certain limitations. The unique performance is in the selection of data and metrics.

First, for the selected data, carbon emission data from Chinese cities is scarce. Existing studies have used a variety of methods to decompose carbon emissions at the national or provincial scales to analyze carbon emissions at the urban scale (Chen et al., 2020b; Fang et al., 2022; Shan et al., 2022). However, due to a lack of statistical data verification support, there may be some uncertainty in the analysis results. Although the data used in this study is widely accepted (Andres et al., 2011; Oda & Maksyutov, 2011), we discovered that it has a good fitting degree with national carbon emission data from Carbon Emission Account and Datasets (CEADs) (Guan et al., 2021; Shan et al., 2018, 2020) when verified, reaching 0.998 (see Fig.S4 in Supplementary Materials), but the fitting degree at the provincial scale is only 0.617 (see Fig.S5 in Supplementary Materials). This may be related to the rasterization of ODIAC's data. This will create some uncertainty in the study's conclusion. However, after discussion, we believe that our conclusion, while not of qualitative value, is instructive to some extent.

Second, while we discovered the effect of population density regulation on CFP, the effect of population on CFP is undeniably complex. Future research can shed light on the effect of the population by taking population age structure and education level into account. The definition of the city in this study is based on the definition of "whole city" in the *China City Statistical Yearbook*, which refers to all regions within the administrative division. As a result, the issue of population urbanization is overlooked. Population urbanization affects energy structure transformation and promotes population density to enhance energy efficiency (Madlener & Sunak, 2011; Zhou et al., 2015). In addition, cities already house more than half of the global population, and this figure is expected to rise further (United Nations, 2018). Simultaneously, as the urban population grows, existing terrestrial habitats suffer and will continue to encroach by impermeable surfaces (Liu et al., 2019). Thus, it is also necessary for the future to consider the effects of population urbanization on CFP.

5. Conclusion

In this study, we first characterized the imbalance between anthropogenic carbon emissions and vegetation carbon sequestration, by investigating the spatial and temporal changes of the CFP, between 370 Chinese cities in the year 2000–2019. We discovered that anthropogenic carbon emissions were increasing far faster than carbon sequestration by vegetation, particularly in urban agglomerations. Similar performance was also reported in critical ecological constructing sites, i.e., "two barriers and three belts". We also clarified the drivers' relative contribution to CFP using the IPAT equation, Kaya identity, and the LMDI decomposition approach. Decomposition analysis indicated that the technological effect mitigated 75% or 28% of the CFP rise caused by the improvement of population or affluence, respectively. Spatially, the CFP of eastern cities was primarily influenced by affluence improvement, whereas that of urban agglomerations and provincial capital cities was primarily influenced by population clustering. Lastly, using a panel data model and a panel quantile regression approach, we clarified the effect of population density on CFP at different quantiles and confirmed the super-linear relationship between population density and CFP at the middle and low quantiles. This study emphasizes the urgent need to adopt differentiated population density regulation on city-scale to further mitigate climate change to enhance cities' sustainability while current technological progress.

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

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2023.104502.

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