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Impact of urban vitality on carbon emission—an analysis of 222 Chinese cities based on the spatial Durbin model

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Urban development is undergoing rapid growth, and the increasingly prominent environmental protection challenge underscores the crucial need to balance urban vitality development with carbon emissions for sustainable goals. how urban vitality affect carbon emissions? By collecting and analyzing data from 222 prefecture-level cities, utilizing long-time series data from 2011 to 2019, and employing Spatial Durbin Method (SDM) to study. The study explores various dimensions of urban vitality, including economic, social, and population indicators. The direct impact of economic vitality on carbon emissions is negative, while the spillover effect is significantly positive, resulting in an overall positive total effect. There are noticeable spillover effects associated with economic vitality; a rise in one city's economic vitality may result in a rise in carbon emissions in nearby prefecture-level cities. The reason behind the increase in carbon emissions in nearby metropolitan areas is the departure of some energy-intensive and highly polluting enterprises from the central sections of nearby cities. While enhancing the economic vitality of cities, it is recommended to strive for the development of a green economy, aiming for a sustainable development balance between economic growth and environmental conservation. Population vitality has a favorable impact on carbon emissions both directly and indirectly, with the direct effect being particularly significant. The population expansion of prefecture-level cities exerts a substantial influence on urban carbon emissions. Additionally, social vitality exhibits positive direct and spillover effects on carbon emissions, as well as a significant overall positive effect. Policymakers are urged to prioritize clean energy use while fostering economic growth, prevent high-polluting industries' migration to neighboring urban areas, manage population expansion, promote environmental awareness, and implement integrated urban planning through collaborative governance for sustainable development.

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Introduction

The process of urbanization (URB) holds significant and far-reaching implications for China's transformation and development. Pentland et al.'s (Balsa-Barreiro et al. 2019) research indicates a shifting focus of GDP and carbon emissions towards the east. This shift suggests that some Southeast Asian countries exhibit an economic growth pattern reliant on high resource consumption, especially notable as China, having matured economically, now demonstrates greater efficiency in resource and energy consumption. In contrast, India and other developing Asian nations are in the early stages of industrialization and are expected to continue industrializing. In addition to aggravating the urban greenhouse effect, China's current growth pattern, which is defined by high consumption and high emissions, has also led to urbanization of various quality levels. In certain regions, the emphasis on fostering urban vitality takes precedence over environmental protection, resulting in less sustainable urban development. Confronted with challenges such as prioritizing development over protection during the urbanization process (Wang et al. 2016), it becomes imperative to look into the connection between carbon emissions and urban vitality. This exploration is vital for the establishment of dynamic and sustainable urban environments.

Jacobs (1961) was the one who initially established the idea of urban vitality, signifying a city's capacity for economic and demographic dynamism. Urban vitality manifests itself in various facets of a city, rendering it a multidimensional urban phenomenon. It is a dynamic process with enduring implications for a city's overall competitiveness. Within the urban context, population, social, and economic vitality are the components that make up urban vitality. Improving the economic vitality of China's cities can depend on the growth of urban services (Long and Huang 2019). Lan et al. (2020) indicate that population inflows affect urban vitality through interactive effects with social infrastructure. The beneficial impact of fiscal expenditure on education on urban vitality will increase as the inflow of people increases.

Urban vitality is typically associated not only with economic prosperity (Ye et al. 2018; Long and Huang 2019; Lv and Wu 2020) but also with indicators such as population (Chen et al. 2019; Jiang et al. 2023) and social (Mouratidis and Poortinga 2020). Carbon emissions are frequently correlated with economic (Li and Li 2020; Mi et al. 2020; Liu et al. 2023), social (Yang et al. 2023), and population activities (Yang et al. 2015). The examination of methods to create a balance between the numerous facets of urban vitality and environmental conservation is made possible by this understanding. Such information can be a great resource for urban planning and sustainable development, helping representatives of the local government create more efficient policies and initiatives to reduce carbon emissions and enhance urban sustainability.

Current research on urban vitality and carbon emissions often predominantly explores the economic aspect (Jiang and Liu 2023), including how GDP and per capita GDP growth affect carbon emissions.. However, it's important to recognize that the economic aspect is just one dimension of urban vitality (He et al. 2018). Very little research investigate how urban vitality affect carbon emission. From a rural standpoint, Zhu et al. (2022) examine the connection between urban vibrancy and carbon emissions. Previous research has typically not explored this relationship at the city level, despite cities being significant contributors to emissions. The ability of cities, as major emission sources, to achieve low-carbon sustainable development is crucial for society as a whole to meet its low-carbon sustainability goals (Tan et al. 2017; Pan et al. 2022). Additionally, this study goes beyond examining short-term impacts and investigates the influence on carbon emissions over a longer time period using time-series data. Analyzing historical data allows for the identification of evolutionary trends, providing valuable insights to inform future decision-making.

Local emissions of pollutants can impact the air quality in neighboring regions. Pollutants can spread and accelerate their diffusion with changes in wind direction and speed (Shan et al. 2023). Xia et al. (2022) found: 1) Fiscal imbalance, from income dispersion, reduced emissions, while expenditure asymmetry hindered control. 2) Central fiscal transfers mitigated fiscal imbalance effects. Fiscal decentralization led to regional budget disparities but influenced local governments' emission control via central transfers, curbing pollution. 3) Fiscal decentralization's impact on emissions depends on industrial structure, showing a U-shaped effect due to intertemporal industrial adjustments. Initial stages saw reduced coal demand and emissions, but increased secondary sector share correlated with higher emissions.

At different scales, research outcomes and patterns may exhibit variations. For instance, in order to prevent inaccurate findings and/or erroneous conclusions, assessments of the spatial dynamics of society related wealth distribution and interpersonal relationships must be carried out within proper circumstances. Analysis of biased data may result in the adoption of brittle and ineffective decision-making procedures (Balsa-Barreiro et al. 2022). Currently, urban vitality is predominantly studied at the national and village scales, with a lack of research at the urban scale. China's 222 prefecture-level cities are selected as the study region based on this gap.

The chosen variables hold high representativeness in their respective domains. The ability and potential of cities to experience economic growth through the stages of urban development is referred to as economic vitality. (Jin 2007). Some scholars employ GDP (Z. Li et al. 2021), fixed assets, and per capita disposable income as indicators. Population vitality, in this context, refers to the potential provided by the population for urban development. Some scholars use population size and education expenditure as indicators (Z. Li et al. 2021). The ability to guarantee social progress and equity is referred to as social vitality. The general public budget primarily consists of fiscal revenue, allocated for ensuring and improving people's livelihoods, promoting economic and social development, maintaining national security, and ensuring the normal operation of national institutions. The Gini coefficient reveals social vitality from the perspective of social equity, hence its inclusion in the indicators of social vitality.

The selected variables are widely recognized and used indicators in existing literature, which effectively reflect the different dimensions of vitality that our research focuses on. While our data source offers a variety of economic, demographic, and social indicators, our study necessitates selecting variables that exhibit completeness and consistency over the time series. This ensures the reliability and validity of our analysis results while minimizing biases due to data gaps or inconsistencies.

In constructing a model, including too many variables may lead to an overly complex model that is difficult to interpret. Therefore, we adhered to a simplification principle in our variable selection to ensure the model's high interpretability and practicality.

In contrast, this study looks into how different dimensions of urban vitality affect carbon emissions and provides information on how things stand right now with regard to the impact mechanism. The research scope encompasses 222 prefecture-level cities, where multidimensional urban vitality indicators are constructed. Furthermore, the study examines the effects of vitality on carbon emissions within cities, considering both direct and spillover effects. The research aims to investigate the following questions: (1) How much do different aspects of urban vitality—economic, population, and social—affect carbon emissions? (2) Does a city's urban vitality—that is, its population, economy, and social life—have an impact on the carbon emissions of nearby cities? (3) How much of an influence do the carbon emissions of one city have on the emissions of nearby cities? The remaining portions of this study are arranged as follows: The literature review and research hypothesis are presented in Section 2; the research approach is explained in Section 3; the estimated results are reported in Section 4; and the discussed in Section 5. The conclusion and recommendations for policy are given in Section 6.

Literature review and research hypothesis

Notably, while most existing studies predominantly explore the economic aspect's impact on carbon emissions (Mi et al. 2020; Huo and Chen 2022; Liu et al. 2023), with few delving into the perspective of urban vitality, which represents just one facet of urban vitality, this study extends its investigation to assess the impact of urban vitality across multiple dimensions. It looks at how various aspects of urban vitality affect carbon emissions and clarifies the state of affairs within the impact mechanism.

Zhu et al. (2022) visualized the geographic distribution of communities with multiple uses based on sustainability, carbon emissions, and mixed-use vibrancy using analytical tools like the Geographic Information System (GIS) and Statistical Information Grid (STiNG). They provide an insightful viewpoint on the sustainable growth of rural mixed-use communities.

Urban vitality's effect on carbon emissions depends on a number of variables, including demographic and economic vitality. (Jin et al. 2017; Huang et al. 2020; Tu et al. 2020; Dong et al. 2021). The choice of indicators for each of these facets exerts distinct influences on carbon emissions. Notably, research has established that human-induced carbon dioxide emissions result in global warming. There is a trend toward higher per capita carbon dioxide emissions associated with urbanization, which is somewhat offset by unemployment. (Wang and Li 2021). As GDP per capita rises, there is a decreasing effect on CO_2 per capita. With increasing levels of aging population and length of life, respectively, the mitigating effects on CO_2 per capita become more pronounced. Additionally, when population density rises, there is less of an inhibitory effect on CO_2 per capita. It is worth noting that while economic growth in cities often coincides with heightened commercial and industrial activities, it can also result in increased carbon emissions. Nevertheless, cities have the capacity to implement policies conducive to fostering low-carbon economic growth, such as the promotion of clean energy adoption and the utilization of green technologies.

Asumadu-Sarkodie and Owusu (2016) conducted an investigation spanning the years 1971 to 2013 in Ghana. They find 21% of forthcoming shocks to CO_2 emissions can be attributed to fluctuations in energy usage, 8% to variations in GDP, and 6% to fluctuations in population. In terms of long-run elasticities, the study suggests that for every 1% increase in Ghana's population, there will be a corresponding 1.72% increase in CO_2 emissions.

Since the initiation of economic reforms and opening up in China, a substantial portion of fixed asset investments has been allocated to infrastructure development, stimulating economic growth. However, this has coincided with a persistent surge in the demand for fossil fuels, consequently leading to an escalation in carbon emissions. Researchers (Wang and Li 2021) have discovered Fixed asset investments in the secondary and tertiary industries are causally related to their carbon emissions in both directions. Furthermore, while environmental conditions already worsen due to rising energy consumption, they are made worse by economic expansion. On the other hand, whereas short-term population growth in urban areas results in higher carbon dioxide emissions, urbanization ultimately improves environmental conditions (Nurgazina et al. 2022).

Pata et al. (2023) Using quarterly data from 2001 to 2019 reveals 'that technology emerges as the most crucial predictive factor for carbon emissions, while energy from renewable sources have a significant impact on their ecological footprint.. Research has explored strategies for decoupling economic growth from carbon emissions. Erdogan et al. (2024) indicate that both China and India have sacrificed substantial environmental quality to achieve a 1% increase in per capita income. Moreover, compared to China, India incurs a higher ecological cost for enhancing economic welfare.

Hypothesis 1. The direct effect of economic vitality on carbon emissions is negative, and the spillover effect is significantly positive.

Hypothesis 2. Both the direct and indirect effects of population vitality on carbon emissions are positive, and the direct effect is significant.

Huo and Chen (2022) undertook an investigation into the influence of provincial income disparity on carbon emissions in China. They calculated the Gini coefficients of residents' incomes in different regions of China for the period spanning 2010 to 2019. The established criterion is consistent with the disposable income per capita of the population. The study's conclusions provide the following insights: Whereas the expanding income inequality in high-income areas has a dampening effect on the growth in carbon emission intensity, income disparity in economically disadvantaged areas shows a positive link with carbon emission intensity. Consequently, they propose policy recommendations aimed at narrowing income disparities and mitigating carbon emission intensity. Kartal et al. (2024) indicate that coal usage significantly impacts CO2 emissions in both China and India, with a causal effect observed between coal usage and CO2 emissions.

Yang et al. (2023) developed a system for evaluating urban vitality that takes into account four important factors: social, economic, cultural, and environmental. It investigated, at the intra-city grid size, the connection between carbon emissions and urban vitality, offering a theoretical foundation for intracity growth. Ulussever et al. (2023) utilized monthly data from January 2000 to December 2021 and deployed a novel quantile-based approach. Results reveal that increases in income, total energy consumption, and energy price index generally have detrimental effects on the environment in Gulf Cooperation Council (GCC) countries. However, political risk index, crude oil prices, and geopolitical risk exhibit mixed effects. Pata et al. (2023) found that: Renewable energy improves environmental quality; Trade openness stimulates environmental quality in the long term; over time, economic expansion and globalization have a negative impact on environmental quality..

Hypothesis 3. The direct effect and spillover effect of social vitality on carbon emissions are both positive, and the total effect is also significantly positive.

In summary, there are many variables that influence the complex link between carbon emissions and urban vitality. Urban policy and planning decisions hold the key to striking a harmonious equilibrium between fostering urban vitality and achieving carbon emission reduction, thereby fostering sustainable urban development.

Research on how urban vitality affects carbon emissions is still scarce. 1) Current research on the impact of carbon emissions tends to focus mainly on the influence of economic vitality,

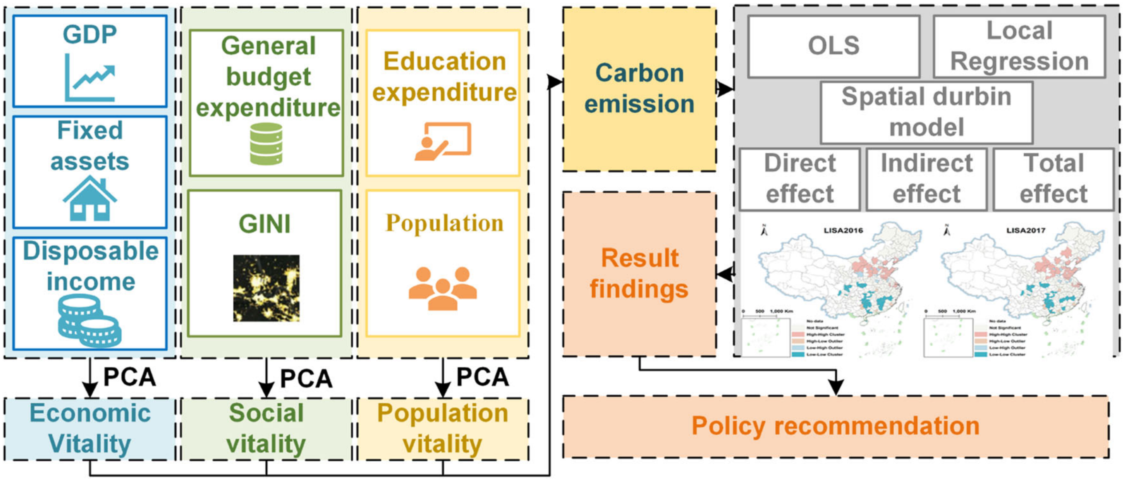

Fig. 1 Research framework.

neglecting a comprehensive exploration from the perspective of urban vitality. A more holistic framework is proposed for evaluation. 2) Existing studies predominantly examine either at the macro level (national) or the micro level (rural), while the meso level (urban) has been scarcely explored. Investigating cities as a unit holds greater exploratory value. 3) While some research has attempted to investigate how urban vitality affects carbon emissions, they often remain qualitative. This approach involves quantitative analysis using long-term data, enhancing the persuasiveness and representativeness of the results.

Method

SDM is utilized to explore the impact of urban vitality on carbon emissions using 222 prefecture-level cities in China. The overall framework is shown in Fig. 1, 1) we first organize and summarize and calculate vitality index; (2) view the global as well as local spatial autocorrelation situation; and (3) choose the best model to inspect the their relationship by using the Ordinary Least Squares (OLS) model and a correlation test.

Model specification. To address the aforementioned scientific inquiries, this study employs a combination of methods, including global spatial autocorrelation, OLS and spatial Durbin modeling. The selection of the OLS model was conducted to test for the presence of multicollinearity among variables. The presence of multicollinearity may lead to biased results. However, our primary focus remains on the SDM. The testing results are imperative as they demonstrate the suitability of our model. Therefore, the OLS model serves as a crucial preliminary step in our analysis. SDM is capable of capturing the interactions and dependencies between the dependent variable and neighboring units in space, thereby modeling the data more accurately (Anselin 2013). SDM allows the inclusion of spatial lag terms of the dependent variable in the model, which helps capture the spatial autocorrelation of the dependent variable (Elhorst 2014). When spatial correlation exists, estimating with SDM is more accurate than models that ignore spatial dependency, enhancing the effectiveness and significance of parameter estimation. SDM is particularly suitable for studies in geography, economics, and other fields where spatial factors significantly influence the data. Additionally, the effect of urban vitality on carbon emissions and its spatial spillover effects are examined. As asserted by Goodchild et al. (1992), spatial autocorrelation is a characteristic inherent in nearly all data. It measures the degree to which an attribute's values in one region are correlated with those of the same attribute in the region's surrounding regions. The investigation of geographical data distribution patterns across the entire system is made possible by global spatial autocorrelation, which sheds light on the typical spatial correlation of processes or entities. Local spatial correlation, conversely, delves into the distribution characteristics within local subsystems. It distinguishes between observations with high and low values and pinpoints the areas that are most responsible for the overall spatial autocorrelation. All while taking into account the geographic distance matrix, as spatial correlation analysis serves as the foundation for spatial econometric analysis. These early evaluations serve as important foundational work before the spatial econometric model is presented. Equations (1) and (2) are given as the equations for the global Moran's I (Anselin 1988):

$$Moran'sI = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{s^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij})} \tag{1}$$

$$s^2 = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \bar{Y})^2,\ \bar{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i \tag{2}$$

The attribute value of area i is represented by Y_i in the supplied equations, where n denotes the total number of regions. The spatial weight matrix is represented by the variable w_{ij}, where $I > 0$ suggests a favorable relationship and $I < 0$ indicates an inverse relationship. Notably, when $-1 < I < 1$, it denotes a correlation that is not zero. The foundation for building spatial models is the spatial weight matrix ($W = \left[W_{ij}\right]_{n\times n}$), which is spatial economic distance matrix. While the 0–1 adjacency matrix is a commonly used tool for analyzing spatial spillover effects, it possesses certain limitations. Specifically, the correlation between spatial units hinges on their adjacency status, imposing regional constraints. Additionally, it assumes uniform interaction levels among adjacent spatial units. However, in the context of economic activity, urban dynamism may extend beyond immediate neighborhoods. Consequently, it is chosen to employ a geographic distance matrix for spatial statistical analysis, offering a more comprehensive perspective on spatial relationships.

OLS regression is used to test for the presence of collinearity in variables. The OLS regression model is used for conducting a global regression analysis (Kutner et al. 2004). The OLS formula, represented by Eq. (3), includes the dependent variable y_i, the ith independent variable x_{ik}, the estimated coefficient a_k that corresponds to it, and the residual error ε.

$$y_i = a_0 + \sum_k a_k x_{ik} + \varepsilon \tag{3}$$

The Variance Inflation Factor (VIF) is used to measure the collinearity between the elements. Typically, a VIF exceeding 10 suggests that the regression model is afflicted with severe multicollinearity.

In addition, spatial regression models are chosen for further explanation. The SDM, Spatial Error Model (SEM), and Spatial Lag Model (SLM) are examples of frequently used spatial models. The Spatial AutoreRressive model (SAR), which is also known as the SLM, is especially well-suited to capturing spontaneous spatial interactions between variables that are dependent, emphasizing the spatial spillover effects that these variables display (Wu et al. 2021; Yang et al. 2022). This model's formulation can be written as follows in Eq. (4).

$$Y_{it} = \rho \sum_{j=1}^{N} W_{ij} Y_{it} + \beta X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{4}$$

In the equation, i represents spatial units, ranging from 1 to N, and t represents temporal dimensions (periods), ranging from 1 to t. Y_{it} stands for the dependent variable, while $\rho\sum_{j=1}^{N} W_{ij} Y_{it}$ denotes the spatial lag term of the dependent variable. The main explanatory variable is denoted by X_{it}, the spatial correlation coefficient is represented by ρ, the geographic distance spatial weight matrix is denoted by W_{it}, the parameter estimates for independent variables are denoted by β, the spatial-specific effects are denoted by λ_i, the time-specific effects are indicated by μ_t, and the error term is indicated by ε_{it}.

The spatial error model, or SEM, can be used to examine spatial heterogeneity when the goal variable's geographic association relies on the random error factor. Equation (5) uses γ to denote the spatial dependence of the sample information, which reflects how much the regional variable has an impact on the nearby locations. There is a distribution that is normal in the vector that represents the random errors. The model can be expressed as follows, as shown by Eq. (5):

$$Y_{it} = X_{it}\beta + \mu_i + \lambda_t + \alpha_{it}\left(\alpha_{it} = \gamma \sum_{j=1}^{N} W_{ij}\alpha_{it} + \varepsilon_{it}\right) \tag{5}$$

A SLM and a SEM can be created from a SAR under certain circumstances. According to the SDM model theory, nearby independent variables as well as neighboring values of the dependent variable have an impact on the observed value of the dependent variable. This offers a more thorough understanding of the endogenous and external influences affecting the dependent variable. SDM can degrade to SLM when certain conditions are met ($\theta = 0$) and to SEM when other conditions apply ($\theta + \rho\beta = 0$). The model is represented as Eq. (6).

$$Y_{it} = \rho \sum_{j=1}^{N} W_{ij} Y_{it} + X_{it}\beta + \sum_{j=1}^{N} W_{ij} X_{it}\theta + \lambda_i + \mu_t + \varepsilon_{it} \tag{6}$$

The Hausman test directs the decision between fixed and random effects for model selection. Second, the existence of spatial or temporal fixed effects is assessed using the Likelihood Ratio (LR) test. Then, in order to choose the best model, To ascertain whether the SDM model can be simplified to the SLM or SEM, the LR and Wald tests are employed. (Liu and Song 2020). The best spatial model can be chosen using this procedure. In conclusion, the spatial Durbin model, as represented by Eq. (7), is constructed.

i is for the province and t stands for the year in Eq. (7). The spatial weight matrix for n-order geographic distance is called W. Spatial correlation coefficients ρ and θ represent the spatial influence intensity from the urban vitality periphery on regional carbon emissions. β represents the direct influence of local urban vitality on carbon emissions. *CE* serves as the explanatory variable, representing carbon emissions. In Eq. (7), the key explanatory variables for urban vitality encompass *eco_vit* for economic vitality, *peo_vit* for population vitality, *soc_vit* for social vitality. Control variables encompass 'urbanization' (*URB*) and 'built-up area' (lnBUI, expressed logarithmically). μ_i denotes spatial-specific effects, λ_t denotes time-specific effects, and ε_{it} indicates the random error term.

$$\begin{aligned} CE_{it} = {} & \rho \sum_{j=1}^{N} W_{ij} CE_{it} + \beta_1 eco\_vit_{it} + \theta_1 \sum_{j=1}^{N} W_{ij} eco\_vit_{it} \\ & + \beta_2 peo\_vit_{it} + \theta_2 \sum_{j=1}^{N} W_{ij} peo\_vit_{it} + \beta_3 soc\_vit_{it} + \theta_3 \sum_{j=1}^{N} soc\_vit_{it} \\ & + \beta_4 URB_{it} + \theta_4 \sum_{j=1}^{N} W_{ij} URB_{it} + \beta_5 \mathrm{lnBUI}_{it} \\ & + \theta_5 \sum_{j=1}^{N} W_{ij} \mathrm{lnBUI}_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{7}$$

The analysis of how explanatory variables affect dependent variables within a city by the SDM takes into account the feedback effect that arises from the spatial spillover of explanatory factors to neighboring cities. According to LeSage and Pace 2009, a remedy to this problem is to decompose spillover effects using partial differential methods. Direct, indirect, and total effects can be used to categorize these spatial spillover effects. Thus, Eq. (8) can be used to represent the SDM.

$$\begin{aligned} Y_{it} = {} & \left(1 - \rho W_{ij}\right)^{-1}\left(X_{it}\beta + W_{ij}\right)X_{it}\theta + \left(1 - \rho W_{ij}\right)^{-1}\partial_i \\ & + \left(1 - \rho W_{ij}\right)^{-1}\gamma_i + \left(1 - \rho W_{ij}\right)^{-1}\lambda_i \end{aligned} \tag{8}$$

The partial derivative of Y to the explanatoryvariable X_k from region i to region N is:

$$\begin{aligned} \left[\frac{\partial Y}{\partial X_{ik}} \cdots \frac{\partial Y}{\partial X_{nk}}\right] & = \begin{bmatrix} \frac{\partial Y_1}{\partial_{1k}} & \cdots & \frac{\partial Y_1}{\partial_{nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial Y_n}{\partial Y_{1k}} & \cdots & \frac{\partial Y_n}{\partial Y_{nk}} \end{bmatrix} \\ & = \left(1 - \rho W_{ij}\right)^{-1} \begin{bmatrix} \beta_k & w_{12}\theta_k & \cdots & w_{1j}\theta_k \\ w_{21}\theta_k & \beta_k & \cdots & w_{2j}\theta_k \\ \vdots & \vdots & \cdots & \vdots \\ w_{i1}\theta_k & w_{i2}\theta_k & \cdots & \beta_k \end{bmatrix} \end{aligned} \tag{9}$$

Here, W_{ij} stands for the geographic weight matrix, where i and j stand for different geographic regions. The direct influence is represented by the mean of the diagonal components in the rightmost matrix, while the indirect effect is represented by the mean of the off-diagonal elements.

Description of variables

Explained variables. The carbon emission data from the China Carbon Accounting Databases (CEADs) by Prof. Dabo Guan's team at Tsinghua University in 2016. For the purpose of generating carbon inventories for China and other emerging economies, CEADs is committed to building a cross-validatable multiscale carbon accounting methodology system. At the national, regional, urban, and infrastructural scales, it intends to provide a uniform, thorough, and accurate carbon accounting data platform, encompassing various socioeconomic sectors and energy sources.

In this study, a carbon emission inventory provided by CEADs is utilized: Emission Inventories for 290 Chinese Cities from 1997 to 2019." This inventory complies with national and provincial inventory criteria in China and covers 47 socioeconomic categories and 17 fossil fuels. It provides data that is clear, precise, comprehensive, comparable, and verifiable to aid in the study of urban emissions and the creation of sustainable and low-carbon development strategies. Furthermore, this dataset provides a valuable, data-constrained emissions accounting methodology that can offer insights for other countries.

Explanatory variables. Measures of urban vitality include measures of economic vitality as well as demographic vitality. Measuring economic vitality is a multifaceted endeavor, involving various indicators. GDP (gross domestic product), fixed asset investment, general public budget, and disposable income are selected as measures of economic vitality. GDP, representing the total value of a country's goods and services over a specific time frame, is a crucial indicator for assessing economic size and growth. However, it has faced criticism for not encompassing quality of life, income distribution, and other factors. Nonetheless, it remains widely used for international comparisons and policymaking. Fixed asset investment encompasses spending on productive capital, buildings, and infrastructure by firms and governments. This indicator reflects a nation's productive capacity and potential for future growth, as exemplified by economist Robert Solow's emphasis on capital accumulation. The general public budget represents a government's fiscal health, impacting its ability to invest in public services like infrastructure, education, and healthcare, thereby fostering economic development. This area overlaps with fiscal policy and macroeconomics, influenced by economists like John Maynard Keynes. Disposable income, the income remaining after taxes and transfers, reflects an individual's or household's economic well-being and living standards. Higher disposable income typically correlates with an improved quality of life and increased consumption, supported by studies in household economics. The Gini coefficient, a statistical indicator of wealth or income inequality with a range from 0 to 1, is also considered (perfect equality). The Gini coefficient measures the effects of government actions, and its value may be correlated with the degree of economic progress of a nation (Huo and Chen 2022). Typically, developing countries may have higher Gini coefficients, which can change with economic development, although exceptions exist. The following formula is used to compute the Gini coefficient using nightlight data.

$$G_j = \frac{\frac{1}{2\bar{Y}_j}\sum_{i=1}^{n_j}\left|\bar{Y}_j - Y_j\right|}{n_j^2} \tag{10}$$

The Gini coefficient of region j, where $\bar{Y}_j$ represents the average value of the level of Night light value in region j, Y_j represents the value of the level of Night light value in region j.

Population size and education expenditure (Zaman et al. 2021) are key indicators for evaluating demographic vitality and a region or country's development. These indicators hold significant representativeness when assessing development levels and societal well-being. Population, as a fundamental element, directly impacts the labor market, market size, and demand for social services. Higher populations typically offer more labor resources, fostering economic growth and social advancement. Research in development economics and demography has explored the relationship between population size and economic growth, exemplified by economist Paul Romer's inclusion of the population factor in his economic growth model. International organizations like the United Nations and the World Bank frequently utilize population data to assess a country's development status. Education, conversely, is a critical component of human capital with lasting effects on a country or region's future development. Education expenditures reflect government investment in the education system, and higher spending correlates with increased human capital accumulation and skills. This enhances the labor force's quality and employment prospects, promoting economic growth and social progress. Studies demonstrate a positive correlation between education spending, a country's economic growth, and its human development index. Economist Eric Hanushek's research underscores the significant contribution of improving education quality and spending to economic growth. In summary, population size and education expenditure are vital indicators for evaluating demographic vitality and development. They are extensively employed in international research and policymaking, supported by a substantial body of literature. However, it is essential to consider these indicators alongside other socioeconomic factors for a comprehensive assessment.

Given the multidimensional nature of urban vitality and its subcategories such as economic vitality, population vitality, and social vitality, it was imperative to select comprehensive indicators that are more representative. Consequently, we opted for PCA to ensure a more representative selection. This approach allowed for a comprehensive representation of the final choice, enhancing its overall representativeness. Principal component analysis is used to distill economic vitality from GDP (lnGDP), fixed assets (lnFIX), and per capita disposable income (lnDIS). Similarly, population vitality is derived from population (lnPEO) and education expenditure (lnEDU), while social vitality is extracted from the general public budget (lnBUG) and nighttime light Gini coefficient (NL_GINI).

These three dimensions cover the main aspects of urban vitality. By considering these dimensions, we can comprehensively and systematically evaluate the overall vitality of a city. Research indicates that urban vitality is primarily driven by economic, demographic, and social factors. These dimensions are interrelated yet independently significant, allowing us to reflect different facets of urban vitality from various perspectives.

Economic vitality is closely linked with demographic vitality; economic development attracts population inflows, while population growth further stimulates economic development. Social vitality, although dependent on economic development, is also influenced by demographic structure and migration patterns. Therefore, a comprehensive consideration of these three dimensions allows for a more accurate reflection of the overall status and developmental trends of urban vitality.

Control variables. Drawing upon prior research (Wang et al. 2021; Zhou et al. 2021; Pu et al. 2022), the following control variables are incorporated: Urbanization (URB) and Built-up area (lnBIU). Urbanization is the percentage of the region's built-up region, while built-up area is the entire built-up area of a city.

Data source. With data from 222 cities reported for the years 2011 to 2020, this analysis spans the years 2010 to 2019. Regions with insufficient data were eliminated to solve data issues. The China City Statistical Yearbook is the source of statistics on urban vitality, whereas CEADS is the specific source of data on carbon emissions. The latter's GDP, fixed assets, general government budget, disposable income, population, and education spending are all determined using the China City Statistical Yearbook. Control factors like built-up area and urbanization are also included in the analysis of how urban vitality affects carbon emissions. The China City Statistical Yearbook is the primary data source for these variables, and the Gini coefficient is also

Table 1 Descriptive statistics of variables.

Variable	Obs	Source	Mean	Std. Dev.	Min	Max
CE	1998	CEADs	3.378046	0.897207	0.296088	6.126338
lnPOP	1998	China City Statistical Yearbook	5.9518	0.67385	2.970414	8.132707
lnFIX	1998	China City Statistical Yearbook	11.82415	0.895657	8.783283	14.49939
lnGDP	1998	China City Statistical Yearbook	16.74625	0.896786	14.24345	19.75978
lnBUG	1998	China City Statistical Yearbook	14.84014	0.790922	11.49427	18.24054
lnDIS	1998	China City Statistical Yearbook	10.23622	0.300734	9.365719	11.20978
lnEDU	1998	China City Statistical Yearbook	13.07583	0.842997	9.091782	16.14328
NL_GINI	1998	DMSP/NPP	0.510838	0.209783	0	0.90651
URB	1998	China City Statistical Yearbook	4.008017	0.251543	3.105259	4.60517
lnBIU	1998	China City Statistical Yearbook	4.639484	0.869706	0	7.556428

considered, Gini coefficients were calculated from nighttime lighting data, nighttime lighting data include the Defense Meteorological Satellite Program (DMSP) and the Visible Infrared Imaging Radiometer Suite (VIRRS).

The DMSP satellites are equipped with a range of sensors, and among them, the VIRRS stands out as a vital component. VIRRS is responsible for collecting data within the visible and infrared spectra. Through VIRRS, DMSP satellites capture radiance emitted from Earth's surface, allowing the generation of nighttime light imagery, and thus, offering valuable information about nighttime illumination in cities and regions. The data obtained through DMSP and its VIRRS sensor have multifaceted applications, notably in meteorology, geographical information systems (GIS), urban planning, and environmental research. Table 1 lists the variables utilized in this study along with an explanation of each one.

The SDM method employed in our study necessitates the utilization of longitudinal data. By leveraging longitudinal data, we can discern more robust and universally applicable patterns. It's important to clarify that '1998' does not denote a specific year; rather, it indicates a total of 1998 data points. Our dataset spans from the year 2011 to 2019.

Study area. The 222 prefecture-level cities in our study are distributed across major regions in China, as shown in Fig. 2. This paper is currently classifying the regions according to China's most typical seven regions. The division of these regions is based on comprehensive factors including geography, economy, culture, and history. with 28 in North China, 26 in Northeast China, 73 in East China, 60 in Central-South China, 17 in Southwest China, and 18 in Northwest China. The performance indicators for each city are as follows: The top three cities with the highest GDP are Shanghai (2019, East China), Beijing (2019, North China), and Shanghai (2018, North China). The cities with the lowest GDP are JiaYuGuan (Northwest China, 2016), DingXi (Northwest China, 2011), and JiaYuGuan (Northwest China, 2015). The top three cities with the highest fixed assets are Chongqing (Southwest China, 2019), Chongqing (Southwest China, 2018), and Chongqing (Southwest China, 2017). The cities with the lowest fixed assets are JiaYuGuan (Northwest China, 2011), YiChun (Northeast China, 2016), and HeGang (Northeast China, 2014). The cities with the highest per capita disposable income are Beijing (North China, 2019), Shanghai (East China, 2016), and Suzhou (East China, 2019). The cities with the lowest per capita disposable income are YiChun (Northeast China, 2011), DingXi (Northwest China, 2011), and SuiHua (Northeast China, 2011). The top three cities with the highest population are Chongqing (Southwest China, 2019), Chongqing (Southwest China, 2017), and Chongqing (Southwest China, 2018). The cities with the lowest population are JiaYuGuan (Northwest China, 2012), JiaYuGuan (Northwest China, 2013), and JiaYuGuan (Northwest China, 2014). The cities with the highest education expenditure are Beijing (North China, 2019), Beijing (North China, 2018), and Shanghai (East China, 2019). The cities with the lowest education expenditure are YaAn (Southwest China, 2011), ShuangYaShan (Northeast China, 2013), and ZhangJiaJie (Central-South China, 2011). The cities with the highest general public budget are Shanghai (East China, 2019), Shanghai (East China, 2018), and Beijing (North China, 2019). The cities with the lowest general public budget are QiQiHaEr (Northeast China, 2011), JiaYuGuan (Northwest China, 2011), and JiaYuGuan (Northwest China, 2017). The cities with the highest Gini coefficient are ZhangJiaJie (Central-South China, 2011), ZhangJiaJie (Central-South China, 2015), and SuiZhou (Central-South China, 2011). The cities with the lowest Gini coefficient are JiaYuGuan (Northwest China, 2017), JiaYuGuan (Northwest China, 2018), and JiaYuGuan (Northwest China, 2019).

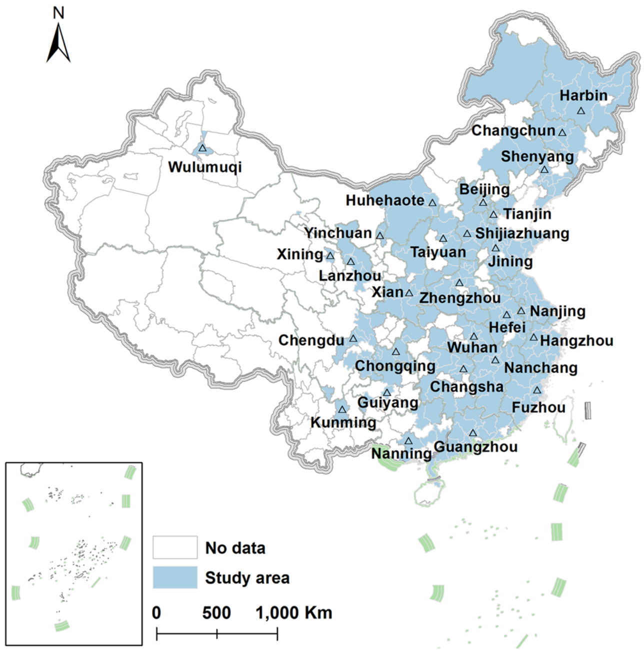

Fig. 2 Study area.

Results

Performance on dimensions of urban vitality. The cross-sectional data for the years 2011 and 2019 were selected to explore spatial distribution characteristics based on Natural Breaks (Jenks) classification into six levels in Fig. 3. Distinct temporal variations are observed in economic vitality, population vitality, and social vitality.

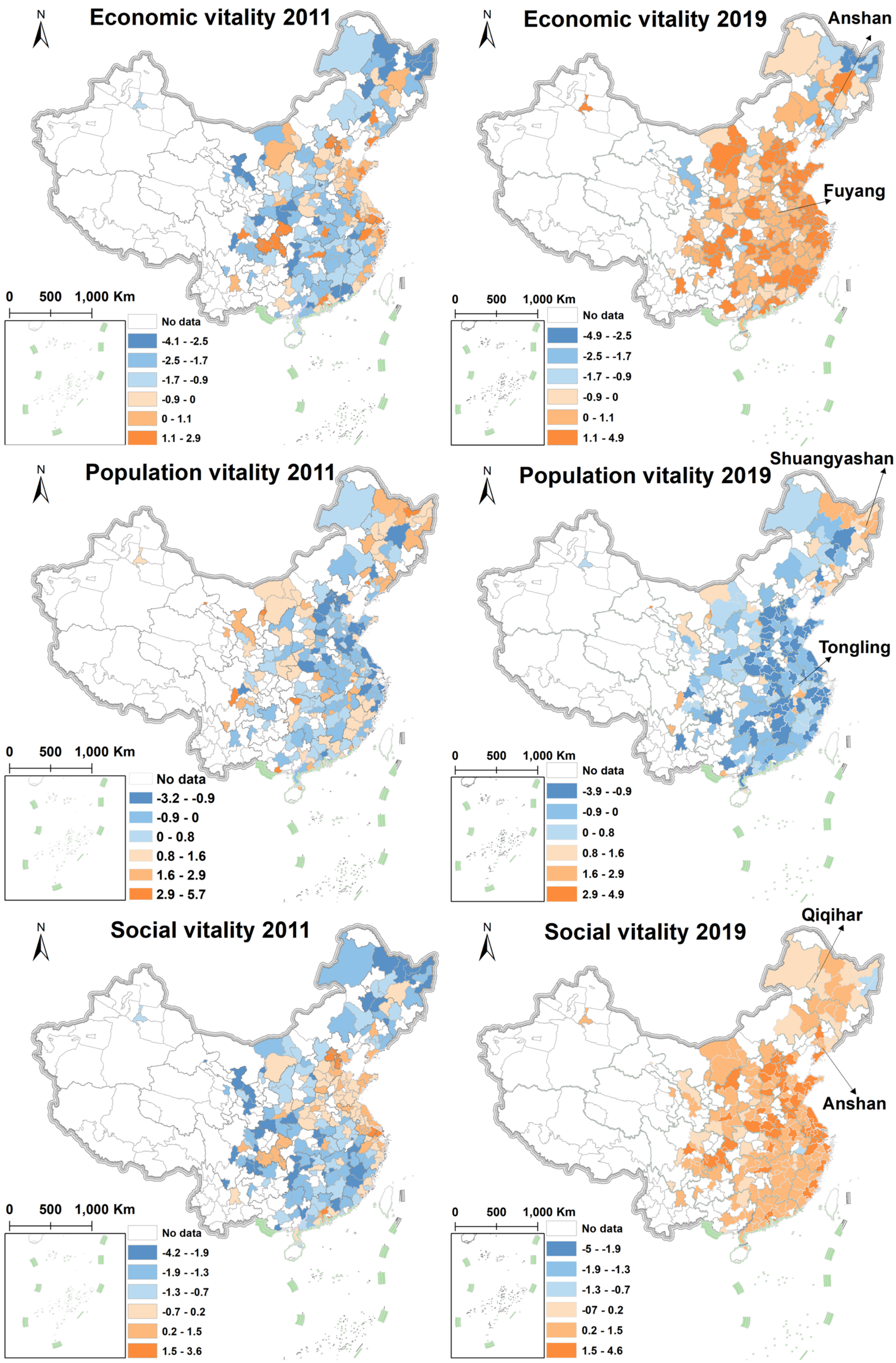

Fig. 3 Spatial distribution of vitality.

Economic vitality exhibited consistent growth across all cities from 2011 to 2019. Notably, Fuyang City experienced the most significant economic vitality increase, rising from −2.234 in 2011 to 0.871 in 2019, while Anshan City showed the smallest increase, changing from −0.315 in 2011 to −0.274 in 2019.

Population vitality displayed diverse trends among cities over the same period, with both increases and decreases observed. Tongling City exhibited the most substantial decrease in population vitality, declining from 4.360 in 2011 to 1.352 in 2019. Conversely, Shuangyashan City demonstrated the highest

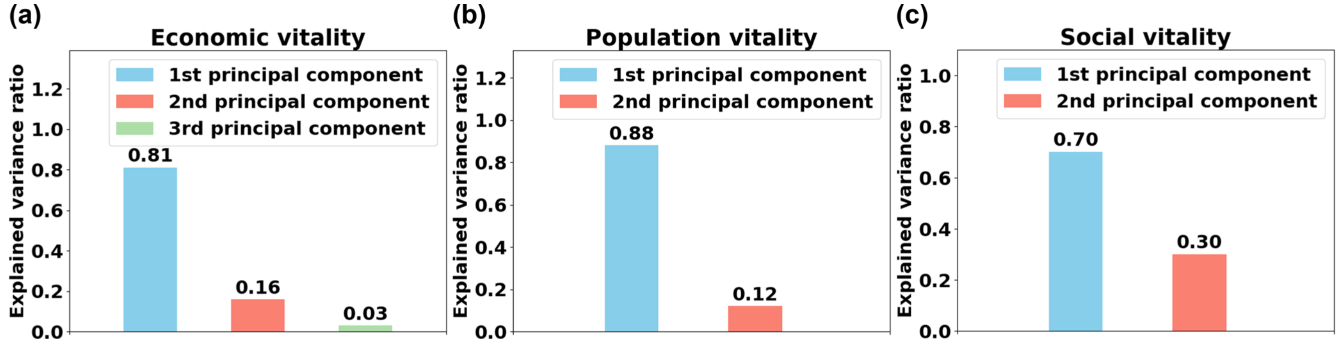

Fig. 4 Urban vitality PCA fitting composition results. **a** Economic vitality, **b** population vitality, **c** social vitality.

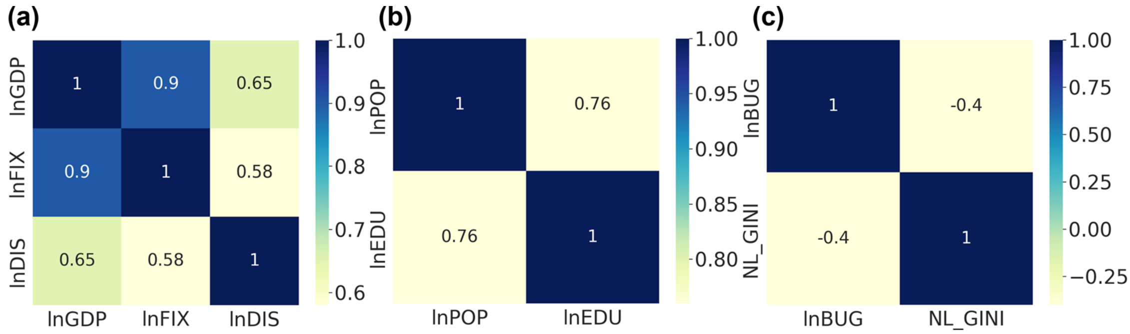

Fig. 5 Correlation coefficient matrix thermodynamic diagram. **a** Economic vitality, **b** population vitality, **c** social vitality.

increase, rising from 1.470 in 2011 to 2.011 in 2019. Social vitality consistently grew in each city from 2011 to 2019. Notably, Qiqihar City experienced the most significant growth, transitioning from −2.234 in 2011 to 0.871 in 2019, while Anshan City showed the smallest increase, moving from −4.165 in 2011 to 0.090 in 2019.

An interesting spatial pattern emerges in Chinese cities, where economic vitality tends to be higher in the southern regions, indicating a relatively developed economy in the south. In contrast, population vitality predominantly thrives in the northern regions, while social vitality is more pronounced in the southern regions. These results advance our knowledge of the regional dynamics influencing China's urban environment.

PCA results. Principal components analysis for economic vitality, population vitality, and social vitality are derived, with the proportion of each component shown in Fig. 4. Economic vitality was derived by extracting a principal component from GDP, fixed assets, and per capita disposable income, with the first principal component exceeding 80%. Population vitality was determined by extracting a principal component from population and education expenditure, achieving an 88% representation in the first principal component. Social vitality was identified by extracting a principal component from the general public budget and the Gini coefficient of night light, with the first principal component surpassing 70%.

The correlation of indicators in various dimensions of vitality is shown in Fig. 5. The correlation coefficient between GDP and fixed assets within economic vitality is 0.9, signifying a substantial correlation. In contrast, the correlation coefficient between fixed assets and per capita disposable income is 0.55, indicating a weaker association. Furthermore, the correlation coefficient between GDP and per capita disposable income is 0.65, demonstrating a robust correlation. The correlation coefficient between population and education expenditure in population vitality is 0.76, indicating a strong positive correlation. Within social vitality, the correlation coefficient between the general public budget and the Gini coefficient of night light is −0.4, reflecting a notable negative correlation.

Table 2 Collinearity Test.

Variable	VIF	1/VIF
Economic vitality	6	0.17
Population vitality	3.99	0.25
Social vitality	3.58	0.28
URB	2.52	0.40
lnBIU	2.94	0.34
R^2	0.36	-

OLS results. To address potential issues related to variable interpretation redundancy in this model, collinearity analysis is conducted on independent variables. Table 2 displays OLS result of the independent variables. The findings reveal an absence of collinear relationships among economic vitality, population vitality, and social vitality. The results from the OLS model indicate that only economic vitality significantly influences carbon emissions, exhibiting a positive impact. In other words, higher economic vitality corresponds to increased carbon emissions.

In summary, these factors collectively contribute to 35.58% of the variance in the carbon emission model.

Spatial Durbin model results. Table 3 displays global Moran's I values. When the z-value exceeds 1.65 or Moran's I has a p-value of less than 0.05., spatial correlation is deemed significant. Moran's I values near 1 suggest a stronger geographic connection. Table 3 shows that the explanatory factors within 222 prefecture-level cities between 2011 and 2019 are spatially dependent.

To understand how carbon emissions vary across cities, a method called Local Indicators of Spatial Association (LISA) was used to identify clusters. The results are shown in Fig. 6. In both 2016 and 2017, the distribution pattern remained largely the same. Cities that were close to one another and had comparable high carbon emission levels were found to be in specific areas, mostly in North China. In northern China, several cities exhibit high carbon emissions due to concentrated economic activities such as industrial production, energy consumption, and transportation. For instance, Hebei and Shanxi provinces are major coal production and consumption areas in China, leading to significantly higher carbon emissions in these cities. Additionally, the climate and geographical conditions in northern China may also contribute to the similarity in high carbon emission levels. For example, the increased demand for heating during the winter months results in higher consumption of coal and other fossil fuels, thereby elevating carbon emissions. This suggests these cities share similar emission patterns or are influenced by each other's emissions. However, there were places where the emissions varied significantly, such as Huanggang, Quanzhou, Guilin, and Guangzhou. In these places, carbon emissions were high within the region but lower in surrounding areas. There were also areas where nearby cities had differing emission levels.

Table 3 moran'I results.

Year	Carbon emission		
	Moran's *I*	*Z*-value	*P*-value
2011	0.053***	8.945	0.000
2012	0.058***	9.731	0.000
2013	0.056***	9.329	0.000
2014	0.06***	9.958	0.000
2015	0.061***	10.101	0.000
2016	0.063***	10.378	0.000
2017	0.068***	11.205	0.000
2018	0.055***	9.176	0.000
2019	0.058***	9.743	0.000

*** indicates significance at the 1% level.

For instance, in North China, some areas with high emissions were close to others with lower emissions. This indicates disparities in emissions between neighboring regions. Additionally, there were areas with consistently low emissions both within the region and nearby, mainly located in central China.

Through the spatial autocorrelation test, indicate clear spatial dependence characteristics in carbon emissions data. Because of this, it can be used in empirical research with a spatial econometric model. This conclusion is supported by the Wald, LM, and LR tests. We use the Wald test and LR test of fixed effects to determine whether the SDM can be simplified to a spatial lag model or a spatial error model. The results show that the values of the Wald spatial lag test and LR spatial lag test are 26.10 ($p = 0.0001$) and 26.05 ($p = 0.0001$)); the values of the Wald spatial error test and LR spatial error test are 24.84 ($p = 0.0001$) and 24.98 ($p = 0.0001$), respectively. Both Wald and LR tests pass the 1% significance test, indicating that the SDM cannot be reduced to a spatial lag model or a spatial error model. Therefore, we chose the fixed effect SDM to analyze the impact of urban vitality on carbon emissions. Table 4 displays the complete outcomes.

In Table 5, OLS regressions were initially conducted without accounting for spatial effects, as shown in the second column. To determine the appropriate estimation approach, the Hausman test was employed, favoring the use of fixed effects in this model. The Hausman Test (Hausman 1975) is a statistical method used to determine model selection, primarily to decide whether a Fixed Effects Model (FEM) or a Random Effects Model (REM) should be employed in panel data analysis. The Fixed Effects Model (FEM) assumes that individual effects are correlated with the explanatory variables, and it aims to eliminate the bias caused by this correlation. In contrast, the Random Effects Model (REM) assumes that individual effects are uncorrelated with the explanatory variables, treating these effects as random variables and using the random effects approach for estimation (Baltagi and Liu 2016). Model (1) presents the OLS estimation results, ignoring spatial effects. However, this approach leads to modeling errors due to the absence of spatial considerations. Comparing the primary effect regression outcomes of Model (1) and Model

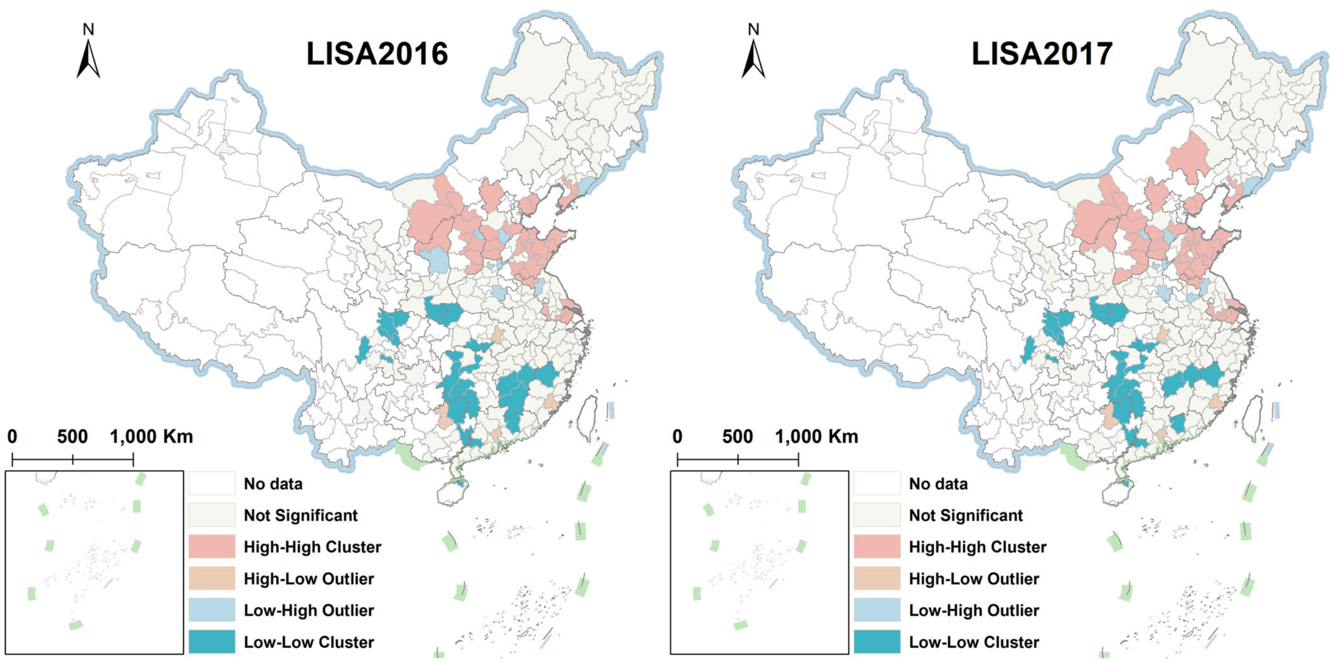

Fig. 6 The LISA cluster diagram of carbon emissions' Moran's I in 2016 and 2017.

Table 4 The LM, Robust LM,wald and LR tests.

Test	*P*-value	Test	*P*-value
LM (error) test	251.767*** (0.000)	LR (sdm sar) test	26.05*** (0.0001)
Robust LM (error) test	345.731*** (0.000)	LR (sdm sem) test	24.98*** (0.0001)
LM (lag) test	11.245*** (0.001)	Wald spatial lag test	26.10*** (0.0001)
Robust LM (lag) test	105.209*** (0.000)	Wald spatial error test	24.84*** (0.0001)
Hausman test	11.62* (0.0404)	-	-

*** and * indicates significance at the 1% and 10% levels, respectively.

Table 5 Impact of urban vitality on carbon emissions.

Variables	OLS Model (1)	Spatial Durbin (Fixed effects) Model (2)	
		Model (2a) (Main)	Model (2b) (Wx)
Economic	0.22	−0.02	0.20
vitality	0	0.29	0.01
Population	0.03	0.05	0.04
vitality	0.19	0.04	0.56
Social	−0.06	0.01	0.02
vitality	0.03	0.39	0.40
lnURB	0.13	0.28	−1.32
	0.21	0	0.01
lnBUI	0.34	−0.01	−0.29
	0	0.63	0.14

Table 6 Decomposition of spatial effects based on the prefecture-level city.

Variables	Model (3) National Region		
	Direct	Indirect	Total
Economic vitality	−0.02	0..35***	0.33**
	0.35	0.01	0.01
Population vitality	0.05**	0.12	0.17
	0.03	0.36	0.20
Social vitality	0.01	0.04	0.06**
	0.31	0.19	0.06
lnURB	0.29***	−2.16**	−1.89**
	0	0.02	0.047
lnBUI	−0.01	−0.58	−0.59
	0.54	0.16	0.16
R^2	0.36		
Obs	1998		
Province	222		

*** and ** indicates significance at the 1% and 5% levels, respectively.

(2), based on the SDM, it is observed that the significance levels of the coefficient estimates remain consistent, but their magnitudes significantly differ. This underscores the importance of considering spatial effects. The Hausman and LR tests yielded statistically significant p-values, indicating the appropriateness of the fixed-effects model. Furthermore, the SDM model proved more suitable for this study, as indicated by statistically significant p-values from the Wald test (Wald-lag, Wald-error) and the LR test (LR-lag, LR-error) at the 1% significance level.

As was already established, the direct marginal effects of independent factors on CE are not accurately captured by the SDM model's regression coefficients (LeSage and Pace 2009). The SDM model accounts for spatial autocorrelation, where changes in one region can influence neighboring regions. Consequently, relying solely on regression coefficients cannot differentiate the impact of an independent variable on its own region from its effects on other regions. In the SDM framework, a variable's changes in one region can create spatial spillover effects, impacting adjacent regions. Regression coefficients alone do not directly reflect these spillover effects, necessitating the decomposition of direct and indirect effects for comprehensive analysis. Additionally, independent variables and the dependent variable may exhibit complex interrelationships, with regression coefficients providing only an overall linear relationship that fails to elucidate the nuanced direct and indirect influences (Elhorst 2014). To address this, as shown in Table 6, the direct and indirect effects of these variables are separated.

The results show that economic activity has a direct negative impact on carbon emissions, but it also has a significant beneficial indirect effect, with a positive total effect. More specifically, at the 1% level, the impact of economic vitality on the carbon emissions of neighboring cities is noteworthy at 0.35. Higher carbon emissions in nearby cities are linked to increased economic vitality, while the local city is not significantly affected. This implies that increased economic activity lowers carbon emissions in the surrounding cities while increasing those in the local ones. The decline in carbon emissions locally may be attributed to the adoption of environmentally friendly consumption habits, such as the purchase of energy-saving appliances (Kelly 2012) and the use of low-carbon vehicles (Yao et al. 2011; Bonsu 2020). Economic prosperity may also drive industrial structure optimization and the development of low-carbon industries like clean energy, technology, and services. On the other hand, the exodus of companies with substantial energy usage and high levels of pollution from nearby metropolitan regions may be the cause of the increase in carbon emissions in nearby urban areas. According to (Uzar and Eyuboglu 2022), (Ali 2023), income has a profound impact on various environmental indicators. This is because, in many cases, environmental indicators initially decline as income increases but tend to improve with the overall prosperity of the country. Conversely, the migration of some companies with high energy consumption and high pollution levels from nearby urban areas may be the cause of the increase in carbon emissions in nearby urban regions. Considering the total effect of economic vitality, the overall impact on carbon emissions in both local and adjacent areas is 0.332734, significant at the 5% level, underscoring the significant contribution of economic vitality to the increase of carbon emissions in the surrounding and local areas.

Population vitality has positive direct and indirect effects on carbon emissions,, with the direct effect being statistically significant, the total effect is positive. Examining the direct impact, population vitality influences carbon emissions in local cities with a significant coefficient of 0.047595 at the 5% level. This aligns with previous research on the association between population and carbon emissions (Zhang 2011; Wang et al. 2017). Additionally, further evidence suggests that the population expansion of prefecture-level cities significantly contributes to urban carbon emissions, consistent with earlier surveys (Liang et al. 2020; Liu and Song 2020).

The direct and spillover effects of social vitality on carbon emissions are both positive, with the total effect being statistically significant positive. When social vitality is taken into account as a whole, the effect it has on carbon emissions in nearby and local cities is considerable at the 5% level, with an overall coefficient of 0.0591415. This emphasizes how important social vitality is in encouraging carbon emissions in the surrounding and local communities.

In the realm of control variables, urbanization exhibits a significant positive direct impact, while its spillover and total effects manifest as significant negative influences. Elevated urbanization contributes to increased carbon emissions in local cities but concurrently aids in reducing carbon dioxide emissions in nearby prefecture-level cities. Consistent with the results of Ali et al. (2019) a one percent rise in urbanization is correlated with a 1.178% growth in per capita carbon dioxide emissions, which is in line with the findings from Wang and Li (2021). Contrarily, the direct, spillover, and total effects of expanding built-up areas on carbon emissions are negative, although not statistically significant. This implies that an increase in built-up areas may not only decrease carbon emissions in local urban zones but also assist in reducing carbon emissions in adjacent urban areas. The optimization and enhancement of infrastructure can improve the public transport system and create a convenient transportation network, diminishing residents' reliance on private cars and lowering traffic-related carbon emissions (Creß et al. 2022). Furthermore, expanded built-up areas offer more cultural, entertainment, and social facilities, promoting closer mobility within the city (F. Li et al. 2021), consequently reducing traffic congestion and carbon emissions in the surrounding regions.

Discussion

In terms of policy recommendations, various aspects of urban vitality have an effect on carbon emissions:

1. Economic vitality exhibits a negative direct impact on local carbon emissions but a significantly positive spillover effect, resulting in an overall positive impact. The findings suggest that increased economic vitality reduces carbon emissions locally but contributes to elevated carbon dioxide emissions in neighboring cities. The local decline in carbon emissions may be attributed to environmentally friendly consumption habits and the promotion of low-carbon industries. Conversely, the upsurge in carbon emissions in adjacent urban areas may result from the relocation of high-energy consumption industries.
2. Regarding population vitality, both direct and spillover effects are positive, with a statistically significant direct effect. The total effect is positive, emphasizing its impact on local carbon emissions, supported by a significant coefficient of 0.047595 at the 5% level. This aligns with prior research on the association between population growth and carbon emissions. Furthermore, evidence suggests that the expansion of prefecture-level cities leads to urban carbon emissions.
3. Similarly, the direct and spillover effects of social vitality and population vitality on carbon emissions are positive, with a statistically significant positive total effect. Examining the total effect of social vitality, it exerts a noteworthy impact on carbon emissions in both local and adjacent cities, with an overall coefficient of 0.0591415, significant at the 5% level. This underscores the substantial role of social vitality in promoting carbon emissions in both local and neighboring areas. To summarise, this research emphasizes the necessity of implementing focused policies to effectively manage and reduce environmental consequences in nearby and local areas.

Increased urbanization is linked to a significant positive direct effect on carbon emissions but a negative indirect effect on carbon emissions in surrounding urban areas. Conversely, an increase in built-up area is associated with negative direct and indirect effects on carbon emissions. These findings imply that urbanization may drive carbon emissions upward, but careful urban planning and enhanced built-up area utilization can mitigate emissions, promoting sustainability.

Balancing economic vitality with reduced carbon emissions should be approached through the lens of developing a green economy, effectively utilizing resources, prioritizing renewable energy, clean technologies, and embracing circular economy practices to protect the environment and mitigate emissions. Simultaneously, fostering population vitality involves advocating for environmental consciousness while controlling population growth, thereby increasing awareness about the importance of reducing carbon emissions and environmental conservation. In promoting societal dynamism, attention should be directed towards ensuring social equity by guaranteeing fair resource distribution, facilitating equitable access to clean energy and green technologies, and making the transition to low-carbon lifestyles financially feasible for all.

Conclusion

This study offers the following policy recommendations to assist governments and policymakers in crafting effective strategies for carbon emission control and sustainable development. Governments should incentivize and support the adoption of clean energy sources such as solar, wind, and hydro power. This can be achieved through tax incentives, subsidies, and concessions to attract investors and businesses towards renewable energy. Invest in environmental education and awareness campaigns to elevate public consciousness regarding environmental issues. Foster green consumption habits and popularize low-carbon lifestyles. Foster a culture of research and innovation, especially in environmental protection and energy-related fields. Fund research projects and provide training to professionals to advance environmental technologies. Optimize urban planning and maximize the utilization of built-up areas. Improve public transportation systems and reduce private car usage to minimize transportation-related carbon emissions.

Economic policies should primarily focus on income distribution and tax policies. Taxes can be designed to be more progressive to prevent the concentration of income and wealth. The revenue obtained in this way can be redirected to public services such as education and healthcare, benefiting the poor more significantly. Additionally, these public service funds can support low-carbon infrastructure projects, such as green buildings, public transportation systems, and renewable energy projects, thereby reducing carbon emissions.

Education is also highly effective in improving income distribution and raising environmental awareness. A good education can help individuals break the cycle of poverty and increase their income levels. Therefore, it is crucial to expand education and increase its inclusiveness. Additionally, incorporating environmental courses at all educational stages and organizing workshops and events can enhance environmental awareness. This is important for creating a society with high environmental consciousness and promoting harmonious and collective action. The education system can also focus on promoting low-carbon lifestyles and technologies, such as sustainable agriculture, energy-saving technologies, and green building design, further reducing carbon emissions.

Moreover, creating jobs in the clean energy and green technology sectors can optimally combine income distribution and environmental policies. The government can support this process through incentives, tax exemptions, and infrastructure investments. Although this may place a burden on the budget, the social benefits of these supports are evidently substantial. Promoting the development of clean energy and green technologies, such as wind power, solar energy, and electric vehicles, can create job opportunities and significantly reduce carbon emissions.

Taxing activities that negatively impact the environment can effectively integrate income distribution and environmental policies. Within this framework, the government can increase taxes on emissions and other pollutants. Increasing such taxes can reduce activities that harm the environment. The revenue from these practices can also be redistributed to disadvantaged groups through public expenditures and direct transfers. These tax revenues can also fund carbon reduction projects, such as research and development of carbon capture and storage (CCS) technology, and support energy efficiency improvement measures, thereby reducing overall carbon emissions.

By integrating these measures, economic policies can not only effectively develop urban vitality but also significantly reduce carbon emissions, promoting sustainable development.

This research has certain limitations: (1) The assessment of urban vitality considers the most common and fundamental dimensions, namely economic, population, and social vitality. However, the inclusion of cultural and tourism vitality, increasingly significant aspects, should also be taken into account. (2) The lack of robustness testing using multiple weight matrices may result in variations in the outcomes due to data differences. (3) Economic, population, and social vitality, constrained by the limitations of yearbook data, did not consider a broader range of indicators. Future studies could supplement results by considering additional indicators in the context of data availability.

Recognize that carbon emissions are a global challenge. Actively participate in international cooperation efforts, engage in international climate agreements, and share experiences and technologies in carbon markets to collectively reduce global carbon emissions. These policy recommendations should be tailored to the unique characteristics and requirements of each region. To ensure a sustainable future for Earth, governments, industry, and society at large should collaborate to minimize carbon emissions and foster sustainable development.

Data availability

The datasets generated and analyzed during the current study are available in the Harvard Dataverse repository, (https://doi.org/10.7910/DVN/O3YIG4).

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