Spatiotemporal heterogeneity and influencing factors on urbanization and eco-environment coupling mechanism in China

Wenxia Zeng · Xi Chen · Qirui Wu · Huizhong Dong

Abstract
High-quality urbanization is the core for realizing human well-beings, for which reason investigating how the relationship evolves between urbanization and eco-environment is of crucial importance. Differing from the rationale of revealing spatial spillover effects using traditional tests, we consider spatial network characteristics to enrich the notion of local coupling and telecoupling from a relational perspective. First, we adopt coupling coordination degree model (CCDM) and decoupling model (DM) to calculate the urbanization and eco-environment coupling coordination degree (UECCD) and the decoupling index (DI) in 30 provinces and municipalities of China from 2008 to 2017. Second, we use gravity model to construct urbanization and eco-environment coupling coordination network (UECCN), in which provinces are nodes and spatial connection relationships of UECCD are edges between nodes. Third, we introduce social network analysis (SNA) to reveal spatial network characteristics of UECCN without using local spatiotemporal heterogeneity. Finally, we employ spatial econometric model to reveal factors that influence urbanization and eco-environment coupling effect. The major findings and conclusions of this study are summarized as follows. (1) The main subclasses of UECCD and DI are basically uncoordinated patterns with eco-environment lagging and weak decoupling, respectively. (2) Only two spatial agglomeration types of UECCD exist, the high-high (H-H) clustering in Shanghai and the low-low (L-L) clustering in western China, whereas no significant spatial agglomeration effect is observed among most provinces. (3) The distribution characteristics of UECCN are sparse in western China and dense in eastern China, and the spatial correlation strength of UECCN improves. (4) Technological innovation plays a critical role in promoting UECCD, while the total population, per capita disposable income, coupling network structure, and environmental regulations exert significant impact on UECCD. Collectively, we propose to prioritize governance provinces with low UECCD in western China as well as adequately utilize the positive externalities of key node provinces in eastern China. Equally importantly, we suggest that it is also critical to fully exert a driving force of technological innovation on improving the UECCD by promoting renewable energy utilization.

Keywords
Urbanization and eco-environment coupling coordination network (UECCN) · Spatiotemporal heterogeneity · Spatial correlation effects · Social network analysis (SNA) · Spatial autocorrelation tests · Spatial Durbin panel model

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Introduction

Historically, it is widely believed that intense human activities have undeniably put enormous pressure on the environmental quality. These human activities are evidenced by extensive use of fossil fuels, increasing economic growth, and excessive consumption of fossil fuel energy, resulting in increased carbon dioxide \((\text{CO}_2)\) emissions (Adebayo and Kirikkaleli 2021; Awosusi et al. 2022; Akadiri et al. 2022). In contrast, renewable energy resources have a positive effect on \(\text{CO}_2\) emissions (Adebayo et al. 2022). Equally importantly, a recent study suggests that the high incidence of COVID-19 is positively impactful on the environment in terms of reduced \(\text{CO}_2\) emission, because the rise in cases leads to the closure of several production sectors that use non-renewable energy consumption (Adebayo et al. 2022). In other words, the unprecedented COVID-19 pandemic, a counterfactual natural experiment, implies that the environmental quality will be improved when the intensity of human activities is reduced.

Urbanization, performing as a global and typical representative behavior of the impact of human activities on natural systems, has become a particular focus (Nagendra et al. 2018). With the emergence of its new paradigm, the urbanization itself is playing a key role as the driving force in stimulating economic development (Bloom et al. 2008; Mata et al. 2021) and motivating agricultural production with large-scale farming (Oueslati et al. 2019). It has been acknowledged that the agglomeration effect of urbanization not only alleviates carbon emission (Wang et al. 2021; Castells-Quintana et al. 2021) but also profits the market of green science and technology (Marra et al. 2017), facilitating carbon neutralization for China. Despite the above advantageous improvements in various aspects, however, the process of urbanization will be unavoidably accompanied with a variety of environmental degradation issues. A recent study points out that urban land expansion is one of the manifestations of rapid urbanization, leading to the pressure of urban population decline, encroachment on cropland and natural habitats, and the risk of producing major food crops (Chen et al. 2020). Furthermore, the expansion of impervious surface is a major consequence of rapid urbanization, contributing to regional heat island and consecutive thermal impacts (Dutta et al. 2021). Additionally, Kim et al. (2021) suggest that urbanization induces thermally driven atmospheric secondary circulation and affects the spread of pollutants over the city. Deng et al. (2021) show that unsound spatial supply-demand of ecosystems will occur when rapid urbanization exceeds the carrying capacity of the local environment and resources. Zhang et al. (2021) demonstrate that rapid urbanization contributes to a continuous increase in carbon dioxide \((\text{CO}_2)\) emissions, deteriorating environmental quality.

It is estimated that China’s urbanization process will be accelerating with an increasing proportion set to 70–75% by 2035. Therefore, the coupling of urbanization with eco-environment becomes an urgent research focus for manland relationships (Fang et al. 2016). In order to achieve coordinated high-quality and cross-regional urbanization, the spatial interaction mechanism must be revealed between urbanization and eco-environment.

There is a paucity of empirical literature that directly explores the spatiotemporal characteristics on urbanization and eco-environment coupling coordination network (UECCN), i.e., the provinces as the nodes and the spatial connection relationships between nodes as the edges, using the complex network method. However, some studies on the interaction between urbanization and eco-environment coupling coordination degree (UECCD) have laid the foundation for our studies. This study primarily reviews the related works in terms of the law interaction between urbanization and eco-environment, the spatiotemporal characteristics of UECCN, the corresponding influencing factors. Firstly, existing studies on the law interaction between urbanization and eco-environment have reported conflicting evidence. The first view is that the expansion of urbanization leads to lagging eco-environments (Han et al. 2021). In contrast, the second opinion holds that urbanization has a positive influence on the eco-environment. Specifically, employing an ecological footprint indicator to represent environmental destruction, Addai et al. (2022) indicate that urbanization has a direct negative consequence on ecological footprint. In addition, countries with high urbanization levels are more likely to achieve coordinated development of UECCD (Feng et al. 2021), and this positive impact comes from urban areas, not urban areas (Zheng et al. 2020). Another fact is that, however, the relationship between urbanization and the eco-environment is not always a simple negative or positive correlation but a complex nonlinear interaction, e.g., conforming to U-shaped (Fang et al. 2021) or S-shaped (Fu et al. 2020) when human intervention is involved (Elmqvist et al. 2019) at various spatial scales. Alternatively, there is an environmental Kuznets inverted U-curve between urbanization and environmental pollution (Liang and Yang 2019), and the inflection point is around 73.80% (Zhang et al. 2017). In addition to the law interaction between urbanization and the eco-environment mentioned above, we also remark that urbanization has no impact on environmental deterioration measured by the load capacity factor (Xu et al. 2022).

Secondly, in response to the spatiotemporal characteristics of UECCN, previous studies categorized the above coupling relationship into local coupling and telecoupling. Traditional local coupling refers to the interaction and interactive influence between urbanization and eco-environment system in one place. Feng et al. (2021) apply a coupling...
coordination degree model to quantitatively evaluate the degree of coordination in the interactive coupling between urbanization and eco-environment systems. However, diverse activities such as globalization, trade, migration, tourism, air circulation, long-distance technology, and/or information transfer are imposing profound influences on China’s provinces. Moreover, for a centered city surrounded by its adjacent cities, the external eco-environments of those cities further affect its own urbanization through the flow of air and water circulation. Under the above background, the notion of telecoupling was proposed to describe long-distance socioeconomic and environmental interactions (Liu et al. 2013; Hull and Liu 2018; Tang et al. 2021); its evolution is characterized with distinctive space-distributed network structure (Bai et al. 2016). Particularly in urban agglomeration process, typical and marked local coupling and telecoupling patterns exist between Eco-environment Coupler (UEs) (Fang et al. 2019). Numerous studies argue that the UECCD is improving by employing a coupling coordination model at different spatial scales (Sun et al. 2021; Chen et al. 2022). Several studies further investigated the spatial agglomeration characteristics of UECCD using spatial autocorrelation analysis (Wu et al. 2018). Arik et al. demonstrate that there are significant differences in the feedback effect of urbanization on the eco-environment employ the temporally weighted regression (GTWR) model in the Silk Road Economic Belt in China. Note that these studies merely explored the relationship between local and neighboring regions depending on the attribute data characterized by numerical distribution. In order to further explain network relationships, social network analysis (SNA) emerges as an effective approach that has been widely used in empirical studies for both natural and social science. Current research mainly use the SNA method in natural resource management research to characterize the impact of different social network structures composed of actors and stakeholders on natural resource management (Bodin et al. 2006). However, the root is to study the management of people in the field of the environment, and it has not been directly applied to environmental management. Subsequently, a few scholars apply complex networks to the cross-regional governance of air pollution based on the characteristics that air pollution conforms to the propagation dynamic mechanism (Carmona-Cabezas et al. 2019; Fellini et al. 2019).

Thirdly, for the corresponding influencing factors of UECCD, some studies reported that traditional regression model was incapable of detecting its driving mechanism effectively due to the UECCD’s spatial agglomeration effects. Accordingly, employ geographic detectors or spatial econometric model; several scholars further empirically investigate the Beijing-Tianjin-Hebei agglomeration (Wang et al. 2019) and the Yellow River Basin in China. Although the above-mentioned methods can be adopted to detect the influencing factors of spatial differentiation of the UECCD, these approaches cannot deal with the influence of structural characteristics of the UECCN on the UECCD.

As discussed before, most existing efforts mainly focus on the law interaction and the coupling between urbanization and the eco-environment from an “attribute data” perspective. Specifically, most scholars analyze the coupling stage by constructing evaluation index systems of urbanization and eco-environment respectively. Nevertheless, these studies can only reflect the dynamic coupling law in the numerical distribution characteristics. In addition, despite a growing literature on the spatial agglomeration characteristics of UECCD applying spatial autocorrelation analysis from the perspective of spatiotemporal heterogeneity, scant evidence currently exists on the overall network structure characteristics of the coupling between urbanization and eco-environment. Lastly, previous studies ignore the impact of geographical location on UECCD.

To fill the research gap, we depict the situation of unbalanced development between urbanization and eco-environment from the “relational” perspective in China. We first use the methods of CCDM and DM to measure the UECCD and DI in 30 provinces and cities in China (excluding Tibet, Hong Kong, Macao, and Taiwan) from 2008 to 2017. And, we apply the gravity model to construct UECCN, i.e., the provinces and cities as the nodes and the association relationship between the nodes as the edge. We then use SNA to quantify the structural characteristics of the UECCN. Lastly, we utilize spatial Durbin model to reveal the spatial spillover effects of government regulation, coupling structure, and other influencing factors on UECCD.

The key contributions of this study can be summarized as follows. Firstly, we present a novel “relational” perspective (i.e., a networked perspective) for investigating the urbanization and eco-environment coupling coordination degree (UECCD), rather than the existing numerical distribution of UECCD from an “attribute data” perspective.

Secondly, we propose a novel concept for UECCN, i.e., the provinces and cities as the nodes and the association relationships between the nodes as the edges, to enrich the existing studies on UECCD. Equally important is that a method of social network analysis (SNA) is applied to depict the structural characters of UECCN.

Thirdly, we introduce and combine the methods of SNA and the spatial econometric model to analyze the influencing factors of the UECCD, which provides new evidence to quantitatively analyze the impact of structural characters of UECCN measured by centrality index on UECCD for related studies. And, we show a concrete way to improve the coordinated status between the environment and the eco-environment.
Materials and methods

Study areas and constructing the index system

This paper selects 30 provinces and municipalities in China (except for Hong Kong, Macau, Taiwan, and Tibet because of unavailability data) as the research objects. Additionally, we divide the research area into three parts (i.e., eastern, central, and western China) to portray the spatial heterogeneity of UECCD. Specifically, eastern China includes Beijing (BJ), Hebei (HB), Tianjin (TJ), Liaoning (LN), Shandong (SD), Shanghai (SH), Jiangsu (JS), Zhejiang (ZJ), Fujian (FJ), Guangdong (GD), and Hainan (HN). Central China includes Shanxi (SX), Jilin (JL), Heilongjiang (HLJ), Anhui (AH), Jiangxi (JX), Henan (HEN), Hubei (HUB), and Hunan (HUN). Western China includes Inner Mongolia (IM), Guangxi (GX), Chongqing (CQ), Sichuan (SC), Guizhou (GZ), Yunnan (YN), Shaanxi (SAX), Gansu (GS), Qinghai (QH), Ningxia (NX), and Xinjiang (XJ).

According to previous studies (Fu et al. 2020; Chen et al. 2022; Zheng et al. 2020; Feng et al. 2021; Ariken et al. 2021), we select corresponding indicators to construct a comprehensive evaluation index system for urbanization and eco-environment. The urbanization system includes population, economy, space, and society (see Table 1). Following Berger and Hodge (1998), the eco-environment comprehensive evaluation index system involves three levels of pressure, state, and response (see Table 2). In addition, we measure the comprehensive urbanization index and comprehensive eco-environment

| Table 1 Urbanization comprehensive evaluation index system |
|-----------------|-----------------|-----------------|-----------------|
| System          | Indicator and weights (%) | Variable | Direction | Unit | Weights (%) |
| Urbanization system | Demographic urbanization (11.28) | V1: Proportion of urban population | + | % | 3.53 |
|                  | V2: Urban population density | + | persons/km² | 4.26 |
|                  | V3: Proportion of employment in tertiary industry | + | % | 3.49 |
| Economic urbanization (27.78) | V4: Per capita GDP | + | yuan | 5.59 |
|                  | V5: The proportion of tertiary industry in GDP | + | % | 4.88 |
|                  | V6: Per capita disposable income of urban residents | + | yuan | 6.11 |
|                  | V7: Per capita consumption expenditure of urban residents | + | yuan | 6.46 |
|                  | V8: Per capita retail sales of consumer goods | + | yuan | 4.74 |
| Spatial urbanization (22.27) | V9: Urban road area per capita | + | m² | 2.93 |
|                  | V10: Built-up area per capita | + | m² | 4.04 |
|                  | V11: Urban drainage pipe length per capita | + | m | 8.98 |
|                  | V12: Total length of urban public transport operating lines per capita | + | m | 6.32 |
| Social urbanization (38.66) | V13: Number of buses per 10,000 people | + | unit | 5.32 |
|                  | V14: Number of beds in hospitals and health centers per thousand people | + | unit | 3.84 |
|                  | V15: Number of personnel in health institutions per thousand people | + | people/1000 people | 2.07 |
|                  | V16: Public toilets per 10,000 people | + | unit | 5.68 |
|                  | V17: Public library collections per 100 people | + | unit | 11.10 |
|                  | V18: Number of college students per 100,000 people | + | people | 4.46 |
|                  | V19: Teacher-student ratio (Student number = 1) | + | % | 4.56 |
|                  | V20: Gas penetration rate | + | % | 1.63 |

+ represents positive indicators, – means negative indicators
index using the Entropy method (Fu et al. 2020). The data come from China Statistical Yearbook, China Environmental Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Yearbook, and Statistical Yearbooks of various provinces (except Hong Kong, Macao, Taiwan, and Tibet).

**Coupling coordination degree model (CCDM) and Decoupling model (DM)**

This paper exploits the CCDM and DM to identify the dynamic and complex relationship between urbanization and eco-environment. The CCDM can examine the current status of the dynamic relationship urbanization and eco-environment, regardless of whether it is coordinated or not.

The term “coupling” originates in the field of physics and refers to the process in which systems influence each other and eventually tend to be coordinated. Subsequently, environmentalists employ the term to describe the process of interaction between humans and natural systems. Thus, we utilize “coupling” to illustrate the interaction between the urbanization system and the eco-environment system.

Step 1 The coupling degree model (CD) is applied to measure the interactive stress relationship between urbanization and eco-environment. The formula is as follows:

\[ C = \left\{ \frac{U \times E}{\left[ \left( U + E \right) \right]^{2}} \right\}^{1/2} \]  

(1)

Step 2 Given that the CD only describes the similarity for urbanization and eco-environment, we further use CCDM to describe the UECCD. The formula is as follows:

\[ T = \alpha \times U + \beta \times E \]  

(2)

\[ D(U, E) = \sqrt{C \times T} \]  

(3)

where \( D \) is the CCD of the two subsystems; \( C \) is the CD of the two subsystems; \( T \) is the comprehensive coordination index of the two subsystems; \( U \) and \( E \) are the comprehensive development levels of the two subsystems, respectively; \( \alpha \) and \( \beta \) are the contributions of the two subsystems to the development of the region taken as 0.5 respectively. Overall, the UECCD are divided into the following classes (see Table 3).

The DM can further examine the future trend of the current coupling state. For instance, if the coupling type of a province is coordinated and its urbanization and eco-environment are decoupled, this coordination status is not sustainable. The DI represents the blocking between variables, which is generally used to depict the relationship between eco-environment pressure and economic driving force. Tapio (2005) improved this method based on the Organisation for Economic Cooperation and Development (OECD) and proposed a more comprehensive and detailed model, introducing the concept

| System                  | Indicator and weights (%) | Variable                                      | Direction | Unit     | Weights (%) |
|-------------------------|---------------------------|-----------------------------------------------|-----------|----------|-------------|
| Eco-environment system  | Pressure (16.5)           | V1: Electricity consumption per capita        | –         | Kw·h     | 2.43        |
|                         |                            | V2: Water consumption per capita              | –         | t        | 1.92        |
|                         |                            | V3: Urban construction area per capita        | –         | m²       | 1.63        |
|                         |                            | V4: Per capital wastewater discharge          | –         | t        | 2.32        |
|                         |                            | V5: SO₂ emissions per capita                  | –         | t        | 2.90        |
|                         |                            | V6: Smoke (dust) emissions per capita         | –         | t        | 4.05        |
|                         |                            | V7: Amount of general industrial solid waste generated per capita | –         | t        | 1.25        |
| State (67.86)           |                            | V8: Park green area per capita                | +         | m²       | 9.08        |
|                         |                            | V9: Coverage rate of green space in built-up area | +         | %        | 3.83        |
|                         |                            | V10: Forest cover rate                        | +         | %        | 13.95       |
|                         |                            | V11: Cultivated land area per capita          | +         | m²       | 20.93       |
|                         |                            | V12: Water supply per capita                  | +         | t        | 20.07       |
| Response (15.63)        |                            | V13: Harmless treatment rate of domestic garbage | +         | %        | 3.36        |
|                         |                            | V14: Municipal sewage treatment rate          | +         | %        | 3.27        |
|                         |                            | V15: Comprehensive utilization rate of industrial solid waste | +         | %        | 9.00        |

+ represents positive indicators, – means negative indicators
of elasticity to measure the sensitivity on incremental values. Beyond the coupling coordination model, we use the DM method to describe the complex relationship between urbanization and eco-environment in each coordinated development stage. The specific calculation formula is as follows:

\[
D_R = \frac{\Delta E}{\Delta U} = \frac{(E_t - E_{t-1})/E_{t-1}}{(U_t - U_{t-1})/U_{t-1}}
\]

where \(E_t\) and \(E_{t-1}\) are the eco-environment level index in year \(t\) and year \(t-1\), respectively. \(U_t\) and \(U_{t-1}\) denote the urbanization level index in year \(t\) and year \(t-1\), respectively. \(D_R\) is the decoupling index of year \(t\). Fig. 1 shows the identification criteria of decoupling of urbanization and eco-environment.

**Spatial autocorrelation tests**

**Global spatial autocorrelation**

Traditional statistical methods may no longer be valid because of the existence of spatial autocorrelation. Because it is contradictory to the independence and randomness of basic assumptions in traditional statistics. Thus, we use the global and local spatial autocorrelation index to comprehensively investigate the spatial autocorrelation of UECCD.

Global spatial autocorrelation reveals the overall trend of the spatial correlation of the UECCD by calculating Moran’s \(I\). The value of Moran’s \(I\) index ranges from \(-1\) to \(1\). If this index is significantly greater than 0, it indicates that there is global autocorrelation between provinces. The larger this index, the stronger the spatial agglomeration effect. A negative value indicates there is a spatial negative autocorrelation, and the smaller the value, the more significant the negative autocorrelation, and the greater the spatial difference. Zero indicates there are no spatial correlation and a random distribution of the spatial units. It is calculated as follows (Deng et al. 2021):

\[
Moran’s I = \frac{n}{W} \sum W_{ij}(x_i - \bar{x})(x_j - \bar{x}) / \left( \sum W_{ij} \sum (x_i - \bar{x})^2 \right)
\]

(5)

where \(n\) is the number of spatial units; \(x_i\) and \(x_j\) are UECCD of spatial units \(i\) and \(j\), respectively; \(\bar{x}\) is the average value of the UCEED; and \(W_{ij}\) is the spatial matrix.
Local spatial autocorrelation

However, the global Moran’s I index has limitations. The index only reflects the overall spatial agglomeration effects in local regions. If the spatial scale is large, they may take the local distribution appear as an atypical situation that cannot be reflected in the presence of spatial heterogeneity. What is worse, the local spatial correlation trend is opposite to the global spatial correlation trend in this context (Anselin 1995). Accordingly, we apply the local spatial autocorrelation to further portray the local spatial correlation of UECCD. The local indicators of spatial association (LISA) map show the spatial heterogeneity or attribute values of the geographic phenomena in each feature and estimate the spatial scope and location of grouping areas. The types of agglomeration are divided into four clustering, i.e., high-high (H-H) clustering, high-low (H-L) clustering, low-low (L-L) clustering, and low-high (L-H) clustering. It is calculated as follows (Deng et al. 2021):

$$\text{Moran’s } I_i = \frac{n \sum_{j} w_{ij} (x_j - \bar{x})}{\sum_{i} (x_i - \bar{x})^2}$$

where the meanings of all parameters here are consistent with those in formula (5).

Constructing and revealing urbanization and eco-environment coupling coordination network (UECCN): gravity model and SNA

Step 1 To construct the UECCN, we first quantify the spatial connection strength of the UECCD between provinces using the gravity model (Liu and Chen). Then, we build a spatial binary incidence matrix by setting a threshold. More specifically, if the spatial connection strength is greater than the threshold, the position of the corresponding spatial binary matrix is 1. This indicates that the two provinces have a spatial relationship (i.e., edge) in the network. Otherwise, there is no spatial correlation between provinces, i.e., the edge is discarded. Finally, we construct a UECCN, i.e., provinces as the nodes and the connection between nodes as the edges. The Gravity model formula is as follows:

$$R_{ij} = \frac{K M_i M_j}{D_{ij}^b}$$

where $R_{ij}$ is the spatial connection strength of UECCD between provinces $i$ and $j$; $M_i$ and $M_j$ are the UECCD in two provinces, respectively; $D_{ij}$ is the shortest driving distance between any two provinces; $K$ is the gravitational constant, generally taking $K = 1$; and $b$ is the distance attenuation index, taking $b = 2$.

Step 2 To reveal the structural characteristics of the UECCN, we apply SNA to explore the two main features from the perspective of “relational data” rather than “attribute data.” First, we exploit network density to uncover the overall structural characteristics of the UECCN. The closer its value is to 1, the more closely the network is connected, and the greater the impact on each node in the UECCN. Second, we employ network centrality divided into three indicators to investigate the node structural characteristics of the UECCN. (1) Point centrality is used to examine the status of a province in the UECCN. The greater the value is, the more it is at the center of the UECCN. (2) Closeness centrality is applied to measure the degree from the control of other provinces. The larger the value is, the higher the degree of control by other provinces. (3) Betweenness centrality is applied to calculate the degree to which a province is located in the “middle” of other provinces in the UECCN. The larger the value is, the stronger the control over other provinces.

Spatiotemporal heterogeneity analysis of the UECCD and DI in China

Time series analysis of the UECCD

Using the improved Entropy method, we select 35 indicators to calculate the urbanization and eco-environment levels of 30 provinces and municipalities in China during 2008–2017. And, we apply the CCDM and DM methods to calculate the UECCD and DI (see Table 4). The results show that the mean urbanization level steadily increased from 0.178 to 0.348, while the mean eco-environment level represents an S-shaped curve slightly varying between 0.395 and 0.472 with rising and falling. The initial value of urbanization

| Year | Urbanization | Eco-environment | UECCD | Year | Urbanization | Eco-environment | UECCD |
|------|--------------|-----------------|-------|------|--------------|-----------------|-------|
| 2008 | 0.178        | 0.395           | 0.506 | 2013 | 0.277        | 0.460           | 0.599 |
| 2009 | 0.194        | 0.430           | 0.523 | 2014 | 0.295        | 0.458           | 0.604 |
| 2010 | 0.225        | 0.443           | 0.549 | 2015 | 0.309        | 0.456           | 0.615 |
| 2011 | 0.244        | 0.431           | 0.563 | 2016 | 0.323        | 0.472           | 0.626 |
| 2012 | 0.260        | 0.440           | 0.584 | 2017 | 0.348        | 0.439           | 0.623 |
(0.178) is much lower than the initial eco-environment level (0.395), but the urbanization level has grown rapidly and narrowed the gap. Additionally, the average value of the UECCD shows a steady upward trend as a whole. The interaction between China’s urbanization and eco-environment systems tends to a better development status, but the growth rate is not large (between 0.506 and 0.626).

**Heat maps of UECCD classes and DI classes**

In this section, we further drew the heat maps of UECCD classes (see Fig. 2) and DI classes (see Fig. 3) according to identification criteria (see Table 3 and Fig. 1) and spatially divide into eastern, central, and western China.

**Heat maps of UECCD classes**

As depicted in Fig. 2, there are four classes of UECCD, i.e., seriously uncoordinated, basically uncoordinated, basically coordinated, and superiorly coordinated. Provinces with initially low levels of UECCD maintain an upward trend. Among them, the main subclass is basically an uncoordinated pattern with eco-environment lag, accounting for 51.7%. And, basically coordinated pattern with eco-environment lag is the second most common type, accounting for 22.7%. Obviously, there is a significant spatial heterogeneity of UECCD in China.

First, there are three classes of UECCD in eastern China: basically uncoordinated, basically coordinated, and superiorly coordinated. And, the main subclasses are basically uncoordinated patterns with the eco-environment lags, basically coordinated patterns with urbanization lags, basically coordinated, and basically coordinated patterns with the eco-environment lags, accounting for 89.1% of all classes. In particular, only Zhejiang reaches a good state of UECCD, i.e., superiorly coordinated. Similarly, Beijing and Tianjin reach a status of superiorly coordinated, but with a subclass being a superiorly coordinated pattern with urbanization lag. Second, there are only two classes of UECCD in Central China: basically uncoordinated and basically coordinated. The main subclasses are basically uncoordinated patterns with the eco-environment lags and basically coordinated patterns with the eco-environment lags, accounting for 93.8% of all classes. Shanxi is basically uncoordinated, a lowest UECCD level. Third, there are three classes of UECCD in western China: seriously uncoordinated, basically uncoordinated, and basically coordinated, accounting for 65.5% of all classes.

![Heat maps of the UECCD classes from 2008 to 2017, China.](image-url)
Heat maps of DI classes

As depicted in Fig. 3, there are four DI classes. Among them, the main subclasses of most provinces are weak decoupling and strong negative decoupling, accounting for 48.5% and 33.7% of all provinces in China, respectively. The former is a relatively coordinated type, a better development model, while the latter is unsustainable and poor coupling development model. Similarly, the characteristics of the distribution type for DI are similar in eastern, central, and western China. Specifically, the DI subclass in central China was expansive negative decoupling, an extensive development model in 2009, shifting toward a relatively good but fluctuating state: weak decoupling and strong negative decoupling. All DI subclasses exhibited weak decoupling in central China by 2017. In particular, Shanghai located in eastern China exhibited strong decoupling, a coordinated development model in 2009. However, Shanghai shifted toward poor status, i.e., weak decoupling and strong negative decoupling, indicating that Shanghai is developing into a bad status. As in Shanghai, Xinjiang also presents a similar evolutionary characteristic of decoupling. In addition, Xinjiang represents a bad status, i.e., recessive decoupling. Nevertheless, Ningxia reaches a better status, i.e., strong decoupling in 2016 shifted toward weak decoupling by 2017.

Put together, despite a few provinces achieved the best DI state (i.e., strong decoupling) in a given year, most provinces are mainly weak decoupling types, a relatively good state. And, weak decoupling types in eastern, central, and western China accounted for 46.5%, 49.3%, and 50.5% of each region, respectively. This suggests that there is not much difference between eastern, central, and western China. Strong negative decoupling was the second most common subclass, accounting for 37.4%, 33.8%, and 30.3% of each region, respectively.

Spatial autocorrelation tests

To analyze the spatial agglomeration characteristics of the UECCD, this paper calculates the global Moran’s $I$ index and local Moran’s $I$ index under the adjacency weight matrix following Tobler’s First Law of Geography (Tobler 1970). The results are shown.

First, the global Moran’s $I$ index is positive, with a value ranging from 0.322 to 0.389 from 2008 to 2017, passing the significance test (see Table 5), indicating that the spatial distribution of the UECCD in China shows spatial agglomeration characteristics. And, the overall
Spatial agglomeration shows a strengthening trend with fluctuating and rising. Second, to further investigate the local spatial clustering and instability characteristics, we employ ArcGIS software to paint the LISA agglomeration map of UECCD in 2008, 2012, and 2017 in China (see Fig. 4). There were only two spatial agglomeration types of China’s UECCD, i.e., H-H clustering and L-L clustering. The first H-H clustering is only distributed in Shanghai, and its main feature is that it has a high UECCD as well as the same for surrounding provinces. The second L-L clustering is mainly distributed in western China, and the number of provinces that are L-L clustering is increasing. Specifically, Sichuan, Yunnan, Chongqing, and Guizhou, located in Western China, were L-L clustering in 2008. By 2012, Shaanxi in Central China changed from no significant clustering to an L-L clustering. However, Shaanxi became a no significant cluster again, while Qinghai and Xinjiang in western China changed from no significant clustering to L-L clustering in 2017. The main feature is that it has a low UECCD as well as the same for surrounding provinces. Additionally, the local Moran’s I in the remaining provinces is not significant, and it does not show the form of spatial agglomeration. Together, the H-H clustering is only distributed in Shanghai, while the L-L clustering present a trend of spreading from the southwest to the northwest. This indicates that Shanghai, China’s coastal area with highly developed economies, plays a radiating and leading role in promoting UECCD in neighboring provinces. And, the economic development of the western China is at the expense of the eco-environment, which is an unsustainable development model.

### Table 5  Moran’s I index of UECCD and its significance level

| Year | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
|------|------|------|------|------|------|------|------|------|------|------|
| Moran’s I | 0.367*** | 0.362*** | 0.377*** | 0.361*** | 0.381*** | 0.374*** | 0.365*** | 0.330*** | 0.322*** | 0.389*** |
| P value | 0.001 | 0.001 | 0.000 | 0.001 | 0.000 | 0.000 | 0.001 | 0.002 | 0.002 | 0.000 |

*statistical significance level at 10%; **statistical significance level at 5%; *** statistical significance level at 1%
The structural characteristics of UECCN

Constructing the UECCN

To further analyze the structural characteristics of the UECCN from the perspective of “relational data,” we first apply the gravity model to calculate the spatial correlation strength between provinces. Second, we convert the spatial correlation strength into a spatial binary matrix by setting a threshold to determine whether there is a spatial correlation. Obviously, the different thresholds will construct different UECCNs. Following the existing literature, there are two main methods for selecting the threshold. One is the row average of the spatial incidence matrix, and the second is the mean value of the spatial correlation strength between provinces. This paper chooses the latter method and sets the threshold to 52.23. That is, if the spatial correlation strength is greater than or equal to 52.23, the value is 1, which means that there is a spatial correlation (edge) between provinces. If the value is less than 52.23, the value is 0, which means that there is no spatial correlation (edge) between provinces. In this way, a 30 × 30 spatial correlation matrix can be constructed, i.e., UECCN (see Fig. 4).

Overall network structure

As depicted in Fig. 4, the UECCN was initially formed in 2008, showing a relatively sparse, complex, and stable spatial network structure. The western China is relatively sparse, while the eastern China is relatively dense. From 2012 to 2017, the number of edges in UECCN increased significantly, indicating that the spatial linkage of UECCD between provinces has been improved. First, the spatial linkage in the western and eastern China has strengthened. In 2008, southwest China showed a sparse spatial connection structure of Sichuan-Chongqing-Yunnan. By 2017, Chongqing and Hubei, Guizhou and Hunan had a spatial linkage relationship, strengthening the spatial connection of the UECCD in the western and eastern China. Second, the number of edges between the Beijing-Tianjin-Hebei and Yangtze River Delta urban agglomerations is significantly greater than other provinces, indicating that the level of spatial connections within the above-mentioned urban agglomeration has been effectively improved. Lastly, Shandong and Jiangsu play a major role in effectively promoting the spatial linkage between the above urban agglomerations.

The network density is further used to analyze the overall structural characteristics of the UECCN (see Table 6). The network density increases from 0.149 in 2008 to 0.209 in 2017, indicating that the spatial correlation strength improved, but there is still a large gap compared with the maximum density in theory. Thus, the overall efficiency of the UECCD between provinces needs to be improved.

Node structure characteristics

Using the SNA, we further analyze the node structure characteristics of the UECCN in 2017 (see Fig. 5). The results are as follows. First, we use the point centrality index to examine the status of each province in the UECCN. The top two nodes with the highest centrality are Shandong and Henan, indicating that these provinces locate in the center of the UECCN and have the most direct spatial linkage relationships with other provinces. Second, the closeness centrality index is used to describe how difficult it is for each province to have a spatial linkage relationship with other provinces. The values of the closeness centrality in 20 provinces, including Henan, Hubei, Jiangsu, Hunan, Shanghai, and Shandong, are lower than the mean value of 79.8. This indicates that these provinces easily have spatial connections with other provinces. Finally, the between centrality index is used to characterize the control ability of each province in promoting UECCD. The values of between centrality in 11 provinces, including Shaanxi, Liaoqing, and Hunan, are higher than the mean value of 19.6. This means that the above-mentioned provinces play a transmission role and effectively control the spatial linkage relationship among other provinces. Jilin, Heilongjiang, Hainan, Qinghai, and Xinjiang with a low centrality level (0) will not exert control and dominance over other provinces, suggesting that these provinces are at the edge of the UECCN.

Overall, we draw different conclusions when determining the key governance areas from two different perspectives, i.e., the “attribute data” and the “relational data.” From the perspective of attribute data, Xinjiang, Shanxi, and other provinces located in low coordination areas should be key governance areas. According

| Year | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
|------|------|------|------|------|------|------|------|------|------|------|
| Density | 0.149 | 0.149 | 0.159 | 0.17 | 0.175 | 0.179 | 0.186 | 0.193 | 0.202 | 0.209 |
to the “relationship” perspective, however, Shandong and Jiangsu play a regulatory role in effectively regulating the development of UECCD for other provinces. To realize cross-regional collaboration, governments should consider not only the attribute data but also the relational data characteristics of UECCD in developing policies.

**Spillover effect of the influencing factors UECCD**

**Model specification**

Based on the IPAT model (Ehrlich and Holdren 1971), Dietz and Rosa Eugene (1997) proposed a modified STIRPAT model with the advantage of incorporating other influencing factors into the model for extension, decomposition, and improvement (York et al. 2003). Previous studies have found that the total population, per capita disposable income, technical level, and environmental regulations have an important impact on UECCD (Wang et al. 2019; Chen et al. 2022; Zheng et al. 2022). Thus, we analyze the spatial spillover effects of the four influencing factors above and the coupling network structure.

Accordingly, we employ a STIRPAT model to configure the following regression model:

\[
\ln(I) = \alpha + \beta \ln(P) + \gamma \ln(A) + \delta \ln(T) + \theta \ln(E_r) + \eta \ln(C_{AB}) + \epsilon
\]  

(8)

where \( I \) is the UECCD; \( P \) is the total population; \( A \) is the regional per capita disposable income; \( T \) represents the technological level and is expressed by energy consumption per unit of GDP; government’s environmental regulation capability \( E_r \) is expressed by the total investment in environmental pollution control \( (E_{r1}) \) and pollution control fees \( (E_{r2}) \); \( C \) represents the structural characteristic of UECCN and is expressed by the betweenness centrality; \( \alpha \) and \( \epsilon \) are the intercept term and the error term, respectively.

Considering the spatial spillover effect of UECCD, the Spatial Durbin panel model (SDM) is used to model the spillover effects of UECCD. The expression is as follows:

\[
y = \rho W y + X \beta + \theta WX + \epsilon
\]  

(9)

where \( \rho \) is the spatial autocorrelation coefficient, \( W \) is the spatial weight matrix, \( X \) is the explanatory variable, \( WX \) is the lag term of the explanatory variable, \( \beta \) is the regression coefficient of the explanatory variable, and \( \epsilon \) is the random
disturbance term. Combining formula (8) and (9), the spatial spillover effect model is as follows:

\[
\ln I_{ij} = \rho \sum_{j=1}^{n} w_{ij} \ln I_{j,t} + \beta_0 + \beta_1 \ln P_{i,t} + \beta_2 \ln A_{i,t} + \beta_3 \ln T_{i,t} + \beta_4 \ln C_{i,t} + \beta_5 \ln Er_{i,t} + \theta_1 \sum_{j=1}^{n} w_{ij} \ln I_{j,t} + \theta_2 \sum_{j=1}^{n} w_{ij} \ln A_{j,t} + \theta_3 \sum_{j=1}^{n} w_{ij} \ln T_{j,t} + \theta_4 \sum_{j=1}^{n} w_{ij} \ln C_{j,t} + \epsilon_{i,t},
\]

(10)

where \( P, t \) represent province \( P \) and year \( t \), respectively; \( j \) is the remaining provinces \((j \neq i)\). \( w_{ij} \) is spatial proximity weight matrix, that is, provinces \( i \) and \( j \) are adjacent to each other as 1, and nonadjacent to 0.

### Table 7: Estimation results of spatial Dublin panel model

| Variable | Fixed model | Time fixed-effects model | Spatiotemporal fixed-effects model |
|----------|-------------|--------------------------|-----------------------------------|
| \( \ln P \) | \(-0.616^{***}\) | \(-0.103^{***}\) | \(-0.541^{***}\) |
| \( \ln P \) | \((-9.680)\) | \((-11.950)\) | \((-8.710)\) |
| \( \ln A \) | \(-0.0118\) | \(0.0628^{**}\) | \(-0.0345\) |
| \( \ln A \) | \((-0.430)\) | \((3.060)\) | \((-1.220)\) |
| \( \ln T \) | \(-0.0959^{***}\) | \(-0.135^{***}\) | \(-0.104^{***}\) |
| \( \ln T \) | \((-4.390)\) | \((-10.43)\) | \((-4.850)\) |
| \( \ln C \) | \(0.0000288\) | \(-0.00267^{***}\) | \(0.000209\) |
| \( \ln C \) | \((0.050)\) | \((-5.920)\) | \((0.390)\) |
| \( \ln Er_{1} \) | \(-0.132\) | \(0.0429^{***}\) | \(-0.0172\) |
| \( \ln Er_{1} \) | \((-1.500)\) | \((6.650)\) | \((-0.200)\) |
| \( \ln Er_{2} \) | \(0.124\) | \(0.0222^{***}\) | \(0.120\) |
| \( \ln Er_{2} \) | \((1.490)\) | \((4.300)\) | \((1.280)\) |
| LR test | \(33.760^{***}\) | | |
| Hausman test | \(89.730^{***}\) | | |
| AIC | \(-1515.400\) | \(-1093.800\) | \(-1568.500\) |
| BIC | \(-1419.100\) | \(-997.500\) | \(-1472.200\) |

The data in parentheses are \( z \) values

*Significance at the significance levels of 10%; **significance at the significance levels of 5%; ***significance at the significance levels of 1%

### Table 8: Effect decomposition of spatial Dublin panel model

| Variable | Direct effect | Indirect effect | Total effect |
|----------|---------------|----------------|--------------|
| \( \ln P \) | \(-0.100^{***}\) \((-11.960)\) | \(-0.156^{***}\) \((-9.950)\) | \(-0.256^{***}\) \((-16.160)\) |
| \( \ln A \) | \(0.067^{***}\) \((3.510)\) | \(-0.242^{***}\) \((-5.12)\) | \(-0.175^{***}\) \((-3.730)\) |
| \( \ln T \) | \(-0.130^{***}\) \((-10.670)\) | \(-0.206^{***}\) \((-8.360)\) | \(-0.336^{***}\) \((-13.710)\) |
| \( \ln C \) | \(-0.003^{***}\) \((-5.880)\) | \(0.002\) \((1.760)\) | \(-0.001\) \((-0.630)\) |
| \( \ln Er_{1} \) | \(0.043^{***}\) \((7.030)\) | \(0.007\) \((0.600)\) | \(0.050^{**}\) \((3.860)\) |
| \( \ln Er_{2} \) | \(0.021^{***}\) \((4.250)\) | \(0.040^{**}\) \((4.110)\) | \(0.061^{**}\) \((5.260)\) |

### Model estimation and result analysis

First, according to the results of the previous section of “Spatial autocorrelation tests,” we find that there is a significant spatial agglomeration effect in the UECCD. Therefore, we are supposed to select a spatial econometric model rather than OLS. Second, the LR test passes the 1% significance level, indicating that the spatial Durbin model cannot degenerate into a spatial error model or a spatial lag model. Third, the Hausman test also passed the 1% level test, indicating that the fixed effect model should be selected. Last, according to the AIC and BIC values of the three models under fixed effects, the spatial Durbin model under time fixed effects should be selected (see Table 7).

As depicted in Table 7, we can draw the following conclusions. First, the total population has a negative effect on the UECCD at the 1% level of significance. That is, the larger the total population, the lower the level of UECCD. The reason may be that the larger the population is, the more likely it is to cause greater environmental damage. Second, per capita disposable income promotes coordinated development, which is significant at the 5% level. The reason is that families with higher per capita disposable income are more inclined to buy environmentally friendly products, reducing environmental pollution. Third, energy consumption per unit of GDP has a negative effect on UECCD at a significance level of 1%. That is, the higher the level of technology, the higher the level of UECCD. Fourth, the total investment in environmental pollution control and the pollution control fees have a significant positive effect on the UECCD, and both are significant at the 1% level. The former is a supportive environmental regulation, which has become a driving force for promoting UECCD. In addition, as an inhibitory environmental regulation, the latter constitutes a pressure factor for the UECCD. Finally, we find that the betweenness centrality has an inhibitory effect on UECCD. That is, the higher the betweenness centrality of a province, the lower its coupled development level, which is significant at the 1% level. This is because provinces with higher centrality tend to have greater environmental pressure.

To further measure the spatial spillover effect, we apply the partial differential method of LeSage and Pace (2009)
to decompose the total marginal effect of direct effects and indirect effects (see Table 8).

As depicted in Table 8, we can reach the following conclusions. First, the direct effect of the total population on the UECCD is −0.0995, and the spatial spillover effect is −0.156 when passing the 1% significance level test. The spatial spillover effect is greater than the direct effect, indicating that the larger the total population, the more serious the local environmental pollution, and the more serious eco-environmental damage to neighboring areas.

Second, the direct effect of per capita disposable income on UECCD is positive, while the spatial spillover effect on neighboring areas is negative at the 1% significance level. People in economically developed areas pay more attention to actions improving the eco-environment quality and evaluating the eco-environment, effectively promoting local UECCD. However, this would transfer highly energy-consuming and highly polluting industries to neighboring economic development areas, causing environmental pollution in neighboring areas.

Third, unlike per capita disposable income, the improvement of technological level significantly promotes the UECCD in the local and neighboring areas with a direct effect of −0.13 and a spillover effect of −0.206, both are significant at the 1% level. The spatial spillover effect of the technological development level on UECCD is far greater than the direct effect, and the total contribution rate to UECCD is also the highest, with a value of 33.6%. This indicates that technological innovation promotes UECCD.

Fourth, the direct effects of the total investment in environmental pollution control and pollution control fees are 0.043 and 0.0212, respectively, at the 1% significance. China’s pollution control fees accounted for only 6.29% of the investment in environmental pollution control in 2017. Supportive environmental regulation plays a more significant role in promoting the development of local coupling compared to inhibitory environmental regulation with less implementation strength. The spatial spillover effects of the above two environmental regulations are 0.007 and 0.04, respectively, at the 1% significance. Pollution control fees pass the 1% significance level test, while the total investment in environmental pollution control did not pass the significance test. The results show that supportive environmental regulations have an impact on UECCD but are limited to the local area, while inhibitory environmental regulations exceed the indirect effects of supportive environmental regulations on the UECCD of neighboring regions.

Last, the direct effect of structural characteristic of the UECCN is −0.003 at the 1% significance level. However, the indirect effect fails the significance test, indicating that the UECCD of the provinces with strong control ability in the UECCN is lower, and it has a lower level of coupling development for neighboring areas. The results suggest that the structural characteristic of UECCN has a small inhibitory effect on UECCD, but its impact cannot be ignored. This reflects that the provinces in the central UECCN bear greater environmental pressures, and it is necessary to fully consider the structural characteristics of the UECCN in formulating environmental regulations and policies.

Discussion and conclusion

Discussion

Spatiotemporal heterogeneity of the UECCD

Time series analysis shows that the UECCD has a steady upward trend overall in the study period, which is consistent with a broader literature that demonstrates UECCD exhibit an increasing trend year by year at different spatial scales (Feng et al. 2021; Sun et al. 2021; Chen et al. 2022). Spatial distribution characteristics suggest that the UECCD of eastern China is higher than western and central China. This finding is broadly consistent with recent work identifying that there are significant differences in the feedback effect of urbanization on the eco-environment in the Silk Road Economic Belt in China: The positive feedback of urbanization on the eco-environment is mainly concentrated on the southwest region and Shaanxi, while the regions with greater negative impacts are more concentrated on the northwest region (Ariken et al. 2021). Our results also find that Zhejiang not only achieves high-quality development but high levels of eco-environment, which parallels recent results by Feng et al. (2021) in their studies that higher urbanization is more favorable for higher UECCD.

The structural characteristics of the UECCN

Because previous models to depict spatiotemporal heterogeneity of UECCD have not considered the structural characters, we introduce the SNA method to fill the gap. Our findings did fit the expectation that the critical nodes (i.e., eastern China) play a critical role in promoting the coordinated development of the whole UECCN. One possible explanation is the higher spillover effect of UECCD along with higher UECCD. Meanwhile, our study also suggests that Shanghai is H-H clustering and its main feature is that it has a high UECCD as well as the same for surrounding provinces, demonstrating the generalizability of our outcome mentioned above. Additionally, the outcome is broadly consistent with prior finding reporting that Shanghai is a highly significant hotspot area (Wu et al. 2018).
Influencing factors of UECCD

Our findings are also similar for a body of literature that identifies the major influencing factor on UECCD. We find that technological level, regional per capita disposable income, and environmental regulation are critical positive factors, while the total population is the primary negative factor (Chen et al. 2022; Wang et al. 2019; Zheng et al. 2022). For example, Wang et al. (2019) suggest that the disposable income of urban residents plays a key role in the development of UECCD in a stage of high-speed urbanization development (2012–2015). While some of our outcomes are similar to prior studies, we find some differences in the intensity of its influencing factors. Specifically, our estimated UECCD rise due to technological advances is much higher than that estimated by Zheng et al. (2022), who reported that every one-unit increase in technological progress is associated with a 9.4% increase in central China. However, our estimated UECCD rise because of the government’s environmental regulation capability is much lower than that estimated by Zheng et al. (2022), who reported that every one-unit increase in government management capability is associated with a 9.8% increase in central China.

Conclusion

In this paper, we explore the spatial agglomeration of UECCD from the perspective of “attribute data,” to which SNA is introduced to further analyze the structural characteristic of UECCN, thereby offering an ingenious approach that uses “relational data” to expand the notion of the coupling mechanism between urbanization and eco-environment. The major research findings of this study are summarized as follows. Firstly, the UECCD level exhibits an upward trend with significant spatial heterogeneity, to which the main subclass of UECCD is a basically uncoordinated pattern with eco-environment lagging. The main subclass of DI is weak decoupling which is considered a relatively good state, and the characteristics of the DI distribution type remain similar in eastern, central, and western China.

Secondly, global Moran’s I suggests that the overall spatial agglomeration of UECCD exhibits a fluctuating upward trend. LISA maps suggest that the first H-H clustering only distributes in Shanghai, playing a dominant role in promoting UECCD in adjacent provinces. The second L-L clustering exhibits a spreading trend from southwest to northwest China.

Thirdly, the distribution characteristics of UECCN are sparse in western China and dense in eastern China. Although the spatial correlation strength of UECCN improves, a large gap still exists compared with the theoretical maximum density. Furthermore, Shandong and Henan locate in the center of the UECCN, exhibiting the most direct spatial relationships with other provinces. We draw different conclusions in determining the key governance areas from two perspectives of attribute data and relational data. From the first perspective, Xinjiang, Shanxi, and other provinces in low coordination areas should be key governance areas. From the second perspective, however, Shandong and Jiangsu play an indispensable role in regulating UECCD for other provinces.

Finally, technological innovation is of critical necessity in promoting UECCD, while the total population, disposable income per capita, the structural characteristic of UECCN, and environmental regulations exert a significant impact on UECCD. Especially, provinces in central UECCN bear greater environmental pressures, upon which the structural characteristics of UECCN must be considered in formulating environmental regulatory laws and policies.

Policy implications

Based on the above conclusions, the following implications for policymakers are presented. Firstly, the policymakers should derive targeted governance policies depending on the different coordination stages of urbanization and ecosystem in China. For western and central China, on the one side, the government should improve the construction of infrastructure to effectively promote local urbanization development in western and central China. On the other side, the government should significantly implement eco-environment construction projects such as soil and water conservation projects and natural shelter forests. Importantly, the urbanization expansion should not be beyond the local ecological carrying capacity; otherwise, it will be difficult to meet the requirements for new urbanization. For eastern China, substantial efforts are required to promote the UECCD to a higher level by improving industrial transformation and upgrading, new energy utilization, etc. Similarly, considering that provinces with high-level urbanization exert a positive impact on the eco-environment, those with low-level urbanization should learn good experience from them.

Secondly, a control and prevention mechanism is a promising approach to comprehensively foster the coordinated development between urbanization and the eco-environment. That is, it is vital to completely consider not only the attribute data but also the relational data characteristics of UECCD in developing cross-regional collaboration policies. On the attribute data view, the provinces with H-H clustering should deepen beneficial cooperation and strengthen their agglomeration advantages, while those with L-L clustering must consider similar constraints to reinforce cooperation. On the relational data view, substantial efforts are required to strengthen the construction of infrastructure such as
high-speed rail that is conducive to the generation of spatial connections between provinces based on the structural characteristic of UECCN. In this way, the government can promote the linkage effect of a coordinated development process of urbanization and eco-environment between provinces. Put in other words, the government should prioritize governance in western China that is in the stage of low coordination. Equally important is that the government should also pay more attention to provinces with strong capabilities of radiation driving and conduction in the UECCN, e.g., Shandong, Henan, and Jiangsu.

Finally, there are some driving forces behind coordinated development between urbanization and the eco-environment that should be considered as follows; that is, increasing investments in research and development (R&D), optimizing population distribution, improving a high-quality economy, and strengthening legislative policies, thus forming a variety of motivation for improving UECCD. More specifically, three caveats should be considered as follows. (1) A fundamental driving force, among many that are actively pursued, is technological advancements such as introducing and developing energy-saving and environmental protection technologies continuously. (2) Another promising governance strategy is to strengthen the government’s macro-control efforts. This includes reaching the full potential of the two types of environmental regulation policies, i.e., environmental pollution control and pollution control fees, especially the latter. (3) The final point is to optimize the structural characteristics of the UCCN. This calls for fully understanding the spatial spillover effect of environmental regulation, i.e., comprehensively considering the environmental policies of adjacent regions.

Author contribution Wenxia Zeng: methodology, formal analysis, writing-original draft, visualization, writing-review and editing. Xi Chen: conceptualization, writing-review and editing, Project administration, supervision, funding acquisition. Qirui Wu: validation, investigation, conceptualization, writing-review and editing. Huizhong Dong: conceptualization, writing-review and editing.

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