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Urban circular economy performance evaluation: A novel fully fuzzy data envelopment analysis with large datasets

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ABSTRACT

This study constructs a fully fuzzy data envelopment analysis (DEA) with large datasets to evaluate the urban circular economy. The proposed fully fuzzy DEA model considers uncertainties of circular economy indicators and introduces fuzzy trigonometric numbers. Additionally, the model provides a modified algorithm to overcome calculation difficulties due to voluminous data and large-scale decision-making units. The proposed model can quickly solve urban circular economy efficiency under uncertainty and with large datasets. An empirical study of 264 Chinese cities over 2009–2018 was conducted. Overall, the average annual fuzzy efficiency scores (theoretically vary from $\widetilde{0}$ to $\widetilde{1}$) of the urban circular economy in these cities are (0.7471, 0.7463, 0.7451), indicating that there is substantial room for improvement. The average efficiency scores and the subitem coordination levels of western cities are the highest compared to those of the other regions. Moreover, Northeast China exhibits the lowest efficiency score, which may be attributed to its decaying industry and unadvanced technical level. The overall urban economy performance presents two distinct trends: in 2009–2015, the urban circular economy exhibited negative growth, whereas it increased in 2015–2018. However, the growth rate declined, and negative growth remains a risk. Based on the results, several policy implications are provided for promoting urban circular economy.

1. Introduction

Cities play a vital role in the global economy and culture. Since the 1950s, the global urban population has grown rapidly, rising from 751 million to 4.2 billion in 2018, accounting for 55% of the total population, which is projected to increase to 68% by 2050 (UN-DAES, 2019). Cities currently consume approximately 75% of the natural resources and 80% of the energy utilized worldwide (UNEP-DTIE, 2012), and they contribute 70% of global greenhouse gas emissions (UN-HABITAT, 2011). Thus, rapid and unplanned urban growth, especially in developing countries, threatens sustainable development. Unsustainable consumption and production patterns lead to severe air pollution, land degradation, species extinction, and water quality deterioration (UNEP, 2019). Developing countries and regions must transform their urban development to achieve the United Nations Sustainable Development Goals and build inclusive, safe, resilient, and sustainable cities.

As the largest developing country and industrial power, China is considered a representative country for recent urban development. It has experienced unprecedented urbanization, with the urbanization rate rising from 17.9% in 1978 to 60.60% in 2019.[1] However, the blind expansion of urban constructions has seriously damaged natural resources and the environment. According to the National Annual Report on The Prevention and Control of Environmental Pollution by Solid Waste in Large- and Medium-sized Cities, in 2019, a total of 211.473 million tons of household waste was generated in 200 large- and medium-sized cities. Many cities have been warned of a structural mismatch between supply and demand regarding waste disposal capacity. These large- and medium-sized cities produced 1.55 billion tons of general industrial solid waste, reutilizing 860 million tons, which only accounts for 41.7% of the total disposal amount (MEE, 2019a). In addition, the 2019 Chinese Ecological Environment Bulletin reported that 180 out of 337 cities failed to satisfy environmental air quality standards. Primary air pollutants include $PM_{2.5}$, O_3, PM_{10}, NO_2, and CO (MEE, 2019b). Serious pollution not only threatens the health of terrestrial organisms but also seriously damages marine ecosystems. According to the Chinese Marine Ecological Environment Bulletin, 15 of

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the 18 marine ecosystems monitored were either sub-healthy or unhealthy in 2019 (MEE, 2019c).

Severe urban sustainability issues call for the adoption of more efficient resource recycling (RR) and pollution reduction (PR) practices in urban activities. The circular economy framework is a new economic model that aims to effectively resolve resource use- and environment-related problems and to decouple economic growth from environmental destruction. In recent decades, China has adopted a top-down circular economy political objective and integrated it into the new urbanization plan.[2] Over 20 years of circular economy practices in urban areas have led to drastic changes. For example, in urban construction, circular economy theory is embedded into urban green management to actively construct ecological (Zhuang, 2015), sponge (Wang et al., 2018a), and no-waste cities (Rao et al., 2020). In industry, many cities have conducted industrial park circular transformation demonstration projects and have attempted to develop a combination of circular production enterprises, circular industrial parks, and circular industries (Li et al., 2017; Xian et al., 2015). The consumption ecological system is jointly governed by multiple entities, including government authorities, industry leaders, enterprises, and consumers, and it has gradually been adopted and promoted in representative cities (Li et al., 2016).

Current urban circular economy research remains rare and incomplete, especially regarding comprehensive urban circular economy assessment. Nevertheless, the application of circular economy strategies in cities is actively encouraged by policies worldwide. There remains a need to quantify urban circular economy performance and to identify strategies that support urban sustainability. A few existing evaluation studies have been conducted for several cities or small samples. For example, Wang et al. (2018b) calculated the urban circular development index of 40 Chinese cities. Sun et al. (2018) determined the socioeconomic and resource environment indices of 18 cities in Henan, China, based on an improved catastrophe progression model. Guo et al. (2017) comparatively assessed circular economy development in four Chinese megacities. There are also case studies that focus on a single city or industry (Ma et al., 2014; Fang et al., 2017).

These pioneering studies are based on small sample sizes, and they can make certain suggestions from the evaluation results for improving the urban circular economy. However, realizing these suggestions not only depends on the action of a city but also the influence of other cities, industries, and markets. Thus, a circular economy should be transferable and scalable across cities and countries (Fratini et al., 2019). This means that decision-makers in different cities must consider the performance of the circular economies of other cities when setting their circular economy targets. In addition, existing studies typically focus only on a certain period, rendering it difficult to understand the dynamic evolution of urban circular economy performance and its determinants in the long term. Therefore, there is an urgent need to develop a long-term, large dataset-oriented evaluation method for the urban circular economies of many cities. In addition, because most circular indicators are uncertain, a certain fuzziness exists, and an evaluation based solely on real numbers can only obtain a single evaluation value (Padilla-Rivera et al., 2021). Therefore, it is critical to evaluate the urban circular economy under uncertainty.

With these issues in mind, this study evaluates Chinese city urban circular economies under large datasets and fuzzy conditions. The primary contributions of this study are as follows:

- A novel fully fuzzy data envelopment analysis (DEA) with large datasets is developed to evaluate the urban circular economy.
- The proposed fully fuzzy DEA model and algorithm can quickly determine the fuzzy urban circular economy performance and factor efficiencies of large-scale decision-making units (DMUs) with large datasets.
- The urban circular economy performances of 264 Chinese cities over 2009–2018 (a total of 126,720 data points) are evaluated for the first time.
- The spatial distribution and temporal evolution of urban circular economy performance in these cities are identified and tracked.

The remainder of this paper is organized as follows. In Section 2, we briefly review existing literature on the practice and evaluation of the circular economy. Section 3 presents the methodological framework of the proposed fully fuzzy DEA. Section 4 presents the results of the empirical study on the Chinese urban circular economy over 2009–2018 at the citizen level, and Section 5 presents the conclusions.

2. Literature review

2.1. Research on Chinese circular economy

Since introduced in the 1990s, China has been committed to incorporating the circular economy into policy and to implementing it. Merli et al. (2018) stated that circular economy implementation has promoted substantial research in this field in China. Yong (2007) reviewed circular economy development in China from its introduction into a national strategy. Mathews et al. (2011) emphasized how the Chinese adoption of the circular economy is a business and national policy decision, and how it was implemented as part of an industrial strategy. Although China has established a comprehensive circular economy policy system and attained many related achievements, several implementation obstacles remain, including financial and technical undersupply (Ritzén and Sandström, 2017), weak smart waste management (Asibey et al., 2021), significant spatial distribution differences (Tang et al., 2020), and insufficient cultural cognition of reuse ((Ranta et al., 2018). To promote Chinese circular economy policy, several scholars have recently suggested novel improvement measures. Ali et al. (2018) proposed incorporating market-based biodiversity offsets into circular economy policy. In addition, Jiao and Boons (2017) addressed policy durability and circular economy dynamics.

UNIDO (1997) defined the industrial park as a tract of land developed and subdivided into plots according to a comprehensive plan with provision for roads, transport, and public utilities for the use of a group of industrialists. The industrial park is a critical path for circular economy practices in China. Many scholars have investigated the application and conditions of the circular economy in an industrial park. For example, Li and Ma (2015) investigated a papermaking park and found that the park integrated papermaking and power industry resources horizontally, thereby forming a unique circular economy development mode. A case study of the printed circuit board industry conducted by Wen and Meng (2015) concluded that, by strengthening the material metabolism of collocated enterprises in leading industrial production chains in eco-industrial parks, an industrial symbiosis system can be developed to improve the circular economy. Wang et al. (2020) designed dimensions, key indicators, and driving factors for circular transformation in industrial parks.

Certain studies have focused on industries related to the circular economy in specific cities. Ma et al. (2014) studied the circular economy mode of the iron and steel industry in Wu'an City, China. Wang and Wei (2011) considered Yulin City, China as an example to clarify the transition of resource-based industries to a circular economy. Cities are

[2] The most influential documents on new urbanization in China released by the State council include the National New Urbanization Plan (2014–2020) (http://www.gov.cn/zhengce/2014-03/16/content_2640075.htm) and Suggestions on further Promoting the New Type of Urbanization (http://www.gov.cn/zhengce/content/2016-02/06/content_ 5039947.htm). Both these documents address improving institutions and mechanisms for promoting green, circular, and low-carbon development through urbanization, implementing strict systems for environmental protection, and forming a spatial pattern, industrial structure, production mode, and way of life that reduces resource use and protects the environment.

essential for enterprise development and industrial clusters. They play an irreplaceable role in circular and eco-industrial parks. Dong et al. (2016) emphasized that integrated industries and urban symbiosis networks with energy exchange and process synergy linkages are key in promoting industry ecology.

Studies on the eco-industrial park and urban symbiosis networks have been conducted on the urban circular economy in China. However, because it is a new concept, the literature on the urban circular economy is scarce and lacks a concrete definition of a circular economy, as noticed by Paiho et al. (2020). Scholars have made fragmented contributions to urban circular economy research. Paiho et al. (2021) theoretically analyzed the creation of a circular city through potential transportation, energy, and food solutions. Woodard (2020) found that 27 cities evaluated in a global sample of 42 cities did not have a mandatory requirement for businesses to recycle, which was a barrier in developing an urban circular economy. Wang et al. (2018b) evaluated the urban circular economy development index through an empirical study of 40 cities.

2.2. Research on circular economy evaluation

Circular economy evaluation is a hot topic in the circular economy field, and our proposed method involves DEA. Thus, the following review focuses on circular economy performance evaluation approaches using DEA technology.

Many approaches have been adopted to evaluate circular economy performance at the meso-, micro-, and macro-levels. These models include the gross value-added method, end of life analysis, material flow analysis, life cycle assessment, points-based questionnaire, energy analysis, and Grey–Delphi method. The reviews of these methods have been conducted by De Pascale et al. (2020) and Finch et al. (2021). Most of the methods use subjective weights to aggregate various indicators involved in a circular economy to obtain a final single performance index. The subjective weights have been criticized for their inevitable arbitrariness and inconsistent evaluation (Song et al., 2018).

Data envelopment analysis (DEA), which is proposed by Charnes et al. (1978) can automatically generate endogenous weights to avoid subjective bias, and it does not require presetting the production function. In recent years, DEA has become popular in circular economy evaluation. Wu et al. (2014) determined the efficiency of the regional circular economy in China using a super-efficiency DEA model. Pagotto and Halog (2016) evaluated the eco-efficiency of various subsectors in Australian agriculture–food systems using radial DEA models. Evaluation results based on radial models, such as the classical CCR model, can achieve overall circular economy efficiency. There are also non-radial models, which can also obtain factor efficiency for circular economy performance. For example, Liu et al. (2019) adopted the slacks-based measure with the undesirable factors model to decompose the eco-efficiency of a circular economy into economic and environmental efficiencies.

Researchers have also utilized network DEA to evaluate the circular economy. Sun et al. (2019) proposed a non-cooperative game network DEA to assess the performance of the Chinese provincial circular economy. They consider that a circular economy is a complex system with bidirectional material flows and a closed-loop. Ding et al. (2020a) further constructed a cooperative game network DEA to measure the marine circular economy. Moreover, Ding et al. (2020b) combined an extended Malmquist index model with cooperative game network DEA to identify the dominant factor of circular economy performance changes in the long term. In network DEA, due to network efficiency pitfalls (Chen et al., 2013), the inefficiency or slacks of intermediate factors cannot typically be placed in the objective function of the model, rendering it difficult to evaluate the PR and RR performances, which are regarded as intermediate factors in the circular economy.

DEA technology has enriched the evaluation results of the circular economy and provided plans for improving the circular economy from multiple perspectives. However, current circular economy evaluations based on the DEA method face two major challenges. The first challenge is the indicator authenticity. In the real world, many indicators are uncertain and are associated with data collection and judgment elicitation. The accessible data are the most common or modal values of the corresponding indicator. The real situation may be ambiguous and within a certain range (Padilla-Rivera et al., 2021). Therefore, a data-driven decision support system must consider the fuzziness of the data involved in a circular economy, which requires the introduction of fuzzy theory to the assessment method. The second challenge is the problem of working with large datasets. A circular economy not only contains many evaluation indicators but also contains a large number of DMUs, such as cities and enterprises involved in the evaluation. Various decision indicators and large-scale DMUs bring voluminous amounts of data into the models (Gupta et al., 2019). Regardless of the DEA model type used in circular economy evaluation, the solving difficulty and calculation time of the model increase sharply with the expansion of the sample size. Traditional DEA and their algorithms for circular economy evaluation are therefore unsuitable when using large datasets.

The DEA method has recently made progress in using fuzzy numbers and large datasets, making it possible to resolve the two major challenges of circular economy evaluation. Different fuzzy DEA models can be used when the data are fuzzy, including a fuzzy slacks-based measure, fuzzy network DEA, and stochastic-fuzzy DEA (e.g., Emrouznejad et al., 2014). For large datasets, several algorithms have been provided, such as restricted basis entry (Ali, 1993), hierarchical decomposition (Barr and Durchholz, 1997), and Build–Hull (Dulá and López, 2013), to use in large-scale DEA. Among these, the Build–Hull algorithm can most optimally determine all efficient DMUs. Jie (2020) analyzed the computational complexity of the Build–Hull algorithm and proposed a two-phase parallel Build–Hull algorithm to enhance the computational efficiency of the original algorithm for large-scale DEA. Khezrimotlagh et al. (2019) established a new algorithm framework to significantly decrease the required DEA calculation time. Their results demonstrated that the new algorithm framework can decrease the running time by 99.9% in comparison with that of the existing techniques. Overall, these algorithms are primarily based on traditional DEA models. However, it is necessary to combine fuzzy numbers with large datasets to develop a fuzzy DEA method for solving the challenges of circular economy evaluation.

2.3. Literature summary

At present, the circular economy is a research hotspot. However, the urban circular economy remains largely unexplored, and there remains a lack of comprehensive and effective evaluations. Many methods can be used for circular economy evaluation. Among these, DEA exhibits unique evaluation advantages and can be utilized to make meaningful discoveries from various perspectives. The circular economy still faces uncertainty and large datasets limitations. Thus, it is urgently required to develop a fuzzy DEA method in big data context for circular economy evaluation.

3. Methodology framework of the proposed fully fuzzy DEA with large datasets

The method framework consists of three parts. The first part (Section 3.1) is about the key criteria of urban circular economy, which provides basic variables and indicators for subsequent modeling. The second and third parts are about the fully fuzzy DEA method. Section 3.2 demonstrates the fully fuzzy DEA model and Section 3.3 provides the corresponding algorithm for solving our proposed model with large datasets.

3.1. The key criteria of urban circular economy

Before modeling, it is necessary to clarify and select the key criteria of urban circular economy. Broadly speaking, circular economy covers almost all indicators related to economy, society, and environment. However, in this case, the difficulty of data collection increases and targeted analysis of circular economy condition is not definite. It is more proper to narrow down the range of indicators studied. Through a review of the literature, we found that there are several major problems in the research of circular economy evaluation index systems for regional and national levels. (1) The established indicator system tends to generalize the concept of circular economy, which is inconsistent with its two-dimensional orientation by equating circular economy with sustainable development. (2) It is from the perspective of material flow analysis method. Most of the indicators in this index system are state indicators, no potential indicators, lack of management-type indicators, and do not fully consider the important factors affecting the development of circular economy and the intrinsic link between circular economy and sustainable development. (3) From the goal-process-conditions perspective. For example, the proposed circular economy indicator system in China by the National Bureau of Statistics is still under study. (4) From the perspective of eco-efficiency. Some scholars have made preliminary research and design on the evaluation index system of circular economy by drawing on the content of the eco-efficiency index system, but further in-depth research is needed. In order to solve the above problems as much as possible, our indicator framework mainly refers to the articles of Ding et al. (2020) and Sun et al. (2019).

In fact, our literature review of Section 2.1 shows that circular economy studies focused more on the production, life, especially consumption fields, which are also addressed by 3R or 5R principles of circular economy. Besides, Sun et al. (2019) argued that the selection of these criteria needs to consider the correlation of the indicators, but, more importantly, the position and flow of the factors represented by these indicators in circular economy. Therefore, by referring to Sun et al. (2019), the following presents some variables and symbols to demonstrate the flow of the inputs and outputs involved in urban circular economy.

Suppose there are N urban circular economies. Each urban circular economy is regarded as a decision making unit (DMU). At period t, each DMU uses K kinds of resource $\tilde{x}^t = (\tilde{x}_1^t, \tilde{x}_2^t, \ldots, \tilde{x}_K^t)$ to produce S kinds of economic output$\tilde{y}^t = (\tilde{y}_1^t, \tilde{y}_2^t, \ldots, \tilde{y}_S^t)$, but inevitably produces B kinds of environmental pollution $\tilde{u}^t = (\tilde{u}_1^t, \tilde{u}_2^t, \ldots, \tilde{u}_B^t)$, which includes both industrial and consumptive pollution, like industrial waste and household garbage. Then, DMUs need to transform these pollution and wastes by investing M kinds of environmental treatment input $\tilde{z}^t = (\tilde{z}_1^t, \tilde{z}_2^t, \ldots, \tilde{z}_M^t)$ and generates H environmental treatment output $\tilde{g}^t = (\tilde{g}_1^t, \tilde{g}_2^t, \ldots, \tilde{g}_H^t)$ and J kinds of recycling resource $\tilde{r}^t = (\tilde{r}_1^t, \tilde{r}_2^t, \ldots, \tilde{r}_J^t)$. Note that all of the above variables are fuzzy variables to meet the uncertainty of indicator, and the tilde on the variables represents the fuzzy number. For fuzzy theory, please see Appendix A. From these material flows, it can be found that urban circular economy mainly involves the following corresponding six aspects: resource utilization (RU), economic output (EO), pollution emission reduction (PR), environmental treatment input (EI), environmental treatment output (ET) and resource recycling (RR). These six subitems are the key aspects of urban circular economy. They not only play an important role in the operation and development of urban circular economy, but also jointly reflect the characteristics of reducing, reusing and recycling of UCE. Their efficiency performance is the crucial part of urban circular economy evaluation. The overall performance of the urban circular economy should be a comprehensive reflection of the performance of these subitems.

3.2. The fully fuzzy DEA model

To evaluate the performance of urban circular economy and its subitems, a fully fuzzy DEA model is proposed as shown in model (1). The model has three characteristics. First, we consider the fully fuzzy number, that is, all the input-output indicators are fuzzy, which can well satisfy the ambiguity of data. If a few indicators are represented by real data, we can also regard it as the fuzzy number of which up and low bounds are the same. Hence, the proposed model can be applied to fully and incomplete fuzzy indicators. Second, since urban circular economy includes undesirable outputs, we also imposed them into the model. Third, the complete non-radial Fare-Lovell inefficiency is introduced into the measure of the model to obtain all factor inefficiency, which allows us to capture the efficiency performance of all factors, rather than just the single overall efficiency of urban circular economy.

$$
\begin{aligned}
& Max\sum_{k=1}^{K}\tilde{\alpha}_k^t + \sum_{m=1}^{M}\tilde{\beta}_m^t + \sum_{s=1}^{S}\tilde{\delta}_s^t + \sum_{h=1}^{H}\tilde{\gamma}_h^t + \sum_{j=1}^{J}\tilde{\theta}_j^t + \sum_{b=1}^{B}\tilde{\eta}_b^t \\
& s.t.\sum_{n=1}^{N}\lambda_n^t\tilde{x}_{kn}^t + \tilde{\alpha}_k\tilde{x}_k^t \preccurlyeq \tilde{x}_k^t k = 1,2,\ldots K \\
& \sum_{n=1}^{N}\lambda_n^t\tilde{z}_{mn}^t + \tilde{\beta}_m\tilde{z}_m^t \preccurlyeq \tilde{z}_m^t m = 1,2,\ldots M \\
& \sum_{n=1}^{N}\lambda_n^t\tilde{y}_{sn}^t - \tilde{\delta}_s\tilde{y}_s^t \succcurlyeq \tilde{y}_s^t s = 1,2,\ldots S \\
& \sum_{n=1}^{N}\lambda_n^t\tilde{g}_{hn}^t - \tilde{\gamma}_h\tilde{g}_h^t \succcurlyeq \tilde{g}_h^t h = 1,2,\ldots H \\
& \sum_{n=1}^{N}\lambda_n^t\tilde{r}_{jn}^t - \tilde{\theta}_j\tilde{r}_j^t \succcurlyeq \tilde{r}_j^t j = 1,2,\ldots J \\
& \sum_{n=1}^{N}\lambda_n^t\tilde{u}_{bn}^t + \tilde{\eta}_b\tilde{u}_b^t \preccurlyeq \tilde{u}_b^t b = 1,2,\ldots B \\
& \tilde{\alpha}_1^t,\tilde{\alpha}_2^t,\ldots,\tilde{\alpha}_K^t \in (TFN)_+;\tilde{\beta}_1^t,\tilde{\beta}_2^t,\ldots,\tilde{\beta}_M^t \in (TFN)_+; \\
& \tilde{\delta}_1^t,\tilde{\delta}_2^t,\ldots,\tilde{\delta}_S^t \in (TFN)_+;\tilde{\gamma}_1^t,\tilde{\gamma}_2^t,\ldots,\tilde{\gamma}_H^t \in (TFN)_+; \\
& \tilde{\theta}_1^t,\tilde{\theta}_2^t,\ldots,\tilde{\theta}_J^t \in (TFN)_+;\tilde{\eta}_1^t,\tilde{\eta}_2^t,\ldots,\tilde{\eta}_B^t \in (TFN)_+; \\
& \lambda_1^t,\lambda_2^t,\ldots\lambda_N^t \geq 0
\end{aligned} \tag{1}
$$

Definition 1. A feasible solution $(\tilde{\boldsymbol{\alpha}}^{t^*},\tilde{\boldsymbol{\beta}}^{t^*},\tilde{\boldsymbol{\delta}}^{t^*},\tilde{\boldsymbol{\gamma}}^{t^*},\tilde{\boldsymbol{\theta}}^{t^*},\tilde{\boldsymbol{\eta}}^{t^*},\tilde{\boldsymbol{\lambda}}^{t^*})$ for model (1) is a fuzzy Pareto solution of model (1) if there does not exist $(\tilde{\boldsymbol{\alpha}}^t,\tilde{\boldsymbol{\beta}}^t,\tilde{\boldsymbol{\delta}}^t,\tilde{\boldsymbol{\gamma}}^t,\tilde{\boldsymbol{\theta}}^t,\tilde{\boldsymbol{\eta}}^t,\tilde{\boldsymbol{\lambda}}^t)$ such that

$$
\begin{aligned}
& \sum_{k=1}^{K}\tilde{\alpha}_k^t + \sum_{m=1}^{M}\tilde{\beta}_m^t + \sum_{s=1}^{S}\tilde{\delta}_s^t + \sum_{h=1}^{H}\tilde{\gamma}_h^t + \sum_{j=1}^{J}\tilde{\theta}_j^t + \sum_{b=1}^{B}\tilde{\eta}_b^t \\
& \succcurlyeq \sum_{k=1}^{K}\tilde{\alpha}_k^{t*} + \sum_{m=1}^{M}\tilde{\beta}_m^{t*} + \sum_{s=1}^{S}\tilde{\delta}_s^{t*} + \sum_{h=1}^{H}\tilde{\gamma}_h^{t*} + \sum_{j=1}^{J}\tilde{\theta}_j^{t*} + \sum_{b=1}^{B}\tilde{\eta}_b^{t*}
\end{aligned}
$$

and

$$
\begin{aligned}
& \sum_{k=1}^{K}\tilde{\alpha}_k^t + \sum_{m=1}^{M}\tilde{\beta}_m^t + \sum_{s=1}^{S}\tilde{\delta}_s^t + \sum_{h=1}^{H}\tilde{\gamma}_h^t + \sum_{j=1}^{J}\tilde{\theta}_j^t + \sum_{b=1}^{B}\tilde{\eta}_b^t \\
& \neq \sum_{k=1}^{K}\tilde{\alpha}_k^{t*} + \sum_{m=1}^{M}\tilde{\beta}_m^{t*} + \sum_{s=1}^{S}\tilde{\delta}_s^{t*} + \sum_{h=1}^{H}\tilde{\gamma}_h^{t*} + \sum_{j=1}^{J}\tilde{\theta}_j^{t*} + \sum_{b=1}^{B}\tilde{\eta}_b^{t*}.
\end{aligned}
$$

Model (1) is fuzzy linear programming and cannot be solved directly. we here attempt to convert it into linear programming. First, the fuzzy measure of model (1) can be turned into a crisp objective function, as shown in model (2)

$$
\begin{aligned}
& Max\sum_{k=1}^{K}\sum_{i=1}^{3}\alpha_k^{ti} + \sum_{m=1}^{M}\sum_{i=1}^{3}\beta_m^{ti} + \sum_{s=1}^{S}\sum_{i=1}^{3}\delta_s^{ti} + \sum_{h=1}^{H}\sum_{i=1}^{3}\gamma_h^{ti} + \sum_{j=1}^{J}\sum_{i=1}^{3}\theta_j^{ti} + \sum_{b=1}^{B}\sum_{i=1}^{3}\eta_b^{ti} \\
& s.t.\ \text{constraints in model (1)}
\end{aligned} \tag{2}
$$

Theorem 1. *Mode (1) and model (2) are equivalent.*

Proof: *both models (1-2) has same constraints. Then, assume* $(\widetilde{\alpha}^{t^*}, \widetilde{\beta}^{t^*}, \widetilde{\delta}^{t^*}, \widetilde{\gamma}^{t^*}, \widetilde{\theta}^{t^*}, \widetilde{\eta}^{t^*}, \widetilde{\lambda}^{t^*})$ *are the optimal solution of model (1), the corresponding expansion* $(\widetilde{\alpha}_k^{t^*}, \widetilde{\beta}_m^{t^*}, \widetilde{\delta}_s^{t^*}, \widetilde{\gamma}_h^{t^*}, \widetilde{\theta}_j^{t^*}, \widetilde{\eta}_b^{t^*}, \widetilde{\lambda}^{t^*})$, $k = 1,2,\cdots,K,\ m = 1,2,\cdots,M,\ s = 1,2,\cdots,S,\ h = 1,2,\cdots,H,\ j = 1,2,\cdots,J,\ b = 1,2,\cdots,B$ *will be the optimal solution of model (2). If not, it means that there is an optimal solution* $(\widetilde{\alpha}_k^{t}, \widetilde{\beta}_m^{t}, \widetilde{\delta}_s^{t}, \widetilde{\gamma}_h^{t}, \widetilde{\theta}_j^{t}, \widetilde{\eta}_b^{t}, \widetilde{\lambda}^{t})$ $k = 1,2,\cdots,K,\ m = 1,2,\cdots,M,\ s = 1,2,\cdots,S,\ h = 1,2,\cdots,H,\ j = 1,2,\cdots,J,\ b = 1,2,\cdots,B$ *such that*

$$\begin{aligned}&\sum_{k=1}^{K}\sum_{i=1}^{3}\alpha_k^{ti}+\sum_{m=1}^{M}\sum_{i=1}^{3}\beta_m^{ti}+\sum_{s=1}^{S}\sum_{i=1}^{3}\delta_s^{ti}\\&+\sum_{h=1}^{H}\sum_{i=1}^{3}\gamma_h^{ti}+\sum_{j=1}^{J}\sum_{i=1}^{3}\theta_j^{ti}+\sum_{b=1}^{B}\sum_{i=1}^{3}\eta_b^{ti}\\&>\sum_{k=1}^{K}\sum_{i=1}^{3}\alpha_k^{ti*}+\sum_{m=1}^{M}\sum_{i=1}^{3}\beta_m^{ti*}+\sum_{s=1}^{S}\sum_{i=1}^{3}\delta_s^{ti*}\\&+\sum_{h=1}^{H}\sum_{i=1}^{3}\gamma_h^{ti*}+\sum_{j=1}^{J}\sum_{i=1}^{3}\theta_j^{ti*}+\sum_{b=1}^{B}\sum_{i=1}^{3}\eta_b^{ti*}\end{aligned}$$

In this case, these exist a feasible solution $(\widetilde{\alpha}^{t}, \widetilde{\beta}^{t}, \widetilde{\delta}^{t}, \widetilde{\gamma}^{t}, \widetilde{\theta}^{t}, \widetilde{\eta}^{t}, \widetilde{\lambda}^{t})$ *such that*:

$$\begin{aligned}&\sum_{k=1}^{K}\widetilde{\alpha}_k^{t}+\sum_{m=1}^{M}\widetilde{\beta}_m^{t}+\sum_{s=1}^{S}\widetilde{\delta}_s^{t}+\sum_{h=1}^{H}\widetilde{\gamma}_h^{t}+\sum_{j=1}^{J}\widetilde{\theta}_j^{t}+\sum_{b=1}^{B}\widetilde{\eta}_b^{t}\\&\succcurlyeq\sum_{k=1}^{K}\widetilde{\alpha}_k^{t*}+\sum_{m=1}^{M}\widetilde{\beta}_m^{t*}+\sum_{s=1}^{S}\widetilde{\delta}_s^{t*}+\sum_{h=1}^{H}\widetilde{\gamma}_h^{t*}+\sum_{j=1}^{J}\widetilde{\theta}_j^{t*}+\sum_{b=1}^{B}\widetilde{\eta}_b^{t*}.\end{aligned}$$

According to Definition 1, it means the $(\widetilde{\alpha}^{t^*}, \widetilde{\beta}^{t^*}, \widetilde{\delta}^{t^*}, \widetilde{\gamma}^{t^*}, \widetilde{\theta}^{t^*}, \widetilde{\eta}^{t^*}, \widetilde{\lambda}^{t^*})$ *is not the optimal solution of model (1) and violates the assumptions. Thus, the corresponding expansion* $(\widetilde{\alpha}_k^{t^*}, \widetilde{\beta}_m^{t^*}, \widetilde{\delta}_s^{t^*}, \widetilde{\gamma}_h^{t^*}, \widetilde{\theta}_j^{t^*}, \widetilde{\eta}_b^{t^*}, \widetilde{\lambda}^{t^*})$, $k = 1,2,\cdots,K,\ m = 1,2,\cdots,M,\ s = 1,2,\cdots,S,\ h = 1,2,\cdots,H,\ j = 1,2,\cdots,J,\ b = 1,2,\cdots,B$ *is the optimal solution of model (2). Similarly, we can obtain that the optional solution of model (2) is the expansion of the optional solution of model (1). In this way, both models are equivalent. Q.E.D.*

Since model (2) has fuzzy constraints, we next expand the fuzzy constraints to linear constraints and get model (3).

Theorem 2. **:** *Model (2) and model (3) are equivalent.*

Proof: *The objective functions of model (3) and model (2) are the same and it only needs to compare the constraints of the two models. It is not difficult to find that the constraint condition of model (3) is the expansion of fuzzy constraints of model (2). Taking resource input constraints as an example, we can rewrite the constraints* $\sum_{n=1}^{N}\lambda_n^t\widetilde{x}_{kn}^t+\widetilde{\alpha}_k\widetilde{x}_k^t\preccurlyeq\widetilde{x}_k^t k=1,2,\ldots K$ *as* $\sum_{n=1}^{N}\lambda_n(x_{kn}^{t1},x_{kn}^{t2},x_{kn}^{t3})+(\alpha_k^{t1},\alpha_k^{t2},\alpha_k^{t3})(x_k^{t1},x_k^{t2},x_k^{t3})\preccurlyeq(x_k^{t1},x_k^{t2},x_k^{t3})$ *and they are equivalent to the constraints*: $\sum_{n=1}^{N}\lambda_n x_{kn}^{ti}+\alpha_k^{ti}x_k^{ti}\preccurlyeq x_k^{ti} k=1,2,\ldots,K,$ $i=1,2,3$*and* $\alpha_k^{ti}\le\alpha_k^{t,i+1}k=1,2,\ldots,K,i=1,2$. *Other corresponding constraints can be analogized and proved equivalent. Therefore, mode (2) and model (3) are equivalent. Q.E.D.*

Theorem 3. *Model (1) and model (3) are equivalent.*

Proof: *According to* Theorem 1, *model (1) is equivalent to model (2). According to Theorem 2, model (2) is equivalent to model (3). Therefore, model (1) and model (3) are equivalent. Q.E.D.*

Model (3) is a completely crisp linear program and can be directly applied to urban circular economy evaluation. However, it can only calculate urban circular economy performance in the contemporaneous period, and urban circular economy performance in different periods is not comparable. To overcome the defect, by referring to Oh (2010), *we introduced the global frontier technology that aggregates and compares DMUs in whole periods to produce a global frontier where efficiency performance of different periods can be compared. Suppose there are T sample periods, under the global frontier, the performance of urban circular economy at period t can be represented by model (4). Note that the introduction of global technology will result in a proliferation of DMUs in the model since the DMUs in all periods are gathered.*

$$\begin{aligned}&Max\sum_{k=1}^{K}\sum_{i=1}^{3}\alpha_k^{ti}+\sum_{m=1}^{M}\sum_{i=1}^{3}\beta_m^{ti}+\sum_{s=1}^{S}\sum_{i=1}^{3}\delta_s^{ti}+\sum_{h=1}^{H}\sum_{i=1}^{3}\gamma_h^{ti}+\sum_{j=1}^{J}\sum_{i=1}^{3}\theta_j^{ti}+\sum_{b=1}^{B}\sum_{i=1}^{3}\eta_b^{ti}\\&s.t.\sum_{n=1}^{N}\lambda_n x_{kn}^{ti}+\alpha_k^{ti}x_k^{ti}\le x_k^{ti}k=1,2,\ldots,K,i=1,2,3\\&\sum_{n=1}^{N}\lambda_n z_{mn}^{ti}+\beta_m^{ti}z_m^{ti}\le z_m^{ti}m=1,2,\ldots,M,i=1,2,3\\&\sum_{n=1}^{N}\lambda_n y_{sn}^{ti}-\delta_s^{ti}y_s^{ti}\ge y_s^{ti}s=1,2,\ldots,S,i=1,2,3\\&\sum_{n=1}^{N}\lambda_n g_{hn}^{ti}-\gamma_h^{ti}g_h^{ti}\ge g_h^{ti}h=1,2,\ldots,H,i=1,2,3\\&\sum_{n=1}^{N}\lambda_n r_{jn}^{ti}-\theta_j^{ti}r_j^{ti}\ge r_j^{ti}j=1,2,\ldots,J,i=1,2,3\\&\sum_{n=1}^{N}\lambda_n u_{bn}^{ti}+\eta_b^{ti}u_b^{ti}\le u_b^{ti}b=1,2,\ldots,B,i=1,2,3\\&\alpha_k^{ti}\le\alpha_k^{t,i+1}k=1,2,\ldots,K,i=1,2\\&\beta_m^{ti}\le\beta_m^{t,i+1}m=1,2,\ldots,M,i=1,2\\&\delta_s^{ti}\le\delta_s^{t,i+1}s=1,2,\ldots,S,i=1,2\\&\gamma_h^{ti}\le\gamma_h^{t,i+1}h=1,2,\ldots,H,i=1,2\\&\theta_j^{ti}\le\theta_j^{t,i+1}j=1,2,\ldots,J,i=1,2\\&\eta_b^{ti}\le\eta_b^{t,i+1}b=1,2,\ldots,B,i=1,2\\&\lambda_1,\lambda_2,\ldots,\lambda_N\ge0\end{aligned}\tag{3}$$

$$
\begin{aligned}
& Max\sum_{k=1}^{K}\sum_{i=1}^{3}\alpha_k^{ti}+\sum_{m=1}^{M}\sum_{i=1}^{3}\beta_m^{ti}+\sum_{s=1}^{S}\sum_{i=1}^{3}\delta_s^{ti}+\sum_{h=1}^{H}\sum_{i=1}^{3}\gamma_h^{ti}+\sum_{j=1}^{J}\sum_{i=1}^{3}\theta_j^{ti}+\sum_{b=1}^{B}\sum_{i=1}^{3}\eta_b^{ti} \\
& s.t.\sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_n^t x_{kn}^{ti}+\alpha_k^{ti}x_k^{ti}\le x_k^{ti} k=1,2,\dots,K,i=1,2,3 \\
& \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_n^t z_{mn}^{ti}+\beta_m^{ti}z_m^{ti}\le z_m^{ti} m=1,2,\dots,M,i=1,2,3 \\
& \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_n^t y_{sn}^{ti}-\delta_s^{ti}y_s^{ti}\ge y_s^{ti} s=1,2,\dots,S,i=1,2,3 \\
& \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_n^t g_{hn}^{ti}-\gamma_h^{ti}g_h^{ti}\ge g_h^{ti} h=1,2,\dots,H,i=1,2,3 \\
& \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_n^t r_{jn}^{ti}-\theta_j^{ti}r_j^{ti}\ge r_j^{ti} j=1,2,\dots,J,i=1,2,3 \\
& \sum_{t=1}^{T}\sum_{n=1}^{N}\lambda_n^t u_{bn}^{ti}+\eta_b^{ti}u_b^{ti}\le u_b^{ti} b=1,2,\dots,B,i=1,2,3 \\
& \alpha_k^{ti}\le\alpha_k^{t,i+1} k=1,2,\dots,K,t=1,2,\dots,T,i=1,2 \\
& \beta_m^{ti}\le\beta_m^{t,i+1} m=1,2,\dots,M,t=1,2,\dots,T,i=1,2 \\
& \delta_s^{ti}\le\delta_s^{t,i+1} s=1,2,\dots,S,t=1,2,\dots,T,i=1,2 \\
& \gamma_h^{ti}\le\gamma_h^{t,i+1} h=1,2,\dots,H,t=1,2,\dots,T,i=1,2 \\
& \theta_j^{ti}\le\theta_j^{t,i+1} j=1,2,\dots,J,t=1,2,\dots,T,i=1,2 \\
& \eta_b^{ti}\le\eta_b^{t,i+1} b=1,2,\dots,B,t=1,2,\dots,T,i=1,2 \\
& \alpha_k^{ti},\beta_m^{ti}\ge 0 k=1,2,\dots,K,m=1,2,\dots,M \\
& \delta_s^{ti},\gamma_h^{ti}\ge 0 s=1,2,\dots,S,h=1,2,\dots,H \\
& \theta_j^{ti},\eta_b^{ti}\ge 0 j=1,2,\dots,J,b=1,2,\dots,B \\
& \lambda_1^t,\lambda_2^t,\dots,\lambda_N^t\ge 0 t=1,2,\dots,T
\end{aligned}
\tag{4}
$$

Definition 3. *For any DMU, fuzzy inefficiency of urban circular economy is defined as follows:*

$$
\begin{aligned}
& I\widetilde{E}_{xk}^t=\left(\alpha_k^{t1},\alpha_k^{t2},\alpha_k^{t3}\right);I\widetilde{E}_{zm}^t=\left(\beta_m^{t1},\beta_m^{t2},\beta_m^{t3}\right);I\widetilde{E}_{ys}^t=\left(\delta_s^{t1},\delta_s^{t2},\delta_s^{t3}\right); \\
& I\widetilde{E}_{gh}^t=\left(\gamma_h^{t1},\gamma_h^{t2},\gamma_h^{t3}\right);I\widetilde{E}_{rj}^t=\left(\theta_j^{t1},\theta_j^{t2},\theta_j^{t3}\right);I\widetilde{E}_{ub}^t=\left(\eta_b^{t1},\eta_b^{t2},\eta_b^{t3}\right)
\end{aligned}
\tag{5}
$$

Definition 4. *For any DMU, fuzzy efficiency of urban circular economy is defined as follows:*

$$
\begin{aligned}
& \widetilde{E}_{xk}^t=\widetilde{1}+(-1)I\widetilde{E}_{xk}^t=\left(1-\alpha_k^{t3},1-\alpha_k^{t2},1-\alpha_k^{t1}\right) \\
& \widetilde{E}_{zm}^t=\widetilde{1}+(-1)I\widetilde{E}_{zm}^t=\left(1-\beta_m^{t3},1-\beta_m^{t2},1-\beta_m^{t1}\right) \\
& \widetilde{E}_{ys}^t=\widetilde{1}+(-1)I\widetilde{E}_{ys}^t=\left(1-\delta_s^{t3},1-\delta_s^{t2},1-\delta_s^{t1}\right) \\
& \widetilde{E}_{gh}^t=\widetilde{1}+(-1)I\widetilde{E}_{gh}^t=\left(1-\gamma_h^{t3},1-\gamma_h^{t2},1-\gamma_h^{t1}\right) \\
& \widetilde{E}_{rj}^t=\widetilde{1}+(-1)I\widetilde{E}_{rj}^t=\left(1-\theta_j^{t3},1-\theta_j^{t2},1-\theta_j^{t1}\right) \\
& \widetilde{E}_{ub}^t=\widetilde{1}+(-1)I\widetilde{E}_{ub}^t=\left(1-\eta_b^{t3},1-\eta_b^{t2},1-\eta_b^{t1}\right)
\end{aligned}
\tag{6}
$$

It is not hard to find that the fuzzy efficiency is between $\widetilde{0}$ and $\widetilde{1}$. The larger the fuzzy value is, the better it performs. Extremely, when the fuzzy efficiency scores of all factors are $\widetilde{0}$, it means urban circular economy is completely inefficient.

As mentioned above, the urban circular economy consists of six subitems: resource utilization (RU), economic output (EO), pollution emission reduction (PR), environmental treatment input (EI), environmental treatment output (ET), and resource recycling (RR). The fuzzy efficiency performance of these subitems is defined as the geometric average of their factor efficiency, shown in formula (7). In formula 7, the fuzzy efficiency performance of these subitems is all between $\widetilde{0}$ and $\widetilde{1}$. When one value reaches $\widetilde{1}$, the corresponding subitem of the urban circular economy is called efficient. Note that the efficiency of these subitems is independent, and they all represent the specific performance of various internal aspects of the urban circular economy.

$$
\begin{aligned}
& \widetilde{E}_{RU}^t=\frac{1}{K}\sum_{k=1}^{K}\widetilde{E}_{xk}^t \\
& \widetilde{E}_{EO}^t=\frac{1}{S}\sum_{s=1}^{S}\widetilde{E}_{ys}^t \\
& \widetilde{E}_{PR}^t=\frac{1}{B}\sum_{b=1}^{B}\widetilde{E}_{ub}^t \\
& \widetilde{E}_{EI}^t=\frac{1}{M}\sum_{m=1}^{M}\widetilde{E}_{zm}^t \\
& \widetilde{E}_{ET}^t=\frac{1}{H}\sum_{h=1}^{H}\widetilde{E}_{gh}^t \\
& \widetilde{E}_{RR}^t=\frac{1}{J}\sum_{j=1}^{J}\widetilde{E}_{rj}^t
\end{aligned}
\tag{7}
$$

Definition 5. *For any DMU, fuzzy efficiency of urban circular economy can be represented as the geometric average of fuzzy efficiency of six subitems.*

$$
\widetilde{E}_{UCE}^t=\left(\widetilde{E}_{RU}^t+\widetilde{E}_{EO}^t+\widetilde{E}_{PR}^t+\widetilde{E}_{EI}^t+\widetilde{E}_{ET}^t+\widetilde{E}_{RR}^t\right)/6 \tag{8}
$$

$\widetilde{E}_{UCE}^t$ is bounded from $\widetilde{0}$ to $\widetilde{1}$. It measures the overall performance of the urban circular economy of the evaluated DMU. When $\widetilde{E}_{UCE}^t=\widetilde{1}$, according to formula (8), efficiency scores of all subitems will be equal to $\widetilde{1}$. Besides, according to formula (6), all factor efficiency scores will be also equal to $\widetilde{1}$, which means the evaluated DMU is efficient and stays on the production frontier.

3.3. The algorithm for the fully fuzzy DEA with large datasets

Compared with the national and provincial levels, there are more samples at the city level. At the same time, the global frontier technology gathers DMUs in all periods. These issues generate large-scale DMUs. Besides, urban circular economy involves various fuzzy indicators, all of which can lead to an explosion in the amount of data. With data increases, the computation time to solve DEA models sharply rises. It is necessary to develop a proper algorithm applied to the proposed fully fuzzy DEA model. Khezrimotlagh et al. (2019) develop a novel algorithm to solve the standard DEA and it can decrease 99.9% running-time in comparison with the existing techniques in the context of large datasets. However, their algorithm is based on the traditional radial DEA model under the VRS assumption, which does not consider fuzzy numbers and undesirable outputs. In this case, it cannot adapt to our model. Hence, by referring to Khezrimotlagh et al. (2019), we next propose a modified algorithm for solving our fully fuzzy DEA model with large datasets.

The overall framework of the modified algorithm applied to the proposed model in section 3.2 is arranged as follows.

Step1. Obtain the sample (Π) of DMUs of all periods,

Step2. Select a subsample (Π^s) of DMUs from Π,

Step3. Solve the global frontier (Ω^s) of Π^s,

Step4. Find efficient DMUs (Ω^e) in $\Pi \backslash \Pi^s$ under the global frontier Ω^s,

Step5. Determine whether Ω^e is an empty set,

Step5.1. If $\Omega^e = \varnothing$, all DMUs have been evaluated in Steps 3–4. Then go to Step 7,

Step5.2. If $\Omega^e \neq \varnothing$, solve the global frontier (Ω^g) of $\Pi^s \cup \Omega^e$,

Step6. Assess DMUs in $\Pi \backslash (\Pi^s \cup \Omega^e)$ under the global frontier Ω^g,

Step7. End.

In the modified algorithm, the most important issue is to select a subsample. In our model, there are various input-output indicators, so the subsample size is set as $N_s = \min(\sqrt{3NT(K+M+S+H+J+B)}, 3NT/2)$. The subsample consists of two parts. The first part (Π_1^s) contains DMUs with the least input, the least undesired output, or the most desirable output. That is, for each input and undesirable indicator, DMUs with minimum value in the sample are selected, and for each desirable output, DMUs with maximum output value in the sample are selected. In this paper, the economic input and environmental treatment input are normal inputs. Undesirable output denotes environmental pollution. The desirable output includes the economic output, recourse recycling, and environmental treatment output. According to Ali (1993), DMUs with the least input, the least undesired output, or the most desirable output must be efficient. the number of these DMUs is denoted by N_s and it is usually no more than $3(K+M+S+H+J+B)$.

The second part (Π_2^s) contains those DMUs with less input, less undesired output, or more desirable output. There might be efficient DMUs among them. To obtain Π_2^s, we apply a pre-score method as formulas (9-10) show. The pre-score reflects the degree to which the DMU has less input, generates less undesired output, and achieves more desirable output in the remaining sample.

$$\begin{aligned}
a_x^i &= \text{count}\left(P_{X^i} - x_n^{ti} \geq 0\right) i = 1,2,3 \\
a_z^i &= \text{count}\left(P_{Z^i} - z_n^{ti} \geq 0\right) i = 1,2,3 \\
a_g^i &= \text{count}\left(g_n^{ti} - P_{G^i} \geq 0\right) i = 1,2,3 \\
a_y^i &= \text{count}\left(y_n^{ti} - P_{Y^i} \geq 0\right) i = 1,2,3 \\
a_r^i &= \text{count}\left(r_n^{ti} - P_{R^i} \geq 0\right) i = 1,2,3 \\
a_u^i &= \text{count}\left(P_{U^i} - u_{bn}^{ti} \geq 0\right) i = 1,2,3
\end{aligned} \tag{9}$$

$$pre-score = \sum_{i=1}^{3} a_x^i + a_z^i + a_g^i + a_y^i + a_r^i + a_u^i \tag{10}$$

In formula (9), let's take the economic input indicator as an example. Count (•) stands for count function. P_{X^i} is the percentages matrix of X^i, while x_n^{ti} represents the columns vector of K kinds of economic inputs of DMU_n. $P_{X^i} - x_n^{ti}$ denotes the matrix that is obtained by subtracting each of the columns of P_{X^i} from x_n^{ti}. Hence, count $(P_{X^i} - x_n^{ti} \geq 0)$ denotes to count the times that economic input values of DMU_n are less than the corresponding percentiles that range from 0 to 100 of X^i. Those DMUs with the greatest pre-scores have better performance in less input, less undesirable output, but more output and will be selected as the second part of the subsample.

by calculating the pre-score of each DMU and sorting these DMUs in descending order according to the assigned pre-scores. The first $N_s - N_e$ DMUs are selected as Π_2^s. The subsample set then is $\Pi^s = \Pi_1^s \cup \Pi_2^s$.

3.4. Indicator selection and data source

Referring to relevant literature on circular economy indicators (Wang et al., 2018b; Sun et al., 2019; De Pascale et al., 2020) and considering the availability of data, the urban circular economy indicators are selected as follows. In terms of resource utilization, capital (K), labor (L), energy (E), and land (LA) are considered as the most critical production factors (Song et al., 2013), and capital is accounted by the perpetual inventory method. Since there is no official data on energy consumption in prefecture-level cities, we use a proxy indicator closely related to energy consumption, namely, annual electricity consumption in cities. In terms of economic output, Gross domestic product (GDP) is selected as the proxy variable of desirable output in this paper. In terms of environmental pollution, the representative pollutants in industry and life in this paper include industrial wastewater (IW), industrial dust (ID), industrial sulfur dioxide (ISD), and household garbage (HG). In terms of environmental treatment input, we choose these that can better reflect the intensity of environmental treatment, including environmental health investment (EHI), sewage treatment capacity (STC), and harmless treatment capacity (HTC). In terms of environmental treatment output, we chose the indicators that could best reflect the treatment effect, including the treatment rate of sewage (TRS), the harmless treatment rate (HTR) of household garbage, and the amount of industrial dust removal (IDR). Besides, resource recycling is denoted by the comprehensive utilization rate of industrial solid waste (UIS).

There are about 300 prefecture-level cities in mainland China. Several cities with serious data missing are deleted from the selected sample to avoid data distortion issues. we finally collect panel data of 264 cities of mainland China from 2009 to 2018. According to the geographical location of these cities, they can be divided into the eastern region, the central region, the western region, and the northeast region respectively (For more details, please see the Supplementary Material). The sample periods cover the latest decade that data is available. Relevant data were obtained from *China City Statistical Yearbook 2010–2019*, *China City Construction Yearbook 2010–2019*, *China Tertiary Industry Statistical Yearbook 2010–2019*, and *China Statistical Yearbook 2010–2019*. For missing data, we adapt the methods of moving average and the regression prediction to make up for it. All financial data are converted to the based period, i.e., 2006. Table 1 reports the descriptive statistics of these data. There is some degree of uncertainty and errors in the data collection in China. Generally, collecting the precise value of urban circular economy indicator is impossible or it needs unbearable time and expense costs. Due to the difference between the actual and available data of urban circular economy indicators, considering some uncertainty in data is more proper. China's statistical authorities do not allow statistical errors above 5%, but the data errors cannot be eliminated. Those errors below 1% are usually considered negligible. Hence, to show the uncertainty of the data, the triangular membership function with a fluctuation ranging from 1% to 5% is considered. In addition, the larger the data, the greater the error due to the difficulty of collecting it, which means the uncertainty degree increases. We use the following formula to calculate the uncertainty degreeζ.

$$\zeta = \frac{4\%data + 1\%\max - 5\%\min}{\max - \min} \in [1\%, 5\%] \tag{11}$$

This formula (11) ensures that the uncertainty degree linearly varies from 1% to 5% with the size of the data. when the data is the maximum of the indicator, the uncertainty degree is 5% and when the data is the minimum of the indicator, the uncertainty degree is 1%.

Table 1
The descriptive statistical characteristics of input and output data involved in UCE.

Variable	Obs.	Unit	Mean	Std.err.	Median	Std.dev.	Kurtosis	Skewness	Min	Max
L	2640	10^4 Persons	58.5606	1.6829	34.61	86.4706	39.2963	5.4906	4.53	986.87
K	2640	10^4 Yuan	6752.2381	153.9181	4128.9004	7908.4549	15.5305	3.2568	294.923	82149.99
E	2640	10^4 KWH	96.2646	2.9932	46.408	153.7943	24.0115	4.2845	0.8055	1486.02
LA	2640	km2	143.6845	3.9778	80.9444	204.3850	29.8956	4.7523	1	1913
EHI	2640	10^4 Yuan	14463.9869	1400.6618	2646.5	71967.3077	368.3621	17.0614	10	1971974
STC	2640	10 Km^3/day	41.9723	1.5458	17	79.425	34.9831	5.1814	1	821
HTC	2640	Ton/day	1615.0242	52.0665	800	2675.224	31.8446	4.8726	20	29478
GDP	2640	10^4 Yuan	479.1509	13.9718	252.0879	717.8825	36.8258	5.0696	19.8089	9154.18
TRS	2640	%	84.5422	0.2652	88.375	13.628	3.707	−1.7925	18.3	100
HTR	2640	%	89.744	0.3513	98	18.0524	22.9886	−0.5892	0.44	100
UIS	2640	%	80.6599	0.4182	89.8217	21.4851	1.3887	−1.4514	0.24	100
IDR	2640	Ton	258.2844	6.1958	177.8863	318.3468	131.7411	7.622	0.0032	7693.394
IW	2640	10^4 Ton	6911.0392	162.8677	4502	8368.2914	23.8453	3.9308	99	93814
ID	2640	Ton	4.1264	0.3202	2.08	16.4509	491.6379	19.8534	0.0056	516.8812
ISD	2640	Ton	4.895	0.1001	3.4926	5.1451	23.4049	3.5565	0.0092	58.6117
HG	2640	10^4 Ton	55.371	1.8934	24.39	97.2853	24.6856	4.5254	3.68	975.12

Table 2
Average annual fuzzy efficiency and inefficiency for urban circular economy.

Subitem	Fuzzy efficiency			Rank	Fuzzy inefficiency			Rank
	Upper	Modal	Lower		Upper	Modal	Lower	
$\widetilde{E}_{UCE}$	0.7471	0.7463	0.7451	–	0.2549	0.2537	0.2529	–
$\widetilde{E}_{RU}$	0.7748	0.7737	0.7727	3	0.2273	0.2263	0.2252	4
$\widetilde{E}_{EI}$	0.7191	0.7185	0.7180	4	0.2820	0.2815	0.2809	3
$\widetilde{E}_{EO}$	0.8740	0.8737	0.8734	1	0.1266	0.1263	0.1260	6
$\widetilde{E}_{ET}$	0.6880	0.6866	0.6844	5	0.3156	0.3134	0.3120	2
$\widetilde{E}_{RR}$	0.6064	0.6057	0.6033	6	0.3967	0.3943	0.3936	1
$\widetilde{E}_{PR}$	0.8201	0.8194	0.8188	2	0.1812	0.1806	0.1799	5

$$\begin{aligned} upperbound &= \text{mod}al^*(1+\zeta) \\ lowerbound &= \text{mod}al^*(1-\zeta) \end{aligned} \tag{12}$$

Note that the indicator of treatment rate of sewage, the harmless treatment rate of household garbage, and the comprehensive utilization rate of industrial solid waste are percentages that cannot exceed 100. Therefore, we make the constraints on their upper bounds as formula (13) shown.

$$upperbound = \min\{\text{mod}al * (1+\zeta), 100\} \tag{13}$$

Taking the upper and lower bounds of fuzzy numbers into consideration, there are 264 × 16 × 10 × 3 = 126,720 pieces of data in this paper.

4. Results and discussion

4.1. Overall analysis of urban circular economy performance

We first solve for the urban circular economy and subitem efficiencies of 264 cities in China over 2009–2018. Table 2 provides an overview of the average annual fuzzy efficiency and room for improvement. Overall, these cities did not obtain high fuzzy efficiency scores ($\geq \widetilde{0.8}$)[3] for urban circular economy performance during the sample period. The average annual fuzzy efficiencies ($\widetilde{E}_{UCE}$) of the urban circular economy are (0.7471, 0.7463, 0.7451), and the corresponding fuzzy inefficiency are (0.2549, 0.2537, 0.2529), indicating that there is still some room for improvement in urban circular economy performance. Moreover, according to the statistics, only five cities exhibited completely efficient circular economy performance during the sample period, accounting for 1.89% of cities assessed.

The economic output (EO) subitem performed best with high average annual fuzzy scores of (0.8740, 0.8737, 0.8734) indicating that there is less than 15% inefficiency for output growth. Pollution emission reduction (PR) also obtained high average fuzzy scores of (0.8201, 0.8194, 0.8188). Only these two subitems exhibited average annual scores above $\widetilde{0.8}$. The fuzzy efficiency scores of resource utilization (RU) and environmental treatment input (EI) efficiency were lower. Their average annual efficiency scores ranged from $\widetilde{0.7}$ to $\widetilde{0.8}$. Moreover, recourse recycling (RR) and environmental treatment output (ET) subitems exhibited the lowest fuzzy efficiency scores, between $\widetilde{0.6}$ and $\widetilde{0.7}$.

The analysis demonstrates that circular economy performance at the urban level in China does not yield a satisfactory score, although its several subitems, such as EO, exhibit sufficient performance. However, more subitems, especially RR and ET, perform particularly poorly. This implies that the urban circular economy of China is primarily economic, whereas weak in the "recycling" and "treatment." In recent years, the Chinese government has increased its support and funding for environmental governance. However, the low efficiencies of EI and RR indicate redundancy in governance investment and a severe shortage of waste utilization. There remains a significant performance decoupling among EO, PR, RR, and ET.

The difference between the upper and lower fuzzy efficiency is not large. Therefore, to analyze the specific performance of each subitem more optimally, we utilize the modal value of the fuzzy efficiency to explore the corresponding performance of each subitem. Fig. 1 displays the histograms and scatter plots of each subitem. These histograms provide further insights into the score distribution of the modal efficiency values for each subitem. RU, EI, and PR efficiencies present

[3] The fuzzy efficiency score varies from $\widetilde{0}$ and $\widetilde{1}$, and its modal value also varies between 0 and 1. Usually, 0.6 out of 1 is considered as a passing score, while ≥0.8 indicates a high score. we mainly refer to the classification standard of the efficiency score of the Marine circular economy conducted by Ding et al. (2020).

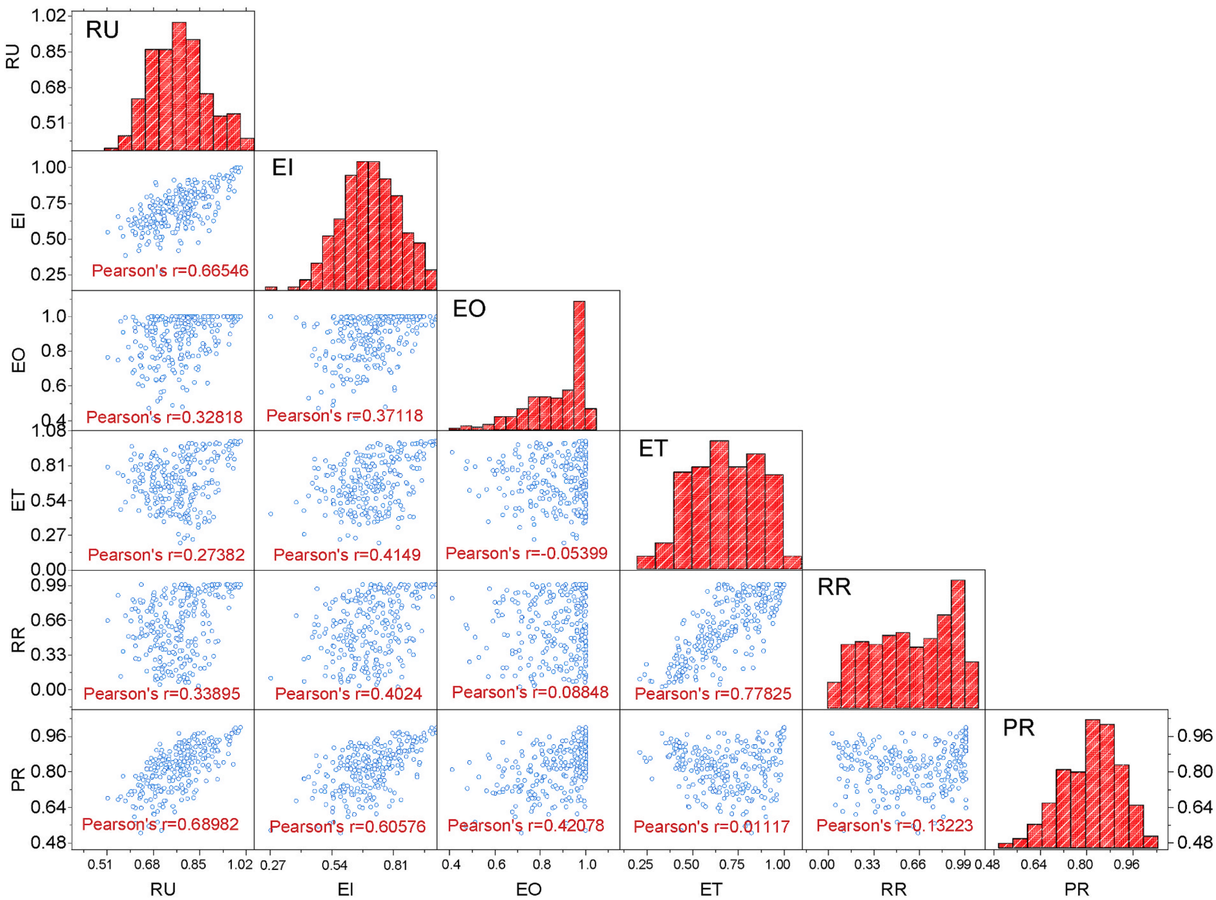

Fig. 1. Efficiency scatter plot and histogram matrix for urban circular economy subitems.
Note: The histograms of these six efficiencies are drawn on the diagonal in Fig. 1 to show the distribution of efficiency of different subitems of UCE. In the lower left of these histograms, 15 scatter plots between the six efficiencies is plotted in order to observe the interdependence between the efficiencies. In each scatter plot, we give the corresponding Pearson correlation coefficient.

Table 3
Average annual fuzzy urban circular economy efficiency scores in four economic regions in China.

Item	Eastern region	Central region	Western region	Northeast region
$\widetilde{E}_{UCE}$	(0.7327, 0.7341, 0.7350)	(0.7253, 0.7264, 0.7271)	(0.7881, 0.7892, 0.7900)	(0.7156, 0.7167, 0.7176)
$\widetilde{E}_{RU}$	(0.7646, 0.7664, 0.7682)	(0.7445, 0.7452, 0.7459)	(0.8127, 0.8135, 0.8142)	(0.7604, 0.7613, 0.7622)
$\widetilde{E}_{EI}$	(0.7324, 0.7333, 0.7342)	(0.6791, 0.6795, 0.6798)	(0.7617, 0.7620, 0.7624)	(0.6606, 0.6610, 0.6615)
$\widetilde{E}_{EO}$	(0.9378, 0.9382, 0.9387)	(0.8282, 0.8285, 0.8288)	(0.8535, 0.8537, 0.8539)	(0.8615, 0.8618, 0.8621)
$\widetilde{E}_{ET}$	(0.5979, 0.5995, 0.6005)	(0.6895, 0.6918, 0.6933)	(0.7698, 0.7719, 0.7735)	(0.6864, 0.6898, 0.6919)
$\widetilde{E}_{RR}$	(0.5193, 0.5219, 0.5221)	(0.6115, 0.6139, 0.6146)	(0.7007, 0.7037, 0.7047)	(0.5574, 0.5583, 0.5594)
$\widetilde{E}_{PR}$	(0.8443, 0.8453, 0.8464)	(0.7992, 0.7997, 0.8001)	(0.8300, 0.8304, 0.8309)	(0.7673, 0.7678, 0.7683)

triangular-like distributions, whereas EO efficiency concentrates between 0.8 and 10, which directly boosts the average scores. Additionally, the correlation coefficients among the six subitem efficiencies can indirectly reflect the relationships between them. There is a high correlation among PR, RU, and EI. One possible explanation is that crude RU produces large amounts of pollution and requires a substantial amount of ET and leading to a greater correlation between their efficiencies. Additionally, the correlation coefficient between ET and RR efficiency is high. They both reflect the output after pollution or waste treatment.

4.2. Regional efficiency disparity and coordination of urban circular economy

This section explores the regional differences in urban circular economy performance. The development conditions typically vary by region, and urban circular economy performance in various regions may exhibit great differences. It is necessary to understand the efficiency characteristics of urban circular economy in different regions to propose evidence-based policy objectives.

Table 3 displays the regional average annual fuzzy efficiency scores of the urban circular economy and its subitems scores. On average, the optimal urban circular economy performance occurs in the western region, where the average fuzzy circular economy score is (0.7881, 0.7892, 0.7900), with high fuzzy efficiency scores of EO (0.8535, 0.8537, 0.8539), PR (0.8300, 0.8304, 0.8309), and RU (0.8127, 0.8135, 0.8142). In the eastern region, the average fuzzy circular economy efficiencies are (0.7327, 0.7341, 0.7350). The fuzzy efficiency scores of EO (0.9378, 0.9382, 0.9387) and PR (0.8443, 0.8453, 0.8464) were high, whereas the fuzzy efficiency performance of RR and EI was particularly poor, not even reaching a passing score at $\widetilde{0.6}$, which greatly lowered the average values. Northeast China was the most poorly

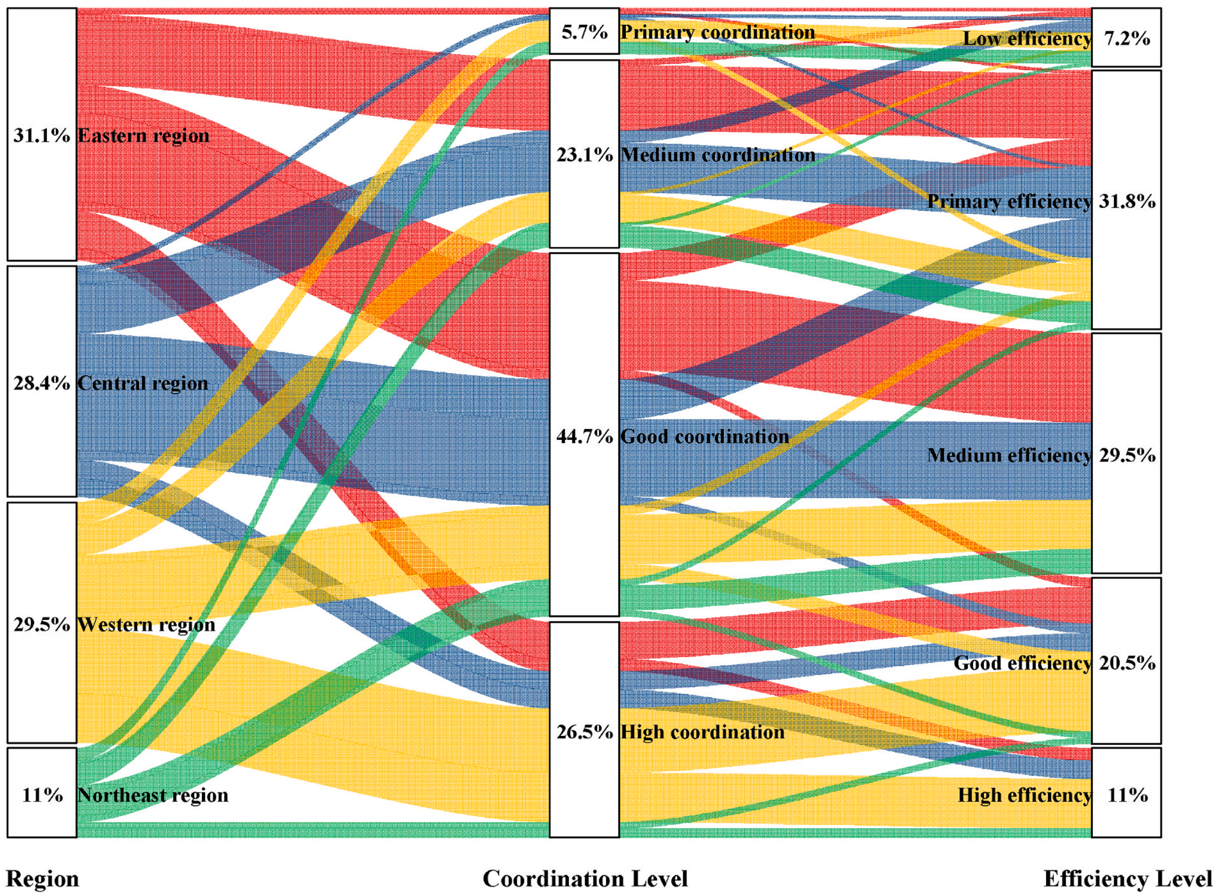

Fig. 2. Coordination level and efficiency level within urban circular economy of China's four economic regions.
Note: The first pillar on the left is a reflection of all the cities in different regions. The second pillar reflects the coordination level of internal subitems of urban circular economy in different cities. The third pillar reflects the urban circular economy of the city. All ribbons issued from a certain position in the first pillar, pass through the second pillar represented by the coordination level and finally flow to the third pillar represented by efficiency level of UCE. Different ribbons reflect the proportion of coordination level and efficiency level of cities in different regions.

Table 4
Fuzzy urban circular economy performance in China during 2009–2018.

Efficiency	Fuzzy number	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
$\widetilde{E}_{UCE}$	Upper	0.8703	0.7946	0.7748	0.7459	0.7222	0.7033	0.6835	0.7103	0.7300	0.7357
	Modal	0.8699	0.7939	0.7741	0.7451	0.7213	0.7024	0.6826	0.7095	0.7292	0.7349
	Lower	0.8694	0.7929	0.7731	0.7438	0.7199	0.7008	0.6811	0.7083	0.7280	0.7337
$\widetilde{E}_{RU}$	Upper	0.8774	0.8149	0.7979	0.7755	0.7544	0.7390	0.7349	0.7341	0.7577	0.7623
	Modal	0.8770	0.8143	0.7972	0.7745	0.7531	0.7376	0.7334	0.7327	0.7563	0.7610
	Lower	0.8767	0.8137	0.7964	0.7736	0.7520	0.7363	0.7319	0.7314	0.7550	0.7597
$\widetilde{E}_{EI}$	Upper	0.8557	0.7424	0.7443	0.7203	0.7113	0.6987	0.6752	0.6761	0.6797	0.6875
	Modal	0.8555	0.7421	0.7439	0.7198	0.7107	0.6980	0.6744	0.6754	0.6789	0.6868
	Lower	0.8553	0.7417	0.7435	0.7193	0.7101	0.6974	0.6737	0.6747	0.6782	0.6861
$\widetilde{E}_{EO}$	Upper	0.9997	0.9898	0.9650	0.9242	0.8609	0.8098	0.7611	0.8072	0.8145	0.8078
	Modal	0.9994	0.9894	0.9646	0.9238	0.8606	0.8095	0.7609	0.8069	0.8143	0.8076
	Lower	0.9990	0.9889	0.9642	0.9235	0.8604	0.8092	0.7606	0.8066	0.8141	0.8073
$\widetilde{E}_{ET}$	Upper	0.8249	0.7299	0.6806	0.6574	0.6348	0.6167	0.6055	0.6760	0.7170	0.7376
	Modal	0.8241	0.7284	0.6790	0.6557	0.6330	0.6149	0.6038	0.6746	0.7158	0.7366
	Lower	0.8231	0.7266	0.6770	0.6536	0.6306	0.6120	0.6011	0.6725	0.7135	0.7345
$\widetilde{E}_{RR}$	Upper	0.7818	0.6656	0.6407	0.5904	0.5743	0.5648	0.5390	0.5574	0.5715	0.5786
	Modal	0.7814	0.6650	0.6401	0.5897	0.5737	0.5642	0.5384	0.5566	0.5706	0.5776
	Lower	0.7803	0.6631	0.6381	0.5869	0.5700	0.5604	0.5350	0.5547	0.5688	0.5755
$\widetilde{E}_{PR}$	Upper	0.8825	0.8248	0.8206	0.8077	0.7978	0.7910	0.7856	0.8112	0.8397	0.8402
	Modal	0.8821	0.8242	0.8199	0.8069	0.7970	0.7901	0.7848	0.8106	0.8391	0.8397
	Lower	0.8818	0.8237	0.8192	0.8061	0.7962	0.7893	0.7839	0.8100	0.8386	0.8392

performed, with average urban circular economy fuzzy efficiency scores of (0.7156, 0.7167, 0.7176). The corresponding fuzzy efficiency scores of EI, ET, and RR are all below $\widetilde{0.7}$. As the oldest industrial base in China, the northeast region was developed by industrial enterprises with high pollution and energy consumption rates. Additionally, its technological and economic levels still lag behind those of the other regions. Its limited treatment capacity and substantial amounts of pollution and waste make Northeast China unlikely to receive a good urban circular economy

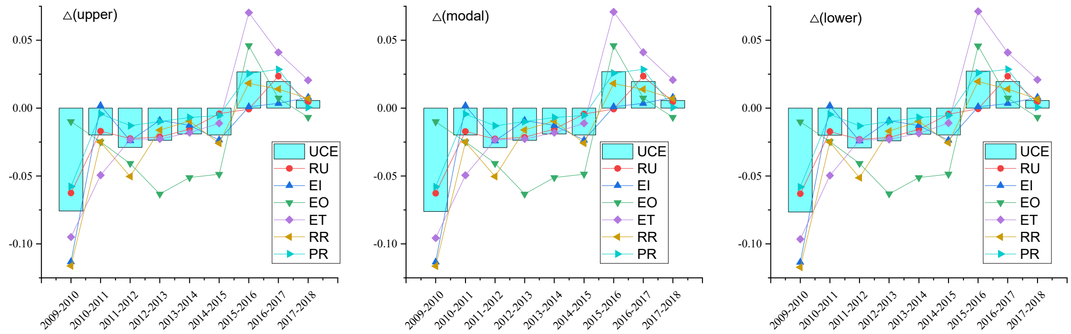

Fig. 3. Urban circular economy performance changes over 2009–2018.
Note: Fig. 3 shows the trend evolution charts of the lower, upper and modal values of fuzzy efficiency during the sample periods from left to right. In each subfigure, six broken lines respectively represent the corresponding efficiency difference between the following period and the previous period of the six subitems of UCE. And the column chart reflects the overall efficiency difference of UCE.

efficiency score.

The urban circular economy disparities across regions reflect the average efficiency differences between them. There are also efficiency differences between different subitems within the urban circular economy. However, it is difficult to count and present these numerous differences due to the multiple subitems. Coordination differences between subitems can reflect their comprehensive efficiency differences. Therefore, we use the coordination degree model to calculate the coordination level of subitem performances. The coordination level measures the degree to which internal subitems develop in harmony with each other.[4] In addition, we further classified the urban circular economy efficiency score into four grades: high efficiency 0.9–1.0), good efficiency (0.8–0.9), medium efficiency (0.6–0.7), and low efficiency (0, 0.6). Both the efficiency and coordination level reflect and quantify the urban circular economy performance.

We further clarify the coordination degree in Appendix B. The coordination degree is theoretically between 0 and 1. In this study, we found that the evaluated coordination degree indicators are all greater than 0.6. Therefore, we classified the coordination degree values into the following four grades: high coordination (0.9–1.0), good coordination (0.8–0.9), medium coordination (0.7–0.8), and primary coordination (0.6–0.7).

Fig. 2 demonstrates the complex single-flow relationships of the region, coordination level, and efficiency level. Over one-quarter of the cities exhibit high coordination, and approximately half of them exhibit good coordination. These cities account for 71.2% of the total, which indicates that most cities are well-coordinated regarding their subitems. In addition, cities with the highest coordination are located in western China, whereas most cities with good coordination are in eastern and central China. Western cities exhibit the highest average coordination levels compared to those of the other regions. Therefore, the western region performs well in the urban circular economy concerning both overall efficiency and subitem coordination. In contrast, cities in the northeast region are more dispersed with instances of high coordination, primary coordination, and medium coordination. This implies that the northeast region is also weak in subitem coordination in addition to its low efficiency.

Cities with high efficiency only account for 11% of the total, which is only 3.8% more than the low efficient DMUs. Most of these are located in western cities and exhibit high coordination. The medium-efficiency (29.5%) and primary-efficiency (31.8%) cities constitute over 61.3% of the total. Most of these cities are located in eastern and central China and exhibit good or medium coordination. The eastern and central China regions are economically developed; however, the evaluation results indicate that their circular economy performance and subitem coordination have substantial room for improvement. In addition, Fig. 2 shows that there is a correlation between coordination and efficiency to a certain degree. For example, cities with high coordination typically exhibit high or good efficiency, which most primary-coordination cities are low efficient.

4.3. *Urban circular economy performance trends*

In this section, we shed light on the intertemporal changes in urban circular economy performance. In the long term, the performance of the urban circular economy typically varies due to internal and external condition changes. Table 4 presents the average fuzzy efficiency scores of the urban circular economy and its subitems from 2009 to 2018. It can be observed in Table 4 that the fuzzy efficiency of each variable fluctuates over time. Analyzing these fluctuations can help us understand the evolutionary characteristics of the circular economy and make predictions.

To facilitate observations and distinguish the circular economy performance trends, we use the differences in efficiency between two adjacent periods to reflect the intertemporal changes in the efficiency of the urban circular economy and its subitems. A positive difference indicates an increase in efficiency, whereas a negative difference means that the performance declines over time. Fig. 3 displays the efficiency difference of the urban circular economy over 2009–2018.

The circular economy exhibits a persistent decline during the first two-thirds of the sample period (2009–2015) and a rising trend during the final one-third of the sample period (2015–2018). From 2009 to 2015, the differences between the circular economy and subitem efficiencies are almost always negative, which means that the circular economy continues to deteriorate over time. The efficiency of the urban circular economy decreased most sharply at the beginning of the sample period (2009–2010). This may be because the environment contained assets that were idle or mismatched and the output falling sharply due to the 2008 global financial crisis. Ding et al. (2020a) also reached a similar conclusion when they found that the crisis harmed the marine circular economy.

After 2015, the urban circular economy performance stopped deteriorating and improved over time. The fuzzy urban circular economy efficiency increased from (0.6835, 0.6826, 0.6811) in 2015 to (0.7357, 0.7349, 0.7337) in 2018. Among the subitems, the EO and ET performances exhibited the greatest increases. $\widetilde{E}_{EO}$ increased from the lowest point (0.7611, 0.7609, 0.7606) in 2015 to (0.8072, 0.8069, 0.8066) in 2016. $\widetilde{E}_{EI}$ increased from (0.6055, 0.6038, 0.6011) in 2015 to (0.6760, 0.6746, 0.6725) in 2016. The rise in efficiency may be related to supply-side structural reforms proposed by the State Council in 2015. Supply-side structural reform reduces the capacities of the steel, coal, cement,

[4] Note that the standard coordination degree model is not applicable to fuzzy numbers, the modal value of the fuzzy efficiency is considered for calculation as handled in section 4.2.

glass, petroleum, and petrochemical industries with high inputs, high consumption, high pollution, low production, and high inefficiency. In 2016, the Ministry of Environmental Protection issued the Guidelines on Actively Playing the Role of Environmental Protection to Promote Supply-Side Structural Reform, which addressed environmental governance implementation, strengthening environmental constraints, and increasing environmental access strictness.[5]

From 2015 to 2018, although the urban circular economy presented positive performance growth, the growth rate of the efficiency performance declined. The efficiency growth of $\widetilde{E}_{UCE}$ narrowed from (0.0268, 0.0269, 0.0273) in 2015–2016 to (0.0057, 0.0057, 0.0057) in 2017–2018. In particular, the efficiency performance of EO became negative again in 2017–2018. In line with this trend, the urban circular economy performance of China may exhibit negative growth again due to the negative efficiency growth of many subitems. This is a warning for us to halt this downward growth trend, especially to reverse or avoid negative performance growth for EO and PR. The declining growth in urban circular economy performance may be related to the economic transformation in China and the US–China trade war. After the Chinese economy entered this new normal, economic growth began to decline, and the decline in EO growth was accompanied by a decline in pollution emissions growth. Therefore, the pollution treatment capacity has not been fully utilized, thereby presenting a lower efficiency (Ding et al., 2020b). Additionally, many key environmental protection equipment and technologies are heavily dependent on imports. Trade frictions have a significant impact on Chinese imports. The lack of such equipment and technology puts environmental industry supply chains under pressure (Liu et al., 2020).

5. Conclusions and discussion

5.1. Main conclusions and policy implications

Circular economy is considered an effective way to promote urbanization and urban sustainability transitions (Tao et al., 2019). Chinese policymakers must understand how well the urban circular economy performs, which needs to be scientifically evaluated. Current circular economy assessments confront two major challenges: circular economy indicator uncertainty and voluminous data with large-scale DMUs. To fill this gap, this study constructs a fully fuzzy DEA method to evaluate the urban circular economy in big data context. The proposed method first introduces fuzzy theory to identify indicator fuzziness. Then, it uses a modified algorithm to handle large DMU sets and various indicators with large datasets. There is a total of 126,720 raw data points in this study. The proposed model can also assess circular economy data with larger orders of magnitude, such as mega data with over 100,000 DMUs.

The evaluation results of 264 Chinese cities highlight the following conclusions. First, the urban circular economy performances of these cities do not obtain high overall efficiency scores. The average annual fuzzy efficiency score is (0.7471, 0.7463, 0.7451), indicating fuzzy room for improvement of (0.2549, 0.2537, 0.2529), respectively. Western cities exhibit the highest average fuzzy efficiency score and coordination level compared to those of the other regions. Additionally, the eastern region demonstrates great EO performance. Poor RR and PR performances reduce the efficiency score of the urban circular economy. Cities in Northeast China exhibit the lowest efficiency scores, which may be attributed to the decaying industry and unadvanced technical level in the area. The urban economy performance presents two distinct growth trends: in 2009–2015, the urban circular economy performance exhibited negative growth, whereas it increased in 2015–2018. However, the growth rate declined, and there remains a risk of returning to negative growth.

Based on the results, there are several policy implications for improving the urban circular economy in China. Subitem performances within the circular economy demonstrate that ET, RR, and EI are relatively inefficient and must be more greatly improved compared to other subitems. These subitems also exhibit strong correlations. The Chinese environmental governance system should reduce inefficient environmental investments and increase treatment outputs. Certain promising initiatives include implementing product–service systems using advanced technologies to reduce material consumption and pollution generation, strengthening the review and supervision of environmental protection projects and cutting inefficient ones, and using rapidly-evolving smart technologies to support smart waste management and promote resource use efficiency.

Northeast China exhibits the worst urban circular economy performance, especially concerning environmental treatment and recourse recycling. Local cities in Northeast China should support and implement new industrialization strategies to achieve circulated production. For example, they can improve light-polluting sectors such as the trade and service industries, shut down backward production, and guide enterprise environmental technological progress. It is also necessary to create comprehensive and coordinated policies regarding environmental protection, including environmental supervision mechanisms, urban ecological compensation measures, and ecological performance appraisal systems.

Curbing declining or negative growth of urban economy performance trends is necessary. The external environment in China, especially that of export-dependent cities in Southeast China, does not currently exhibit a positive outlook due to the US–China trade war and the effect of the SARS-CoV-2 pandemic. Therefore, cities should continue to improve their environmentally conscious supply chains through localization, improved agility, and digitization to manage potential external adverse impacts and maintain the stability of resources and equipment required for the circular economy. Additional targeted financial support policies should also be implemented, such as those providing diversified financing channels for city circular sector enterprises such as the pollution treatment and recycling industries.

5.2. Limitations and discussions

Several limitations and discussions should be mentioned regarding the proposed model and findings that offer useful directions for future research. In modeling, certain studies insist that a circular economy is a complex network system rather than a black box, which implies that network DEA technology can be used for its evaluation. Two obstacles remain in utilizing this method. First, the required intermediate factor data is difficult to fully obtain from existing databases. In addition, due to network efficiency pitfalls, intermediate factor efficiency cannot be solved by using network DEA technology. However, with additional data and improved models, a fuzzy network DEA model under large datasets can be constructed to assess urban circular economy performance more accurately. Moreover, we focused on the primary results and their explanations. As the results demonstrate, urban circular economy performance exhibits significant regional differences. Therefore, a more fine-grained analysis of improvement strategies should be considered according to the urban physical characteristics, development trajectories, and sectoral structures of cities. Thirdly, some scholars believe that the DEA method could be used to evaluate efficiency but could not be used to improve the performance of the DMU since different DMUs are naturally different. This view is meaningful. DEA method usually determines the improvement path and efficiency of DMU through target points, but it must be acknowledged that, in real life, some improvement paths for a few inefficient DMUs may be difficult to implement, so they may not be able to find a conductive promotion path. In this way,

[5] http://www.gov.cn/xinwen/2016-05/20/content_5075252.htm.

whether to design, how to design the improvement path of DMU is worth discussing. Fourthly, due to the limited availability of data, we are unable to obtain all the indicators involved in the six subitems of urban circular economy studied in this paper. What's worse, besides these subitems, as one reviewer pointed out, there are other related subitems, and the performance of these subitems is worthy of further discussion and differentiation.

CRediT authorship contribution statement

Shuhong Wang: conceived and designed the study. wrote the paper. **Liang Lei:** conceived and designed the study. performed the methods and experiments. wrote the paper. **Lu Xing:** reviewed and edited the manuscript. All authors read and approved the manuscript.

Declaration of competing interest

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

Appendix A

A fuzzy set on $\mathbb{R}^n$ is a mapping $\mu_{\widetilde{A}}: \mathbb{R}^n \rightarrow [0, 1]$. μ_A is the membership function that determines a fuzzy subset A of U. For any $x \in X$, where the values of $\mu_{\widetilde{A}}(x)$ shows the grade of membership of x in $\widetilde{A}$.

Definition A1. A fuzzy number $u = (u_1, u_2, u_3)$ is said to be a triangular fuzzy number (TFN) if its membership function is given by

$$\mu_A(x) = \begin{cases} \dfrac{x - u_1}{u_2 - u_1} u_1 \leq x < u_2 \\ 1 x = u_2 \\ \dfrac{u_3 - x}{u_3 - u_2} u_2 < x \leq u_3 \end{cases} \tag{A1}$$

Definition A2. Given two trapezoidal fuzzy numbers $w = (w_1, w_2, w_3) \in$ TFN and $v = (v_1, v_2, v_3) \in$ TFN, the following arithmetical operations are defined:

(1) Addition

$$\widetilde{z} = \widetilde{w} + \widetilde{v} = (w_1 + v_1, w_2 + v_2, w_3 + v_3) \tag{A2}$$

(2) Multiplication by a scalar ρ

$$\rho \widetilde{w} = \begin{cases} (\rho w_1, \rho w_2, \rho w_3) if \rho \geq 0 \\ (\rho w_1, \rho w_2, \rho w_3) if \rho < 0 \end{cases} \tag{A3}$$

(3) Multiplication of two TFN, $\widetilde{w}\widetilde{v} = \widetilde{z} = (z_1, z_2, z_3)$ where

$$\begin{aligned} z_1 &= \min(w_1 v_1, w_3 v_3, w_1 v_3, w_3 v_1) \\ z_2 &= w_2 v_2 \\ z_3 &= \max(w_1 v_1, w_3 v_3, w_1 v_3, w_3 v_1) \end{aligned} \tag{A4}$$

Note that, in real world, urban circular economy indicators are usually positive. Therefore, the input and output variables are TFN_+. Besides, we also use the well-known LU-fuzzy partial orders to provide the partial order relationship among different TFN. That is, $\widetilde{w} \preccurlyeq (\succcurlyeq) \widetilde{v}$ if and only if $w_i \leq (\geq) v_i$ for i = 1, 2, 3.

Appendix B

A coordination degree model was used to analyze the coordination levels of various systems or items. It reflects the degree of benign coordination among the systems or items. For an urban circular economy, suppose there are N subitems and the performance of ith subitem is E_i; then, the coupling degree among these subitems can be written as formula B1.

$$C = \left\{ \frac{\prod_{i=1}^{N} E_i}{\left(\sum_{i=1}^{N} E_i / N\right)^N} \right\}. \tag{B1}$$

where C is the coupling degree indicator; it denotes the degree of interdependence and mutual restraint among these subitems. The value range of C is 0–1. The closer C is to 1, the greater the coupling degree is. When C is equal to zero, all subitems are in an independent state.

$$T = \sum_{i=1}^{N} \omega_i E_i. \tag{B2}$$

where T is the comprehensive evaluation index for coupling the coordination development of the urban circular economy; it reflects the overall synergy and development level of all subitems. ω_i represents the undetermined coefficients of subitem i. The coordination degree index D of all subitems can be represented by formula (B3).

$$D = \sqrt{C \times T}. \tag{B3}$$

where the value range of D is $[0, 1]$. The larger the D is, the more coordinated these subitems are. The coordination level can typically be divided into several different types as illustrated by Table B.

Table B
Coordination model types and criteria

D score range	Coordination level	Coordination type
$0 \le D < 0.1$	1	Extreme maladjustment
$0.1 \le D < 0.2$	2	Severe maladjustment
$0.2 \le D < 0.3$	3	Moderate maladjustment
$0.3 \le D < 0.4$	4	Mild maladjustment
$0.4 \le D < 0.5$	5	On the verge of maladjustment
$0.5 \le D < 0.6$	6	Grudging coordination
$0.6 \le D < 0.7$	7	Primary coordination
$0.7 \le D < 0.8$	8	Medium coordination
$0.8 \le D < 0.9$	9	Good coordination
$0.9 \le D \le 1.0$	10	High coordination

Appendix C

Nomenclature

CCR	the radial DEA model
DEA	data envelopment analysis
DMU	decision making units
E	energy
EHI	environmental health investment
EI	environmental treatment input
EO	economic output
ET	environmental treatment output
GDP	gross domestic product
HG	household garbage
HTC	harmless treatment capacity
HTR	harmless treatment rate
IDR	industrial dust removal
ISD	industrial sulfur dioxide
IW	industrial wastewater
K	capital
L	labor
LA	land
PR	pollution emission reduction
RR	resource recycling
RU	resource utilization
STC	sewage treatment capacity
TRS	treatment rate of sewage
UCE	urban circular economy

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2021.129214.

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