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Research Article

Measuring Sustainable Development Efficiency of Urban Logistics Industry

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Logistics plays a basic supporting role in the growth of national economy. However, tail gas, noise, and traffic congestion caused by logistics have a negative impact on the environment. An effective evaluation mechanism for sustainable development of urban logistics industry is necessary. Data envelopment analysis (DEA) is a common tool for efficiency evaluation. But, DEA has a limited effect on resource allocation in advance because it is ex-post evaluation. It requires input-output indications and the output is after-the-fact data. This defect is particularly prominent in the evaluation of ecological logistics because pollution indicators belong to ex-post output data that threaten the human environment. First prediction and then evaluation is a possible idea. In addition, DEA efficiency ranking does not have a good discrimination due to its coarse granularity. To solve the issues, combining DEA with the Bayes method, we propose an efficiency evaluation model without after-the-fact data, where an efficiency level is predicted and an evaluation value is calculated according to different investment combinations. Then, it is applied to logistics industries of Jiangsu province in China. The results show that our DEA-Bayes method has good discrimination and is easy to operate; a city with geographical advantage and environmental awareness generally gets a higher efficiency score. So the method can help decision makers to allocate resources rationally and further promote the coordinated development of logistics industry.

1. Introduction

With increasingly serious energy and environment issues in recent years, sustainable development becomes the common development goal of all countries in the world. As logistics industry plays an increasingly important role in economic development [1], it is necessary to establish an effective evaluation system for measuring sustainable development ability for urban logistics.

Logistics is a complex system, and data envelopment analysis (DEA) is an effective evaluation method for a multi-input and multioutput complex system. But, DEA is an ex-post analysis; it is difficult really to give some advice in advance before decisions. In China, e-commerce has brought tremendous opportunities for logistics industry. But it is the common phenomenon of sacrificing the environment for rapid economic growth. Some works [2–8] focus on socioeconomic contributions and ignore environmental effects. In fact, they are both the key contents of sustainable development.

Therefore, besides the socioeconomic contribution indications, we choose dioxide emissions produced by logistics as evaluation indications from the perspective of low carbon economy. Since the Bayes classifier has the advantages of stable classification and simple implementation, we combine DEA with the Bayes method to establish an evaluation model without after-the-fact data, where the Bayes method is used to predict the DEA classification. The model can provide some proposals on resource allocation for logistics industry in advance, particularly from the perspective of sustainable development. Meanwhile, it is easy to operate.

The remainder of this paper is organized as follows. Section 2 reports an in-depth literature survey that focuses on efficiency evaluation of logistic industry. Section 3 illustrates the approach to calculate the efficiency value, and an efficiency ranking algorithm is presented. Section 4 shows the application process of the approach and discusses some results of case study for urban logistics industries of Jiangsu province in China. Finally, Section 5 presents some concluding remarks.

2. Literature Review

2.1. Logistic Efficiency. Some methods are used to evaluate efficiency levels of logistics enterprises, such as grey analytic hierarchy process, fuzzy comprehensive evaluation, and data envelopment analysis (DEA).

DEA has been widely used in efficiency evaluation due to objective factors and simple algorithms [9]. Ni et al. [2] evaluated logistics efficiency of Jiangxi province from 2005 to 2013 by the DEA model, and they analyzed the influencing factors using the Tobit regression model. Hokey et al. [3] extended the research to the outside of the enterprise and found that an external market is also an important factor. An extended DEA model [4] on different input constraints was defined, and then the efficiency of energy utilization for logistics enterprises in Hefei was evaluated. Markovits et al. [5] combined DEA with analytic hierarchy process and studied the efficiency of logistics enterprises in 29 European countries. Yang et al. [6] provided the DEA and IAHP method, where the entropy method is used to determine the weights. Pan et al. [7] constructed three sets of evaluation indices and scientifically analyzed the research efficiency of Chinese universities. Using the DEA model, Deng et al. [8] conducted an empirical analysis on production efficiency and scale efficiency for 55 logistics enterprises in the stock markets of Shanghai and Shenzhen.

In the above research works [2–8], there are some issues that need to be further explored. (1) As we know, a conventional DEA method requires input-output indications. The output indications are after-the-fact data, and DEA has the function of ex-post analysis. So it is difficult for DEA to give some advice before an enterprise makes a decision. (2) The DEA results include technical efficiency, purely technical efficiency, scale efficiency, scale reward, and classification analysis. They are coarser and it is difficult to achieve effective ranking. For example, CCR-DEA classification analysis includes two results: efficient and inefficient. Based on the results, some companies will have the same ranking when they are in the same class. It means that parallel ranking will occur at high frequencies. (3) On the other hand, DEA algorithm usually aims at independent decision-making unit (DMU), and it does not consider the overall distribution of the data set. But, ranking results are usually related to the overall data distribution.

In terms of other ranking methods, DEA was enhanced with fuzzy analytic hierarchy process (FAHP), where each decision maker makes a dual comparison of decision criteria and qualities and assigns each one a relative score [10]. In [11], socioeconomic ranking of the cities of Turkey was presented based on DEA and linear discriminant analysis (LDA), and the cities were compared to each other according to the socioeconomic development scores. In order to achieve effective ranking, [10, 11] try to introduce a new method into DEA. In this paper, we combine DEA and the Bayes theory to construct a new efficiency evaluation model.

2.2. Sustainable Development. Literatures [2–8] focus on the economic factors and ignore environmental pollution. Some scholars studied low carbon economy and discussed carbon emission efficiency. Combining DEA cross-efficiency and Shannon's entropy, Storto et al. [12] obtained urban ecological efficiency after the calculation of efficiency scores, the calculation of cross-efficiency scores, and the combination of the efficiency scores. Then, the ecological efficiency of 116 Italian provincial capital cities in 2011 was as a case study, and the results show that the proposed index has a good discrimination power. In [13], the negative impacts of the emissions, such as particle matter and other emissions (NO_x, O_3, and SO_x), were of concern on the whole ecosystem. In [14], the main factors affecting CO_2 emissions in energy intensive industries were investigated; the results show that industrial scale and labor productivity are the main factors.

Works [12–14] focus on how to reduce harmful gases emissions. However, the issue of optimizing logistics system and improving the contribution to the regional economy needs to be studied.

2.3. Sustainable Development Efficiency of Logistics Industry. Several scholars have suggested some methods to measure the efficiency of urban logistics industry. Zhang et al. [15] constructed a measure function of carbon emission performance; based on provincial panel data of 2003 to 2009 in China, they analyzed dioxide emissions and regional disparity. In [16], a biobjective optimization model for a carbon-capped just-in-time distribution of multiple products in a multiperiod and multiechelon distribution network was constructed. The aims are to jointly minimize total logistics cost and to minimize the maximum carbon quota per period. Based on the model of EKC (Environmental Kuznets Curve), Zhou et al. [17] measured the carbon emissions of provincial logistics industries.

In [15], only carbon emission was discussed; systematic analysis and comprehensive evaluation were lacking. In [17], the relationship between CO_2 and GDP was presented, but an efficiency evaluation method was not offered. In [15–17], there is the lack of warning function in advance. Both the emission of harmful gases and the economy contribution belong to the ex-post data, so the evaluation is an ex-post evaluation.

In our work, the DEA efficiency evaluation without the ex-post data is represented to optimize the resources allocation from the aspect of coordinated development of economy and environment. The main contributions are as follows. (1) DEA efficiency level is predicted only according to investment data. It will help local government to make strategic deployment in advance to allocate limited resources. (2) Based on the Bayesian prediction result, the overall probability distribution of data set is considered, and an efficiency evaluation algorithm is designed. Empirical analysis shows that the method has good discrimination to distinguish the efficiency levels of logistics industries in different cities.

3. Efficiency Measurement Model for Sustainable Development

First, we use the Bayes method to predict the efficiency level. Then, the efficiency ranking of urban logistics is obtained.

3.1. DEA Evaluation. DEA was put forward by Charnes, Cooper, and Rhodes in 1978 [9]. It is a nonparametric method in operation research. The idea behind DEA is that one can compare different organizations, called decision-making units (DMUs), all of which have the same input and output indicators. The CCR-DEA model [18] is used in the paper as follows:

$$\begin{aligned} \max \quad & h_o = \sum_{r=1}^{s} u_r y_{ro} \\ s.t. \quad & \sum_{i=1}^{m} v_i x_{io} = 1 \\ & \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \quad j = 1, 2, \ldots, n \\ & u_r \ge 0, \ r = 1, 2, \ldots, s \\ & v_i \ge 0, \ i = 1, 2, \ldots, m. \end{aligned} \tag{1}$$

It is assumed that there are n DMUs with m inputs and s outputs to be evaluated. Let x_{ij} be the value of the ith input and let y_{rj} be the value of the rth output for the jth DMU. Here, j is the DMU index, and $j = 1, \ldots, n$; i is the input index, and $i = 1, \ldots, m$; r is the output index, and $r = 1, \ldots, s$; v_i is the weight to the ith input; u_r is the weight to the rth output. DMU_o is under the evaluation. In the model, DMU_o is efficient only if the objective function value is 1. Otherwise, DMU_o is inefficient.

3.2. Bayes Prediction. For the convenience of evaluation, we quantify DEA results as 1 and 2, which represent inefficiency and efficiency, respectively. Meanwhile, they are as the classification labels.

Parameter Estimation. In our model, investment indicators are continuous variables. To obtain a probability distribution and conduct an efficiency level prediction, discretization and parameter estimation of continuous variables are two common methods. For the former, if the granularity is small, the computational complexity increases; if the granularity is coarse, it is difficult to get the right decision boundary. Therefore, we adopted the latter: parameter estimation. Here, we assume that data distribution obeys a normal distribution; then the maximum likelihood method is used to estimate parameters.

Bayesian Classification. For logistics industry of one city to be evaluated, assuming that its feature vector is $x = (x_1, \ldots, x_n)$ and its classification is y, the conditional probability is $P(y \mid x_1, \ldots, x_n) = P(y)\prod_{i=1}^{n} P(x_i \mid y)/P(x_1, \ldots, x_n)$. For any given input x, $P(x_1, \ldots, x_n)$ is a constant, and thus the classification output is $\arg\max_y P(y \mid x_1, \ldots, x_n) = \arg\max_y P(y)\prod_{i=1}^{n} P(x_i \mid y)$.

3.3. Efficiency Measurement Algorithm. Assume training data contain nf continuous features $x_1, x_2, \ldots, x_{nf}$, where x_i is the ith feature value. Compute the mean and variance of x_i in different DEA efficiency levels. Further, the conditional probability distribution and the joint probability are obtained.

Calculation of Mean and Variance. Assume that the data obey the normal distribution $N(\mu_{k,i}, \sigma_{k,i}^2)$ under the given feature i associated with the efficiency level k. Here, $\mu_{k,i}$ and $\sigma_{k,i}$ are the mean and the variance, respectively. Assume that $D_1, D_2, \ldots, D_n$ are the corresponding samples. Then, the sample mean $\overline{D}$ is an unbiased estimate of $\mu_{k,i}$ as follows:

$$\mu_{k,i} = \overline{D} = \frac{1}{n}\sum_{j=1}^{n} D_j. \tag{2}$$

The sample variance S^2 is an unbiased estimate of $\sigma_{k,i}$ as follows:

$$\sigma_{k,i} = S^2 = \frac{1}{n-1}\sum_{j=1}^{n}\left(D_j - \overline{D}\right)^2. \tag{3}$$

Calculation of Conditional Probability. For one data item in the kth classification, when its ith feature is v, the conditional probability is obtained:

$$P\left(x_i = v \mid y = k\right) = \frac{1}{\sqrt{2\pi}\sigma_{k,i}} e^{-(v-u_{k,i})^2/2\sigma_{k,i}^2}. \tag{4}$$

Calculation of Joint Probability. For one DMU $(x_1, x_2, \ldots, x_{nf})$ that needs to be evaluated, compute the join probability

$$P(y)\prod_{i=1}^{nf} P\left(x_i \mid y\right), \tag{5}$$

where $P(y)$ is the occurrence probability of efficiency level y in the data set.

Output of Classification Results. In all y $(1 \le y \le nc)$, return the value c that maximizes the following probability:

$$c = \arg\max_y P(y)\prod_{i=1}^{nf} P\left(x_i \mid y\right). \tag{6}$$

Here, c is the predicted efficiency level of $(x_1, x_2, \ldots, x_{nf})$; nc and nf are the number of classifications and features, respectively.

Calculation of Efficiency Evaluation. Define sustainable development efficiency value as
$SDEV = \sum_{y=1}^{nc} yP(y \mid x_1, \ldots, x_{nf})$. Since $P(y \mid x_1, \ldots, x_n) \sim P(y)\prod_{i=1}^{nf} P(x_i \mid y)$,

$$SDEV \sim \sum_{y=1}^{nc} yP(y)\prod_{i=1}^{nf} P\left(x_i \mid y\right). \tag{7}$$

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Input: Feature vectors TX, classification vectors TY and the size m_1 for training set;
Feature vectors CX, and the size m_2 for test set.
The number of classifications and features are nc and nf, respectively.
Output: Predicted classifications c, efficiency values SDEV and ranking list.
for t = 1, 2, ..., m_1
    TX(t) is added into the classification set X{TY(t)}according to TY(t)
end for
for k = 1, 2, ..., nc
    Compute the classification probability p(k)= size(X{k})/m_1;
    for i = 1, 2, ..., nf
        Compute the mean value μ_{k,i} according to Eq. (2);
        Compute the variance σ_{k,i} according to Eq. (3);
    end for
end for
for t = 1, 2, ..., m_2
    for y = 1, 2, ..., nc
        for i = 1, 2, ..., nf
            Compute conditional probability according to Eq. (4);
        end for
        Compute joint probability using Eq. (5)
    end for
    Obtain the predicted level c using Eq. (6)
    Compute SDEV using Eq. (7)
end for
Return a ranking list according to SDEV.
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Algorithm 1: Efficiency evaluation algorithm.

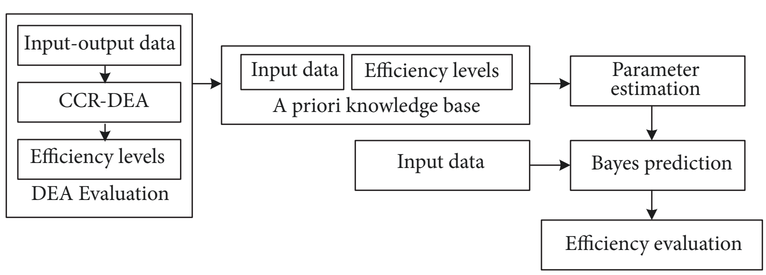

Figure 1: DEA-Bayes evaluation process.

Here, $\sum_{y=1}^{nc} yP(y \mid x_1, \ldots, x_{nf})$ is the average efficiency level. It takes into account the probability distribution of the DEA classification.

Output of Efficiency Ranking. According to the *SDEV*s, we output the cities ranking. More specifically, the efficiency ranking algorithm is given as in Algorithm 1.

4. Evaluation Case

4.1. Evaluation Process. The case data comes from statistical yearbook and research report on logistics index of Jiangsu province. The evaluation process mainly includes two parts: DEA evaluation and Bayesian prediction. In the first part, according to input-output data, the evaluation results including efficiency levels are obtained by the CCR-DEA model. Then, efficiency levels are combined with input data to form an a priori knowledge base. In the second part, the parameters of probability density function are estimated, and the prior probability distribution is obtained. When an input data item is provided, its joint conditional probability is calculated. After probability comparison, the classification result is obtained. Finally, the efficiency evaluation and ranking are obtained. In the process, only during the generation stage of the a priori knowledge base are input-output data needed. At a later Bayesian prediction stage, output data are not needed. The diagram flow is shown in Figure 1.

4.2. Sample. In the case study, we use statistical indicators and logistics data of thirteen cities in Jiangsu province [19]. Staff, total logistics amounts, and cargo vehicles are chosen as the DEA input variables (Table 1). Considering economic-social contribution and ecological environment effect, we choose economic added value and environmental protection ability (*EPA*) as output indicators. In view of low carbon economy, we define *EPA* as the reciprocal

Table 1: Input and output indicators.

Types	Items	Units	Descriptions
Input	Staff	Ten thousand	Human resources investment
	Total social logistics	Trillion Yuan	Regional logistics demand
	Cargo vehicles	Ten thousand	Logistics transportation capacity
Output	Economic added value	Billion Yuan	Contribution to national economy
	Environmental protection ability		The impact on the environment

Table 2: DEA evaluation.

DMUs	Technology efficiency	Efficiency level
Nanjing	0.477	Inefficiency
Wuxi	0.477	Inefficiency
Xuzhou	0.817	Inefficiency
Changzhou	0.544	Inefficiency
Suzhou	0.477	Inefficiency
Nantong	0.554	Inefficiency
Lianyungang	0.771	Inefficiency
Huaian	0.778	Inefficiency
Yancheng	0.785	Inefficiency
Zhenjiang	0.866	Inefficiency
Yangzhou	1	Efficiency
Taizhou	1	Efficiency
Suqian	1	Efficiency

Table 3: DEA slack movement.

DMUs	s_1^+	s_2^+	s_1^-	s_2^-	s_3^-
Nanjing	0	0.003	0	-0.113	-0.052
Wuxi	0	0.001	0	-0.216	-0.983
Xuzhou	0	0.012	0	0	-2.275
Changzhou	0	0	0	-0.139	-0.831
Suzhou	0	0.003	0	-1.144	-0.291
Nantong	0	0	-2.204	-0.211	0
Lianyungang	0	0	-0.475	0	0
Huaian	0	0	0	0	-0.321
Yancheng	0	0	0	0	-1.838
Zhenjiang	0	0	0	-0.004	-0.481
Yangzhou	0	0	0	0	0
Taizhou	0	0	0	0	0
Suqian	0	0	0	0	0

of carbon dioxide emissions from cargo vehicles as follows:

$$EPA = \frac{1}{n_{CO_2}}. \tag{8}$$

Here, n_{CO_2} is carbon dioxide emission. It is a simplified definition. *EPA* may be expanded to a broader meaning, for example, integrating road noise, particulate matter, sulfur dioxide, and other emissions.

Data items in Table 1 were obtained from statistical yearbook and research report on logistics index of Jiangsu province in China [19]. And the data were issued by the Jiangsu Provincial Commission of Economy and Information Technology.

4.3. Results. Based on the logistics industry data of thirteen cities (S1 Table), the CCR-DEA model is implemented (S2 File) and technology efficiency is returned from the model (Table 2). If the value is equal to 1, efficiency level is efficient; otherwise, it is inefficient. Among thirteen DMUs, ten are inefficient, and three are efficient. It reflects that most unban logistics industries in Jiangsu province need to improve sustainable development level.

DEA relaxation variables are in Table 3, where s_1^+ and s_2^+ belong to the output indicators (economic added value and environmental protection ability), and s_1^-, s_2^-, and s_3^- belong the input indicators (staff, total logistics, and cargo vehicles). Take Nanjing as an example, its sustainable development efficiency level is inefficient. In Table 3, its relaxation variable for the EPA is 0.003, which means that EPA needs to be increased; i.e., carbon dioxide emissions need to be decreased. Its second and third input relaxation variables are -0.113 and -0.052, which means that less total logistics and less cargo vehicles are required. To sum up, Nanjing should reduce carbon emissions, total logistics, and cargo vehicles under the current input and output status.

According to the slack movement, the environmental protection abilities (*EPA*) of Nanjing, Wuxi, Xuzhou, and Suzhou are insufficient and need to be increased. Meanwhile, there is redundancy in staff investment of Nantong and Lianyungang. Similarly, total logistics of Nanjing, Wuxi, Changzhou, Suzhou, Nantong, and Zhenjiang need to be reduced. Cargo vehicle investments of Nanjing, Wuxi, Xuzhou, Changzhou, Suzhou, Huaian, Yancheng, and Zhenjiang need to be reduced.

Furthermore, based on the efficiency prediction algorithm (Algorithm 1), efficiency classification prediction can be obtained only using the input data. In Table 4, staff,total logistics, and cargo vehicles are the input indicators. DEA level 1 represents inefficiency and DEA level 2 represents efficiency; they are used as classification labels. Here, DEA levels are obtained by the CCR-DEA model; the predicted levels are obtained by Algorithm 1. Table 4 shows there are three prediction errors among thirteen DMUs, and thus the correct rate reaches 76.92%.

Using (5) and (7), the calculation results of joint probability $P(y)\prod_{i=1}^{nf} P(x_i \mid y)$ and the *SDEV* values are obtained, respectively (see Table 5).

As can be seen from Figure 2, the *SDEV*s of efficient DMUs are in general greater than those of inefficient DMUs.

Table 4: DEA efficiency level prediction.

DMUs	Staff	Total logistics	Cargo vehicles	DEA level	Predicted level
Nanjing	56.74	1.51191	6.877	1	1
Wuxi	57.61	1.746375	8.9311	1	1
Xuzhou	47.28	0.479744	8.1255	1	1
Changzhou	31.82	1.055296	5.6801	1	1
Suzhou	67.31	3.91	8.6376	1	1
Nantong	33.42	1.0565	3.5706	1	1
Lianyungang	21.29	0.296848	2.4646	1	2
Huaian	17.98	0.276853	2.6159	1	2
Yancheng	19.05	0.495022	5.0992	1	1
Zhenjiang	14.19	0.46013	2.8291	1	2
Yangzhou	27.08	0.608538	3.2299	2	2
Taizhou	16.17	0.545014	2.6993	2	2
Suqian	19.37	0.135026	2.1558	2	2

Table 5: Joint probability and SDEVs of DMUs.

DMUs	Inefficient	Efficient	*SDEV*
Nanjing	4.23E-04	2.39E-28	4.23E-04
Wuxi	1.72E-04	9.59E-47	1.72E-04
Xuzhou	3.81E-04	1.79E-29	3.81E-04
Changzhou	8.66E-04	2.84E-11	8.66E-04
Suzhou	4.94E-06	9.59E-84	4.94E-06
Nantong	6.69E-04	2.09E-05	7.11E-04
Lianyungang	2.45E-04	1.51E-02	3.04E-02
Huaian	2.22E-04	1.37E-02	2.77E-02
Yancheng	4.95E-04	7.74E-07	4.97E-04
Zhenjiang	2.21E-04	8.96E-03	1.81E-02
Yangzhou	4.82E-04	4.90E-03	1.03E-02
Taizhou	2.45E-04	1.20E-02	2.43E-02
Suqian	1.72E-04	5.72E-03	1.16E-02

Table 6: Ranking algorithms comparisons.

Types	Discrimination	Prediction	Expert required
DEA [9]	Poor	No	No
DEA-FAHP [10]	Poor	No	Yes
LDA [11]	Good	No	No
Our method	Good	Yes	No

For example, Taizhou and Suqian have high *SDEV*s; Nanjing and Wuxi have low *SDEV*s.

4.4. Algorithms Comparison. Table 6 shows the results of comparison with more research works that are intended to evaluate logistics efficiency. For DEA [9], technology efficiency is used as a ranking indicator; the result is lack of obvious discrimination. In [10], through combining DEA and a fuzzy AHP, a multicriteria decision-making method is studied to measure the efficiency of hospitals. The method requires that a decision maker executes comparisons by pair; then, the pairwise comparison matrix and the eigenvector are determined to specify the importance of each factor in the decision. And the expert experiences are required in [10]. The empirical results show that there exist the same efficiency levels, and their ranking results cannot be distinguished. So DEA [9] and DEA-AHP [10] do not have good discrimination. In [11], DEA and linear discriminant analysis (LDA) are used for efficiency evaluation methods. Fisher's discriminant function is used to determine the coefficients for both input and output variables. Each DMU has Fisher's discriminant function score as the weighted sum of inputs and outputs. Then, the scores are directly used for ranking. We introduce the Bayes classification and consider the overall distribution of the data. Our ranking has reached a good resolution according to *SDEV*. So both LDA and our method have good discrimination. But LDA does not predict efficiency level.

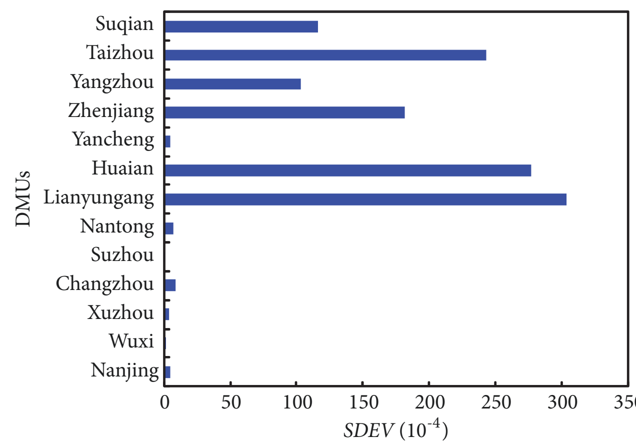

Figure 2: Sustainable development efficiency value (*SDEV*) of urban logistics industries.

Therefore, compared with [9–11], our method has the ability of efficiency level prediction. Without expert scoring, it is easy to achieve automated ranking. Also, it has good distinguishing ability.

The same data are applied to DEA technology efficiency [9], DEA-LDA [11], and our DEA-Bayes method, and the

Table 7: Socioeconomic and ecological rankings of urban logistics.

Cities	DEA technical efficiency [9]	DEA-LDA [11]	Our method
Nanjing	11	5	10
Wuxi	11	7	12
Xuzhou	5	13	11
Changzhou	10	11	7
Suzhou	11	12	13
Nantong	9	10	8
Lianyungang	8	4	1
Huaian	7	9	2
Yancheng	6	8	9
Zhenjiang	4	6	4
Yangzhou	1	1	6
Taizhou	1	2	3
Suqian	1	3	5

evaluation details of DEA-LDA [11] are shown in S3 Table. Table 7 shows socioeconomic and ecological ranking results of urban logistics. It is easily observed that Yangzhou, Taizhou, and Suqian have the same ranking using [9]. It means that it is difficult to distinguish the efficiency levels of the cities by [9]. Both LDA [11] and our method have good discrimination, but there are some differences. For example, Lianyungang is the first in our ranking, but it is the fourth in LDA [11] and Yangzhou is the first in [11]. On the one hand, Lianyungang, as a port city, is connected to the Yangtze River Delta in the south and to the Bohai Bay in the north. With multiple transportation tools, logistics industry of Lianyungang has developed rapidly. In 2017, its total logistics income accounted for 14.9% of its GDP. Local government pays attention to environmental protection and carries out the rules to control the discharge of sewage, waste gas, and garbage. On the other hand, in terms of diversity of transportation and government investment in environmental protection, Yangzhou is lower than Lianyungang. So we think Lianyungang ranking first is a reasonable result.

5. Discussion and Conclusion

Decision makers often need to know the efficiency levels from social-economic and environmental aspects before making investment plans. So it is important to evaluate sustainable development efficiency of logistics industries.

Jiangsu province is studied as a case by means of empirical analysis. According to our results, inefficient cities account for 76.9%, which indicates that logistics industries of most cities in Jiangsu province have the low efficiency levels. For inefficient cities, their environmental protection abilities need to be increased.

In particular, the cities with the *SDEVs* in the top 5 are found as Lianyungang, Huaian, Taizhou, Zhenjiang, and Suqian. Lianyungang has good performances in terms of transportation diversity and environmental protection. Huaian is located in the core area north of the Yangtze River and it is an important transportation hub for Jiangsu province. For Taizhou, the south is on the Yangtze River; the north is Yancheng; the east is Nantong; the west is Yangzhou. Zhenjiang has the Zhenjiang port that is the third largest shipping centre in the Yangtze River Basin. Suqian is an important gateway from the coastal area to the midwest region, and it is also one of the most important e-commerce centres in China. These cities have obvious geographical advantage, which provides favourable conditions for logistics development.

On the other hand, Suzhou, Wuxi, and Xuzhou have the worst rankings. Though their logistics industry incomes are high, their environmental protection abilities are not relatively enough. In order to overcome the uncoordinated situation, some proposals are presented as follows.

(1) Strengthen evaluation. Logistics enterprises in China are in a rapid development period. Evaluation can help them clarify their positions and make reasonable decisions. Therefore, it is necessary to study scientific and objective methods for logistical efficiency evaluation.

(2) Optimize technology and scale efficiency. Logistics enterprises should strengthen staff training, extend the scope of intelligent operations, and realize the transformation from the traditional logistics to the modern logistics. In terms of investment scale, the enterprises should avoid the waste of resources such as the repeated construction of equipment and warehousing. For the enterprises with limited funds, they should choose a differentiation strategy to reduce the homogeneity of logistics services. For large logistics enterprises, they should pay attention to expand the market, establish strategic alliances, improve service quality, and gain market credibility.

(3) At present, the low carbonization level of China's logistics industry is not high. The ways of sacrificing environment often happen. The situation of energy saving and emission reduction is critical. Local government should make the green standards for goods in the process of transportation, handling, and management. Also, it should encourage logistics enterprises to study environmental protection technology, develop green materials, and reduce pollution.

(4) In terms of research method, our efficiency evaluation approach achieves good discrimination. Unlike expert scoring, it can ensure the objectivity of the results. Through predicting the efficiency level under different input combinations, it also provides planning proposals for local government to further promote the regional logistics industry development.

But, there are some limitations of our proposed approach: (1) In this work, our research object is the urban logistics industry of Jiangsu province, while Jiangsu province only has 13 cities; and we only use carbon dioxide emissions as ecological environmental indication; in fact, more data should be considered such as noise and dust; but the data are difficult to obtain. As a result, there are only 13 DMUs and insufficient environmental data for a case study. Considering that DEA is a technique that is very sensitive to outliers and sample size, some situations could happen: DEA efficiency value is larger than actual value or an inefficient DMU is judged as an efficient DMU. The possible situations will affect the results of the Bayesian prediction. (2) Due to the lack of government data on urban logistics rankings from the socioeconomic and ecological view, our performance analysis lacks a comprehensive comparison.

In order to solve the problem of efficiency evaluation for a small size sample, fuzzy theory and bootstrap-DEA might be used, and we will study them or other possible solutions in further work. In addition, we plan to collect more data to construct a comprehensive indicator system and make a comprehensive ranking performance analysis.

Data Availability

All relevant data used to support the findings of this study are included within the supplementary information files.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this article.

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Supplementary Materials

Supplementary 1. S1 Table: logistics indicator data of thirteen cities in Jiangsu, China.

Supplementary 2. S2 File: DEA evaluation process.

Supplementary 3. S3 Table: DEA-LDA evaluation.

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