With the advancement of Internet technology and the widespread use of mobile smartphones, urban e-commerce has gradually become saturated, and rural e-commerce has ushered in a new development opportunity. Data from the 46th China Statistical Report on Internet Development showed that by June 2020, the number of Chinese netizens had reached 940 million, with an Internet penetration rate of 67%. Among them, the proportion of Internet users using mobile phones reached 99.2%. Meanwhile, data from China Business Information Network show that the online retail sales of rural areas reached 1.79 trillion yuan in 2020, with a year-on-year growth of 5.3%.

However, the rapidly developing rural e-commerce also faces multiple challenges from the logistics side: (1) the demand for agricultural product logistics is unstable. All the time, the sale of agricultural products is facing “big year and small year” trouble. That is, in years of good harvests, prices fell because supply far outstripped demand. As a result, many farmers prefer to let their produce rot in the fields rather than affording the costs of picking and transporting it. When agricultural products fail to harvest and prices rise, the backward rural logistics infrastructure restricts the upward movement (agricultural products are sold from the countryside to the cities) of agricultural products. (2) Imperfect rural logistics system: at present, in most areas of China, only provinces, cities, counties, and towns have rural logistics, but there is no logistics distribution in the vast rural areas. (3) Agricultural products are scattered with high
logistics costs. Most of China’s rural areas still retain small-scale peasant economy, with peasant households living in different locations in villages. This leads to insufficient concentration of agricultural products, which directly increases the transport costs of rural logistics [2]. Logistics distribution is becoming increasingly consumer-centered in the context of rural e-commerce growth. Building intelligent and high precision logistics demand forecasting systems with the use of advanced information communication and intelligent computing technology, in order to alleviate or address the aforementioned challenges, has become a large practical need in the present market.

Recently, most scholars focus on the distribution cost (e.g., Crowell [3], Holl and Mariotti [4], and Li [5]), influencing factors (e.g., Crowell [3], Ren et al. [6], Wang [7], and Hao [8]), concepts (e.g., Gebresenbet and Bosona [9] and Bernhardt et al. [10]), modes of rural logistics (e.g., Zhou and Yuan [11], Huang et al. [12], and Yang and Hu [13]), and lack of study on the demand forecast of rural logistics (e.g., Pan [14], Ding et al. [15], and Gong [16]). In order to fill the research gap, this study uses the gray forecasting model to predict the rural logistics demand in Guangdong Province. Specifically, in the context of e-commerce development, what are the potential variables that comprise the indicator system for logistics demand prediction? How accurate is the GM (1, 1) gray forecasting model? This study’s theoretical contribution is in the development of a logistics demand forecasting index system, the expansion of the application of the gray forecasting model, and the enrichment of the literature in the field of rural logistics. Meanwhile, our study findings may be useful to the government, rural logistics businesses, and other relevant sectors for making logistics demand forecasting decisions.

The rest of this study are arranged as follows: the second part proposes the literature review; the third part introduces the study method; the fourth part puts forward the demand forecast indicator system of rural logistics, predicting results as well as discusses the theoretical and practical implications; the fifth part presents the conclusion, limitations, and the future study work.

2. Literature Review

Due to the higher modernization degree of logistics industry in foreign countries, there are not many studies on rural logistics, and they are usually aimed at agricultural product logistics. Crowell, for example, discussed the distribution cost and influencing factors of agricultural products for the first time, which opened the prelude to the study of rural logistics by foreign scholars [3]. Gebresenbet and Bosona expounded the concept of agricultural product supply chain and logistics from the perspective of management and service [8]. Holl et al. analyzed the positive impact of highway development on the performance of rural logistics enterprises [4]. Bernhardt et al. first proposed the concept of “agricultural digital logistics” with the German market as the study object [10]. Simultaneously, they compared the differences between traditional agricultural logistics and agricultural digital logistics, and discussed the ownership and privacy of data [10].

In China, the study of rural logistics began in 2002. Wang and Zhang introduced the concept of modern logistics into the management system of rural agricultural products and proposed to establish China’s rural logistics system for the first time [17]. Since then, Wang [18], Yi et al. [19], Chen [20], and Chen [21] have carried out further research on the necessity of establishing rural logistics system, the development prospect, and the role of rural logistics. In fact, rural logistics has been widely concerned and studied by scholars since 2010. Especially, the rapid development of rural e-commerce in China accelerates the study of rural logistics into a hot period [22]. Chinese scholars focus on the rural logistics mode, existing problems, system construction, and other topics. Huang et al., for example, took rural e-commerce in Hunan Province as the research object and discussed a coordinated operation mode of rural logistics based on supply chain integration, common logistics, and industrial chain integration [12]. Hu and Bao studied the development status of rural logistics in China from the perspective of supply side reform [23]. Zhang proposed the development path of rural logistics in view of the two major problems: “consumer goods unable to go down” and “agricultural products unable to go up” [24]. Li proposed corresponding improvement measures for the existing problems in infrastructure, management, informatization, talent situation, and service of rural logistics in China [25].

In the choice of the logistics demand predicting model, scholars mainly use quantitative method, which can be divided into the traditional linear model, modern nonlinear model, and combination predicting model. For example, Yang [26], Zhao and Chen [27], and Yang et al. [28], respectively, used the regression analysis method, time series method, gray prediction model, and other linear models to predict logistics demand. Zhao [29], Li et al. [30], Li et al. [31], and Lin et al. [32], respectively, used hidden Markov models, artificial neural networks, least-squares support vector machines, traffic section material flow prediction, and other nonlinear models to predict logistics demand. Yu et al. [33] and Guo et al. [34] proposed that higher prediction accuracy could be achieved by using a combination of multiple prediction models.

The existing literature serves as a rich research foundation for this study. It specifically provides a constructive reference for the construction of a logistics demand index system and the selection of research methods. Previous studies, however, have ignored relevant indicators of rural e-commerce development. Based on the previous studies, this study uses the improved gray prediction model to predict the rural logistics demand in Guangdong Province, so as to grasp the change of rural logistics demand in this region and judge its demand scale.

3. Methods

There are many methods to make data predictions. However, the accuracy and effectiveness of the prediction can be increased only by selecting the method that matches the characteristics of the research object. The indicator system of rural logistics demand is characterized by lack of research
information and small sample size, and the system will change with time and situation. The system of rural logistics demand is characterized by lack of research information and small samples [35], and the system will change with the time and conditions [36, 37]. The gray prediction model can forecast the uncertainty system with known and unknown information, its prediction accuracy is high, and it is suitable for short and medium-term prediction [38]. Therefore, the prediction model is highly compatible with the object studied in this study.

The gray prediction model GM (1,1) was first proposed by Deng [38]. From this method, the original data are accumulated to generate approximate exponential law, and then the modeling is carried out. The basic principle of this model is as follows [38]:

Suppose the original sequence is listed as

\[ x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n)\}. \]  

Accumulate the original sequence and produce the first-order sequence.

\[ x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(t), k = 1, 2, \ldots, n. \]  

Calculate parameter variables, where \( a \) is the development coefficient of the GM (1,1) model and \( b \) is the coordinate coefficient of \( x \), namely, the driving term.

\[ \bar{a} = [a, b]^T, \]

\[ y_n' = [x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n)]^T, \]

\[ \bar{a} = (B^T B)^{-1} B^T y_n'. \]  

Establish the time corresponding function of GM (1,1).

\[ \bar{x}^{(1)}(k) = \left[ x^{(0)} - \frac{b}{a} \right] e^{-a(k-1)} + \frac{b}{a} \]  

For the test of the model, the posterior difference ratio is \( c \).

\[ \frac{1}{c} = \frac{S_1}{S_2} = \sqrt[2n]{\frac{\sum_{k=1}^{n} (x^{(0)}(k) - \bar{x})^2}{\sum_{k=1}^{n} q(k) - \bar{q}^2}} \cdot q(k) \]

\[ \bar{x}^{(0)}(k) - \bar{x}^{(0)}(k); \ \bar{q} = \frac{1}{n} \sum_{k=1}^{n} q(k). \]

If the posterior difference ratio \( c \) of the model is less than 0.35 and the small probability error \( p \) value is greater than 0.9, it indicates that the fitting effect of the model is good and the results are credible. Therefore, this model can be used for prediction.

It is worth noting that the internal law of the model cannot be well explained due to the distortion of indicator data caused by the interference of many external factors. In order to solve this problem, Liu put forward the concept of buffer operator and constructed a practical weakening operator (i.e., average weakening buffer operator) [39]. The method is to apply the buffer operator to the original sequence and then model the data after processing. On this basis, Xie and Liu [40], Dang et al. [41], Guan and Liu [42], and other scholars proposed the buffer operator of the new structure. The research of these scholars shows that the use of weakening buffer operator can reduce the interference from the external factors, weaken its randomness, make the data index regular, and reduce the error of the prediction results. Later, Cui et al. [43], Ning et al. [44], Ye et al. [45], and other scholars studied the predictive effect and applicability of the GM (1,1) model by using the weakened buffer operator. Shan and Ma [46], Huang et al. [47], and other scholars used the GM (1,1) model based on weakening operator to make the prediction.

Based on previous contributions to the gray prediction model of the weakened buffer operator, this study adopts the second-order average weakened buffer operator for data processing, and its calculation is as follows:

Average weakening buffer operator:

\[ x(k)d = \frac{1}{n-k+1} [x(k) + x(k+1) + \cdots + x(n)]; k = 1, 2, \ldots, n. \]  

Second-order average weakening buffer operator:

\[ x(k)d^2 = \frac{1}{n-k+1} [x(k)d + x(k+1)d + \cdots + x(n)d]; k = 1, 2, \ldots, n. \]  

4. Indicator System and Empirical Results

4.1. Indicator Selection. Some scholars have investigated the rural logistics demand indicator system. These provide references for our study. Pan, for example, established the rural logistics demand indicator system of Henan Province, which specifically includes the total retail sales of rural consumer goods, the total grain volume of Henan Province, the expenditure of provincial finance for agriculture, forestry and water, the net income per capita of rural residents, and the average consumption expenditure of rural residents [14]. Ding et al. proposed an indicator system for rural logistics demand in Anhui Province, which specifically includes four indicators, namely, agricultural capital consumption, grain freight volume, agricultural, forestry, animal husbandry, and fishery freight volume, and rural main food consumption [15]. Gong believes that the indicator system of rural logistics demand should include regional GDP, total output value of
tertiary industry, agricultural output value, industrial output value, total foreign trade in rural areas, total retail sales in rural areas, and per capita consumption level [16].

Based on the previous literature on the selection of rural logistics demand indicators [48], following the principles of comprehensive, systematic, and applicability, and considering the availability of data and the characteristics of rural logistics demand [49], this study determined three categories of indicators. Among them, economic indicators include per capita disposable income of rural residents and rural retail sales of consumer goods added value; the scale indicators include grain output and pesticide dosage; transport indicators include freight volume and highway mileage. The details are as follows:

- Economic indicators: per capita disposable income of rural residents \( (X_0) \) and rural retail sales of consumer goods added value \( (X_1) \)
- Scale indicators: grain output \( (X_2) \) and pesticide dosage \( (X_3) \)
- Transport indicators: freight volume \( (X_4) \) and highway mileage \( (X_5) \)

To some extent, the volume of freight reflects the flow of goods, which is approximately expressed by the volume of freight. Highway mileage determines the logistics supply capacity of rural areas, reflecting the rural logistics infrastructure. Hence, the situation of rural logistics infrastructure is approximately expressed by highway mileage. Through freight volume and highway mileage, they can reflect the current situation of rural logistics demand in Guangdong Province.

In this study, statistical data from 2013 to 2017 are selected for analysis. The data are from Statistical Yearbook of Guangdong Province and Statistical Yearbook of China. The original data of each indicator are given in Table 1.

4.2. Demand Forecasting. Based on the above analysis, this study takes the per capita disposable income of rural residents \( (X_0) \), rural retail sales of consumer goods added value \( (X_1) \), grain output \( (X_2) \), pesticide dosage \( (X_3) \), freight volume \( (X_4) \), and highway mileage \( (X_5) \) as the indicators for predicting rural logistics demand in Guangdong Province. Considering the consistency and correlation principle of the prediction, we use the average weakening buffer operator to process the original data of the above six indicators. This can better explain the inherent law of the model. Hence, the six indicators are treated with a second-order average weakening buffer operator (2 decimal places are reserved), as given in Table 2.

According to the data in Table 2, this study forecasts the future values of these six indicators. First, we forecast the value of \( X_0 \), and the prediction model is as follows:

\[
x(t+1) = 714228.782108e^{0.019806t} - 700203.982108,
\]

where \( a = -0.019806, b = 13867.995446 \), the evaluation of the model is \( c = 0.0071 \) (good), and \( p = 1.0000 \) (good). The fitting value and error of the model are given in Table 3.

Second, we forecast the value of \( X_1 \), and the prediction model is as follows:

\[
x(t+1) = 179751.912707e^{0.023352t} - 175587.722707,
\]

where \( a = -0.023352, b = 4100.267810 \), the evaluation of the model is \( c = 0.0125 \) (good), and \( p = 1.0000 \) (good). The fitting value and error of the model are given in Table 4.

Third, we forecast the value of \( X_2 \), and the prediction model is as follows:

\[
x(t+1) = -101490.57681e^{-0.012951t} + 102792.36681,
\]

where \( a = -0.012951, b = 1331.223881 \), the evaluation of the model is \( c = 0.3212 \) (good), and \( p = 1.0000 \) (good). The fitting value and error of the model are given in Table 5.

Fourth, we forecast the value of \( X_3 \), and the prediction model is as follows:

\[
x(t+1) = -1206.331178e^{-0.009182t} + 1217.321178,
\]

where \( a = 0.009182, b = 11.177081 \), the evaluation of the model is \( c = 0.3499 \) (good), and \( p = 1.0000 \) (good). The fitting value and error of the model are given in Table 6.

Fifth, we forecast the value of \( X_4 \), and the prediction model is as follows:

\[
x(t+1) = 32735713.370918e^{0.011274t} - 32370982.860918,
\]

where \( a = 0.00623, b = 1212.150063 \), the evaluation of the model is \( c = 0.0430 \) (good), and \( p = 1.0000 \) (good). The fitting value and error of the model are given in Table 7.

Sixth, we forecast the value of \( X_5 \), and the prediction model is as follows:

\[
x(t+1) = 70978609.282910e^{0.003046t} - 70763628.312910,
\]

where \( a = -0.003046, b = 215561.319654 \), the evaluation of the model is \( c = 0.1616 \) (good), and \( p = 1.0000 \) (good). The fitting value and error of the model are given in Table 8.
rural residents in Guangdong Province will reach 17,416.03
next five years, as given in Table 9.

Table 1: Raw data of logistics demand indicators from 2013 to 2017.

<table>
<thead>
<tr>
<th>Indicator year</th>
<th>$X_0$ (unit: yuan)</th>
<th>$X_1$ (unit: 100 million yuan)</th>
<th>$X_2$ (unit: 10 thousand tons)</th>
<th>$X_3$ (unit: 10 thousand tons)</th>
<th>$X_4$ (unit: 10 thousand tons)</th>
<th>$X_5$ (unit: kilometers)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2011</td>
<td>9371.7</td>
<td>336.36</td>
<td>1306.95</td>
<td>11.41</td>
<td>234978</td>
<td>190724</td>
</tr>
<tr>
<td>2012</td>
<td>10542.8</td>
<td>11.34</td>
<td>1396.33</td>
<td>11.39</td>
<td>266359</td>
<td>194943</td>
</tr>
<tr>
<td>2013</td>
<td>11067.8</td>
<td>262.35</td>
<td>1315.90</td>
<td>11.01</td>
<td>328138</td>
<td>202915</td>
</tr>
<tr>
<td>2014</td>
<td>12245.6</td>
<td>374.32</td>
<td>1357.34</td>
<td>11.27</td>
<td>353732</td>
<td>212094</td>
</tr>
<tr>
<td>2015</td>
<td>13360.4</td>
<td>351.24</td>
<td>1358.13</td>
<td>11.38</td>
<td>349832</td>
<td>216023</td>
</tr>
<tr>
<td>2016</td>
<td>14512.2</td>
<td>423.77</td>
<td>1360.22</td>
<td>11.37</td>
<td>377645</td>
<td>218085</td>
</tr>
<tr>
<td>2017</td>
<td>15779.7</td>
<td>455.49</td>
<td>1208.56</td>
<td>10.43</td>
<td>392381</td>
<td>219580</td>
</tr>
</tbody>
</table>

As can be seen from the results, the disposable income of rural residents in Guangdong Province will reach 17,416.03 yuan by 2022, and the added value of rural retail sales of consumer goods will reach 536.398 billion yuan, showing a state of continuous and stable rise in five years. This means that the rural logistics demand of Guangdong Province will show a stable rising trend on the whole with the increase of per capita disposable income of rural residents, rural retail sales of consumer goods, the continuous stability of grain output and pesticide dosage, and the increase of freight volume and highway mileage.

4.3. Results Analysis. In the prediction analysis of the above six indicators, the posterior difference ratio $c$ and the small probability error $p$ value obtained by each model passed the accuracy test. This indicates that the modified GM (1,1) model fits well with the rural logistics demand forecast in Guangdong Province. This further indicates that the prediction results are highly reliable.
According to the results in Table 9, the per capita disposable income of rural residents and the added value of rural retail sales of consumer goods showed a slow upward trend. This is closely related to the economic development in Guangdong Province. The government of Guangdong Province has issued the Three-Year Action Plan on Winning the Battle against Poverty (2018–2020), which is a key period in the battle against poverty, and intensified efforts to alleviate poverty in rural areas. Therefore, the improvement of rural residents’ living standard stimulates the further growth of rural logistics demand. Grain output and pesticide dosage will maintain a relatively stable range in the future. In addition to the impact of imported rice on the grain market, there are abundant grain stocks in Guangdong and even overstocking in some areas. This is the main reason for the stagnation of grain production in Guangdong Province. The reason for the sharp drop in pesticide application in Guangdong Province since 2017 is closely related to the supply side structural reform and sustainable agricultural development promoted by relevant government departments. Freight volume and highway mileage have been further improved, and these two indicators directly affect and stimulate the growth of rural logistics demand.

In the long run, the demand for rural logistics in Guangdong Province is rising, but the growth rate is slowing down. Therefore, the focus is to continue to maintain the growth of rural logistics in Guangdong Province and actively seek the driving forces.

5. Conclusions

Logistics distribution is becoming more consumer-centered as rural e-commerce grows. This necessitates accurate forecasting of present logistics demand in order to determine if the total societal logistics demand can fulfill the individual demand of future customers from the supply side. In this study, the GM (1,1) model of the weakening buffer operator is used to predict the demand of rural logistics in Guangdong Province. The results show that the demand for rural logistics in Guangdong Province will rise in the short and medium term. Based on the findings of this study, we suggest that the government needs to stimulate the demand for rural consumer goods, encourage technological innovation, develop Internet-rural logistics mode, and meet the supply requirements of rural logistics according to the situation of different regions.

However, it is undeniable that there are some limitations in this study. First, in the process of prediction, some selected data indicators cannot be obtained directly, so we can only use similar indicators instead. In fact, it is sometimes difficult to fully reflect the content of the original indicators. For example, this article uses freight volume instead of volume of material flow. Second, this study adopts the data processed by the second-order average weakening buffering operator to predict the gray system, which has good fitting effect and precision. But there may be other approaches that are more applicable. Therefore, in future studies, we need to try to use new models (e.g., back propagation neural network, deep neural network, and combination prediction model) to make predictions and compare the prediction results from various models. Third, due to the particularity of location, economy, and traffic in Guangdong Province, the indicator system constructed in this study may not be directly applied to the prediction of rural logistics demand in other regions. So, we also need to pay attention to the construction of rural logistics demand indicator system in different regions.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was funded by the Teaching Reform Project of General Category of Teaching Steering Committee of E-Commerce in Guangdong Universities (202009) and Quality Engineering Construction Project in Software Engineering Institute of Guangzhou (JYJG202103).

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