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Retraction

Retracted: A Study of Regional Economic Disparities and Coordinated Development Based on Improving Grey Model Combinations

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] B. Yang, "A Study of Regional Economic Disparities and Coordinated Development Based on Improving Grey Model Combinations," *Scientific Programming*, vol. 2022, Article ID 3695361, 8 pages, 2022.

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RETRACTED

Research Article

A Study of Regional Economic Disparities and Coordinated Development Based on Improving Grey Model Combinations

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The positive promotion of regional economic growth is largely consistent with expectations, while there is also a promotion effect on the economic growth of neighboring regions. In this paper, the individual cognitive term of the particle swarm algorithm is introduced into the bath algorithm, and economic forecasting analysis is carried out based on the improved combination of grey model improvements. The main reason for the negative correlation between government investment and economic growth is that, although OFDI promotes economic growth, industrial upgrading, and optimizes industrial structure, it may also reduce regional export capacity, reduce employment opportunities, and increase agency costs. The estimated coefficients for human capital, labor input, capital stock, and urbanization rate are all positive, indicating that each variable is conducive to promoting regional economic growth.

1. Introduction

The implementation of the "One Belt, One Road" initiative provides a good opportunity to expand the scale of China's outward foreign direct investment (OFDI), which is bound to have an important impact on the domestic economy. The article constructs a spatial panel model from the perspective of the regional economy to study the impact of regional OFDI on economic growth. The results find that: regional OFDI development significantly contributes to the economic growth of the region; regional OFDI has significant spillover effects; and to a certain extent, OFDI inhibits regional exports, reduces employment, and raises agency costs [1].

OFDI is the best way to solve overcapacity and absorb advanced technology, and also has a good promotion effect on economic growth. In this context, some scholars have studied the issue of OFDI and economic growth in provincial regions, exploring how provincial regions can make use of their favorable advantages and resources to join international economic development more quickly. The study by Natasha et al. [2] used panel threshold regression to examine the impact of OFDI spillover effects on the economic growth and regional innovation capacity of the three northeastern provinces. The study by Wang et al. [3] found that the efficiency spillover of OFDI has typical single-threshold nonlinear characteristics and significant positive effects and that OFDI and R&D investment becomes the key to improving the efficiency of regional capacity cooperation. Reference [4] investigated the convenience of OFDI business in countries along the Belt and Road, which contribute to the upgrading of the industrial structure and economic growth of related countries. The study by Wellings et al. [5] investigated the nonlinear impact of OFDI on the upgrading of regional industrial structures. The study found that the direction and magnitude of the effect of OFDI on the upgrading of the industrial structure are influenced by the operational efficiency of the financial ecology, and there is a single significant threshold effect, but there is significant regional heterogeneity in this effect.

Based on relevant literature studies, this paper constructs a spatial panel model to examine the impact of OFDI on regional economic development levels and compares it with a nonspatial model to explore in-depth the direct and spillover effects of regional OFDI on economic growth.

2. Related Work

2.1. Current State of Economic Forecasting Research. Traditional economic forecasting has mostly used time series analysis and multiple regression methods. In recent years, with technological innovations, neural network models have also emerged in economic forecasting.

The datasets used in economic forecasting are generally time series data. A time series is a series formed by ordering a statistical variable in chronological order [6].

Shevchuk et al. [1] applied neural networks to economic forecasting, pioneering the use of artificial neural networks to solve time series problems. Greysen et al. [7] successfully applied neural networks to stock index forecasting. Jouvet et al. [8] demonstrated that the prediction performance of neural networks for time series forecasting problems was comparable to that of ARMA models through comparative tests. Daams and Sijtsma [9]compared statistical models such as ARMA, exponential smoothing, and portfolio forecasting with neural network models, and the comparison showed that neural network forecasts outperformed traditional methods in statistics, especially for multi-step forecasting, where the advantages of neural networks were more obvious.

Li et al. [10] applied neural networks to multistep forecasting. The above research results show that the property that neural networks can approximate arbitrary nonlinear functions is a great advantage for solving complex problems such as economic forecasting. With the development of big data technology, the application of neural networks in economic forecasting is also increasing. In the study by Wei et al. [11], a radial basis neural network was applied to macroeconomic forecasting to predict the gross domestic product of Shaanxi Province with good prediction results [12], and two economic indicators, consumer price index and total import and export, were predicted in Fujian Province using the DBN deep learning method and the BP neural network method, which confirmed the excellent performance of deep learning applied to economic forecasting in terms of prediction accuracy and convergence speed performance. In the study by Yang et al. [13], a chaotic neural network was established to forecast the marine economy as a nonlinear object.

2.2. Regional Economic Development. Regional economic development is the result of a combination of factors, from the masters of classical economics like Adam Smith and David Ricardo to some of the leading Western economists of modern times, and domestic economists have attached great importance to the study of economic growth factors. Yu et al. [14] pointed out that regional economies play an important role in socioeconomic and environmental sustainability; Wong et al. [15]used Porter's diamond model to evaluate the competitiveness of major regional economies in Asia, Singapore, and Japan are significantly higher than China, South Korea, and Malaysia; and Fathian et al. [16] pointed out that synergistic cooperation of regional economies will promote sustainable economic development and social equity. Cao et al. [17] analyzed the correlation mechanism between the embedding of multinational companies and the innovation performance of regional economies through a study of three regional economies of different types in Fuzhou, Xiamen, and Quanzhou; the study by Wu et al. [18] pointed out that the higher the level of development of the regional economy, the stronger the pulling effect on the economy; the study by Wang et al. [19] pointed out that the regional economy of ports can drive the development of related industries, generating scale, division of labor, and optimization effects, thus promoting economic growth.

In terms of research on regional economic development, Li et al. [20] chose 22 factors to establish a regression model of economic growth to study the issue of economic growth. Leng [21] empirically studied the relationship between the amount of fixed asset investment and economic growth, and concluded that fixed-asset investment can drive economic development in the long run. Honda [22] showed that investment in the Chinese economy has a significant impact on economic growth, but with a certain time lag. Xu et al. [23] used a panel model with data from 106 countries and found that the positive effect of human capital on economic growth remained significant when other relevant variables were included. Qi et al. [24] showed that education expenditure had a catalytic effect on economic development. Zhang et al. [25] studied the impact of science and technology innovation on economic growth. Wang et al. [19]found that GDP per capita growth in Belgium is not only positively influenced by traditional indicators, but also by investments in transport infrastructure.

3. Improving BA-LSTM Models by Combining Grey Models

Grey forecasting, refers to the prediction of the development of changes in the characteristic values of the behavior of a system, that is, the prediction of a system that contains both known and uncertain information. Grey models have the advantages of generality, high prediction accuracy, and computational simplicity. It has good predictive performance for small data samples [20]. The grey model has been widely used in many fields such as agricultural production, traffic and passenger transportation, and engineering projects [21]. The modeling process is as follows:

(1) Let the original data sequence be $x^{(0)}$,

$$x^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n)\right\}. \tag{1}$$

(2) A single accumulation of the original sequence $x^{(0)}$ gives the data sequence $x^{(1)}$,

$$x^{(1)} = \left\{x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \ldots, x^{(1)}(n)\right\}, \tag{2}$$

where, $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1, 2, 3, \ldots, n.$

(3) Let us define the nearest neighbor mean sequence $z^{(1)}$ of the data sequence $x^{(1)}$ as

$$z^{(1)} = \left\{z^{(1)}(1), z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n)\right\}, \tag{3}$$

where, $\begin{cases} z^{(1)}(1) = x^{(1)}(1) \\ z^{(1)}(k) = \end{cases}$ $1/2x^{(1)}(k) + 1/2x^{(1)}$ $(k-1), k = 2, 3, 4, \ldots, n.$

(4) The differential equation model is established: $\begin{cases} d(k) + az^{(1)}(k) = b \\ x^{(0)}(k) + az^{(1)}(k) = b \end{cases}$, where $z^{(1)}(k)$ is the whitening background value, $x^{(0)}(k)$ is the grey derivative, a is the development coefficient, B is the grey action amount, and $k = 1,2,3, \ldots, n$.

(5) Least-squares solution for the predicted values of a and b is

$$\begin{pmatrix} \hat{a} \\ \hat{b} \end{pmatrix} = \left(B^T B\right)^{-1} B^T Y, \tag{4}$$

where, $B = \begin{pmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \\ -z^{(1)}(n) & 1 \end{pmatrix}, Y = \begin{pmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{pmatrix}.$

(6) Solving equation (4) yields the predicted value $\hat{x}(k+1)$ as follows:

$$\hat{x}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a}, \tag{5}$$

where the sequence of the original data can be calculated according to $\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k), k = 1, 2, 3, \ldots, n-1$ as $\hat{x}^{(0)}$ as follows:

$$\hat{x}^{(0)} = \left\{\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \hat{x}^{(0)}(3), \ldots, \hat{x}^{(0)}(n)\right\}. \tag{6}$$

(7) The residual ε and the relative error p can be obtained from the predicted and original values as follows:

$$\begin{aligned} \varepsilon(k) &= x^{(0)}(k) - \hat{x}^{(0)}(k), k = 1, 2, 3, \ldots, n-1 \\ p(k) &= \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)}, k = 1, 2, 3, \ldots, n-1. \end{aligned} \tag{7}$$

The predictions were estimated for the original data using a grey GM(1,1) prediction model, which gives both the predicted values of the original data and the residuals between them, as well as the relative residuals, as well as the predicted values of the unknown data.

In 2000, Honda [22] proposed the unbiased GM(1,1) model, which corrects a, b, and reduces the bias due to the development of the grey number, compared to the traditional GM(1,1) model. The unbiased GM(1,1) modeling process is as follows:

Steps (1) to (5) are identical to the conventional GM(1,1) model modeling and will not be repeated here.

(8) Let us calculate the model parameters c and A as follows:

$$c = \ln\frac{2-a}{2+a}, A = \frac{2b}{2+a}. \tag{8}$$

(9) Building the original data prediction model as follows:

$$\hat{x}^{(0)}(1) = \hat{x}^{(0)}(1), \hat{x}^{(0)}(k+1) = Ae^{ck}, \tag{9}$$

where $k = 1, 2, 3, \ldots, n-1$; when $k \geq n$, $\hat{x}^{(0)}(k+1)$ is the original sequence prediction.

The sliding average method is based on the simple average in which a moving average, is calculated by sequentially adding and subtracting old and new data period by period in order to eliminate chance variations, identify trends, and make forecasts accordingly.

The process of the modified GM(1,1) model based on the sliding average method is

Step 1. We use the sliding average to locally average the original data over small intervals to reduce the influence of random factors and make the data more regular, thus improving the forecast accuracy.

The raw data is processed as follows:

Step 2. We simply take the data after the smoothing process in Step 1, feed it into a traditional GM(1,1) model, and follow the modeling steps presented to model the data.

Since economic forecasting is highly time-sensitive, in most cases, we need to make economic forecasts without knowing the exact values of the influencing factor indicators. To address this type of problem, the experiments in this section introduce a grey model. At the same time, although the traditional grey model is suitable for small sample forecasting and generalizable, it also suffers from defects such as being susceptible to random factors and poor long-term forecasting. The unbiased grey model can well solve the problem of limited prediction length of the traditional grey model, while the improved grey model based on the sliding average method can well eliminate the influence of random factors. Therefore, the experiments in this section establish a combined grey model for predicting the values of influencing factors, as shown in Figure 1.

Experiments have been conducted using combined grey models to predict the serviceability of asphalt pavements, effectively improving the prediction accuracy. The experiments first used three grey models to predict each single economic prediction influencing factor, and the resulting three sets of prediction values were weighted and averaged. Then the prediction results of the combined grey model were passed into the improved model as the influencing factor values:

4. Variables and Data Sources

The explanatory variable in this paper is the level of economic development. Referring to Duning's theories of outward investment development [23], there is a significant correlation between OFDI and the level of economic development, and OFDI in developed and nondeveloped countries also shows different characteristics [24].

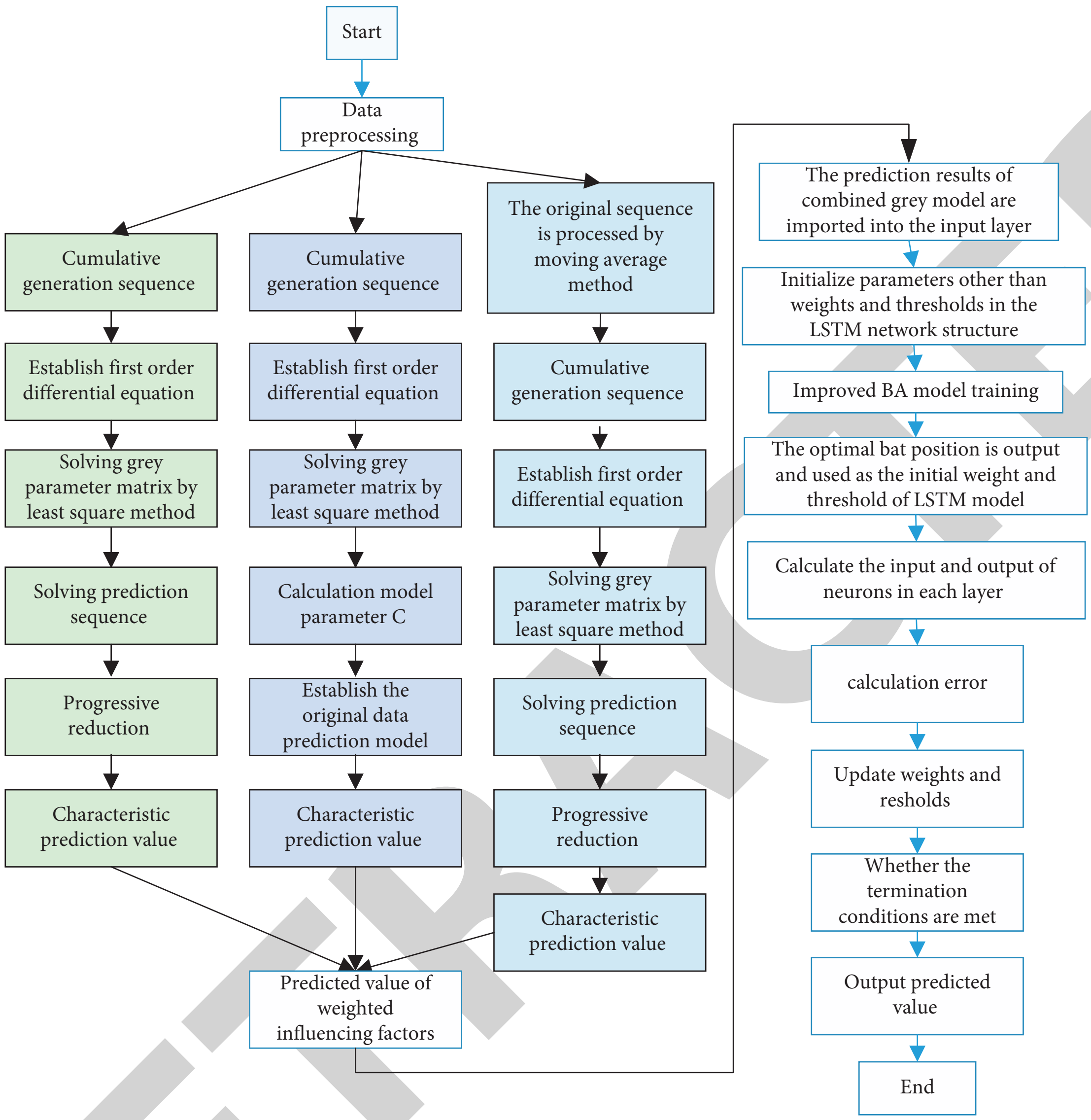

Figure 1: Schematic diagram of the combined grey-improvement model modeling process.

Therefore, the data of OFDI flows are selected from the China Outward Foreign Direct Investment Statistical Bulletin.

For human capital as an explanatory variable, the existing literature [25] has verified that EDU is strongly linked to OFDI. This paper examines the relationship between EDU and regional OFDI spatial effects from a spatial perspective and compares research inferences with real-world issues to draw similarities and differences. EDU is calculated using the average educational attainment of the labor force as a measure, and its calculation criteria are based on the education indicator method.

The estimation of the capital stock (K) was performed using the perpetual inventory method proposed by [26], which selected 2008 as the base period and used the fixed capital and depreciation rate of that year as the basis to measure the fixed capital stock of each region from 2008 to 2017 using nominal investment, the fixed asset investment price index, and the fixed asset depreciation rate, respectively.

5. Empirical Analysis

5.1. Processing of Sample Data. In order to prevent pseudoregressions, a series of tests need to be performed on the sample data. In this paper, the time series of lnY, lnOFDI, lnEDU, lnK, lnL, G, and U is tested using the LLC, ADF, and PP tests, respectively. The results overall show that the hypothesis of the existence of a unit root is overwhelmingly rejected for the explanatory, and control variables at the 1%, 5%, and 10% confidence levels. The selected variables all passed the seasonality test under at least two tests and met the requirements of the regression model [27].

5.2. Choice of Spatial Model. This paper uses a spatial panel model to focus on the impact of OFDI on economic growth,

Table 1: Estimation and test statistics for nonspatial panel models.

Variable	Spatial fixation effect	Time fixed effect	Fixed effect of space and time	Mixed estimation
Intercept term	—	—	—	5.349
Ln EDU	0.114	0.167	0.136	0.188
LnOFDI	0.212	0.194	0.285	0.221
LnK	0.465	0.434	0.429	0.403
LnL	0.146	0.148	0.121	0.117
G	-0.164	-0.169	0.151	-0.124
U	0.186	0.165	0.202	0.217
R^2	0.956	0.794	0.986	0.905
LM(lag)	215.982	30.673	36.576	168.245
LM(err)	80.274	26.963	27.657	156.124
R- LM(lag)	401.365	33.765	26.349	95.124
R- LM(err)	266.147	35.861	28.168	21.635
Spatial fixed effect LR statistics		702.361		
Time fixed effect LR statistics		289.936		

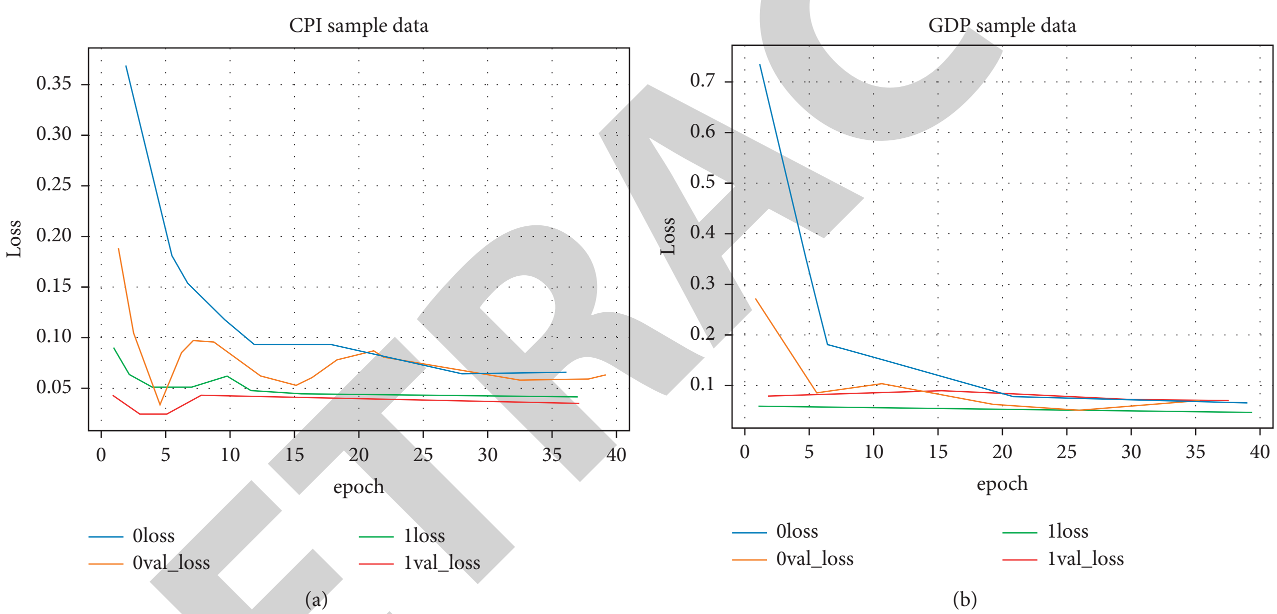

Figure 2: Model performance of the economic dataset under the combined grey-improved BA-LSTM model: (a) model performance based on CPI sample data and (b) model performance based on GDP sample data.

first to determine the type of spatial panel model. In order to facilitate data comparison after adding spatial factors, the nonspatial panel model is first analyzed the following expressions:

$$Y_{it} = a_0 + a_1 \mathrm{OFDI}_{it} + a_2 \mathrm{EDU}_{it} + a_3 K_{it} + a_4 L_{it} + a_5 G_{it} + a_6 U_{it} + \mu_i + \varepsilon_{it}. \tag{10}$$

Four fit results are set up for the regression of equation (10), and LM statistics are constructed to assist in model selection; additional LR statistics for spatial fixed effects or time fixed effects are needed to determine which LM statistic is chosen for the fit results.

The spatial correlation is further tested by applying two Lagrange multipliers in the form of LM(err) and LM(lag). The principle of through identification: if in the statistical test, LM(err) is insignificant and LM(lag) is significant, SLM is generally considered more appropriate; while if in the test, LM(err) is significant and LM(lag) is insignificant, SEM is generally considered more appropriate than SLM; if both statistics are significant, it means that the model is relatively well estimated, and then the R-LM(lag) and R-LM(err) statistics, the identification principle is the same as above, and the larger of the two is usually taken. The specific test statistics are shown in Table 1.

In Table 1, LR statistical tests for both the spatial and temporal fixed effects models are significant at the 1% confidence level, with statistics of 702.361 and 289.936, respectively. In addition, the LR tests for the other two different models are also significant. The largest coefficient of 0.986 was found in the spatial and temporal fixed effects

Table 2: Error rates (MSE) for the economic forecasting dataset under the four models.

Model name	CPI	GDP
Traditional grey-improved BA-LSTM	0.002002	0.004628
Unbiased grey-improved BA-LSTM	0.001865	0.004385
Moving average method improved grey-improved BA-LSTM	0.001903	0.004215
Combined grey-improved BA-LSTM	0.001998	0.004458

Table 3: Comparison of forecast results for 2018 under the four combined models of the CPI dataset.

Model	January	February	March	April	May	June	July	August	September	October
True value	101.5	102.3	102.4	101.7	10.2.1	101.8	101.6	102.6	102.3	102.5
Traditional GM	101.8	101.7	101.7	101.8	101.7	101.7	101.7	101.6	101.6	101.6
Unbiased GM	102	102.1	102.3	102.2	102.5	102.3	102.3	102.2	102.2	102.1
Improved GM	102.2	102.2	102.3	102.2	102.5	102.2	102.1	102.2	102.4	102.6
Combined GM	101.8	101.7	102.4	101.8	101.2	101.4	101.5	101.6	101.7	101.7

Table 4: Comparison of forecast results for 2018 under four combinations of models for the GDP dataset.

Unit (100 million yuan)	Q1	Q1-Q2	Q1-Q2	Q1-Q2
True value	198786	418961	650128	900309
Traditional GM	223142	451382	653887	915478
Unbiased GM	222365	449138	682547	912358
Moving average GM	221457	447586	6478252	912789
Combined GM	222543	449985	684571	914587

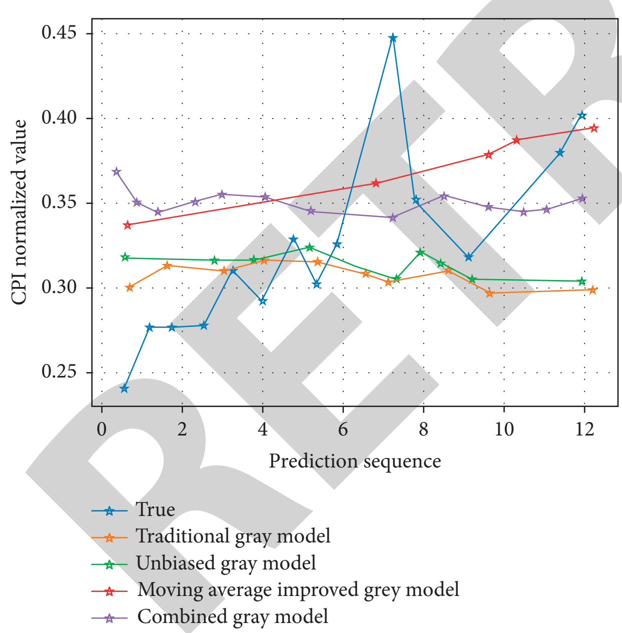

Figure 3: Comparison of CPI forecasts under various combinations of models.

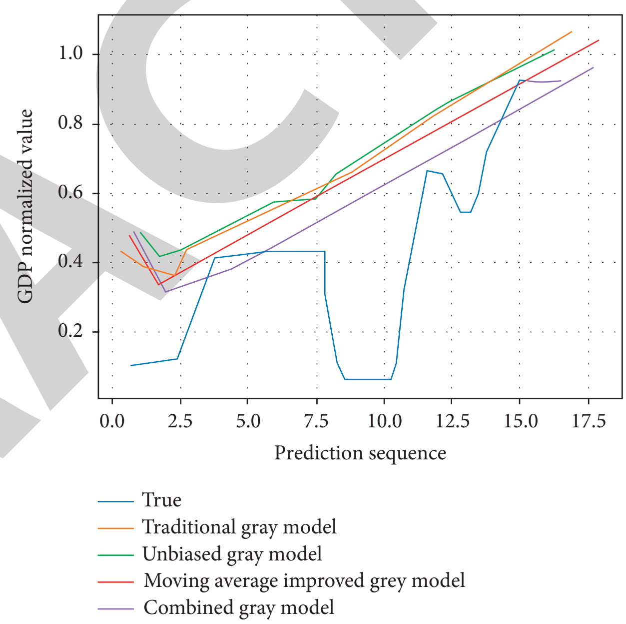

Figure 4: Comparison of GDP forecasting results under various combinations of models.

model, and the corresponding LM(lag) and LM(err) were also significant at the 1% confidence level with statistics of 36.576 and 27.657, respectively, thus the value of LM(lag) was relatively larger. Furthermore, the R-LM(lag) and R-LM(err) were found to be significant at the 5% confidence level. It is further found that the R-LM(lag) and R-LM(err) statistics are also significant at a 5% confidence level, and the former is larger. From the above analysis, it can be basically concluded that the spatial panel lag model with both spatial and temporal fixation is suitable for the sample data [28].

5.3. Simulation Experiments and Analysis. The performance of the models under the combined grey-LSTM model and the combined grey-improved BA-LSTM model [29] for the CPI forecasting dataset and the GDP forecasting dataset, respectively, is shown in Figure 2, where the blue and green loss curves indicate the performance of the two models in the training set, and the yellow and red valleys curves indicate the performance of the two models in the test set [30].Table 2.

Data reduction of the GPI and GDP forecasts was carried out to collate the forecasts for January to October 2018 as shown in Tables 3 and 4, and for a more direct observation, the graphs are shown in Figures 3 and 4, and a comparison of

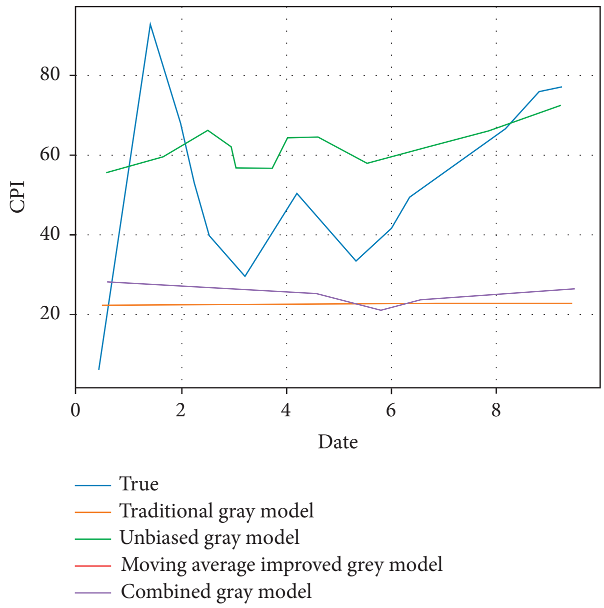

Figure 5: Comparison of economic forecast sample data under various combinations of models for 2018 forecast results.

the economic forecast sample data for 2018 under various combinations of models is shown in Figure 5.

6. Conclusions

With the help of a spatial panel model, the direct impact and spillover effects of OFDI on regional economic growth were systematically analyzed. It is found that regional OFDI makes a positive contribution to the economic growth of the region, which is basically consistent with expectations. The economic growth index of each region tends to rise as the scale of OFDI expands, and also has a boosting effect on the economic growth of neighboring regions, i.e., there is a significant spillover effect. The estimated coefficients of human capital, labor input, capital stock, and urbanization rate are all positive, indicating that each variable is conducive to promoting regional economic growth.

This paper uses the model to verify that regional OFDI development is conducive to local economic growth. The direct contribution of OFDI to regional economic growth is 0.2242 when spatial factors are taken into account, and as the feedback effect exists in the direct effect, it accounts for 2.4%, indicating that as the scale of OFDI develops, it not only promotes the economic growth of the region but also contributes to the economic development of neighboring regions. There are three main reasons for this: firstly, through OFDI, the region has participated in international competition, deepened globalization, and boosted trade exports and labor exports; secondly, by making use of OFDI's transnational business model, it has fully enjoyed a series of foreign preferential measures on tariffs, credit, markets and other tools to improve local economic efficiency; and thirdly, it has absorbed other countries' resource endowments and introduced advanced technology and management experience to boost local economic growth.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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