ORIGINAL ARTICLE

Forecasting of municipal solid waste generation in China based on an optimized grey multiple regression model

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Abstract

The massive generation of municipal solid waste (MSW) has become an essential social problem that not only damages the ecological environment but also affects human health. To effectively manage MSW, it is necessary to forecast waste generation accurately. In this study, a grey multiple non-linear regression (GMNLR) model is developed to achieve the effective forecasting of MSW generation in China. Using grey relational analysis (GRA) to rank the influential factors of MSW generation, it is found that urban road area, residential consumption level, and total population are the main factors. Then, these factors are used as the input variables of the model to forecast MSW generation. Meanwhile, four performance indicators with adjusted R^2 (R^2_{adj}), absolute percentage error (APE), mean absolute percentage error (MAPE), and root mean square error (RMSE) are used to evaluate the performance of these models. The results demonstrate that the GMNLR model has a highest prediction accuracy among the four models. According to the forecast results, China's MSW generation will reach 332.41 million tons in 2025, with an annual growth rate of 8.28%. The combined model proposed in this paper is helpful for the government in policies and regulations making for MSW management.

Keywords Municipal solid waste · Grey multiple non-linear regression model · Forecasting · Grey relational analysis

Introduction

Nowadays, China is in the stage of rapid development. The increasing economic level and the fast growth of population make the generation of municipal solid waste (MSW) increase dramatically. A large number of studies have shown that there is a relationship between the management of MSW and greenhouse gas (GHG) emissions and that GHGs are generated in the generation, transportation, and treatment of the waste [1]. It is estimated that 2.8% of GHG emissions come from waste disposal, and landfills account for 3% to 4% of total GHG emissions [2]. According to the statistics of the Ministry of Ecology and Environment of the People's Republic of China, GHG emissions of China from waste treatment were 195 million tons CO_2-eq in 2014, of which 104 million tons CO_2-eq were emitted from solid waste treatment, accounting for 53.2% [3]. As a country with a large population, China has reached 141,212 million in 2020. With a growing population, there will also be a continuous increase in MSW generated [4]. Therefore, it is necessary to predict the output of MSW in China to carry out effective management and recycling, and reduce the generation of GHG [5].

Currently, there are many methods to forecast MSW generation, including descriptive statistical analysis (DSA) [6], time series analysis (TSA) [7–10], artificial neural network (ANN) [11–13], grey model (GM) [14] and regression analysis (RA) [15–17]. DSA is often used to forecast the per capita waste generation [18]. However, the generation of solid waste is affected by some variable factors such as socio-economic, population, and climate conditions; and this method does not explain well the variation of the relationship between these factors and MSW generation [19]. Therefore, this method is no longer applicable. TSA is applying past data to speculate on future development trends. It requires more data to forecast more accurately and

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is generally only available for short-term forecasting. However, as a popular forecasting model, ANN is used in MSW management because of its high advantages in handling a large amount of data, mapping non-linear relationships, and providing forecasting results [20]. Azadi and Karimi-Jashni [21] selected four factors of population, waste collection frequency, maximum seasonal temperature, and elevation, applying ANN to predict the average rate of seasonal MSW generation. Ferreira et al. [22] built ANN models to predict and optimize the frequency, quantity, and type of collection required at different locations, taking into account demographic and socio-economic factors. However, a forecast with the neural network model demands a large amount of data and essential relevant parameters to get the desired results. So, it was difficult to obtain the best results with limited data [23].

Different from ANN, GM is a more mature model for application. Instead of using statistical methods to deal with the grey quantity which is a random variable that varies within a specific range, they are directly used to process the original data and study the intrinsic regularity [24]. This model has been applied in various fields such as MSW forecasting and socio-economic systems, and more accurate results have also been obtained. Intharathirat et al. [25] used an optimistic multivariate GM to predict the amount of MSW collected in Thailand and make concluding that population density is the most important influential factor. Meanwhile, the accuracy of the model is high, with a minimum error of 1.16%. Among the grey models, the first order grey model with one variable GM (1,1) is the most widely applied. This model does not require massive sample data, and no regular distribution of data is needed, with the little computational workload, which is used for short-term and medium to long-term forecasting, as well as high forecasting accuracy. Based on the advantages of this model and the fact that solid waste generation can be influenced by several factors, it is applied to forecast the influential factors and, thus, improve the prediction accuracy of MSW generation. In addition, RA is used in most studies and can be used to predict solid waste generation based on socio-economic factors or other influential factors [26]. This approach is widely used due to its simplicity and data availability [27]. Multiple regression (MR) model is one of the forms which is used for the analysis of the variation of two or more independent variables with one dependent variable. Based on the multiple linear regression, Wei et al. [28] developed a factor-model-based model to predict the future MSW generation in China. Combined with the ridge regression model and GM model, Zhang et al. [29] established a hybrid prediction model of MSW generation. The ridge regression model is a type of updated MR model that has some advantages in solving data covariance

problems. Applying MR model not only can predict solid waste generation, but also can help researchers to analyze the factors that influence solid waste generation [30]. Kolekar et al. [31] studied a review of modeling methods used in 20 papers related to MSW generation forecasting and the results showed that regression models was the best method.

In the past studies, most scholars adopted a single model or multiple model comparisons to forecast the solid waste generation of individual cities. Chhay et al. [5] compared three forecasting models: GM (1,1), linear regression, and ANN, to select the model with the highest accuracy to predict MSW generation in China, while also considering the impact of socio-economic factors on MSW generation. This study is the method used to compare several single models to select the optimal model for forecasting, while the use of combined models is a combination of several single models in a certain way, which can combine the advantages of each single model to forecast the data and improve the accuracy of forecasting to some extent. In terms of factor analysis, the grey relational analysis method can be used to analyze the correlation degree between factors so that important factors can be identified and input into the model for forecasting. At present, there are few combined models used to forecast MSW generation and analyze the factors influencing MSW generation in China. Due to not so much data collected, it could be a new trying to choose GM (1,1) and MR models in combination to forecast MSW generation in China. At the same time, the optimal forecasting model is obtained through the optimization and adjustment of the model, which further improves the forecasting accuracy. In addition, China's MSW generation is large, and if the annual volume of generation reaches 300 million tons, every 1% increase in forecast accuracy can reduce the error of generation by 3 million tons. Therefore, the higher the forecast accuracy, the better it is for the government to develop an efficient management plan.

The contributions of this study function at two aspects: (1) Establishing a combined forecasting model to achieve the forecast of China's MSW generation in the next 5 years based on a grey multiple non-linear regression (GMNLR) model. This model can be combined with China's national conditions to achieve high accuracy in forecasting with limited data. (2) Based on scholars' research and China's actual national conditions, three types of influential factors: social, economic, and demographic factors, are considered and analyzed with the help of grey relational analysis. The results are added to the model to make the prediction results more practically meaningful. According to the analysis results, targeted management measures can be taken to significantly reduce the MSW generation, which is more beneficial to the future sustainable development of China.

Background

MSW management is an essential issue for all countries. Proper planning and management involve the whole process of MSW generated to disposed of. The scarcity and reliability of existing data on waste generation does make solid waste management work hampered in many ways [32]. The modeling estimates MSW generation and contributes to the development of management strategies.

Most developed countries and some developing countries have implemented MSW management strategies [33]. Developed countries such as the United States, Germany, and Japan are more successful in MSW management. They started earlier, with advanced processing technology and a more mature legal system. The United States established a waste management hierarchy [34]. Germany forms the MSW management system from three legislations of refund systems, separated curbside collection and landfills [35]. Japan has implemented the Basic Law for the Development of a Recycling Society; the 3R principle of Reduce, Reuse, Recycle was first proposed in this law [36]. In waste recycling, developed countries have achieved remarkable management results. The detailed classification of MSW and the adoption of targeted means for innovative treatment have enhanced the utilization rate of waste resources and recycling. Moreover, residents have a good sense of environmental protection, sorting and sending themselves to designate community locations and paying the corresponding disposal fees [37]. The MSW generated is converted to renewable energy through incineration, which effectively reduces carbon emissions [38].

In China, MSW management is based on reduction, resources, harmlessness, and production responsibility [39]. According to statistics from China's National Bureau of Statistics, the volume of MSW clearance in China reached 235.12 million tons in 2020, and the rate of harmless disposal of MSW reached 99.7%. In terms of MSW treatment, sanitary landfills and incineration are the main methods [40]. However, because of the rapid development of incineration technology in China in recent years, the state has also introduced policies to encourage and subsidy, making it a standard method of MSW treatment [41]. To effectively manage MSW, China has introduced some policies and regulations. In September 2020, the latest revision of the Law of the People's Republic of China on the Prevention and Control of Environmental Pollution by Solid Waste was the primary legislation for solid waste management and pollution control. Other related policies, such as a uniform fee system for MSW disposal that lacks economic incentives do not achieve the effect of reducing MSW generation [42]. In a recent study, it is found that the problems of MSW management in China are focused on mixed waste collection, inadequate laws and regulations, poor management system, lagging construction of MSW collection and treatment facilities, greenhouse gases emissions, and weak environmental awareness among residents. Thus, China urgently needs an actual effective practice under an efficient MSW management system.

Methodology

By developing the combination of the GM (1,1) and MR model, the advantages of both models are combined to achieve the prediction of MSW generation in China. First, grey relational analysis is used to select the factors that have a significant relationship with MSW generation. Then, using the GM (1,1) to make predictions for the selected influence factors, the obtained results are used as independent variables in the MR model. Finally, to forecast the amount of MSW generated in China for the next five years. To obtain more accurate results, validation comparisons are implemented for single and combined models, and the most suitable model is selected for prediction. The difficulty of waste generation forecasting lies in the lack of comprehensive historical data and the choice of models [26]. This research develops a combined model to effectively improve the forecasting accuracy of MSW generation, which can be well applied in practice and help decision-makers design management plans for MSW. The process of forecasting MSW generation in China based on the GMNLR model is shown in Fig. 1.
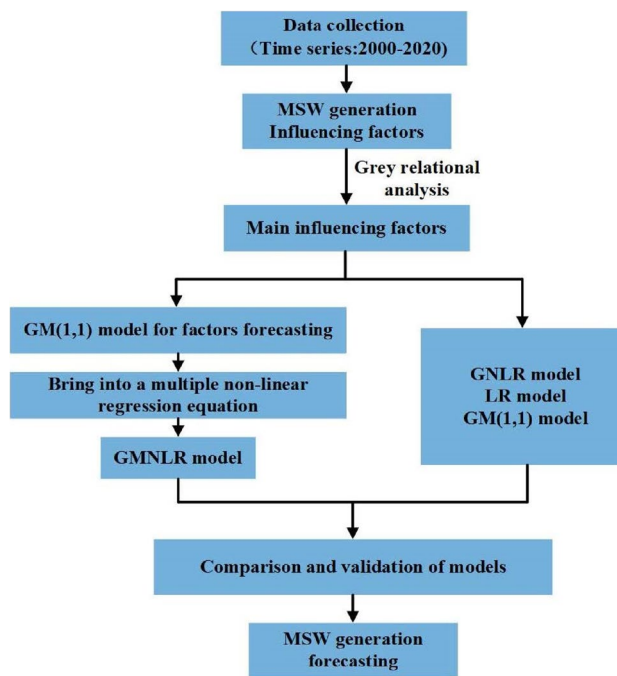

Fig. 1 Flowchart of MSW generation forecasting model

Data source and preprocessing

Forecasting waste generation is an essential part of waste management, and accurate forecasting of future MSW generation is beneficial for planning an efficient waste management system [43]. All stages of MSW management from waste collection to disposal are directly related to its quantity and characteristics, and it is difficult to achieve optimal management from waste generation and characteristics alone, which requires consideration of many influencing factors [44]. The changing influential factors in different regions and the different ways of data acquisition can affect the prediction results. Therefore, analyzing the key influential factors of MSW generation is beneficial for more accurate prediction results. So far, the study of the influential factors of MSW generation has mainly focused on social factors, economic factors, and demographic factors [45]. Among them, social factors include urban greening coverage [46] and urban road area [47]; economic factors include gross domestic product [48, 49] and residential consumption level [50]; demographic factors mainly include total population and education level [51].

With rapid municipal development and population growth, resource consumption is accelerating, resulting in increasing solid waste generation to the detriment of environmental quality [52]. Some social factors such as urban green cover and urban road area affect the generation of MSW. Wang et al. [53] used exploratory spatial data analysis (ESDA) method to explore the spatial association of MSW generation. The analysis concluded that population, technology, urbanization, and green cover inhibit the generation of MSW, while the study also showed that changes in industrial structure, per capita sickbeds and urban road area increase contribute to the growth of MSW generation. In recent years, urban central heating has developed rapidly. According to China Statistical Yearbook data, the national heating area reached 9.88 billion square meters in 2020 [54]. Centralized heating can effectively improve energy utilization and increase the comprehensive use of waste as fuel, which has obvious environmental benefits. Therefore, in the research on the relationship between influential factors and MSW generation, the inclusion of this factor is considered to make the prediction model more practical. In addition, the relationship between economic development and MSW generation has become the focus of many scholars' research. The faster the economy develops, the more solid waste will be generated. The effects of employment status and education level on waste management have also attracted much attention from scholars. The increase in employment brings about the growth of MSW generation. Better education can enhance people's awareness of environmental protection, and people with higher education levels are more concerned about environmental issues [55]. Chen et al. [56] found that population size, urbanization, GDP, education level, natural gas permeation rate, and the proportion of tertiary industry all affect MSW generation. Based on the research results of scholars and available data, the nine influential factors selected in this paper are social, economic, and demographic aspects. These three social factors are urban road area (URA), road cleaning area (RCA), and urban central heating area (UCHA). And the three economic factors are gross domestic product (GDP), residential consumption level (RCL), and tax revenue (TR). In addition, there are three demographic factors: total population (TPop), employed people (EP), and college and above people (CAAP). Then, the relationship between the nine factors and MSW generation is analyzed with grey relational analysis. Finally, according to the ranking results of the three categories of factors, a key factor is selected as the input variable for the forecasting model in each category.

The datasets used for model forecasting in this study consisted of the influence factor dataset and the MSW generation dataset, with 21 sets (i.e., rows) of data are for each year from 2000 to 2020 for the whole country. Among them, the influential factors dataset includes nine factor variables. Due to the availability of data, the annual MSW removal volume was used as the annual MSW generation for forecasting. The descriptions of specific variables are shown in Table 1. The data on MSW generation and nine influential factors for 2000–2020 were collected from the China Statistical Yearbook published by the China Statistics Bureau [54]. Therefore, the data used in this study are newer and more comprehensive than the data used by Chhay et al. [5] from 2000 to 2015.

Grey relational analysis

In this study, grey relational analysis (GRA) is used to compare the effects of the nine parameters mentioned above. GRA is used to measure the degree of correlation between factors and can be applied to analyze the degree of influence of each element on MSW generation [57]. This method first divides all variables into a reference series and a comparison series, and finally qualifies the degree of correlation between the two series [58]. The detailed process of calculation follows.

Set the reference series $x_0 = \left\{ x_0(k) | k = 1, 2, \cdots, n \right\}$ and the comparison series $x_i = \left\{ x_i(k) | k = 1, 2, \cdots, n \right\} (i = 1, 2, \cdots, m)$, where n is the number of input data and m is the number of indicators.

First, the data need to be normalized so that all data are in the same range, which is between 0 and 1. As shown in Eq. (1).

$$y_i(k) = \frac{x_i(k)}{\frac{1}{n} \sum_m^n x_i(m)}. \tag{1}$$

Then, the grey relational coefficients of the comparison series x_i on the reference series x_0 at the k index are calculated as shown in Eq. (2).

Table 1 Descriptions of variables

Symbol	Variable	Definition	Mean	Median	Standard deviation	Max	Min	Unit
MSW	The annual generation of MSW	The annual total amount of MSW collected and transported, replaced by the MSW removal volume	172.40	158.05	34.42	242.06	118.19	Million tons
URA	Urban road area	The total area occupied by roads in the completed urban area	5.50	5.21	2.26	9.70	1.90	Billion square meters
RCA	Road cleaning area	The annual area of urban roads and public places cleaned	5.32	4.85	2.59	9.76	1.66	Billion square meters
UCHA	Urban central heating area	Annual floor area supplied with heat to all types of urban housing buildings, structures and other facilities	4.77	4.36	2.77	9.88	1.11	Billion square meters
GDP	Gross domestic product	The end result of the productive activity of all resident units in a country over a certain period of time	46,862	41,212	30,728	101,599	10,028	Billion yuan
RCL	Residential consumption level	The sum of the annual living expenses of residents	12,939	10,575	8174	27,504	3712	yuan
TR	Tax revenue	The revenue from the state levy tax	7973	7321	5265	15,800	1258	Billion yuan
TPop	Total population	Total population at the end of the year	1344	1341	47	1,412	1267	Million people
EP	Employed people	The total number of employed people per year	752	756	13	763	721	Million people
CAAP	College and above people	Number of people with advanced degrees attained at college and above	14.86	0.12	48.26	217.22	0.04	Million people

$$\xi_i(k) = \frac{\min_i \min_k |y_0(k) - y_i(k)| + \rho \max_i \max_k |y_0(k) - y_i(k)|}{|y_0(k) - y_i(k)| + \rho \max_i \max_k |y_0(k) - y_i(k)|}, \quad (2)$$

where, $\xi_i(k)$ is the grey relational coefficient, ρ is the resolution coefficient which ranges from 0 to 1, $\min_i \min_k |y_0(k) - y_i(k)|$ is the minimum value of the difference between the two levels, $\max_i \max_k |y_0(k) - y_i(k)|$ is the maximum value of the difference between the two levels.

Finally, the weight corresponding to each index was determined by calculating the average of the correlation coefficients, given by Eq. (3).

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k). \quad (3)$$

The factors are ranked according to the calculated results. The value is higher, indicating that the factor is

more strongly correlated with MSW generation, and vice versa, the correlation is weaker.

Multiple regression model

Multiple regression (MR) is a method of generating multiple equations to study the relationship between one or more independent variables and the dependent variable [59]. Its general form is as follows Eq. (4):

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \varepsilon, \quad (4)$$

where Y is the dependent variable, $x_1, x_2, \cdots, x_p$ (p is the number of independent variables) is the number of independent variables, β_0 is the constant term of the regression equation, $\beta_1, \beta_2, \cdots, \beta_p$ is the partial regression coefficient, and ε is random error.

This method is applied to establish a model of the relationship between influential factors and MSW generation to obtain a mathematical equation that is used to calculate the predicted value of future MSW generation in China.

Grey model

The GM (1,1) is one of the most commonly used models in the grey theory system proposed by Professor Ju-Long Deng, which is used primarily to process the original data to find out the change regulation and realize the forecast of future development trends [60]. The basic calculation steps are as follows:

Let the sequence $X^{(0)} = (X^{(0)}(1), X^{(0)}(2), \cdots, X^{(0)}(n))$ $x^{(0)}(k) \geq 0, k = 1, 2, \cdots, n$, by accumulating the original data $X^{(0)}$, a new sequence is generated, defined as Eq. (5).

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)), \tag{5}$$

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

The grey differential equation of GM is established by Eq. (6).

$$x^{(0)}(k) + az^{(1)}(k) = b. \tag{6}$$

Based on Eq. (7), the whitening equation is defined as:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b, \tag{7}$$

where a is the development coefficient of the model and b represents the endogenous control grayscale.

Construct data matrix B (Eq. (8)) and data vector Y (Eq. (9)), $\hat{a} = [a, b]^T$ is the parameter column.

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix}, \tag{8}$$

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}. \tag{9}$$

Then the least square estimation parameters of the model satisfy Eq. (10).

$$\hat{a} = (B^T B)^{-1} B^T Y. \tag{10}$$

The time response equation of GM is defined by Eq. (11).

$$\hat{x}^{(1)}(k + 1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a}, k = 1, 2, \cdots, n. \tag{11}$$

The actual predicted value can be calculated by Eq. (12).

$$\hat{x}^{(0)}(k + 1) = \hat{x}^{(1)}(k + 1) - \hat{x}^{(1)}(k), k = 1, 2, \cdots, n. \tag{12}$$

According to the above calculation process, the data are brought into the specific grey prediction formula that can be determined.

Model performance evaluation

The use of R^2 to determine the accuracy of the model has the disadvantage that the value of R^2 increases with the number of independent variables. Moreover, the value approaches 1 when the number of independent variables is close to the sample size. Therefore, to overcome this drawback, an adjusted R^2 (R^2_{adj}), which takes the sample size and the number of independent variables into account, is used for model evaluation. The expression for R^2_{adj} is given by Eq. (13) [29].

$$R^2_{adj} = 1 - (1 - R^2)\frac{n - 1}{n - p - 1}. \tag{13}$$

When $p > 1$, R^2_{adj} will be smaller than R^2, which indicates that increasing the number of variables, R^2_{adj} grows more slowly than R^2. Also, the R^2_{adj} obtained according to the equation may have negative values.

Assessing the simulation and forecasting performance of the model can also be reflected by the absolute percentage error (APE), mean absolute percentage error (MAPE), and root mean square error (RMSE), which are calculated as shown in Eqs. (14–16):

$$APE(\%) = \left| \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \right| \times 100, \tag{14}$$

$$MAPE(\%) = \frac{1}{n} \sum_{k=1}^{n} \left| \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \right| \times 100, \tag{15}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{k=1}^{n} (x^{(0)}(k) - \hat{x}^{(0)}(k))^2}, \tag{16}$$

where $x^{(0)}(k)$ is the actual value and $\hat{x}^{(0)}(k)$ is the predicted value. APE is a statistical metric commonly used to measure the accuracy of the prediction of a model, which can reflect the degree of confidence in the prediction [61]. MAPE is a more widely- used method to verify the performance of a model, and as its value approaches zero, it indicates better model performance. Table 2 lists the MAPE criteria for accurately measuring the model. RMSE indicates the expected value of the square of the error and is one of the commonly used methods to test model performance, while a value close to zero also indicates good model performance [21].

Table 2 MAPE criteria [62]

MAPE (%)	Forecasting performance
< 5	Excellent
5–15	Good
15–50	Reasonable
> 50	Incorrect

Table 3 Factor correlation ranking

Category	Factor name	Correlation	Sorting
Social factors	URA	0.7312	1
	RCA	0.7063	2
	UCHA	0.6191	3
Economic factors	RCL	0.7666	1
	GDP	0.6870	2
	TR	0.6064	3
Demographic factors	TPop	0.7906	1
	EP	0.7853	2
	CAAP	0.5244	3

Results and discussion

Factor analysis

GRA is applied to the screening of influence factors of MSW generation in China. The correlation coefficients between social, economic, and demographic factors and MSW generation are calculated separately using this method. The results are ranked from the largest to the smallest to derive the most significant influence factors. Table 3 shows the results of the correlation ranking between the three types of factors and MSW generation. After the analysis, it was found that the social factors have the strongest correlation between URA and MSW generation, with a correlation of 0.7312. There is a high correlation between RCL and MSW generation among economic factors, a relatively low correlation between GDP and TR. TPop has a stronger correlation with MSW generation among the three demographic factors with a correlation of 0.7906, while the number of EP is the second strongest.

According to the results of GRA, the correlation between URA, RCL, TPop and MSW generation is analyzed in the form of data charts. The relationship between the main influential factors and MSW generation is shown in Fig. 2. The results show that the three influence factors selected in this paper are closely related to MSW generation. With the increase of URA, RCL, and TPop, the amount of MSW generation trends to increase. Therefore, URA, RCL, and TPop are the most critical factors which affect MSW generation, and they are considered as the independent variables of the forecast model. In addition, Fig. 2 also shows a non-linear relationship between these three influence factors and MSW generation. So, this study adopts the GMNLR model to forecast the amount of MSW generation in China is more suitable.

The use of GRA to first analyze the influential factors of MSW is beneficial to improve the accuracy of model forecasting. With the rapid development of China in recent years, people's consumption level, living habits, and the surrounding environment have changed a lot, which brings the amount of MSW generated is gradually increasing. The continuous growth of URA indicates the increase of municipal public service level and the improvement of the municipal environment. At the same time, it also promotes an increase in population movement, which leads to economic development and a rapid rise in the level of electricity generation from MSW. The growth in RCL and TPop highlights the number of products purchased and consumed by the residents is rising. And the growth of population brings a massive consumption of natural resources, which promotes the generation of large amounts of MSW.

Model building

The GMNLR model is optimized based on the GMLR model, which improves the accuracy of the model to some extent. At first, GM (1,1) is used to generate the predicted values of each factor for the next five years, and the obtained results are brought into a multiple non-linear regression equation to forecast the amount of MSW generation. By applying MATLAB software, the selected factors are used as input data for grey forecasting separately, and the equations for the three factors are given by Eqs. (17–19).

$$\widehat{x}_{URA}^{(1)} = 4387640 \exp(0.0640922t) - 4197280, \tag{17}$$

$$\widehat{x}_{RCL}^{(1)} = 40803.4 \exp(0.102903t) - 37091.4, \tag{18}$$

$$\widehat{x}_{TPop}^{(1)} = 23012300 \exp(0.00553829t) - 22885500. \tag{19}$$

Figure 3 shows the forecast results of the future values of the main influential factors. The results show that the TPop growth rate is 2.24%, URA and RCL growth rates are 29.22% and 50.92%, respectively. With the rapid development of China, the URA and RCL will grow faster in the next five years. The continuing decline in the number of women of childbearing age and the rising cost of childbearing and rearing, it results in a slow population growth trend.

Through correlation analysis, x_1-URA, x_2-RCL, and x_3-TPop are selected as independent variables and Y-MSW
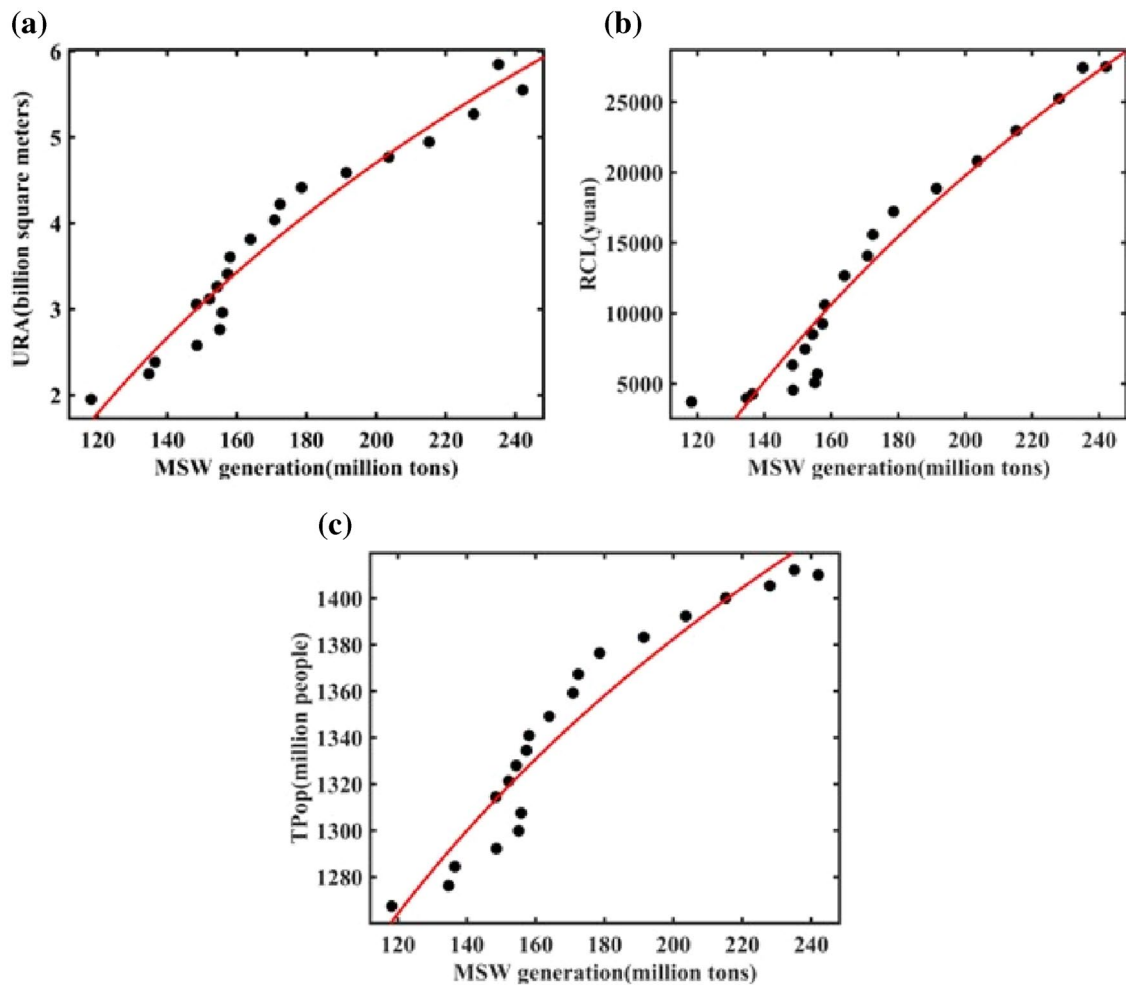
Fig. 2 Relationship between the main influential factors (**a** urban road area (URA); **b** residential consumption level (RCL); **c** total population (TPop)) and MSW generation

generation as a dependent variable to establish a multiple non-linear regression equation as follows (Eq. (20)):

$$Y = k_0 + k_1 Ln(x_1) + k_2 x_2^2 - k_3 Ln(x_3). \quad (20)$$

The SPSS software was also used to calculate the results of the equation coefficients, as shown in Table 4.

After performing regression on the data, the results showed that the compound judgment coefficient $R^2 = 0.968$. Obviously, this model fits the data better, with R^2 very close to 1, and better results are obtained. Table 5 shows the analysis of variance (ANOVA) table, which is a significance test for the regression equation. The test statistic F-value is 171.615, and the P-value is less than 0.01. The statistical test indicates that the relationship of the regression equation is significant. Finally, the forecast results of the GM (1,1) are brought (Eq. (20)) to obtain the amount of MSW generation in China in the next five years.

In addition to using a GMNLR model, a GMLR model, a linear regression (LR) model, and a GM (1,1) are selected for comparison. By implementing the validation comparison of these models, the optimal model was chosen to forecast the amount of MSW generation.

Comparison and validation

Model validation is required to illustrate the applicability of the model in practical applications. The sixteen years data from 2000 to 2015 are used for estimation and fitted performance validation, and the following five years data from 2016 to 2020 are used for testing. The APEs of the four models are compared in Fig. 4. The volatility of the single model is greater than that of the combined model. Moreover, the APE of the GMNLR model is less than 6% in both fitted and forecast stages, except for the relatively large error
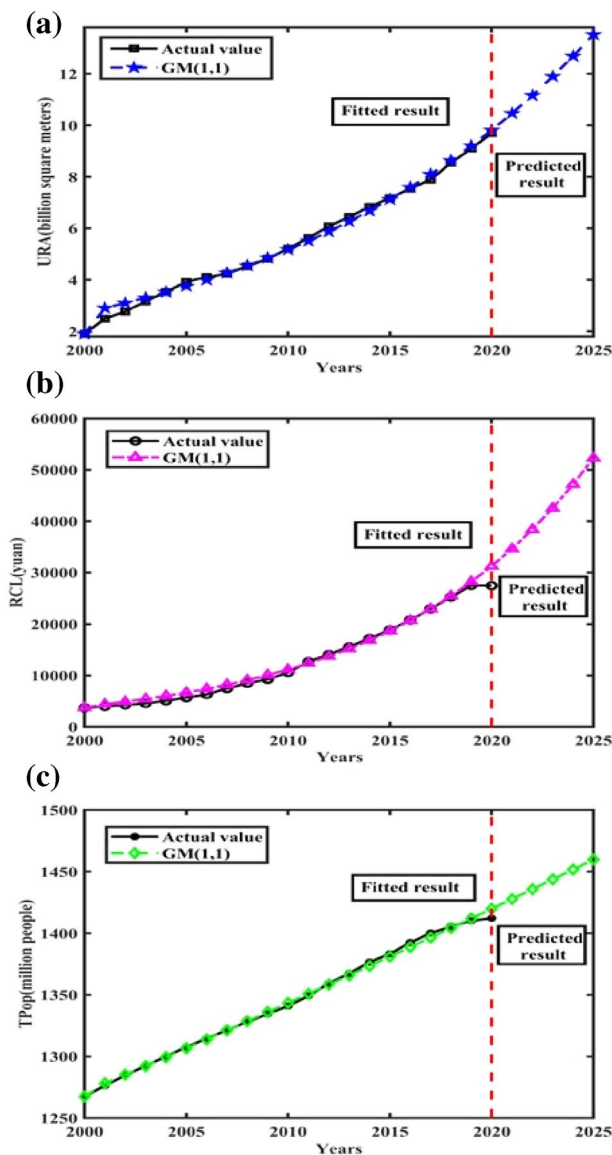
(a)

(b)

(c)

Fig. 3 The forecast results of future values of main influential factors in China (**a** urban road area (URA); **b** residential consumption level (RCL); **c** total population (TPop))

Table 4 The results of the equation coefficients

	Coefficient value
k_0	288,892.598
k_1	5,348.337
k_2	7.983×10^{-6}
k_3	29,123.737

in the forecast value for 2020. Considering the epidemic and Chinese national conditions that led to the shutdown for some time in 2020, the generation of MSW has decreased. However, this value does not affect the overall forecast of the model. Therefore, the model performs well in general and

can forecast MSW generation in the future years. Moreover, the GMNLR model is superior to the other three models. As can be seen from Table 6, the MAPE value of the GMNLR model is 2.05%, while the GMLR model, the LR model, and the GM (1,1) are 2.15%, 3.18%, and 2.54%, respectively. The results show that the combined model has a higher degree of fit than every single model.

To compare the prediction accuracy of the models, these four models are used to forecast the amount of MSW generation in China from 2016 to 2020. As shown in Table 6, the R^2_{adj} and RMSE values of the GMNLR model are 0.9288 and 409.4597, respectively, while the R^2_{adj} values of the other three models are 0.9120, 0.8640, and 0.8975, respectively, and the RMSE values are 479.2056, 611.9404, and 491.7226, respectively, indicating that the fitting effect of the single model is poor. In addition, the MAPE value of the GMNLR model is 4.13%, while the MAPE values of the other three models are higher than 10%. It is concluded that the GMNLR model can get a better prediction value. At the same time, the model is also an effective and practical method to forecast MSW generation in China.

In addition, Fig. 5 shows the forecast performance of the four models. The results show that the estimated value of the GMNLR model is closer to the actual value, the overall trend curve almost coincides with the actual value, and the fluctuation is slight. In the prediction part, there is a significant deviation between the predicted value and the actual value of the other three models. Therefore, the GMNLR model has better prediction performance. The figure also shows the reduction in MSW generated in 2020. Besides, the shutdown due to the epidemic would cause such a result. The government's increased control of MSW generation and more focus on waste reduction at source is also an essential reason for the lower generation. This leads to a lower actual value of MSW generation in 2020 than the predicted value.

MSW generation forecasting

In summary, after comparing the GMNLR model with the other three models, it is found that the model has the best prediction ability in terms of prediction accuracy. In addition, in the absence and less availability of solid waste data, it is beneficial to use this forecasting model. Moreover, the GMNLR model can be used to forecast not only the total MSW generation in China but also can be applied to other countries for the forecasting of waste generation, recyclable quantity, and comprehensive utilization rate. This study can provide data support for MSW management based on the model forecasting results to achieve high efficiency, thus contributing to the control and management of GHG emissions such as carbon dioxide.

Table 5 ANOVA table for MSW generation

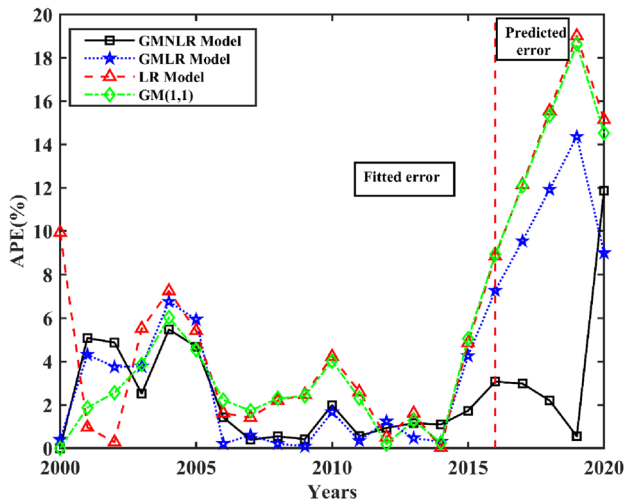| Model	Sum of squares (SS)	Degree of freedom (df)	Mean square (MS)	F-value	P-value
Regression	229,400,000	3	76,466,216.380	171.615	0.000
Residual	7,574,640.661	17	445,567.098		
Total	237,000,000	20			

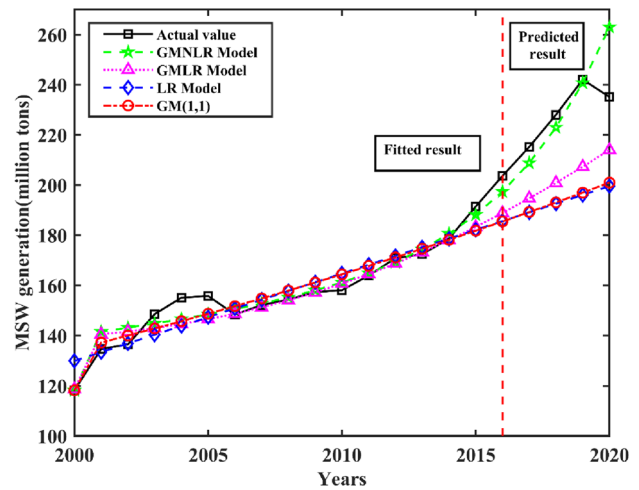**Fig. 4** Comparison of APEs of the four models (GMNLR (grey multiple non-linear regression); GMLR (grey multiple linear regression); LR (linear regression))

Fig. 5 The four models forecast performance (GMNLR (grey multiple non-linear regression); GMLR (grey multiple linear regression); LR (linear regression))

Table 6 Comparative results of four model performances for forecasting MSW generation

Model	MAPE of fitting stage (%)	MAPE of forecasting stage (%)	R^2_{adj}	RMSE
GMNLR	2.05	4.13	0.9288	409.4597
GMLR	2.15	10.42	0.9120	479.2056
LR	3.18	14.13	0.8640	611.9404
GM (1,1)	2.54	13.90	0.8975	491.7226

According to the GMNLR model, the forecast values of MSW generation in China from 2021 to 2025 were obtained, as shown in Fig. 6. The forecast results show that the generation of MSW in China will continue to rise with an annual growth rate of 8.28%. It is expected that China's MSW generation will reach 332.41 million tons in 2025. The study shows that social, economic, and demographic factors will directly contribute to the changes in MSW generation. The forecast finds that urban road area, residential consumption level, and total population values will continue to grow in the next five years, which will also lead to the growth of MSW generation. By analyzing the trend of MSW generation through the changes of these factors, the forecast value of MSW generation in China can be obtained. As China
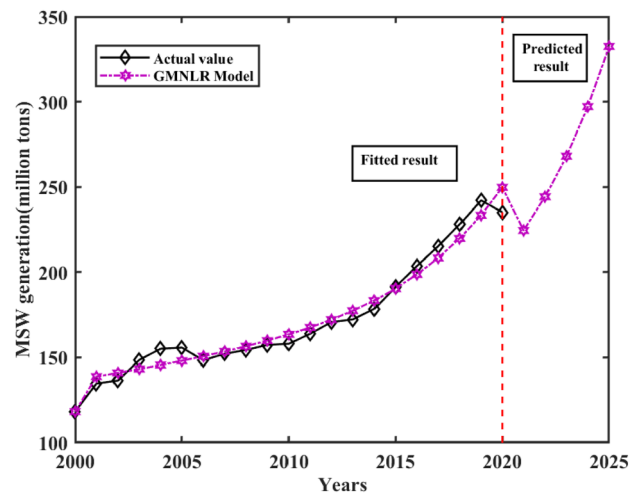

Fig. 6 The forecast values of MSW generation in China by the GMNLR (grey multiple non-linear regression) model

pays more and more attention to waste management and takes a series of actions and policies, the growth of MSW generation tends to slow down. However, the current waste amount is still huge, which is a significant problem for MSW management in China. The control of MSW generation is essential.

Analysis of the results of other scholars showed that the forecast obtained an annual growth rate of MSW generation in China between 2 and 11% [5, 28, 63]. Our results are compared with their results. Our results are lower than those predicted by Wei et al. [28], but higher than those of Chhay et al. [5]. This indicates that our results are within a reasonable range. Table 7 shows the prediction performance of different models. The comparison found that the R^2 value of our developed model is higher than the other models. Therefore, the combined model developed in this paper is more accurate and the prediction results obtained are more accurate.

To achieve the goal of carbon neutrality at an early date, China also needs to strengthen waste management and pay attention to the separation and source reduction of MSW under the principles of reduction, resourcefulness, and harmlessness. Achieve reduction in MSW generation through recycling, reuse, and incineration of waste. Consideration should be given to increasing MSW recycling by specifying the total amount of waste recycling in waste management documents and planning. At the same time, research and development of new technologies without increasing the cost of treatment to improve the resource utilization rate of MSW also play a role in reducing carbon emissions. The lack of environmental awareness is one of the main factors contributing to the continued growth of MSW generation. Compiling and distributing corresponding instruction manuals and establishing a website on waste recycling knowledge to promote the active participation of citizens and develop the habit of waste classification. It is suggested that the ecological environment and green environmental protection are included in the teaching content of compulsory education, and waste classification activities are carried out to strengthen students' awareness on the resource utilization of MSW. Therefore, while improving the governance system, it is more important to focus on the cultivation of the attention of environmental protection among residents and actively promote the source reduction of MSW to achieve low-carbon cycle development and promote the construction of ecological civilization.

Conclusion

The selection of influencing factors is an essential problem for forecasting the MSW generation. To ensure the accuracy of the prediction results, nine factors related to MSW are selected to cover the social, economic, and demographic aspects of the study area. Through GRA, it is concluded that urban road area, residential consumption level, and total population have significant effects on MSW generation in China. This indicates that improving the level of public services in cities, stabilizing the level of economic development and controlling the total population are effective means to control MSW generation. Based on the four evaluation indexes of R^2_{adj} APE, MAPE and RMSE, four models including GMNLR, GMLR, LR, and GM (1,1) were compared to select the best forecasting model. The results show that the GMNLR model has good forecasting performance with MAPE values lower than 5%. The forecast results show that China's MSW generation will decrease due to the epidemic, but the overall trend is still growing. It is expected that China's MSW generation will reach 332.41 million tons in 2025, with an annual growth rate of 8.28% in the next five years. The results of this study will help the government to achieve effective waste management. In the future, the government can make a reasonable waste reduction policy based on the forecast results and specify the solid waste reduction target. Enterprises should reasonably regulate the production and treatment of MSW, and citizens should raise awareness of waste recycling to reduce MSW generation at the source. In addition, solid waste resource treatment can effectively reduce carbon emissions. Nowadays, in order to cope with global warming, all countries in the world have reached a consensus to actively commit to carbon neutral targets. China has proposed to reach the peak by 2030 and achieve carbon neutrality by 2060. Putting plans into action is an effective way to achieve this goal as soon as possible.

The combined model developed in this study has the best prediction effect for other countries or research areas where historical data are scarce. Meanwhile, a limitation of this study is that the selection of factors related to MSW generation should also be considered to waste characteristics, other social factors, and environmental policies. In addition, the new crown epidemic also affects the generation of MSW, and the data can be considered to be corrected and multiplied by

Table 7 Model performances in MSW forecasting

Regions	Models	Model performances	References
China	LSTM	$R^2=0.92$, RMSE = 935.08, MAPE = 114.36	Niu et al. [64]
China	ANN	$R^2=0.92$, RMSE = 57	Wu et al. [65]
USA	GBRT	$R^2=0.87$	Kontokosta et al. [66]
China	GMNLR	$R^2=0.968$, RMSE = 409.4597, MAPE = 4.13	Our study

the corresponding coefficients to obtain accurate prediction results, which also needs to be further studied.

Author contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by RG, HML and HHS. The first draft of the manuscript was written by RG and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript. Conceptualization: HML; Methodology: RG, DW; Formal analysis and investigation: HHS, DW, DDRA; Writing—original draft preparation: RG; Writing—review and editing: HML, LY; Funding acquisition: HML, HY; Resources: HHS; Supervision: LY.

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