Prediction and Allocation of EDP Based on Gray Model and Fuzzy Comprehensive Evaluation

Jinhe Zhou, Anlai Wang, Xiangyuan Su, Caiya Zhang, and Xusheng Kang

Zhejiang University City College, Hangzhou, China

Correspondence should be addressed to Caiya Zhang; zhangcy@zucc.edu.cn and Xusheng Kang; kangxs@zucc.edu.cn

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Abstract

Global warming is accelerating the sea level to rise, which increases the risk of major coastal areas being submerged. Then, the residents may become environmentally displaced persons (EDP). A method of prediction and allocation of EDP is proposed in this paper. Firstly, the gray model is used to predict sea level and the amount of EDP. Then, the evaluation criterion for the responsibility ability of the EDP migration target countries is given based on the entropy and fuzzy comprehensive evaluation method. In addition, a two-way selection mechanism for EDP is constructed. Finally, the amounts of EDP for the next 10 years are predicted, and the allocation plan in 2030 is made by applying the proposed method.

1. Introduction

Climate change is widely acknowledged as a global issue. Climate change has become the leading cause of displacement in some countries, according to one of the British poverty alleviation charity organizations, at the United Nations Climate Change Conference in Oxfam in 2019. Additionally, the proportion of climate refugees in all refugees has been gradually increasing. A report from World Bank in 2018 predicted that more than 1 billion people will become climate refugees by 2050.

Climate change not only causes catastrophic weather events such as heat waves, droughts, floods, tsunamis, or hurricanes, and it also gradually brings about sea level rise (SLR). In the past two decades, there has been a lot of literature discussing the impacts of SLR (see Nicholls and Leatherman[1], Nicholls et al. [2], Nerem et al. [3], and Oppenheimer and Glavovic [4]). Due to SLR, some island countries may face the risk of being submerged; then, its residents may be forced to become environmentally displaced persons (EDP). How to arrange the population of EDP has become a populous topic in recent years. Cao and Chen [5] proposed some suggestions on formulating an international climate migration law based on the situation and development trend of EDP. Zhang and Shen [6] put forward some strategic measures for coastal countries to deal with extinction disasters, which are divided into three types: retreat, obedience, and protection. Arenilla and Hawkins [7] proposed a forced immigration solution based on current international human rights law. Lawrence [8] suggested that accepting climate refugee countries should consider medical methods. Hauer et al. [9] further studies the basic mechanism, critical points, thresholds and feedback, risk perception, and migration of SLR based on the response of immigrants to SLR.

As far as we know, there are relatively few studies on the prediction and allocation of EDP due to SLR with mathematical models. Recently, Xiao et al. [10] proposed a procedure on how to arrange EDP with statistical modeling. Instead of discussing the issue from a global perspective, the author focused on four island nations that are most at risk of being submerged, namely, the Maldives, Tuvalu, Kiribati, and Marshall Islands. In addition, the populations of the four island countries in the next 30 years were predicted by using a simple linear growth model based on the past population data, and the influence of SLR on the amount of EDP was not quantitatively analyzed through the model. Xie et al. [11] made a prediction of the future population of EDP based on the past data of 241 countries or regions from 2008 to 2018 through an ARIMA model, in which the population
of EDP includes not only those caused by SLR but also those caused by war, politics, and other climate factors. So, Xie et al. [11] did not quantify the impact of SLR on the EDP population either. To overcome the above shortcomings, we propose an improved procedure of prediction and allocation of EDP from a global perspective based on the gray model and fuzzy comprehensive evaluation. First, we forecast the average sea level by using a gray model and then the population of EDP is predicted by combining the Google Earth and the average population density. Then, a method of national responsibility evaluation based on fuzzy comprehensive evaluation is proposed. Finally, a two-way selection mechanism is constructed to allocate EDP.

The paper is organized in the following way. The basic theory and implementation process of the new solution to the EDP problem are introduced in Section 2. In Section 3, the application is carried out to make the allocation plan for EDP in 2030. Conclusions are made in Section 4.

2. The Method of Prediction and Allocation for EDP

In this section, we first introduce how to predict the sea level and the amount of EDP. Then, a model is constructed to evaluate the acceptability of a target country. Finally, a two-way selection mechanism between EDP and target countries is given.

2.1. Prediction of the Sea Level. Due to its high prediction accuracy, the gray prediction model has been successfully applied in many fields such as finance, physical control, engineering, and economics. For the GM (1, 1) model, it not only is suitable for small sample size but also has no strict requirements on the change characteristics of the time series. Furthermore, the GM (1, 1) model is suitable for short-term and long-term forecasts. Hence, we choose this model to predict the sea level.

Let \( h(t) \) be the average sea level height in the \( t \)th year, \( t = 1, \ldots, T \). To build the GM (1, 1) model, we need to construct the accumulate sequence:

\[
\begin{align*}
\hat{h}^{(1)}(t) &= \sum_{i=1}^{t} h(i), \quad t = 1, \ldots, T, \\
\end{align*}
\]

and the mean sequence

\[
\begin{align*}
\hat{s}^{(1)}(t) &= \frac{1}{2} \left( h^{(1)}(t) + h^{(1)}(t-1) \right), \quad t = 2, 3, \ldots, T.
\end{align*}
\]

It is reasonable to assume that \( h(t) \) will be approximated by a linear function of \( \hat{s}^{(1)}(t) \), that is,

\[
\hat{h}(t) = -a \hat{s}^{(1)}(t) + b \hat{s}^{(1)}(t).
\]

Then, the GM (1, 1) model has the following equation:

\[
\frac{\text{d}h^{(1)}(t)}{\text{d}t} + ah^{(1)}(t) = b,
\]

where \( a \) and \( b \) are called the development index and the gray effect, respectively.

To estimate the parameters \( a \) and \( b \), let

\[
\begin{align*}
B &= \begin{bmatrix}
-s^{(1)}(2) & 1 \\
-s^{(1)}(3) & 1 \\
\vdots & \vdots \\
-s^{(1)}(T) & 1
\end{bmatrix}, \\
Y &= \begin{bmatrix}
h(2) \\
h(3) \\
\vdots \\
h(T)
\end{bmatrix},
\end{align*}
\]

(5)

Then, the least square estimation of \( a \) and \( b \) is as follows:

\[
\begin{bmatrix}
\hat{a} \\
\hat{b}
\end{bmatrix} = (B^T B)^{-1}(B^T Y).
\]

(6)

By equation (4), we have

\[
\hat{h}^{(1)}(t) = \left( h(1) - \frac{\hat{b}}{\hat{a}} \right) e^{-\frac{\hat{a}}{\hat{a}}(t-1)} + \frac{\hat{b}}{\hat{a}}, \quad t = 2, 3, \ldots, T,
\]

and

\[
\hat{h}(t) = \left( 1 - e^{\hat{a}} \right) \left( h(1) - \frac{\hat{b}}{\hat{a}} \right) e^{-\frac{\hat{a}}{\hat{a}}(t-1)}, \quad t = 2, 3, \ldots, T.
\]

(8)

To evaluate the prediction effect of the model, the mean relative residual criterion will be applied, which is defined by

\[
\bar{e} = \frac{1}{T-1} \sum_{t=2}^{T} \left| \frac{h(t) - \hat{h}(t)}{h(t)} \right|.
\]

(9)

In addition, the mean ratio residual is an optional evaluation criterion, which is defined as follows:

\[
\bar{e} = \frac{1}{T-1} \sum_{t=2}^{T} \left| 1 - 0.5a \frac{1}{1 + 0.5a} \sigma(t) \right|,
\]

(10)

where \( \sigma(t) = h(t)/h(t-1), t = 2, \ldots, T \). Empirically, when both \( \bar{e} \) and \( \bar{e} \) are less than 0.1, it means that the prediction effect is very good.

2.2. Prediction of the Amount of EDP. In the following, let us give the process to predict the amount of EDP.

Figure 1 represents the simulation of the sea level rise. The average angle \( \theta \) between the coast and the sea level will be simulated by Google Earth. To predict the amount of EDP, assume that the total length of the global coastline and the average population density in the \( t \)th year are known, denoted by \( C(t) \) and \( P(t) \), respectively.

Let \( \Delta h(t) = h(t) - h(t-1) \); then, the average land distance displaced by sea water in the \( t \)th year will be approximated by
and the average land area covered by seawater in the $t^{th}$ year will be approximated by

$$\Delta S(t) = \Delta L(t) \cdot C(t). \quad (12)$$

So, the increased number of EDP in the $t^{th}$ year can be predicted by

$$P(t) = \Delta S(t) \cdot \overline{P}(t). \quad (13)$$

2.3. Assessment of Country Responsibility

2.3.1. Evaluation Indicators. According to the principle of “common but different responsibilities” in the “Paris Agreement” (https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement), we choose contribution to climate change and acceptance capacity as two most important factors that influence the capacity of country responsibility. Contribution of climate change will be characterized by annual growth rate of CO2 emissions, annual growth rate of vegetation coverage, and annual growth rate of industrialization. Acceptance capacity will be characterized by annual growth rate of average population density, annual growth rate of per capita GDP, and annual growth of the investment in science and technology. Details are presented in Table 1.

Here, we assume the weights of the first-level indicators are equal, that is, $a_1 = a_2 = 0.5$. The weights $\{a_{ij}, i = 1, 2; j = 1, 2, 3\}$ of the second-level indicators will be estimated by the entropy method. The estimation process is as follows:

1. Select $Q$ countries with the top GDP per capita.
2. Collect the data of the second-level indicators of the $Q$ countries in the most recent year.
3. Normalize the data, calculate the entropy value and redundancy of each indicator, and then get the weights $\{a_{ij}, i = 1, 2; j = 1, 2, 3\}$

2.3.2. Fuzzy Evaluation for Country Responsibility. The fuzzy evaluation method will be applied to evaluate country responsibility. Firstly, we need to construct the evaluation matrix.

Consider the second-level indicators during recent $M$ years. Let $\{\mu_{ki}(t), k = 1, 2; i = 1, 2, 3\}$ represent the global mean values of the second-level indicators in the $t^{th}$ year, and $\{X_{ki}(t), k = 1, 2; i = 1, 2, 3\}$ represent the corresponding observations of a target country in the $t^{th}$ year. According to the deviation between $X_{ki}(t)$ and $\mu_{ki}(t)$, the value of each indicator is divided into 4 levels, denoted by $W_{ki}(t)$, which is defined as follows:

$$W_{ki}(t) = \begin{cases} 
I, & 1 < X_{ki}(t) - \mu_{ki}(t), \\
II, & 0 \leq X_{ki}(t) - \mu_{ki}(t) < 1, \\
III, & -1 \leq X_{ki}(t) - \mu_{ki}(t) < 0, \\
IV, & X_{ki}(t) - \mu_{ki}(t) \leq -1.
\end{cases} \quad (14)$$

Write

$$N_{ki}(j) = \#\{t: W_{ki}(t) = j, t = 1, \ldots, M\}, \quad j = I, II, III, IV, i = 1, 2, 3; k = 1, 2,$$

$$R_{ki}(j) = \frac{N_{ki}(j)}{M}, \quad j = I, II, III, IV, i = 1, 2, 3; k = 1, 2. \quad (15)$$

Then, we get the evaluation matrix:

$$R = \begin{pmatrix} 
R_{11}(I) & R_{11}(II) & R_{11}(III) & R_{11}(IV) \\
R_{12}(I) & R_{12}(II) & R_{12}(III) & R_{12}(IV) \\
R_{13}(I) & R_{13}(II) & R_{13}(III) & R_{13}(IV) \\
R_{21}(I) & R_{21}(II) & R_{21}(III) & R_{21}(IV) \\
R_{22}(I) & R_{22}(II) & R_{22}(III) & R_{22}(IV) \\
R_{23}(I) & R_{23}(II) & R_{23}(III) & R_{23}(IV) \\
\end{pmatrix}. \quad (16)$$

Combining the weight vectors $A_k = (a_{k1}, a_{k2}, a_{k3}), k = 1, 2$, and the evaluation matrix $R$, the affliction vector corresponding to each evaluation level can be obtained by

$$B = (A_1, A_2)R. \quad (17)$$

Assume the score vector of responsibility is

$$C^T = (C_1 \ C_2 \ C_3 \ C_4), \quad (18)$$
Step 3. Calculating the amount of EDP successfully allocated to Q target countries:

\[ P_1 = \sum_{l=1}^{Q} \min(m_l, n_l) \]  

which satisfies \( C_1 > C_2 > C_3 > C_4 \). Then, the responsibility coefficient of a target country is defined as \( Z = B \cdot C \).

2.4. Allocation Mechanism Based on Two-Way Selection.

For the convenience of discussion, we do not consider the influence of factors such as politics, religion, and psychological will as well. In the following, we will combine the historical migration of EDP and the responsibility capacity of the target countries to provide a two-way selection allocation mechanism. The steps of allocation are as follows.

Step 1. Allocation EDP to target countries.

According to the data of the amount of EDP moving to the \( Q \) target countries during recent \( D \) years, we can use the corresponding proportion \( f_{l}^{1} \) to estimate the probability of the willing to the target country \( l \), \( l = 1, \ldots, Q \). Assume that the total number of EDP to allocate is \( P \), so the amount of EDP to the target country \( l \) is

\[ n_l = P \cdot f_{l}^{1}, \quad l = 1, \ldots, Q. \]  

(19)

We can use proportional random sampling to divide all EDP into \( Q \) groups.

Step 2. EDP accepted by target countries.

Let \( z_{l} \) be the responsibility coefficient of the target country \( l \), and define

\[ v_{l} = \frac{Z_{l}}{\sum_{l=1}^{Q} Z_{l}}, \quad l = 1, \ldots, Q. \]  

(20)

So, the amount of EDP accepted by the target country \( l \) is

\[ m_{l} = P \cdot v_{l}, \quad l = 1, \ldots, Q. \]  

(21)

If \( m_{l} < n_{l} \), then select \( m_{l} \) members randomly from \( n_{l} \) EDP. Else, all \( n_{l} \) EDP will be accepted by the target country \( l, l = 1, \ldots, Q \).

Step 3. The amount of EDP successfully allocated.

Calculate the amount of EDP successfully allocated to \( Q \) target countries:

\[ P_1 = \sum_{l=1}^{Q} \min(m_{l}, n_{l}). \]  

For the remaining \( P - P_1 \) members of EDP, repeat the above steps until all EDP are successfully allocated. The specific process is shown in Figure 2.

3. Application

In this section, we will apply the proposed method in Section 2 to predict the amounts of EDP for next 10 years and the two-way selection plan of EDP in 2030 will be carried out.

3.1. Sea Level Prediction for the Next Ten Years.

Based on the average sea level data from 2000 to 2020 from National Aeronautics and Space Administration (https://www.nasa.gov), the cumulative series \( h^{(1)}(t) \) and the mean value sequence \( s^{(1)}(t) \) can be calculated by (1) and (2). The results are shown in Table 2.

According to (6), we get the estimations of the parameters \( \hat{a} \) and \( \hat{b} \) as follows:

\[ \hat{a} = 1.0312, \]  

\[ \hat{b} = -0.0003. \]  

(23)

(24)

Then, by (7) and (8), we have

\[ \hat{h}^{(1)}(t + 1) = 0.016825e^{-0.0312t} - 0.00029 \]  

and

\[ \hat{h}(t) = 0.016825(1 - e^{0.0312})e^{-0.0312(t-1)}. \]  

(25)

For the sea level data from 2000 to 2020, by (9) and (10), we get the mean relative residual \( \bar{e} = 0.087437 < 0.1 \) and the mean ratio residual \( \tilde{e} = 0.07924 < 0.10.07924 < 0.1 \), which means that the model fits the data very well, see Figure 3 and 4.

Furthermore, using (25), we can forecast the global average sea levels from 2021 to 2030, as shown in Figure 5. It can be seen that the average sea level in 2030 will reach 0.081 meter.

3.2. Prediction of the Amounts of EDP for the Next Ten Years.

According to the data from World Bank (https://www.worldbank.org/en/home), the average population density in 2019 is \( \bar{P} = 0.000039 \) people/m². The coastline length in 2019 is \( C = 370000 \) km from Central Intelligence Agency.
When the estimated amounts of EDP from 2020 to 2030 can be obtained by the technique proposed in Section 2.2, as shown in Figure 6. The estimated amount of EDP in 2030 is 56,247.

### 3.3. Responsibility Evaluation for Ten Countries.

Based on the data from World Bank (https://www.worldbank.org/en/home), we choose the top 10 countries with per capita GDP in 2019. They are United States, Switzerland, Denmark, Australia, Singapore, Ireland, Norway, Iceland, Luxembourg, and Qatar, respectively. Moreover, we can get the

| Year | $h(t)$ | $h^{(1)}(t)$ | $s^{(1)}(t)$ |
|------|--------|--------------|--------------|
| 2000 | 0.000285 | 0.000285 | 0.003162 |
| 2001 | 0.005754 | 0.006039 | 0.010599 |
| 2002 | 0.00912 | 0.015159 | 0.023975 |
| 2003 | 0.017632 | 0.032791 | 0.03969 |
| 2004 | 0.013797 | 0.046588 | 0.0435 |
| 2005 | 0.026614 | 0.049011 | 0.06634 |
| 2006 | 0.019067 | 0.092269 | 0.105817 |
| 2007 | 0.027095 | 0.119364 | 0.134582 |
| 2008 | 0.030435 | 0.149799 | 0.167999 |
| 2009 | 0.0364 | 0.186199 | 0.201406 |
| 2010 | 0.030414 | 0.216613 | 0.233816 |
| 2011 | 0.034406 | 0.251019 | 0.269218 |
| 2012 | 0.036397 | 0.287416 | 0.301044 |
| 2013 | 0.046056 | 0.333472 | 0.349478 |
| 2014 | 0.032012 | 0.365484 | 0.384355 |
| 2015 | 0.037741 | 0.403225 | 0.424452 |
| 2016 | 0.042454 | 0.445679 | 0.468351 |
| 2017 | 0.045343 | 0.491022 | 0.517326 |
| 2018 | 0.052608 | 0.54363 | 0.567194 |
| 2019 | 0.047128 | 0.590758 | 0.615863 |
| 2020 | 0.050209 | 0.640967 | 0.668024 |
Figure 4: Ratio residual.

Figure 5: Trend forecast of the global average sea level.

Figure 6: Prediction of the amounts of EDPS from 2020 to 2030.
weights of six second-level indicators by the entropy method in Section 2.3, see Table 3. So, the weight vectors are:

\[
A_1 = (0.1536, 0.5540, 0.2925),
A_2 = (0.1146, 0.4429, 0.4425).
\]

In the following, let us take the United States as an example to calculate the national responsibility coefficient. Based on the data of above six second-level indicators from 2000 to 2018 from World Bank [11], we get the evaluation matrix

\[
R = \begin{bmatrix}
0 & 0.06 & 0.56 & 0.39 \\
0.06 & 0.17 & 0.78 & 0 \\
0.11 & 0.11 & 0.33 & 0.44 \\
0.11 & 0.89 & 0 & 0 \\
0 & 0 & 0.72 & 0.28 \\
0.40 & 0.30 & 0.11 & 0.09
\end{bmatrix},
\]

where

\[
R_1 = \begin{bmatrix}
0 & 0.06 & 0.56 & 0.39 \\
0.06 & 0.17 & 0.78 & 0 \\
0.11 & 0.11 & 0.33 & 0.44 \\
0.11 & 0.89 & 0 & 0 \\
0 & 0 & 0.72 & 0.28 \\
0.40 & 0.30 & 0.11 & 0.09
\end{bmatrix},
R_2 = \begin{bmatrix}
\end{bmatrix}
\]

Then, the membership vector corresponding to each evaluation level is

\[
B_{\text{United States}} = [ A_1 \quad A_2 ] \ast R = \begin{bmatrix}
0.1275 & 0.1852 \\
0.4911 & 0.1762
\end{bmatrix}.
\]

Define the responsibility score vector for the four evaluation levels as

\[
C^T = \begin{bmatrix}
10 & 8 \\
6 & 4
\end{bmatrix},
\]

and then, the responsibility coefficient of the United States is

\[
Z_{\text{United States}} = B \ast C = 6.4079.
\]

Similarly, we can obtain the responsibility coefficients of other nine countries as follows:

\[
Z_{\text{Australia}} = 7.1260,
Z_{\text{Singapore}} = 7.6648,
Z_{\text{Switzerland}} = 8.4055,
Z_{\text{Denmark}} = 5.1260,
Z_{\text{Ireland}} = 9.1322,
Z_{\text{Norway}} = 8.0794,
Z_{\text{Iceland}} = 5.8760,
Z_{\text{Luxembourg}} = 5.0038,
Z_{\text{Qatar}} = 5.0188.
\]

From the above results, it can be seen that Ireland has the greatest responsibility coefficient followed by Switzerland and Norway. Note that if the data span of the six second-level indicators is short, the coefficients of different countries may be relatively close. To achieve a relatively fair distribution of responsibilities, we can adjust the value of \( C \) to expand the responsibility coefficient of different countries.

Next, taking the EDP forecast population \( P = 56247 \) in 2030 as an example, let us give a migration plan based on the two-way selection mechanism. According to the steps in Section 2.4, six cycles are carried. The cumulative amounts of EDP who are allocated successfully in each cycle are presented in Table 4.
4. Conclusions and Discussion

In this article, we have proposed a method of prediction and allocation for EDP based on the GM (1, 1) model and fuzzy comprehensive evaluation. Firstly, we use the GM (1, 1) model to predict sea level and the amount of EDP is predicted combining with the population density. Then, six evaluation indicators which reflect the responsibility capability of a country has been constructed, and the responsibility coefficient has been proposed based on the fuzzy comprehensive evaluation method. Finally, the two-way selection allocation mechanism for EDP is given. With the proposed method, the amounts of EDP for next 10 years have been predicted and the two-way selection of EDP in 2030 has been set up. The proposed method may provide some guidelines on handling EDP immigration issues for some relevant international agencies and countries.

In our subsequent research, we will try to improve the allocation mechanism based on two-way selection through other techniques such as probabilistic gray relational analysis (GRA). The method of probabilistic GRA has been frequently applied in multiple attribute group decision making (see Lei et al. [12], Wei et al. [13], and Wang et al. [14]). Therefore, it may be a good choice to make a more reasonable allocation between the countries of EDP and the target migration countries.

Data Availability

The average sea level data in Section 3.1 is from NASA (https://www.nasa.gov/). The coastline length in 2019 in Section 3.2 is from Central Intelligence Agency (https://www.cia.gov/the-world-factbook/field/coastline) and Wikipedia (https://en.wikipedia.org/wiki/List_of_countries_by_length_of_coastline). The average population density in Section 3.2, the per capita GDP in 2019, and the six second-level indicators in Section 3.3 are from Word Bank (https://www.worldbank.org/en/home).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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