Gray System Prediction in the Alpine–Himalayan Earthquake Zone

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Abstract. Increasingly frequent earthquakes pose a serious threat to human lives and properties. However, the prediction of seismic activity is a major problem in seismic research. In this paper, we use the gray model to study seismic activity patterns. The Alpine–Himalayan seismic zone is selected as a study area for this work. Using seismic activity in the region, we analyze characteristics of time series related to seismic activity. Results show that the gray model for predicting seismic activity is available. The timing of the seismic activity of the Alpine–Himalayan seismic zone displays certain regularity. On the basis of computational analysis on July 20, 2015, a strong earthquake will occur in 26 years. In this paper, we use the application of a gray system that provides a new modeling approach in the field of disaster prevention to predict seismic activity, which is important in disaster prevention, disaster management, and rescue.

1. Introduction

In recent years, earthquake activities have become frequent around the world, suggesting that global seismic activity is in a relatively active phase [1, 2]. In recent years, natural disasters [3-5] have caused huge damage to the world [6-8], and earthquake losses are particularly serious. Earthquakes do not only cause a large number of casualties and immeasurable economic losses directly but also affect thousands of displaced people indirectly. Earthquakes also cause a series of secondary disasters, such as landslides, avalanches, and fires, which are directly or indirectly dangerous and cause serious threat and damage to the safety of residents’ lives, properties, and daily life. The earthquake forms are complex and involve numerous factors, which greatly limit the study of earthquakes. A breakthrough in earthquake prediction is difficult to obtain, which poses a catastrophic threat to human’s daily life, production, and development [9].

The laws of seismic activity are covered by a wide range of knowledge of various subjects, such as geophysics [10], geodynamics [11], mechanics [12], geology [13], structural geology [14], and geodesy [15]. Research on the laws of seismic activity can be seen as a discipline or a highly integrated and complex subject, which is why earthquake prediction has been recognized as one of the world’s major problems. With the development of the industrial revolution and the vigorous research on artificial intelligence [16-18], more and more machine learning methods [19,20], deep learning methods [21,22] came into being, applied to image processing [23-26], natural language processing [27-29] and recommendation system [30,31] and many other scenes. This has set off a wave of
research trends in earthquakes. The conception and eventual occurrence of an earthquake can be regarded as an essentially complex fuzzy processor gray process[32], which means that the properties of an earthquake, such as time, strength, depth, and spatial distribution, are essentially inhomogeneous and complex. Thus, the birth of the discipline of the gray system, in which its basic principle is to use the method of gray system disciplines as a means to study nature, characteristics, and laws, lays the theoretical foundation of the corresponding decisions and provides technical support. This paper begins with the gray system method of seismic activity to study seismic activities and random events that are similar to such activities [33]. This new method has characteristics of the gray system, and it may be used for prediction research of earthquakes.

2. Related work

System research can be traced back to the 20th century, and various fields have revealed uncertain systematical theories and methods [34]. In the 1980s, Professor Deng Julong and Professor Z. Pawlak created representative gray system theory and rough set theory[35, 36]. When people analyze a system, the course of its research and the results obtained contain a few uncertainties because of the complexity of the system structure. However, no difficulty can stop people from understanding and studying a system. With advances in related disciplines and society, the study and understanding of systems will certainly become more in-depth and clear [37].

The essence of gray system theory is that it regards the known but incomplete information as the study objects, of which many or even most information is unknown. Simply speaking, the gray system means a combination of information between some of the information from known and unknown parts of the system. The basic principle of this theory is that unknown information is inferred through the analysis and study of the known information [38,39]. Specifically, the gray forecast system is a new method that is mainly based on the sample data. The gray system analyzes and extracts the dissimilarity and correlation between various factors in these sample data. On this basis, the regularity between the original data is enhanced through the creation of a certain equation algorithm [40]. Through analysis and study, the potential and essential characteristics of the system are determined, and the changes in the study are predicted rationally[41].

Given the characteristics and advantages of gray prediction system theory, it is widely used in all trades and professions. With its continuous development and maturity, the theory was not used in the study of seismic activity until the late 1980s [42-44]; initially, this theory was used to analyze large earthquakes on massive areas, by which better predictions were obtained[45]. For seismic activity, numerous unexplained factors about the preparation and mechanism of earthquakes exist, because of the significant limitations and blind spots in the current knowledge and understanding about earthquakes. In other words, current earthquake prediction is conducted in situations with known and unknown conditions, which is consistent with the principle of gray prediction. Thus, using gray prediction to predict an earthquake is a reliable prediction method.

3. Study area and data source

3.1 Study area

The Alpine–Himalayan seismic zone[46,47] traverses southern Asia and Europe and northwest Africa. It is the second largest seismic zone in the world [48,49]. The total energy released by this zone accounts for about 15% of the total energy released by earthquakes worldwide [50]. The whole length of the Alpine–Himalayan seismic zone is about more than 20,000 km. The Alpine–Himalayan seismic zone is also known by other names. Given its close relationship with the Alpine fold zone, it is also called the Alpine seismic zone. Moreover, the source of the Alpine–Himalayan seismic zone is the north shore of the Mediterranean, so it is also known as the Mediterranean seismic zone. The Eurasian earthquake zone [51] is extensive, with a complex geological structure and geographical environment. Earthquakes occur in this region frequently, which makes the seismic activity in this earthquake zone representative of the world’s seismic activity. Therefore, the seismic data recorded in this seismic zone are of great significance and research value. Since ancient times, seismic activity in this seismic zone has been a topic of interest among seismologists at home and abroad.
This paper selects the entire Alpine–Himalayan seismic zone as its study area. The total energy released by an earthquake in the Alpine–Himalayan seismic zone accounts for about 15% of the total energy released by all earthquakes in the world. Most of the earthquakes in the Alpine–Himalayan seismic zone are shallow-focus earthquakes, which result in disasters and pose a great threat to the safety of residents’ lives and properties. The Alpine–Himalayan seismic zone involves and impacts a vast region. The earthquakes occurring in this seismic zone are analyzed to obtain the temporal and spatial propagation characteristics of seismic activities and predict seismic activities of this seismic zone.

3.2 Data source

This data used in this paper are original seismic data downloaded from the US Geological Survey official website. The longitude is [63°, −11°] and the latitude is [−23°, 152°]. The time range is from January 1900 to July 2015. The original data include the earthquake’s time, longitude, latitude, magnitude, depth, and focal attribute information. The data downloaded are converted to text format first and then imported into ArcGIS. The coordinate system and projection are transformed. This paper uses WGS1984 coordinate. The final result is shown in Figure 1.

4. Method and analysis

4.1 Method

The gray prediction model analyzes and processes the known information to predict the unknown information, from which we can determine the importance of gray forecast in gray system theory. The common gray system models are \( GM(1,1) \) model, \( GM(1,N) \) model, \( GM(0,N) \) model, \( GM(2,1) \) model, and Verhulst model. In these models, the \( GM(1,1) \) model proposed by Professor Deng Julong is extensively used in the field.

The gray model \( GM(1,1) \) can analyze study subjects quantitatively. This model can be divided into gray time series forecasting, prediction distortion, wave prediction, and forecasting systems. Similar to the establishment of the gray prediction model, the steps to establish the \( GM(1,1) \) gray prediction model include the establishment of the model, solving of parameters, establishment of the prediction formula, and inspection of models.

Let \( X_k^{(0)} = \{x(0), x(1), \ldots, x(N)\} \), where the superscript 0 indicates the sequence observed. The main purpose of this superscript is to distinguish this sequence with the cumulative number of sequence. The data are randomized. To reduce the randomness of the original data sequence and strengthen regularity, the data are processed by accumulated transformation as follows:

\[
X_k^{(1)} = \sum_{t=1}^{N} x(t), \quad k = 1, 2, \ldots, N
\]  

The result \( X_k^{(1)} \) (superscript 1 represents the cumulative times of label 1 with the front label to distinguish the original data 0.) is a growth-oriented, non-negative sequence.
According to the principles proposed by Professor Deng Julong, a one-dimensional and first-order differential equation of \( GM(1,1) \) can be established:

\[
\frac{X^{(1)}(k+1) - X^{(0)}(k+1)}{T} = \mu \\
\frac{X^{(1)}(k) - X^{(1)}(k+1)}{T} + aX^{(1)}(k) = \mu \\
d\frac{T^2}{dt^2} + aX^{(1)} = \mu 
\]

In the equations above, \( a \) and \( \mu \) are the constants to be determined. According to the principle of least squares, the equation can be converted into:

\[
T^1 (B^T B) T a = b - \mu Y 
\]

The B matrix in Equation (5):

\[
b = \begin{pmatrix}
-\frac{1}{2}(x^{(0)}(1) + x^{(0)}(2)) \\
-\frac{1}{2}(x^{(0)}(2) + x^{(0)}(3)) \\
\vdots \\
\frac{1}{2}(x^{(0)}(N-1) + x^{(0)}(N))
\end{pmatrix}
\]

Y Matrix:

\[
Y = \begin{pmatrix}
x^{(0)}(2) \\
x^{(0)}(3) \\
\vdots \\
x^{(0)}(N)
\end{pmatrix}
\]

The solution to Equation (7) is as follows:

\[
\hat{X}^{(1)}(k+1) = \left( X^{(0)}(1) - \frac{\mu}{a} \right) e^{-ak} + \frac{\mu}{a} 
\]

In the formula, \( \hat{X}^{(1)}(k+1) \) is the estimated value of \( X^{(1)}(k) \). \( X^{(1)}(k+1) \) is processed by reduction treatment to obtain the prediction estimate of original series \( X^{(0)}(k) \), which is:

\[
\hat{X}^{(0)}(k+1) = \hat{X}^{(1)}(k+1) - X^{(1)}(k) 
\]

After conducting the steps above, the gray prediction model \( GM(1,1) \) is established.

4.2 Model test

Under normal circumstances, a difference exists between \( X^{(0)}(k) \) and \( \hat{X}^{(0)}(k) \). To determine whether the difference is significant and whether the estimated accuracy \( \hat{X}^{(0)}(k) \) is reasonable, the reliability of the established prediction model must be tested for evaluating whether the predicted value is reasonable. This paper uses two classic examination methods.

4.2.1 T-test. Residuals between each pair of [52] are computed:

\[
\varepsilon_k = \hat{X}^{(0)}(k) - X^{(0)}(k) 
\]

The mean of the residuals is calculated as follows:

\[
\varepsilon = \frac{1}{N} \sum_{k=1}^{N} \varepsilon_k 
\]

A prediction error in the formula is calculated as follows:

\[
S_1 = \sqrt{\frac{1}{N} \sum_{k=1}^{N} (\varepsilon_k - \varepsilon)^2} 
\]

The test value is then determined:

\[
t = \frac{\varepsilon - \varepsilon_k}{S_1} \sqrt{N} 
\]

In Equation (13), \( N \) is the total number of samples of the original data series, and \( \varepsilon_0 \) is the residual true value, which is usually zero. Therefore, Equation (14) can be reduced to
\[ t = \frac{\bar{X} - \mu}{S_2} \sqrt{N} \]  

The two-tailed test place value \( t_{a/2} \) can be calculated from \( \alpha \) and degree of freedom \( N - 1 \). If \( t < t_{a/2} \) is calculated by Equation (14), no significant difference exists between \( X^{(0)}_{(k)} \) and \( \overline{X^{(0)}_{(k)}} \). Therefore, the constructed \( GM(1,1) \) prediction model is credible.

4.2.2 Posterior difference test.

The mean square error \( S_2 \) of each pair with both \( X^{(0)}_{(k)} \) and \( \overline{X^{(0)}_{(k)}} \) is calculated, and Equations (15)–(17) show the calculation process of the test method [52].

The mean of the original data series is calculated as follows:

\[ X^{(0)}_{(k)} = \frac{1}{N} \sum_{k=1}^{N} X^{(0)}_{(k)} \]  

The mean square error of the original data series is determined using the following equation:

\[ S_2^2 = \frac{1}{N-1} \sum_{k=1}^{N} (X^{(0)}_{(k)} - \overline{X^{(0)}_{(k)}})^2 \]  

The ratio after calculation is:

\[ c = \frac{S_1}{S_2} \]  

The value of \( c \) in the formula above is one of the parameters for determining the reliability of the prediction model. The smaller \( c \) is, the greater \( S_2 \) is and the smaller \( S_1 \) will be. Given that \( S_2 \) is high, the randomness of the original data series is great. By contrast, if \( S_1 \) is low, the error dispersion of the prediction model established by the original data sequence is small. From this perspective, error dispersion is relatively small even though the randomness of the original data series is large. This finding indicates that the prediction model is reliable. In the theory proposed by Professor Deng Julong, the reliability of the prediction model can be assessed by the value of \( c : c < 0.35 \) means the prediction model is good; \( c < 0.5 \) means the prediction model is qualified; \( c < 0.65 \) means the prediction model is barely represented; \( c \geq 0.65 \) means the prediction model is unqualified [53].

4.3 Analysis of the prediction of seismic activity of the Alpine–Himalayan seismic zone

To predict earthquakes in seismic zones better, we extract data from earthquakes with a magnitude of seven or above in this seismic zone. As a collection of strong earthquakes in the study area, a total of 204 earthquake data are obtained (Ms \( \geq 7.0 \)).

Furthermore, we use the gray prediction method to analyze and research the time series of earthquakes greater than a magnitude of seven in this seismic zone since 1900. To obtain a reference value of the calculated values, we set the first group of data from the 204 seismic data since 1900 in this seismic zone as the reference data, and data from the last group is used as verification data. The remaining 202 groups of data are calculated by the gray prediction method. According to \( X^{(0)}_{(k)} \) and \( \overline{X^{(0)}_{(k)}} \), a gray prediction map can be drawn:

As shown in Figure 2, large differences exist between the original value and accumulated value, because of the strong interference factors in the single-stage gray forecast. For the cumulative gray prediction, a good linear correlation is found between the original value and the accumulated value. This result indicates that the relationships between data are enhanced after accumulation, and the interference factors between them are reduced.
The single-stage gray prediction

The cumulative gray prediction

Figure 2. Gray prediction of strong earthquakes in Alpine-Himalayan seismic zone

Subsequently, we substitute $K = 201$ and $K = 202$ into Equation (18). The values of $X^{(1)}_{(202)}$ and $X^{(1)}_{(203)}$ are calculated, and $X^{(0)}_{(203)} = 138.9050$. A reduction treatment is conducted using Equation (9). We are then able to predict the next earthquake with a magnitude of seven or above according to $X^{(0)}_{(203)}$ and $S_{2}$. Specifically, the next earthquake with a magnitude of seven or above is likely to occur in $26 \pm 3.21$ years, and this conclusion is consistent with that of the earthquake period in this seismic zone using wavelet analysis.

Finally, according to the formula, we calculate that $S_{2} = 7.9225$, $t = 8.3270$, and $\alpha = 0.01$. According to $\alpha$ and freedom $N - 1 = 202$, $t_{N\left(\frac{\alpha}{2}\right)} = 2.947$ and $t < t_{N\left(\frac{\alpha}{2}\right)}$. These findings indicate that the prediction established in this paper is credible. According to Equations (10)–(17), we obtain $c = 0.2420$. The results show that $c < 0.35$, which suggests that the constructed prediction model meets the requirements.

5. Result

Upon applying the gray prediction model $GM(1,1)$ proposed by Professor Deng Julong to the analysis of time sequence of earthquake with magnitude that is seven or above after pretreatment in the Alpine–Himalayan seismic zone, we obtain the following conclusions:

1. The $GM(1,1)$ model can analyze the time series of the Alpine–Himalayan seismic zone to yield an ideal result. Using the $GM(1,1)$ model, we accumulate time series of the original data pre-processed first, which weakens interference factors between data and enhances the rule of data. Combined with the principle of the method, a relatively strong earthquake is predicted to occur about 26 years from July 20, 2015, after a reasonable prediction calculation.

2. According to the test formula, which corresponds to the prediction model, validation results show that the established prediction model meets the requirements. Simultaneously, by examining two classical prediction models, we know that $t < t_{N\left(\frac{\alpha}{2}\right)}$ and $c$ is less than 0.35. Therefore, the established prediction model is better than the other tested model. Moreover, the accuracy of the results obtained meets the requirements.

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