Application of Multivariate Modelling to Global Warming Projections

Zhaorui Liu[1], Meiling Cui[1, #], Shuai Sun[2, #], Qiang Wang[3, #], Wenjing Yang[1, #], Ruizhen Li[1, #], Xiucheng Yue[1, #]

[1]School of Economics, Qingdao University, Qingdao, Shandong Province, 266061, China
[2]College of Electronics and Information, Qingdao University, Qingdao, Shandong Province, 266075, China
[3]School of Mathematics and Statistics, Qingdao University, Qingdao, Shandong Province, 266071, China
[#]These authors contributed equally.

Abstract: Global warming is a natural phenomenon in which the accumulation of energy in the Earth's atmospheric system leads to an increase in temperature. To build the model, we collected multiple datasets from the 20th century: average annual global temperatures, average monthly temperatures at different latitudes, global losses from various natural disasters, global emissions of various chemicals, and population. We then pre-processed and visualized the data. In our quantitative analysis, we found that the increase in global temperature in March 2022 did not exceed the increase in the past 10 years. We then developed three models to describe past and project future global temperature levels: the GM(1,1) model, the ARIMA(0,1,1) model, and the Holt model. By primarily comparing the fit of the three models, we concluded that the Holt model has the highest prediction accuracy. We found that the relationship between time and global temperature.

Keywords: ARIMA, GM(1,1), Holt Model, Prediction.

1. Introduction

Since the Industrial Revolution, the "greenhouse effect" has begun to take shape with the acceleration of industrialization and the increasing carbon emissions generated by human production activities. After a short respite from global warming, the large-scale use of fossil fuels such as oil and coal in the early 1960s accelerated the pace of global warming. It is widely recognized in the scientific community that the cause of global warming is the increasing levels of carbon dioxide and other greenhouse gases in the Earth's atmosphere. These greenhouse gases are highly permeable to visible light from the sun, which strongly absorbs long-wave radiation infrared rays from the ground, thus raising the temperature of the Earth, which is known as the "greenhouse effect". The "greenhouse effect" causes an imbalance in the amount of energy absorbed and released by the Earth's atmospheric system.

In the face of global warming, human beings must reflect on their lifestyles and living habits and actively take corresponding measures to cope with the changes in climate and environment. In recent decades, global warming has seriously affected people's life and production [1], and the issue of climate and climate change has become one of the core issues affecting the sustainable development of countries [2]. More than a hundred years ago, mathematician Fourier proposed that the earth's atmosphere has a "greenhouse effect" [3], and the surface temperature is determined by the balance between receiving external energy and losing external energy [4] and Hu [5] believed that climate change is affected by a variety of factors, including the earth's heat uptake and exothermicity, the surface temperature of the oceans, the concentration of carbon dioxide, the vegetation on the earth's surface, and human activities, and therefore constructed a multivariate regression model to analyse global warming; In order to better present the prediction of climate change trends, Guo [6] and Luo [7] extended the grey GM(1, 1) model into a multivariate grey GM(1, n) model for short-term prediction of future climate change trends; Chen et al. [8] used correlation analysis and multivariate nonlinear regression analysis to quantify and qualify the correlation between the geosystem temperatures and radiations of the Canadian region, the ocean surface temperatures and the global carbon emissions; Qi et al [9] proposed that the factors affecting climate change are closely related to ocean heat absorption in addition to greenhouse gas emissions. Relevant studies at home and abroad show that although the long-term trend of global temperature is mainly determined by greenhouse gases, there are many other factors affecting global temperature, such as volcanic eruptions, forest fires, COVID- 19 and so on. Moreover, the formation and evolution of these influencing factors are very complex, and there are still many deficiencies in observation, research, diagnosis, attribution analysis and model construction[10]. Therefore, it is of great significance to strengthen the connection between various disciplines and technologies related to global warming and to provide a better support point for the climate field through mathematical modelling.

2. The Fundamental of Data Analysis

We have modelled the future changes in global temperature and found that the global temperature will show a slow growth trend in the future. First, we selected the global average temperature in March of each year from 2012 to 2022, and then defined the temperature growth rate as follows.

$$G_i = T_{i+1} - T_i \tag{1}$$

Where, Ti is the Global Mean Temperature in March of the year.

The results are shown in Figure 1. The left panel shows the results of Gi calculations, and the right panel shows the global average temperature from 2012 to March 2022.

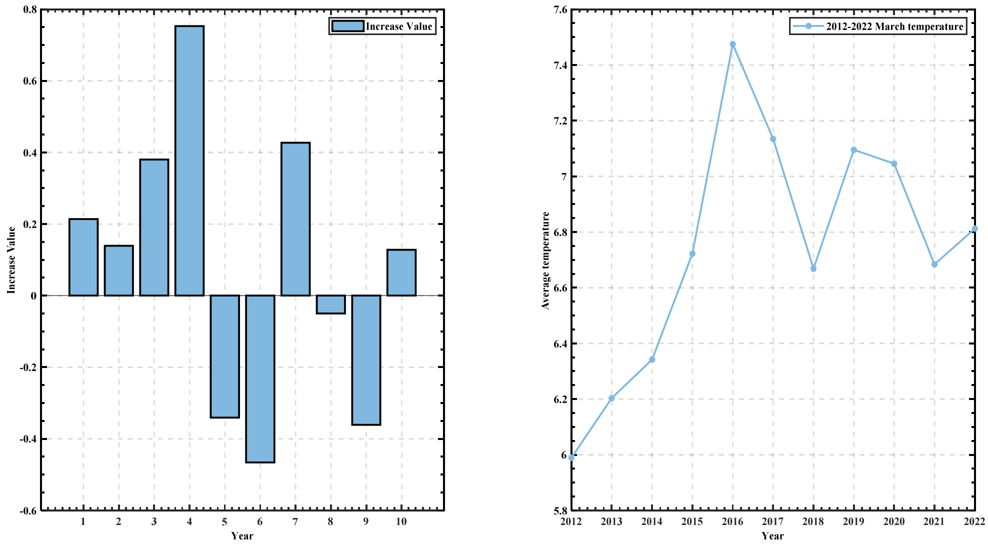

Figure 1. Temperature growth rate

The ARIMA(p, d, q) is an extension of the ARMA(p, q) . In ARIMA(p, d, q), AR is "autoregressive", p is the number of autoregressive terms; MA is "sliding average", q is the number of sliding average terms, and d is the number of differences made to make it a smooth series.The ARIMA(p, d, q) can be expressed as (2).

$$(1-\sum_{i=1}^{p}\phi_i L^i)(1-L)^d X_t=(1+\sum_{i=1}^{q}\theta_i L^i)\varepsilon_t \qquad (2)$$

Where, L is the lag operator. It is important to note that the ARIMA model requires that the series meet the smoothness. We first check the results of the ADF test of the data to determine whether it can significantly reject the hypothesis of series non-stationarity based on the analyzed P. The results of the ADF test are shown in the following table 1.

Table 1. ADF Test

Variables	Differential Order	t	P	AIC	Threshold values 1%	Threshold values 5%	Threshold values 10%
Temperature Average	0	1.39	0.997	-23.614	-3.558	-2.917	-2.596
	1	-5.835	0.000***	-23.506	-3.558	-2.917	-2.596
	2	-5.438	0.000***	- 16.511	-3.568	-2.921	-2.599

We find that the significance P is 0.997 at the difference of order 0, which does not present significance at the level, then we consider that the original hypothesis cannot be rejected, so the series is an unsteady time seriesThe significance P is .000 * ** at both the 1st and 2nd order of the difference, which presents significance at the level, then we reject the original hypothesis and consider the series as a smooth time series.We use the established ARIMA(0,1,1) model to predict the global average temperature in 2050 and 2100 as following Figure 1.

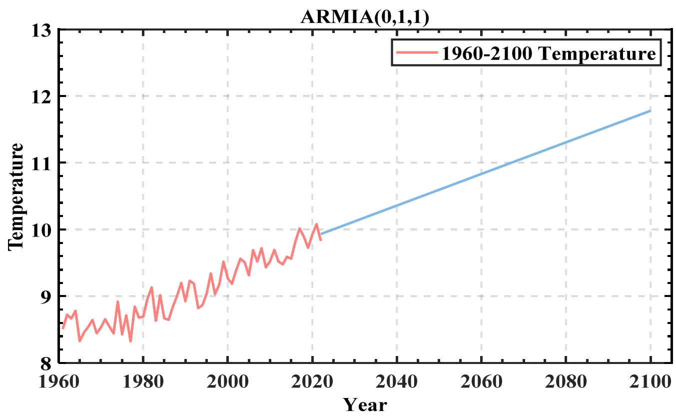

Figure 1. ARIMA (0, 1, 1) Prediction

It is predicted that the global temperature will reach 10.6°Cin 2050 and 11.78°C in 2100. So we do not agree that the global temperature will reach 20°C in 2050 or 2100. According to our model we predict that the global temperature will reach 20°C in 2447.

The gray prediction model can predict systems that contain uncertain information and is a prediction model that contains uncertainty. Equation (5) is known as the whitening equation of GM (1, 1) .

$$\frac{dx^{(1)}(t)}{dt} = -\hat{a}x^{(1)}(t) + \hat{b} \tag{3}$$

The basic form of GM (1, 1) is equation 6, also known as the gray differential equation.

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{4}$$

Firstly, we perform a level-ratio test on the time series. We find that all the level ratios of the translational transformed series lie within the interval (0.969, 1.032), indicating that the translational transformed series are suitable for constructing a gray forecasting model. Therefore, we construct the following gray model GM (1, 1).

Table 2. GM (1,1) Parameters

Development factor a	Grey effect quantity b	Posterior test difference ratio C
-0.001	19.33	0. 136

Where, the development coefficient indicates the development pattern and trend of the series, and the gray action quantity reflects the change relationship of the series. The posterior difference ratio can verify the accuracy of gray prediction, and the smaller the posterior difference ratio is, the higher the accuracy of gray prediction is. The posterior difference ratio value obtained from the solution is 0. 136, and the model accuracy is high.

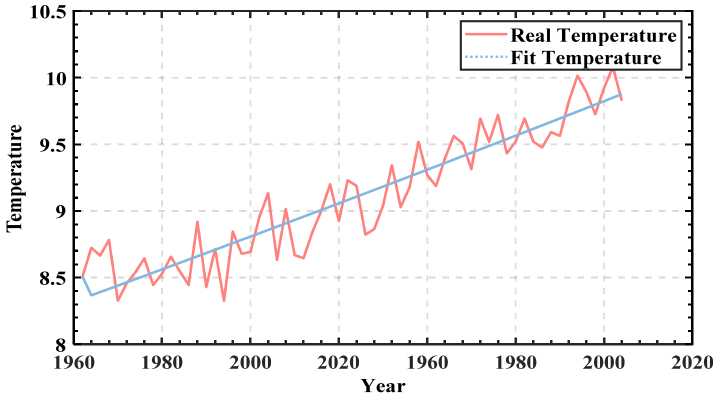

Figure 2. GM (1, 1) Fitting

Figure 2 shows the model fit of the gray prediction, and we find that the fit is good and the model can largely reflect the temperature change trend. We use the established GM (1, 1) model to predict the global average temperature in 2050 and 2100 and plot the following prediction series as Figure 3.

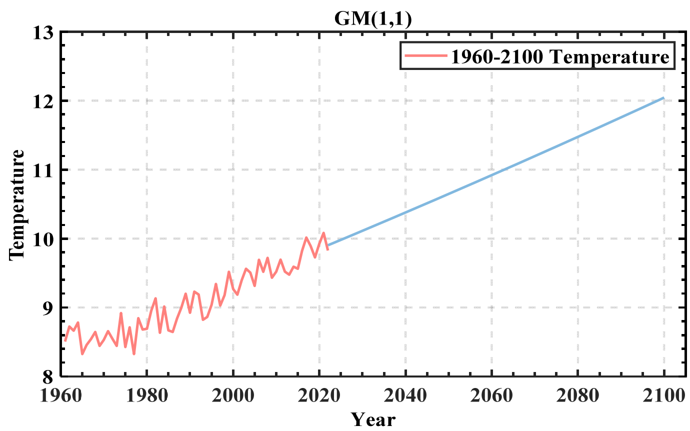

Figure 3. GM (1, 1) Prediction

It is predicted that the global temperature will reach 10.65°Cin 2050 and 12.04°C in 2100. So, we do not agree that the global temperature will reach 20°Cin 2050 or 2100. According to GM (1, 1) we can predict that the global temperature will reach 20°C in 2338.

3. Holt Model

3.1 The establishment of data computation

The Holt model is an upgraded version of the simple linear exponential smoothing model with the advantage of great flexibility in smoothing the two factors of the original series using different smoothing parameters. The difference between it and the general exponential smoothing model is that it directly smoothes the trend data and forecasts the original time series, and all that needs to be taken into account is the selection of the two smoothing parameters and the initial values, which is also known as the Holt two-parameter linear exponential smoothing model.

$$L_{t+1} = \alpha D_t + (1-\alpha)(L_t + T_t)$$
$$T_{t+1} = \gamma(L_{t+1} - L_t) + (1-\gamma)T_t \tag{5}$$

It is predicted by the following equation.

$$F_{t+1} = L_{t+1} + T_{t+1} \tag{6}$$

where, α and γ represent the two smoothing parameters that affect the forecasted values; D_t represents the actual value; F_{t+1} represents the forecasted value; L_t represents the average demand; T_t represents the trend of growth, the former is a smoothing equation for the trend of the time series; the latter is a smoothing equation for the increment of the trend.

In Figure 4, we can see that the data used is really not seasonal and linear, so we considered trying to use the Holt model to describe and predict the data. We used SPSS to solve the Holt model, using the historical global annual average temperature as input, which gives us the following results.

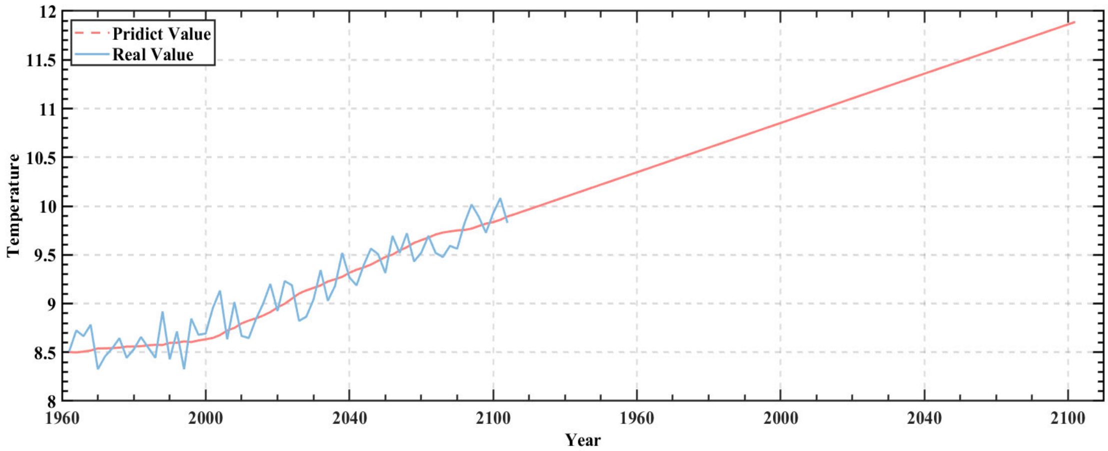

Figure 4. Holt Prediction

We can obtain the model parameter table.

Table 3. Holt Parameters

	Estimation	Standard Error	Significance
Alpha	0.032	0.037	0.401
Gamma	0.845	1.060	0.428

We use Holt model for global average temperature prediction and we can find that in the prediction model the global average annual temperature will reach 10.62℃ in 2050 and 11.89℃ in 2100. Therefore, the model does not agree that the global average annual temperature will reach 20℃ in 2050 or 2100. After Holt's model calculation, we think that the global annual average temperature will reach 20℃ in the year 2421.

By comparing the parameters of the three models, we choose R^2 as the three main parameters to compare the accuracy of the models. Finally, we found that Holt model is more accurate among these three models.

4. Conclusions

Global warming is a natural phenomenon in which the accumulation of energy in the Earth's atmospheric system leads to an increase in temperature, which poses a serious risk to the lives of populations around the world. In order to quantitatively analyse the process of global temperature change, and to effectively prevent the further harm caused by temperature rise, this paper establishes models to predict the process of temperature change, and we establish the GM(1,1) model, ARIMA(0,1,1) model and Holt model. By primarily comparing the fit of the three models, we concluded that the Holt model has the highest predictive accuracy.

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