DOI: 10.54254/2753-8818/36/20240530

Prediction of ocean temperature based on ARIMA model

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Abstract. As an important parameter of the Earth's ecosystem, ocean temperature has always been a hot research field for scholars, and the rise in ocean temperature caused by global warming is a topic related to the fate of humanity. The prediction of future ocean temperature is of great significance. The ARIMA model, as a typical prediction model, is highly favored by scholars from various countries due to its accuracy and adaptability. In this paper, the ARIMA multiplication model with seasonal effect is used to forecast the trend of ocean temperature change in the next year, and to prediction graph as well as specific reference values are given. The conclusion is as follows: The global average monthly ocean temperature will continue to rise in the next year. Therefore, this article believes that the government should promptly introduce relevant policies to address the rise in ocean temperature caused by global warming, and people should also fulfill their obligations to protect the environment.

Keywords: Prediction, ocean temperature, ARIMA model, test.

1. Introduction

The severity of climate change is receiving increasing attention from the international community. Scholars at the 2024 Davos World Economic Forum have indicated that global warming and rising ocean temperatures may lead to the melting of permafrost, potentially leading to the awakening of many 'zombie viruses'. Ocean temperature is a key variable in the Earth's climate system. Therefore, how to grasp the trend of ocean temperature fluctuations and accurately predict them has become a focus of research by world organizations.

With the intensification of global warming, changes in ocean temperature not only affect marine life and ecosystems, but also have profound impacts on human society. Chen and Sun point out that abnormal changes in tropical ocean temperature and the resulting abnormal atmospheric circulation may be a key factor in the rapid melting of Arctic sea ice, which will cause extreme weather to occur globally [1]. In addition, Guo and Zhou found that the ocean initialization simulation experiment can well simulate the spatial distribution of ocean temperature and low cloud climate states [2]. Zhao et al. used the high spatiotemporal resolution ocean temperature products provided by the China Sea Marine Environment Numerical Forecasting System as the bottom boundary conditions of the Weather Research and Forecasting Model (WRF) model, analyze and study the impact of ocean temperature on typhoon path and intensity. [3]. Zhao et al. quantitatively investigated the influence of sea surface temperature on wind velocity and backscattering measurements obtained by the Chinese-French Marine Satellite Scatterometer (CSCAT). The results showed that the backscattering coefficients measured by both

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polarization modes of CSCAT are affected by sea surface temperature [4]. Katelyn discussed the impact of rising sea surface temperatures on the hatching behavior of rare seabirds. Studies revealed a noteworthy inverse correlation between the incubation period's seawater temperature and the level of parental attentiveness [5]. Paige predicted that ocean warming will reduce the size of many fish species, which may increase the natural mortality rate of most marine fish on the Scotia Continental Shelf in Canada [6].

Many Scholars are constantly researching in the hope of obtaining more accurate prediction models. Peng and Zhang extracted the attribute parameters of marine seismic data, used the optimized seismic attributes of principal component analysis as input, and then trained the support vector regression machine using grid cross validation. Combined with the data, the support vector regression machine predicted seawater temperature significantly in the case of a small number of seawater temperature samples, and could accurately divide water layers [7]. Du et al. proposed a deep neural network based on global cross-scale spatiotemporal attention. The multi-scale local spatial modeling module that extracts spatial distribution pattern features from the mean of SST sequences and the spatiotemporal attention fusion module based on global cross scale are used to model the global autocorrelation of each grid point [8]. Li et al. used two neural network methods, Back Propagation (BP) and Radial Basis Function (RBF), to carry out short-term prediction, and verified that the RBF neural network model has strong applicability and higher accuracy [9]. Aditya presented the Bay of Bengal region's sea surface temperature prediction using a novel neural architecture called Long Short Term Memory [10].

To conclude, the investigation of ocean temperature, a pivotal indicator, has garnered significant attention from scholars. This paper will primarily employ the ARIMA model to predict the forthcoming year's ocean temperature and provide recommendations based on the forecasted outcomes.

2. Methodology

2.1. Data source

The data analyzed in this paper is sourced from the National Oceanic and Atmospheric Administration (NOAA) website. The data is the global monthly average ocean temperature of 0-700 meters from January 2000 to December 2023.

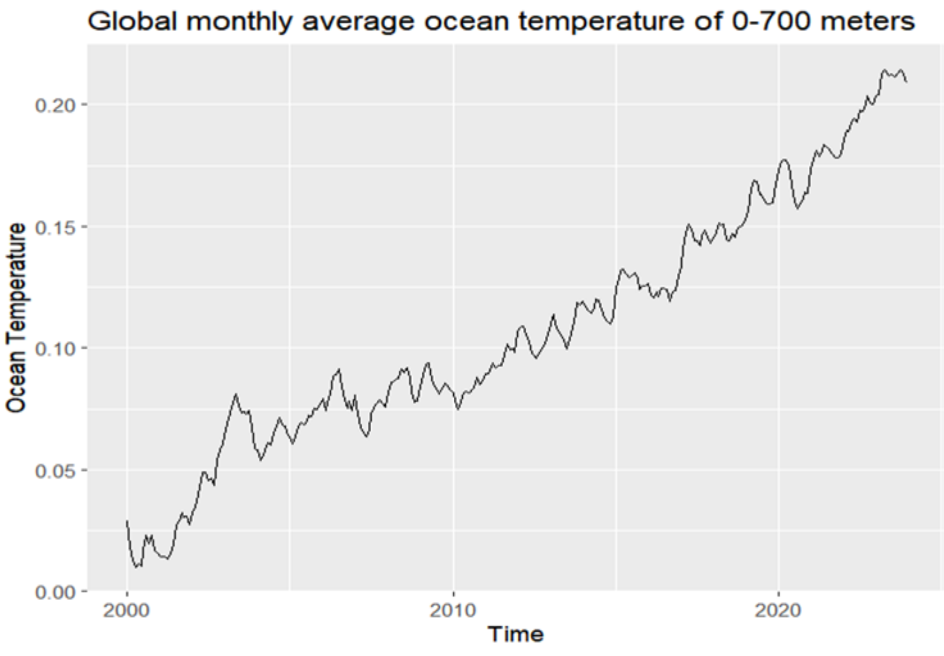

Figure 1. Global monthly average ocean temperature.

From Figure 1, it can be seen that the overall trend of the time series chart is upward, which means that the ocean temperature continues to rise over time, and it is obvious that it has a periodic characteristic with seasonal changes.

2.2. Variable selection

The variable studied in this paper is the global 0-700m ocean monthly mean temperature. The temperature of seawater is a physical quantity that reflects the thermal condition of seawater. The temperature of seawater has periodic and irregular changes such as day, month, year, and many years, which mainly depend on the state of ocean heat budget and its temporal changes.

2.3. Method introduction

This paper selects Autoregressive Integrated Moving Average Model (ARIMA) multiplication model with seasonal effect. The ARIMA model mainly consists of three parts, namely autoregressive model (AR), differential process (I), and moving average model (MA). The ARIMA model attempts to extract time series patterns hidden behind data through autocorrelation and differentiation, and then use these patterns to predict future data. The autoregressive portion of the time series, which takes into account the influence of data from earlier periods on the current level, is processed by the AR portion. Part I is used to make non-stationary time series stationary, eliminating trend and seasonal factors in the time series through first-order or second-order differential processing. The moving average component of a time series, which accounts for the effect of previous forecasting errors on the current level, is processed by the MA component. The ARIMA model combines the advantages of the AR model to capture data with long historical trends and the MA model to better handle time series data with temporary, sudden changes or loud noise.

3. Results and discussion

3.1. Stationary test

By observing the time series diagram, it was found that the sequence has a clear increasing trend. Since the study focuses on the global average ocean temperature, and different sea areas are in different seasons at the same time, the period cannot be determined as 12 months. Next, draw a factor decomposition diagram to determine periodicity (Figure 2).

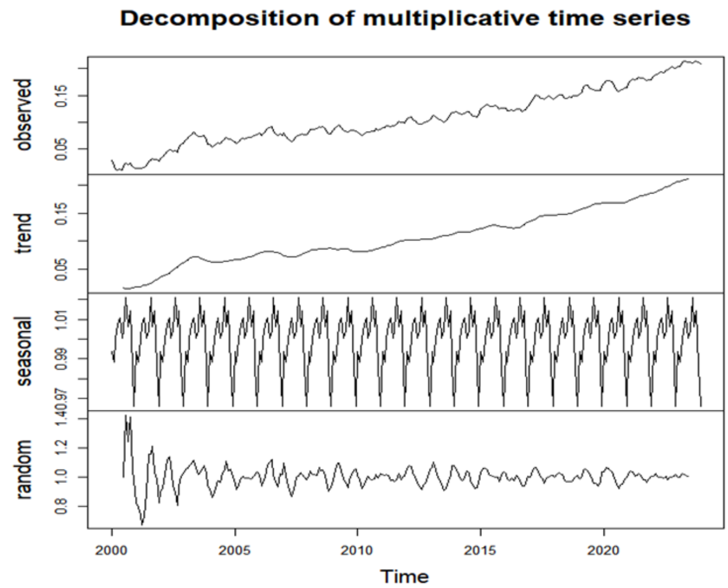

Figure 2. Time series factor decomposition diagram.

From Figure 2, it can be seen that the sequence has periodicity and a period of 12 months. The Arima model requires that the temporal data be either stationary or stationary after differentiation (Figure 3). Therefore, a first-order 12 step difference is applied to the sequence to eliminate the influence of seasonal effects. By observing the differential time series diagram, it can be roughly determined that the sequence is stationary.

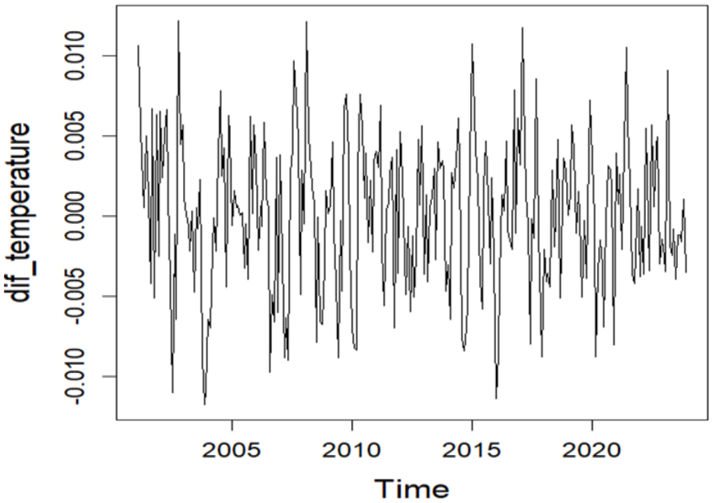

Figure 3. Time series diagram after differentiation.

3.2. Stability test

The modeling of ARIMA model needs to ensure that the sequence has stationary characteristics. Augmented Dickey-Fuller test (ADF test) is a method used to test whether time series data has a Unit Root. If the sequence is stationary, there is no unit root, otherwise, there will be unit roots. Therefore, the null hypothesis of ADF test is the existence of unit roots. If the obtained significance test statistic is less than a certain confidence level, then the confidence level corresponding to that confidence level is used to reject the original hypothesis. Table 1 shows the ADF detection results.

Table 1. Stability test.

Type 1: No drift no trend	lag	ADF	p.value
[1]	1	-12.2	0.01
[2]	2	-8.8	0.01
[3]	3	-10.4	0.01
Type 2: with drift no trend	lag	ADF	p.value
[1]	1	-12.19	0.01
[2]	2	-8.78	0.01
[3]	3	-10.41	0.01
Type 3: with drift and trend	lag	ADF	p.value
[1]	1	-12.16	0.01
[2]	2	-8.76	0.01
[3]	3	-10.39	0.01

The P-values are all less than 0.01, so the differential model passed the Box Ljung test for stationarity and can continue to establish a predictive model.

3.3. White noise test

Ljung box statistic is essentially an improved Q-statistic. The Q-statistic that follows the chi square distribution performs well in large sample scenarios (in traditional testing methods, a sample size greater than 30 is considered a large sample size), but it is not very accurate in small sample scenarios. Box and Ljung derived the LB (Ljung Box) statistic. If the white noise data, the data has no value extraction, that is, there is no need to continue the analysis (Table 2).

Table 2. Ljung-Box test.

X-squared	drift	p-value
135.72	12	< 2.2e-16

The p-value is much less than 0.01, indicating that the model passes the white noise test after difference, and the model is a stable non-white noise model, which is valuable for further study.

3.4. Model recognition and evaluation

Next, the model needs to be graded to make predictions. First, through observing the autocorrelation graph (ACF) and partial autocorrelation graph (PACF), the order of the model is roughly determined (Figure 4 and 5).

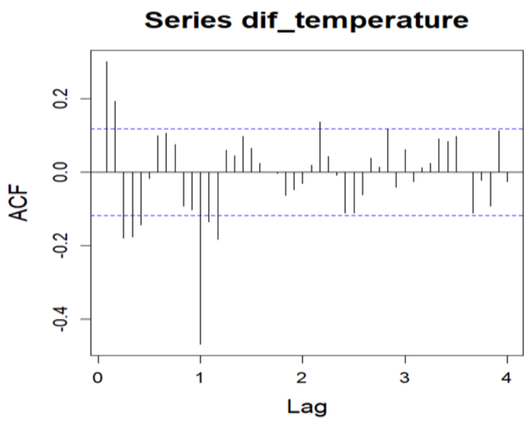

Figure 4. ACF plot of ocean temperature.

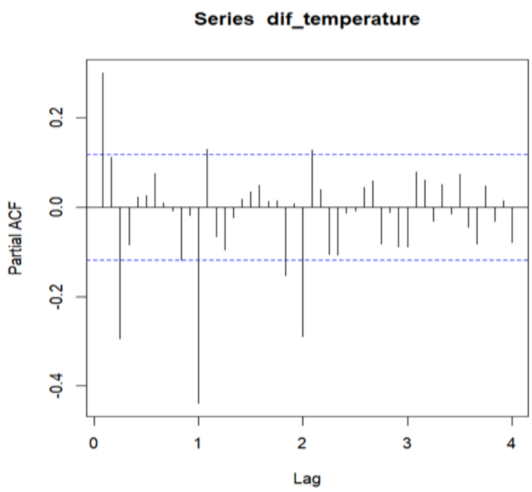

Figure 5. PACF plot of ocean temperature.

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The tail of the aperiodic part of the autocorrelator and partial autocorrelator can be evaluated up to 3rd order truncation. Based on this, the aperiodic part is tentatively identified as ARMA (3,2), while the pre-difference model is considered as ARIMA (3,1,2). Although both periodic partial autocorrelations and partial autocorrelations are trailing, accurate orders cannot be determined from observations alone. Therefore, this research compares AIC values of potential models to determine the best fit. The model with the smallest AIC value is the best. List possible models using the auto.arima function in R language, and filter out the best model by comparing R values and AIC values. Finally, the best model this research get is $ARIMA\ (3,1,2) * (2,0,0)\ [12]$ model (Table 3).

Table 3. Model evaluation.

Alternative model	AIC
ARIMA(3,1,2)(2,0,1)[12]	-2464.18
ARIMA(3,1,2)(1,0,1)[12]	-2460.478
ARIMA(3,1,2)(2,0,0)[12]	-2474.003
ARIMA(3,1,2)(1,0,0)[12]	-2461.693
ARIMA(3,1,2)(1,0,2)[12]	-2459.831
ARIMA(3,1,1)(2,0,1)[12]	-2473.767

3.5. Residual test

Check whether the residual is white noise, if not, it indicates that the autocorrelation feature extraction is insufficient, and if the residual is white noise, it indicates that the extraction is sufficient. In the ACF diagram, the residuals all fall within the dotted line, that is, significantly 0, and the residuals are white noise (Figure 6).

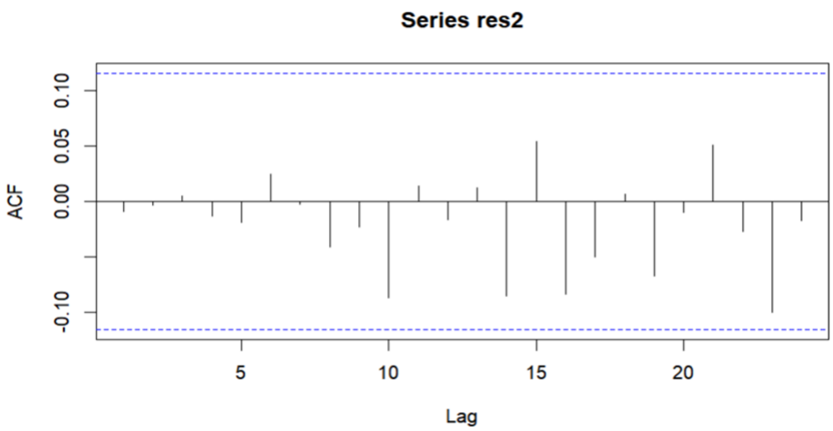

Figure 6. Residual test plot.

3.6. Forecast results

The blue line at the end of the image is the forecast data, and the nearby shaded part is the confidence interval (Figure 7). From the following data, it can be concluded that ocean temperatures will continue to rise in 2024 (Table 4). The forecast shows that within the year 2024, the global average monthly ocean temperature will increase by 0.01 degrees. It is very significant for this indicator.

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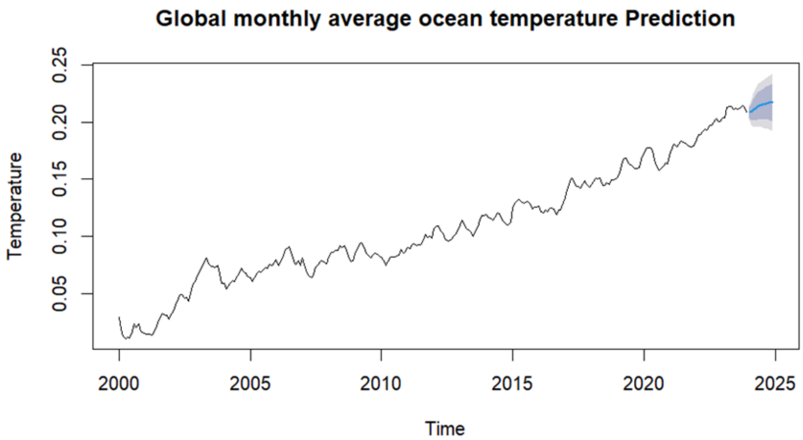

Figure 7. Ocean temperature prediction plot.

Table 4. Ocean temperature prediction.

Time	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2024/1	0.209	0.204	0.213	0.202	0.215
2024/2	0.209	0.202	0.216	0.198	0.219
2024/3	0.211	0.201	0.220	0.197	0.225
2024/4	0.213	0.202	0.224	0.196	0.229
2024/5	0.214	0.202	0.226	0.196	0.233
2024/6	0.215	0.202	0.228	0.195	0.234
2024/7	0.216	0.203	0.229	0.196	0.236
2024/8	0.216	0.202	0.230	0.195	0.237
2024/9	0.217	0.202	0.231	0.194	0.239
2024/10	0.217	0.202	0.233	0.194	0.241
2024/11	0.217	0.202	0.233	0.193	0.242
2024/12	0.218	0.201	0.234	0.192	0.243

4. Conclusion

Through the research in this article, it can be concluded that the global monthly average ocean temperature will continue to rise in the next year. Although the changes in the international situation are uncertain in the future, human emissions causing global warming continue indefinitely. Therefore, the continuous rise in ocean temperatures seems to be something that will continue to happen in the future. This article analyzes historical data on global monthly average ocean temperatures since 2000 and has undergone various tests. By establishing a time series model, the ocean temperature for the next year was predicted, and the research results have a certain degree of credibility. According to the research in this article, it is concluded that the global monthly average ocean temperature will continue to rise in the next year. Although the future is still uncertain due to changes in the international situation, the trend of global warming caused by human activity emissions is still ongoing. Therefore, the continuous rise in ocean temperatures seems to be an inevitable trend in the future.

Through this study, this paper can draw some conclusions. For governments around the world, it is imperative to develop policies to protect the environment and address global warming. The continuously rising ocean temperature will damage the harmonious ecological environment of the Earth for a long time, causing many unimaginable losses. Meanwhile, actively promoting and advocating environmental awareness is also crucial. Enterprises also need to actively respond to policies, fulfill obligations, and

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assist the government in its work. For every individual, it is also crucial to establish a sense of responsibility to protect the environment and work together to protect our planet.

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