Frontiers in Computing and Intelligent Systems
ISSN: 2832-6024 | Vol. 7, No. 2, 2024

Construction of a Climate Early Warning System: Predicting Future Temperatures and Climate Security Using BiLSTM

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Abstract: In light of the worsening global climate, providing predictive models for surface temperature and energy consumption is crucial for formulating effective climate action strategies. Initially, a Bi-directional Long Short-Term Memory (BiLSTM) network model is established to predict the maximum surface temperatures over the next century, with the Seasonal AutoRegressive Integrated Moving Average (SARIMA) model serving as a benchmark. To assess the risk levels of climate security, the k-means clustering algorithm is utilized to classify the growth rates of carbon dioxide emissions, enabling the construction of a three-tier climate security early warning index. Subsequently, a hybrid classification model based on Support Vector Machine (SVM) and Random Forest (RF) takes the energy consumption growth rates as inputs and the warning indices as outputs to construct a climate security early warning system. The BiLSTM model is employed to predict the energy consumption growth rates for the upcoming decade, and these rates are input into the SVM-RF model to forecast future warning levels. The study demonstrates that the model can effectively predict the maximum surface temperatures and provide a three-tier safety warning system for future climate risk management. The intent of this research is to offer a novel tool for global climate prevention and to deliver practical application value to policymakers in finance, energy, and environmental sectors.

Keywords: BiLSTM; K-means; SVM-RF; Safety Early Warning.

1. Introduction

As technological advancements continue, the continuous growth of the first and second industrial revolutions, along with modern industrial development, has led to a steady increase in energy consumption and carbon dioxide emissions, consequently causing a rise in surface temperatures. The control of rising surface temperatures is imperative, as they have a significant impact on human livelihood and survival. Over the past several decades, the increase in global temperatures has far exceeded the range of natural climate fluctuations, with greenhouse gases, primarily due to the burning of fossil fuels, as the main culprits [1]. The "greenhouse" effect of carbon dioxide appears to be discounted when considering the supply of renewable resources, allowing for an increase in the mining of fossil fuels within energy policies [2]. However, there is still a lack of research on how to control the growth rate of fossil fuel consumption effectively.

A pause in the rise of global surface temperatures during the 2000s led some scholars to believe that global warming had been interrupted. In reality, the increase in atmospheric carbon dioxide caused an energy imbalance, leading to phenomena such as rising sea levels, indicating that global warming has not stopped but is manifesting in different ways [3]. The impacts of global warming on humanity are also incalculable; it has affected food production and indirectly altered the social and economic impacts on people [4]. Researchers have noted that agricultural production data highlights the significant economic impacts of extreme climate events [5]. Besides economic effects, global warming also directly impacts human social life, increasing unemployment rates through inflation and agricultural productivity, with a significant effect on male unemployment rates [6]. Global warming can also indirectly increase the disparity between rich and poor countries, with many impoverished nations severely damaged by the warming caused by affluent countries' energy consumption [7].

Addressing global warming, some scholars argue that carbon dioxide is the primary cause, estimating it will account for about 60% of warming in the next century and proposing the use of renewable biomass to mitigate global warming [8]. Much research shows that the burning of fossil fuels releases large amounts of carbon dioxide, thereby exacerbating the current state of global warming. As the trend of global warming steadily increases, it is crucial to plan energy consumption rationally and predict climate security risks. Most researchers opt to directly predict future temperature trends as a reference for policymakers, starting with machine learning predictions, such as using DTW, SVM, and LSPSO to predict sea surface temperatures [9], and later evolving towards deep learning, such as constructing Memory Graph Convolutional Neural Networks for predicting sea surface temperatures [10] and establishing different types of LSTM to predict sea surface temperatures [11].

In summary, the current literature contributes to the following: (1) highlighting the current state of global warming and analyzing the factors leading to warming; (2) assessing the damage of global warming to the economy and society; (3) employing model algorithms to predict future temperatures to guide policy formulation. However, many studies are limited by their one-sided approach, such as ignoring the effects of carbon dioxide and energy consumption when predicting temperatures. When explaining the dangers of rising temperatures, they are constrained to existing historical data. In fragmented research, scholars often focus on specific regions, lacking consideration of global temperature impacts and ignoring regional interconnections.

Moreover, after studying future temperatures, many have failed to provide effective recommendations, leaving policymakers unable to fully utilize the research value based solely on temperature data.

Building on this basis, this study will collect data from a global scope, and while predicting future trends using deep learning models, it will construct a climate security early warning system to forecast future climate security. This study aims to provide insights and offer policymakers additional effective value by: (1) using deep learning models to predict surface temperature trends over the next 100 years; (2) building a climate security early warning index that can be influenced by humanity; (3) establishing an efficient energy consumption warning classifier, and predicting future warning levels over the next decade. This paper is intended to predict the highest surface temperatures for the next century, as well as offer a new tool for global climate prevention, and provide practical application value to policymakers in finance, energy, and environmental sectors. The subsequent research will unfold in sections including "Literature Review," "Methodology," "Result Analysis," and "Conclusions and Recommendations."

2. Literature Review

2.1. Research on Temperature Prediction

The academic community is gradually shifting from machine learning to deep learning for temperature prediction. In the realm of deep learning models, Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM) are commonly used for temperature prediction. For example, Han (2023) and colleagues have combined CNNs with Gated Recurrent Unit (GRU) networks to study sea surface temperatures [12], while Choi (2023) et al. have utilized LSTMs to predict sea surface temperatures near the Korean Peninsula [13]. These deep learning models have demonstrated good performance and low error in temperature predictions. Farhangi (2023) compared the differences in sea surface temperature prediction using CNNs, LSTMs, and CNN-LSTM hybrid models, finding that all three models performed well without significant differences when time cost was not considered [14]. Cui (2022) proposed the establishment of a BiLSTM model for predicting land surface temperatures, which showed high accuracy when compared with empirical data [15]. Further review of the literature reveals the BiLSTM model's good performance in other predictive domains, such as soil structure prediction [16], traffic flow prediction [17], and stock price forecasting [18]. BiLSTM has not yet been applied to predict the future trend of global land surface temperature. Combining the BiLSTM's uses and performance, it may provide superior results for predicting land surface temperatures and offers a comparison with the commonly used SARIMA model.

2.2. Research on Early Warning Systems

Early warning systems function by alerting the public when pre-set conditions and thresholds are triggered. Commonly seen early warning systems include landslide early warning systems [19] and pregnancy complication warning systems [20]. As such, early warning systems are equally important for climate security. Xie (2019) et al. previously proposed using the kurtosis coefficient as a climate system early warning indicator. However, the results showed that the kurtosis coefficient was not a reliable signal of abrupt climate changes [21]. Several years later, Xie (2023) and colleagues in follow-up research proposed a Box-Cox transformation-based abrupt climate change early warning indicator, which proved to be effective [22]. Many studies have also used climate indicators to warn of other issues, such as predicting preterm crop production [23] and public health [24]. Based on existing research, few scholars have constructed a precise climate safety early warning system using mature AI technology. The climate safety warning system can also indirectly reflect warnings for premature crop production or public health, making the construction of such a system necessary. Zhu (2021) et al. utilized the K-means algorithm to establish a financial risk warning [25], and Seo (2022) et al. applied the K-means algorithm to build an industrial safety warning system [26]. While some scholars in early warning systems use existing data or resources as warning indicators [19-20], others construct warning indicators through certain algorithms or other methods [25-26]. In constructing the climate security warning system, this paper aims to create indicators that can be manipulated to enable adjustments in response to warnings.

In summary, this paper draws from existing literature to use mature technological algorithms to supplement necessary but unfinished work. The approach and contributions of this paper are as follows: (1) use the BiLSTM model to predict future land surface maximum temperatures and analyze the good performance of BiLSTM for temperature prediction; (2) utilize the K-means clustering algorithm to construct refined climate safety early warning indicators that can be manually regulated; (3) use the SVM-RF (Support Vector Machine-Random Forest) model for predictive control of energy consumption growth. The paper aims to complete the above tasks and contribute practical application value to global climate policy.

3. Data Sources and Methodology

3.1. Data Sources

When researching temperature, the global nature and geographical differences must not be overlooked, with variations in temperature due to differences in latitude and longitude and influences of factors such as monsoons. Surface maximum temperature has a significant impact on human society, making it a pertinent subject of study for temperature prediction. Additionally, to construct adjustable early warning indicators, the global carbon dioxide (CO_2) emissions and various primary energy consumption volumes were included. Data on Land annual average high temperature (℃) from 1850-2022 were collected from Berkeley Earth, and CO_2 emissions (Million metric tons), Coal and coke consumption (Million short tons), Refined petroleum products consumption (Million barrels per day), Dry natural gas consumption (Billion cubic feet), Electricity net consumption (Billion kilowatt-hours), and Biofuels consumption (Million barrels per day) for the years 1980-2021 were sourced from the U.S. Energy Information Administration (EIA).

3.2. Research Methodology

3.2.1. BiLSTM

Accurately predicting the trend of global land surface maximum temperatures is crucial to understanding and formulating appropriate climate policies. This paper uses a Bidirectional Long Short-Term Memory (BiLSTM) neural network model for time series prediction to capture the historical temperature data relationships and provide accurate predictions effectively. The BiLSTM's basic structure is shown in Figure 1. The unidirectional LSTM contains forget gates f_t, input gates i_t, and output gates o_t and is represented with different gate weight matrices W_f, W_i, W_c, W_o, and bias vectors b_f, b_i, b_c, b_o. The formulae for these gates are:

Forget gate f_t:

$$f_t = \sigma\left(W_f \times \left[h_{t-1}, x_t\right] + b_f\right). \quad (1)$$

Input gate i_t:

$$i_t = \sigma\left(W_i \times \left[h_{t-1}, x_t\right] + b_i\right). \quad (2)$$

Candidate cell state $\widetilde{c}_t$:

$$\widetilde{c}_t = \tanh\left(W_c \times \left[h_{t-1}, x_t\right] + b_c\right). \quad (3)$$

New cell state c_t:

$$c_t = f_t \times c_{t-1} + i_t \times \widetilde{c}_t. \quad (4)$$

Output gate o_t:

$$o_t = \sigma\left(W_o \times \left[h_{t-1}, x_t\right] + b_o\right). \quad (5)$$

Current information output h_t:

$$h_t = o_t \times \tanh\left(c_t\right). \quad (6)$$

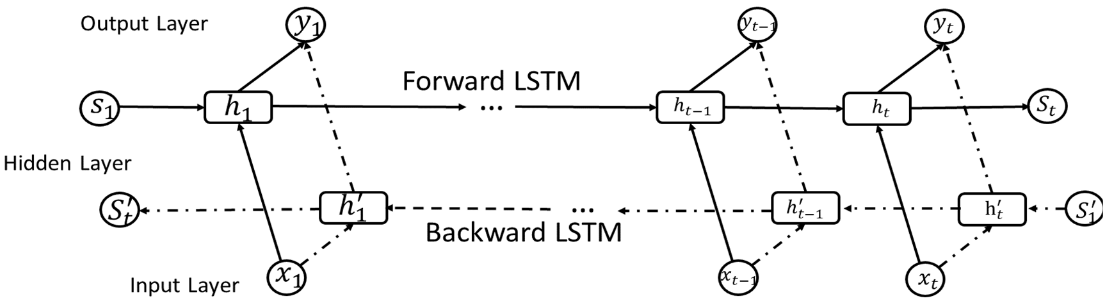

Figure 1. Represents the BiLSTM model structure

The structure's formulas are as follows:

$$\overrightarrow{h_t} = \overrightarrow{LSTM}\left(h_{t-1}, x_t, c_{t-1}\right), t \in \left[1, T\right], \quad (7)$$

$$\overleftarrow{h_t} = \overleftarrow{LSTM}\left(h_{t+1}, x_t, c_{t+1}\right), t \in \left[T, 1\right], \quad (8)$$

$$H_t = \left[\overrightarrow{h_t}, \overleftarrow{h_t}\right]. \quad (9)$$

3.2.2. Fourier Series

The Fourier series represents a periodic function as a sum of sine and cosine waves, serving to estimate the cyclical nature of the land temperature growth rate. The Fourier series can be defined as the following infinite series:

$$f\left(t\right) = a_0 + \sum_{n=1}^{\infty}\left(a_n \cos\left(nw_0 t\right) + b_n \sin\left(nw_0 t\right)\right). \quad (10)$$

$$a_0 = \frac{1}{T}\int_0^T f\left(t\right)dt, \quad (11)$$

$$a_n = \frac{2}{T}\int_0^T f\left(t\right)\cos\left(nw_0 t\right)dt, \quad (12)$$

$$b_n = \frac{2}{T}\int_0^T f\left(t\right)\sin\left(nw_0 t\right)dt. \quad (13)$$

Where:

- $f\left(t\right)$ is the periodic function at time t;
- a_0 is the constant term representing the function's mean (DC component);
- a_n, b_n are the Fourier coefficients indicating the different frequencies of the sine/cosine waves' amplitudes;
- w_0 is the fundamental frequency related to the periodicity T;
- n is a positive integer corresponding to different harmonic frequencies.

3.2.3. SARIMA

The performance of BiLSTM needs comparison with other models; SARIMA, an extension of the ARIMA model, is a commonly used time series forecasting model designed for data with seasonal cycles. The SARIMA model integrates seasonal parameters to handle repetition within fixed seasonal lengths and has the structure SARIMA(p,d,q)(P,D,Q)[s], where p, d, q have the same definitions as in the ARIMA model. P, D, Q correspond to the AR, I, MA portions of the seasonal cycle, with s representing the length of the data's seasonal periods.

The SARIMA model requires data to be stationary; otherwise, it may introduce large errors. Its formula is represented as:

$$\begin{aligned}&\left(1-\varphi_1 L-\varphi_2 L^2 \cdots-\varphi_p L^p\right)\left(1-\phi_1 L^s-\phi_2 L^{2s} \cdots-\phi_P L^{Ps}\right)\left(1-L\right)^d\left(1-L^s\right)^D y_t = \\ &\left(1+\theta_1 L+\theta_2 L^2 \cdots+\theta_q L^q\right)\left(1+\vartheta_1 L^s+\vartheta_2 L^{2s} \cdots+\vartheta_Q L^{Qs}\right)\varepsilon_t.\end{aligned} \quad (14)$$

Where:

- L is the lag operator;
- φ_i are the non-seasonal AR parameters;
- ϕ_i are the seasonal AR parameters;
- s is the periodicity of the seasonal cycle;
- d, D are the differencing steps;
- θ_i are the non-seasonal MA parameters;
- ϑ_i are the seasonal MA parameters;
- ε_t is the white noise error term.

The paper compares the SARIMA model with the BiLSTM model using the Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) as performance metrics, where smaller values indicate lower errors:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \widehat{y}_i\right|, \tag{15}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y}_i\right)^2, \tag{16}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y}_i\right)^2}. \tag{17}$$

Where:

- n is the number of samples in the test set;
- y_i is the actual value of the i-th data point in the test set;
- $\widehat{y}_i$ is the predicted value for the i-th data point in the test set.

3.2.4. K-means

For clustering and creating early warning indicators, we selected CO_2 emissions and the growth rate of surface temperature. K-means aims to discover inherent groupings by dividing data into K clusters. Each cluster is represented by the mean (centroid) of the data points within it. The algorithm steps for K-means involve: initializing with K random data points as the cluster centers, assigning each data point to the nearest centroid to form K clusters, updating by computing the mean of all points in each cluster to obtain new centroids, and repeating these steps until a certain stopping criterion is satisfied (usually when the change in centroids is below a threshold or a predetermined number of iterations has been reached).

3.2.5. SVM-RF

Upon obtaining the warning indicators, the paper establishes an SVM-RF (Support Vector Machine-Random Forest) model for predicting future warning levels over the next ten years. SVM is a classification model that defines a linear classifier based on margin maximization in feature space. RandomForest (RF) is an ensemble learning method comprising multiple decision trees used for classification problems. It enhances prediction accuracy and prevents overfitting by building several trees and aggregating their results. RF is well-suited for handling data with complex interactions, is scalable, and tolerates faults, often treated as a "black box" in non-deep learning algorithms.

SVM is suitable for dealing with complex small data set problems, while RF effectively handles complex structure issues. The SVM-RF model can leverage the advantages of both SVM and RF, providing robustness in dealing with small samples and managing nonlinear features effectively. Ensemble learning further aids in selecting important features and enhancing the model's robustness and accuracy. The structure of the SVM-RF is shown in Figure 2.

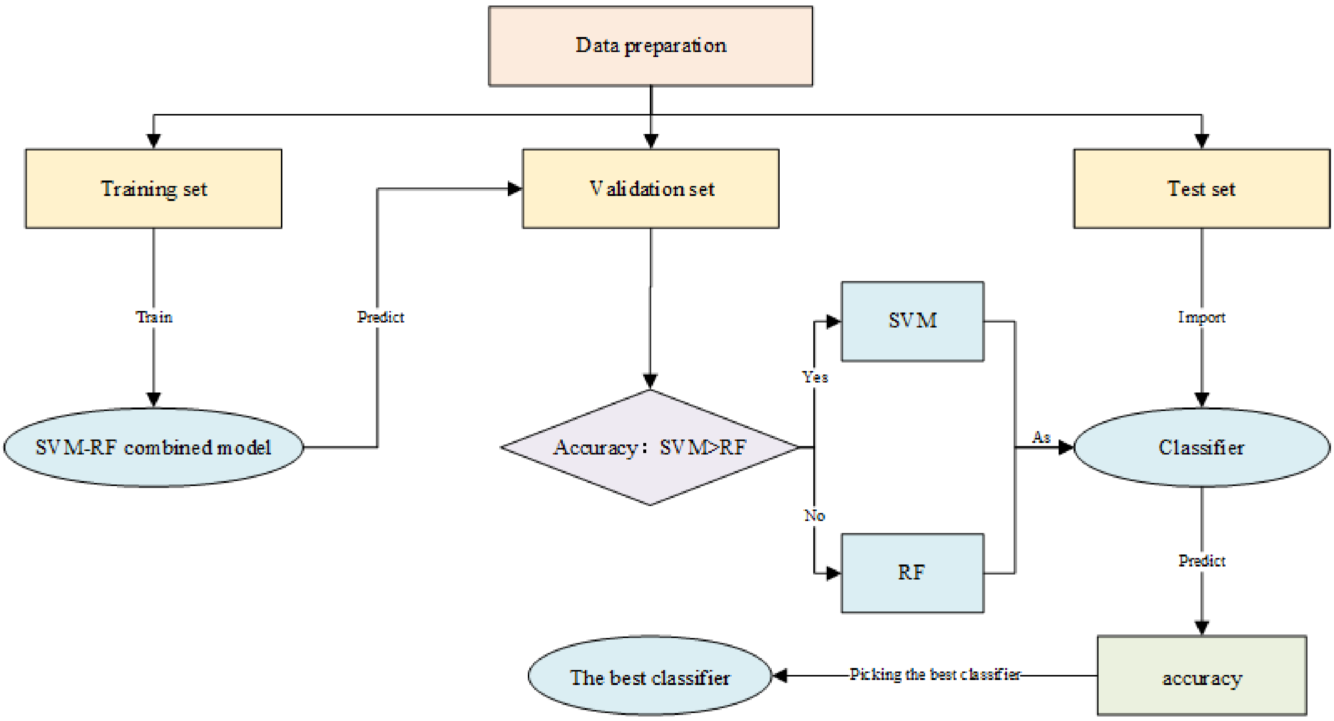

Figure 2. SVM-RF Model Architecture

3.3. Variable Explanation

This paper first predicts the surface temperature to observe the future trend of surface temperature and constructs a climate safety early warning system while predicting future early warning situations. The main variables used in this study are as follows:

(1) Early warning indicators: Since surface temperature is difficult to control but carbon dioxide emissions can change with human intervention, we use the k-means clustering algorithm to cluster the carbon dioxide emission growth rate to get the early warning indicators.

(2) Energy consumption: Coal and coke consumption (Million short tons) is denoted as variable C, Refined petroleum products consumption (Million barrels per day) as variable O, Dry natural gas consumption (Billion cubic feet) as variable G, Electricity net consumption (Billion kilowatt-hours) as variable E, and Biofuels consumption (Million barrels per day) as variable B.

(3) Input variables: In the SVM-RF model, we use growth rates of energy values, such as the coal consumption growth rate, as input values.

(4) Output variables: In the SVM-RF model, we use the early warning indicators as the output values to build the early warning system.

4. Results Analysis

4.1. Surface Temperature Prediction

4.1.1. Prediction based on the BiLSTM Model

The BiLSTM model, which contains both forward and backward LSTM sequences, demonstrated significant divergence from actual values when predicting surface temperatures using raw data. Considering the limitations of neural networks, such as poor performance on non-stationary series, it is inferred that the raw data constitutes a non-stationary time series. However, when transforming the raw data into growth rates, the prediction closely matched the actual values, allowing for an indirect derivation of the corresponding maximum surface temperatures. In Figure 3, the left graph illustrates the forecasted growth rates of surface maximum temperatures by the BiLSTM model, while the right graph shows the future trend of surface temperatures from 1850 to 2122.

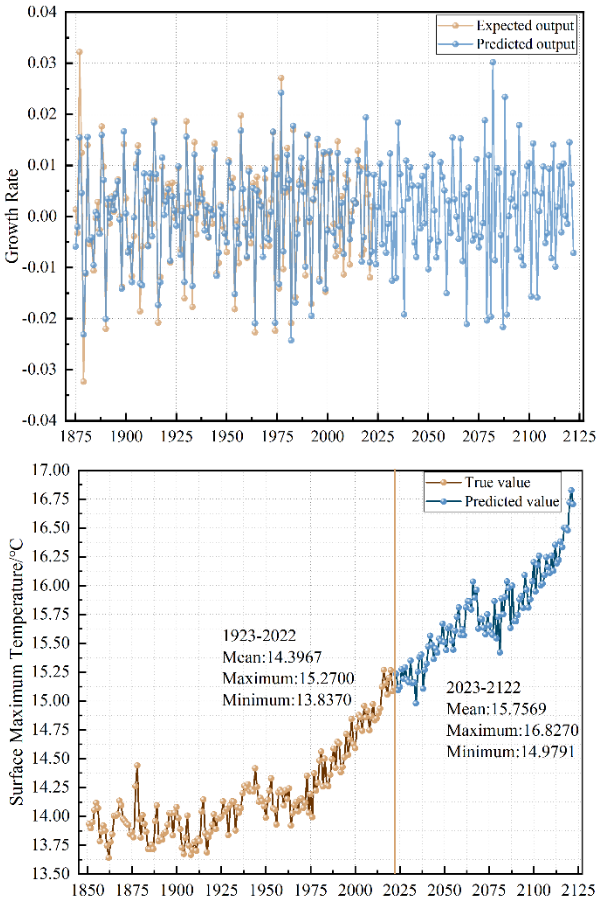

Figure 3. Output results of the BiLSTM model (left) and the trend line of surface temperature from

According to the left graph in Figure 3, future surface maximum temperatures are expected to continue fluctuating. The right graph indicates that these temperatures will initially follow the existing upward trend, then experience a decline before resuming the rise. Similar effects have been reported in some studies [3], suggesting potentials for a temporary halt in the increasing temperatures. If left unimpeded, a sharp rise could occur once again. Descriptive statistics show that from 1923 to 2022, the average maximum surface temperature was 14.3967°C, with a peak at 15.2700°C and a low at 13.8370°C. For the period 2023 to 2122, the forecasted average maximum surface temperature is 15.7569°C, with the highest value being 16.8270°C and the lowest value at 14.9791°C. A century later, worsening climate conditions could intensify, with the lowest temperatures being only 0.2909°C less than the peak temperatures from 1923-2022. Additionally, the highest temperature is projected to increase by 1.557°C compared to the period from 1923-2022, which suggests an increase in extreme weather events. The average maximum surface temperature over the century is expected to rise by 1.3602°C, potentially leading to a heightened trend in sea-level rise, impacts on crop yields [22], and human health [23]. Previous predictions estimated that surface temperatures could rise by 1.4-5.8°C (Dhillon RS and von Wuehlisch G 2013) in the future. The continual increase in primary energy consumption and corresponding carbon dioxide emissions could mean that actual temperatures may exceed the predictions of this study, corroborating these scholarly estimates.

4.1.2. BiLSTM Performance Comparison - Based on the SARIMA Model

To demonstrate the performance of BiLSTM, it suffices to show that it outperforms the SARIMA model in its optimal state with higher errors. This study does not purposefully deteriorate the SARIMA model; on the contrary, it utilizes Fourier series to capture the periodicity in the growth rates of maximum surface temperatures. Based on the period T derived from Fourier series, we set the seasonal index for SARIMA at 5. Guided by the AIC criterion and setting maximum values for the orders p, q, P, Q at 4, and for d and D at 2 (with all minimum values being zero), we conducted a search for optimal parameters. The best structure identified was SARIMA (4,0,4) (4,0,4) [5].

Using a dataset split into a training set of 167 samples and a test set of 5 samples, we employed consistent settings to train our BiLSTM model. The comparative outcomes for Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) are presented in Table 1.

Table 1. Error Testing for BiLSTM and SARIMA

Model	MAE	MSE	RMSE
BiLSTM	0.0056	0.0000	0.0064
SARIMA	0.0060	0.0001	0.0071

Despite its larger number of parameters and longer runtime, without undergoing parameter optimization, the BiLSTM model still surpasses SARIMA models with orders below five, indicating excellent performance and predictive capabilities of BiLSTM. This underscores the advantages of the BiLSTM model in time series analysis. Additionally, it suggests that with accurate parameter tuning, statistical models or machine learning models can also achieve impressive prediction results.

4.2. Construction and Prediction of the Early Warning System

4.2.1. Construction of Early Warning Indicators based on the K-means Clustering Algorithm

The establishment of an early warning system is aimed at alerting people of potential dangers or emergencies to enable appropriate preventive and protective measures to be taken, thereby reducing losses and safeguarding personal safety. We consider early warning indicators as the threshold for the warning system. When warning indicators include controllable human factors, suitable measures can more easily be taken to reduce potential risks. Furthermore, early warning indicators can be improved through regulatory, policy, and legal means when they depend on human factors. Therefore, this study selects the carbon dioxide emission growth rate as the early warning indicator. On one hand, CO2 emissions account for approximately 60% of global warming (Dhillon RS and von Wuehlisch G 2013) and significantly impact the degree of global warming. On the other hand, the rate of CO2 emission growth can be artificially adjusted by controlling energy consumption. Using the K-means clustering algorithm, we classified CO2 emission growth rates from 1981-2021 into three categories: "low risk," "medium risk," and "high risk." There were 18 instances of low risk, 17 cases of medium risk, and 6 occurrences of high risk, with a silhouette coefficient of 0.7314, indicating satisfactory clustering and defining the three levels of early warning indicators as seen in Figure 4. A descriptive statistical analysis through pivot tables was performed for the three safety warning levels, as shown in Table 2.

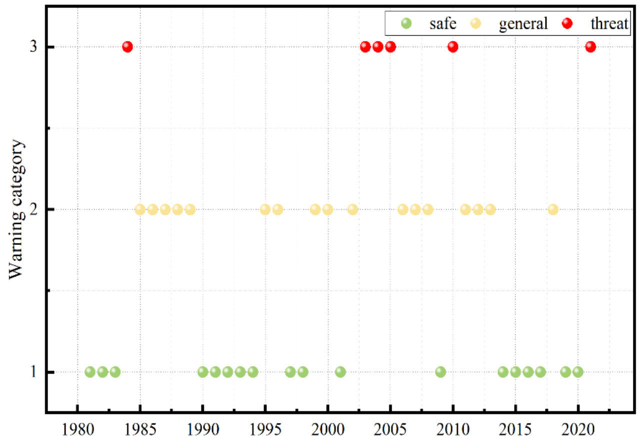

Figure 4. Climate Security Early Warning Indicator Distribution

Table 2. Descriptive Statistics of CO2 Emission Growth Rates by Warning Category

Category	Average	Median	Maximum	Minimum
Low Risk	-0.0032	0.0001	0.0108	-0.0544
Medium Risk	0.0233	0.0222	0.0342	0.0123
High Risk	0.0524	0.0531	0.0622	0.0394

According to Table 2, in the "low risk" category, the average growth rate is -0.0032, the median is 0.0001, the maximum is 0.0108, and the minimum is -0.0544. The growth rate is about -0.3%, which is considered in line with sustainable development principles, thus warranting a level one warning. In the "medium risk" category, the growth rate average is 0.0233, the median is 0.0222, the maximum is 0.0342, and the minimum is 0.0123. At this point, the CO2 emission growth rate is relatively high at approximately 2.33%, which is not deemed sustainable, necessitating a level two warning. In the "high risk" category, the growth rate average is 0.0524, the median is 0.0531, the maximum is 0.0622, and the minimum is 0.0394. The CO2 emissions have reached an alarming level of around 5.31%, indicating the need for a level three warning and an intensification of energy policy refinement and regulation.

Similarly, we performed a data pivot for the growth rates of various energy consumptions, as shown in Table 3. According to Table 3, the growth rate of energy consumption increases from the "low risk" to "high risk" safety warning levels, suggesting that the energy consumption growth rate has a significant impact on the tiered safety warnings.

Table 3. Average Growth Rate of Energy Consumption by Warning Category

Warning Level	Variable C Growth	Variable O Growth	Variable G Growth	Variable E Growth	Variable B Growth
Level One	-0.0055	-0.0010	0.0074	0.0197	0.0782
Level Two	0.0284	0.0162	0.0339	0.0349	0.0941
Level Three	0.0664	0.0310	0.0533	0.0529	0.2041

4.2.2. Construction of the Early Warning System based on the SVM-RF Model

After completing the construction of the three-tiered safety warning indicators, and considering a potential connection between energy consumption growth rates and warning levels, we established the SVM-RF model for predicting warning levels. By randomly shuffling the original data and setting the training, validation, and test set ratios to 8:1:1, we conducted multiple training sessions to find the most effective SVM-RF classification predictor. Figure 5 showcases the confusion matrices for the training and test sets of the best classifier.

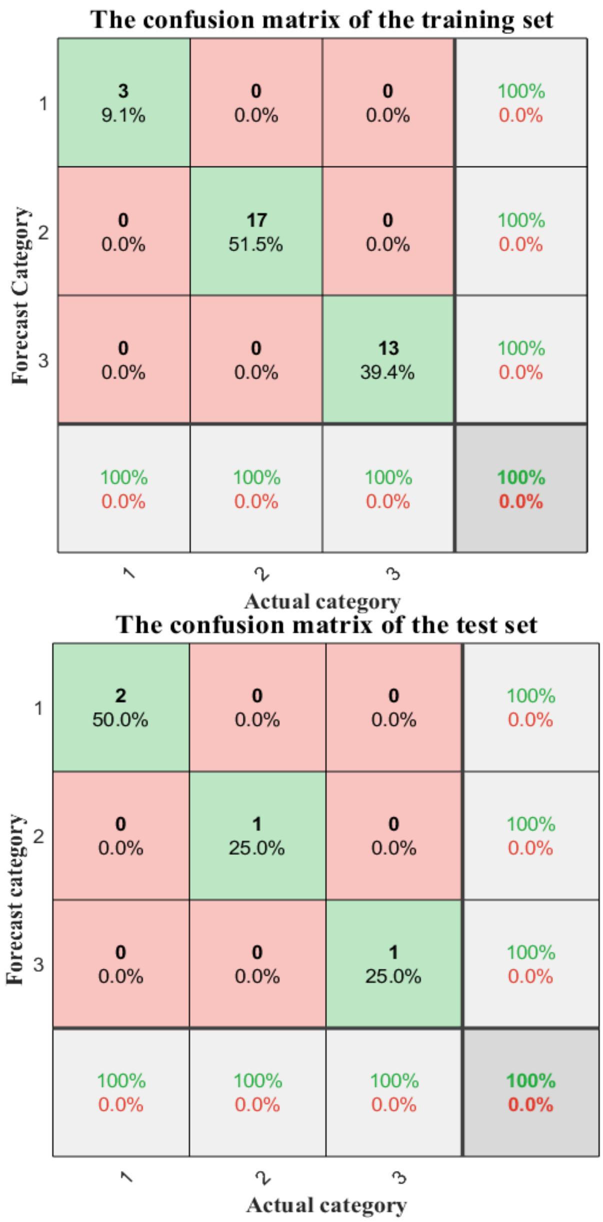

Figure 5. Confusion Matrix of the Training Set (left) and Test Set (right)

At present, the model's accuracy for the training, validation, and test sets is 100%, demonstrating strong predictive performance suitable for classification predictions. Using the BiLSTM model, we predicted the growth rates of five energy consumptions for 2022-2031 and entered the values into the trained model, obtaining the three-tiered safety warning levels, as shown in Table 4. From Table 4, it is evident that between 2022-2031, there were five instances of "low risk," signifying compliance with sustainable development principles and triggering a level one warning. There also were five occurrences of "medium risk," warranting a level two warning. Hence, it is imperative to strengthen regulatory measures during those years and strictly control the growth rate of energy consumption to downgrade the warning from level two to level one. By predicting the warning levels for the next decade, we can take necessary measures when the warning level is at two or even three to prevent mass CO2 emissions and further exacerbate climate deterioration.

Table 4. Predictions of Energy Consumption Growth Rates based on the BiLSTM Model

Year	Variable C Growth	Variable O Growth	Variable G Growth	Variable E Growth	Variable B Growth	Warning Level
2022	0.0164	0.0138	0.0062	0.0359	0.0366	Level Two
2023	-0.0073	0.0139	0.0352	0.0217	0.0830	Level One
2024	-0.0086	0.0169	0.0056	0.0272	0.0674	Level One
2025	-0.0123	0.0194	0.0138	0.0310	0.0535	Level One
2026	0.0004	0.0160	0.0323	0.0334	0.0217	Level Two
2027	0.0141	0.0171	0.0354	0.0314	-0.0013	Level Two
2028	0.0099	0.0093	0.0283	0.0258	0.0775	Level Two
2029	0.0076	0.0061	0.0127	0.0200	0.0571	Level One
2030	-0.0011	-0.0067	0.0197	0.0365	-0.0609	Level One
2031	0.0534	0.0179	0.0268	0.0395	0.0904	Level Two

4.3. Data and Model Robustness Verification

4.3.1. Stationarity Test of Data

In this study, time series forecasting has been extensively applied for projecting the growth rates of variables, and neural network models such as BiLSTM often depend on data stationarity to diminish forecasting errors. The presence of non-stationary data can adversely affect the performance of models; therefore, testing for data stationarity is particularly critical to ensure the reliability and scientific validity of this research.

This paper references the studies of Silva et al. (2021) and other scholars, who utilized the Augmented Dickey-Fuller (ADF) test to assess data stationarity, thereby refining the prediction errors of ARIMA and deep learning models [27]. The ADF test is a widely employed method to evaluate whether a time series has a unit root and to determine its stationarity. In our research, this testing approach was employed to analyze the stationarity of surface maximum temperature, energy consumption, and their respective growth rates, using zero and one lag periods. The null hypothesis H_0 posits the existence of a unit root, indicating non-stationarity. The logic variable h is used to determine the ability to reject this null hypothesis. The test outcomes are displayed in Table 5.

Table 5. ADF Test Results for Time Series and Their Growth Rates

Original Index	0 Lag	1 Lag	Corresponding Growth Rate Indicator	0 Lag	1 Lag
Surface Max Temperature	0	0	Surface Max Temp Growth Rate	1	1
Coal	0	0	Coal Growth Rate	1	1
Refined Petroleum Products	0	0	Refined Petroleum Products Growth Rate	1	1
Dry Natural Gas Consumption	0	0	Dry Natural Gas Consumption Growth Rate	1	1
Electricity Net Consumption	0	0	Electricity Net Consumption Growth Rate	0	0
Consumption of Biofuels	0	0	Consumption of Biofuels Growth Rate	1	1

Since h=1 signifies rejection of the null hypothesis, indicating stationarity, and h=0 implies the null hypothesis cannot be rejected, suggesting non-stationarity. Based on the results of Table 5, none of the original indicators could reject the null hypothesis at both zeros and one lag, indicating the presence of a unit root, thus non-stationary. This status can lead to potential biases in the BiLSTM model during forecasting. Nevertheless, the growth rates demonstrate consistent stationarity, except for the growth rate of electricity net consumption, which could not reject the null hypothesis at any lag order. This suggests that, except for electricity net consumption, other indicators' growth rates may be more appropriate for forecasting using the BiLSTM model. Although the ADF test does not confirm the stationarity of the electricity net consumption growth rate, this research still opts to use the BiLSTM model to predict electricity net consumption data over the next ten years when assessing future risk levels. Despite limitations in handling non-stationary time series data, the model's unique capacity to capture long-term dependencies and complex patterns can still provide valuable predictions; thus, we consider the BiLSTM model to be an effective forecasting tool. However, incorporating other preprocessing methods (like differencing) in practice could enhance prediction accuracy further.

4.3.2. Model Robustness Analysis

In this research, the BiLSTM model was employed for forecasting surface maximum temperature. Since deep learning models are highly susceptible to parameter changes, including the number of neurons in the hidden layers, the number of training iterations, and the learning rate, which directly affect model performance. In particular, the number of neurons in the hidden layers decisively controls the complexity and performance of the neural network model. To ensure the veracity and rigor of our conclusions, a detailed sensitivity analysis was conducted on the BiLSTM model to assess its robustness.

An adjustment coefficient α was introduced to precisely modulate the number of neurons in the hidden layers by a range of -20% to +20%, in 5% increments, ensuring that other potential variables, such as iteration counts, remained consistent during this process. By this approach, we systematically altered critical model parameters and recorded the resulting RMSE to gauge model performance. Our BiLSTM model comprises three hidden neuron layers, denoted as H1, H2, and H3, with outcomes illustrated in Figure 6.

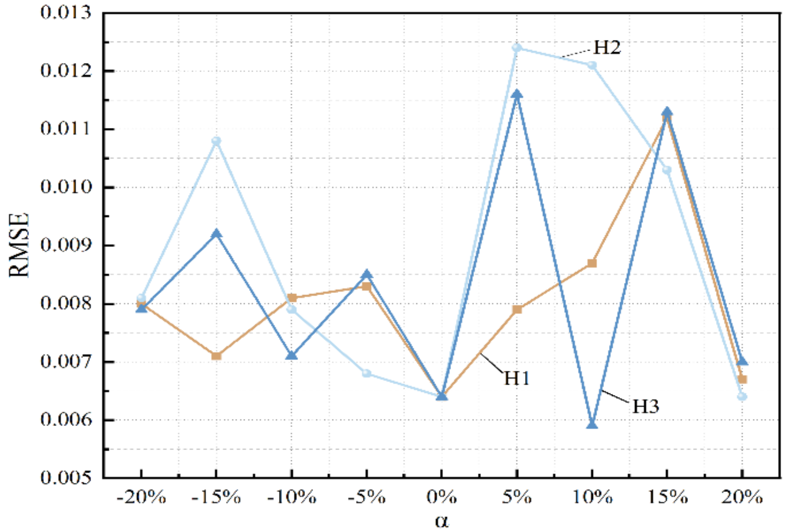

Figure 6. BiLSTM Model Robustness Analysis

According to Figure 6, RMSE exhibits a trend of variation when the number of neurons in the hidden layers is adjusted, but no clear pattern emerges. Additionally, our analysis reveals that, without any adjustments (α=0%), the layers H1 and H2 manifest optimal performance with an RMSE value of 0.0064. Concurrently, H3 displays optimum performance with a 10% increase adjustment, reducing the RMSE to 0.0059. These findings indicate that minor adjustments could suffice in optimizing model performance without the need for substantial changes in the number of neurons. During optimization, there must be caution regarding the optimization algorithm potentially converging to local optima. Comparing H3's performance at a +10% adjustment with the unadjusted scenario, we infer that fine-tuning H3 may not be essential. The sensitivity analysis of the neuron count in hidden layers helped ascertain the optimal configuration for the BiLSTM model, serving as a reference for achieving precise temperature forecasting.

5. Conclusion and Implications

This research develops a BiLSTM model to predict the trend of surface maximum temperature changes over the next century and uses the K-means clustering algorithm to establish warning indicators. Subsequently, an early warning system is constructed using an SVM-RF hybrid model, providing a methodological approach for identifying potential trends in climate change and energy consumption dynamics. The study forecasts a pattern of an initial increase, followed by a decrease and then another increase in surface highest temperatures over the next 100 years, signaling a rise in extreme weather events and the potential impacts on sea levels, agricultural output, and human health. The analysis of the forecast results corroborates earlier scholars' predictions of future temperature increases and underscores the dangers of rising carbon dioxide emissions and energy consumption rates.

The research underlines the importance of prioritizing the reduction of carbon dioxide emissions and controlling the growth rate of energy consumption to avoid undermining the principles of sustainable development. It advocates for the acceleration of optimizing the energy structure, reducing dependency on fossil fuels, and increasing the utilization of renewable energy sources. Moreover, the study emphasizes the need to establish a multi-level, dynamic early warning mechanism to take timely action when emission growth rates reach or exceed predetermined thresholds. In terms of constructing the early warning system, this study encourages all stakeholders, including governments and businesses, to enhance awareness of carbon emission and energy consumption control, to promote the development of related policy measures, focusing on the foresight and adaptability of the policies, to ensure early response capability, and to mitigate the potential risks of climate change.

6. Discussion

The study highlights the potential of utilizing deep learning and machine learning models in the field of climate change and energy consumption growth prediction and the insights these tools can bring. Although the forecasting models and their results presented exhibit technical advancement and high accuracy, this does not guarantee their future predictive accuracy due to the intrinsic complexity and uncertainty of weather and climate systems. Likewise, the precision of model forecasts is constrained by the quality of historical data, the accuracy of quantifying model input parameters, and the assumptions within the models themselves. To improve the reliability of future predictions, continuous model validation, updates, and refinement are necessary. Additionally, the classification of emission growth rates and the establishment of warning indicators require further exploration and optimization to ensure the effectiveness and adaptability of the warning system categories and threshold settings. Furthermore, in the face of the uncertainty of future climate risks, the study encourages intensified interdisciplinary cooperation, integrating knowledge and technologies from the fields of climate science, environmental economics, and social policy, to formulate more comprehensive and precise early warning systems. The goal is to provide solid scientific foundations and decision-making support for global climate governance and sustainable energy transition through multifaceted, systematic efforts. This paper also has several shortcomings, including not considering other factors affecting climate change and not performing a global optimization of the parameters for the BiLSTM model. Future research may further optimize the BiLSTM algorithm or continue developing the early warning system.

Acknowledgments

This paper is grateful for the funding of the Undergraduate Research and Innovation Fund of Anhui University of Finance and Economics "Research on the Rational Allocation of Energy Resources in the Context of Climate Security" (XSKY23229). We also extend our thanks to Xin Zhao for his guidance, expertise, and encouragement throughout the research process. Their insights and suggestions have been invaluable in shaping the direction of this study. Furthermore, we appreciate the assistance and cooperation of Anhui University of Finance and Economics who provided resources, data, and assistance that were essential to the success of this project. Lastly, we are grateful to our families, friends, and colleagues for their unwavering support and understanding during the course of this research endeavor.

Thank you to all who have contributed to the completion of this research project.

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