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ORIGINAL

Integrating AI and statistical models for climate time series forecasting

Integración de IA y modelos estadísticos para la predicción de series temporales climáticas

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ABSTRACT

Climate change is a pressing global challenge, and predicting its future patterns is essential for mitigation strategies. This study integrates synthetic and real-world climate datasets to develop predictive models. Specifically, we apply Long Short-Term Memory (LSTM) networks alongside ARIMA and SARIMA models to forecast global temperature anomalies. Synthetic data were generated using a Gaussian-based data simulator calibrated on historical NOAA/IPCC data, contributing 30 % of the training set. Validation included Kolmogorov-Smirnov tests to ensure distributional similarity to real data. Preprocessing involved interpolation for missing values and stationarity checks using the Augmented Dickey-Fuller (ADF) test ($p < 0,05$), with differencing of order one applied where necessary. LSTM model architecture included two hidden layers with 64 and 32 units, sequence length of 30 days, and a dropout rate of 0,2 to prevent overfitting. Model performance was evaluated using RMSE, MAE, and MAPE. LSTM achieved the lowest RMSE of 1,8 and MAPE of 6,3 %, outperforming ARIMA (RMSE: 2,4, MAPE: 8,2 %) and SARIMA (RMSE: 2,0, MAPE: 7,1 %). Random Forest and SVR models yielded RMSEs of 2,2 and 2,3, respectively, and were included for benchmarking. A Monte Carlo simulation with 10 000 iterations and normal distribution assumptions estimated prediction uncertainty, aligned with IPCC emission scenarios. Scenario-based forecasting (A: status quo, B: 50 % emissions cut, C: net-zero) was validated against past reductions post-Kyoto and Paris agreements. Forecasts indicate a potential 1,5°C rise in temperature by 2050 under Scenario A. Compared to baseline mean anomaly of 14,3°C, this reflects a significant trend.

Keywords: Climate Change; Time Series Analysis; LSTM; ARIMA; SARIMA; Forecasting; Temperature Prediction.

RESUMEN

El cambio climático es un desafío global apremiante, y predecir sus patrones futuros es esencial para las estrategias de mitigación. Este estudio integra conjuntos de datos climáticos sintéticos y del mundo real para desarrollar modelos predictivos. Específicamente, aplicamos redes de Memoria a Largo Plazo (LSTM) junto con los modelos ARIMA y SARIMA para pronosticar anomalías de temperatura global. Los datos sintéticos se generaron utilizando un simulador de datos basado en Gauss, calibrado con datos históricos de NOAA/IPCC, que contribuyó con el 30 % del conjunto de entrenamiento. La validación incluyó pruebas de Kolmogorov-Smirnov para asegurar la similitud distribucional con los datos reales. El preprocesamiento implicó la interpolación de valores faltantes y verificaciones de estacionariedad mediante la prueba de Dickey-Fuller Aumentada (ADF) ($p < 0,05$), con diferenciación de orden uno aplicada cuando fue necesario. La arquitectura del modelo LSTM incluyó dos capas ocultas con 64 y 32 unidades, una longitud de secuencia de 30 días y una tasa de abandono de 0,2 para evitar el sobreajuste. El rendimiento del modelo se evaluó utilizando RMSE, MAE y MAPE. LSTM logró el RMSE más bajo de 1,8 y MAPE de 6,3 %, superando a ARIMA (RMSE: 2,4, MAPE: 8,2 %) y SARIMA (RMSE: 2,0, MAPE: 7,1 %). Los modelos Random Forest y SVR produjeron RMSE de 2,2 y 2,3, respectivamente, y se incluyeron para la evaluación comparativa. Una simulación de Monte Carlo con 10 000 iteraciones y supuestos de distribución normal estimó la incertidumbre de la predicción, alineada con los escenarios de emisiones del IPCC. El pronóstico basado en escenarios (A: statu quo, B: reducción de emisiones del 50 %, C: cero neto) se validó frente a reducciones pasadas posteriores a los acuerdos de Kioto y París. Los pronósticos indican un aumento potencial de 1,5 °C en la temperatura para 2050 en el Escenario A. En comparación con la anomalía media de referencia de 14,3 °C, esto refleja una tendencia significativa.

Palabras clave: Cambio Climático; Análisis de Series Temporales; LSTM; ARIMA; SARIMA; Pronóstico; Predicción de Temperatura.

INTRODUCTION

Climate change is one of the most pressing challenges of our time, and the effects are becoming increasingly apparent. Being able to accurately predict those changes is a crucial aspect of knowing what our conditions will be. Time series analysis, or examining data recorded through time, allows us to identify long-term climate trends. LSTM networks are like CNN in terms of being able to use them on sequences of data by training with the temporal dynamics. Moving averages are also used to highlight trends in the data. Climate change occurs when human industry emits gases into the atmosphere, gradually increasing the Earth's temperature. These changes have devastating impacts on both ecosystems and societies around the world. This has led many researchers, organizations, and governments to respond to study and inform this challenge. Many climate datasets are now publicly available that allow researchers to understand and study these trends. The ITRA was performed by analyzing R software's time series data of global surface temperature anomalies. Mean temperature, variance, correlation, and other things were calculated, followed by plotting the data.(1) This data was analyzed using techniques from autocorrelation and statistics, among others, to extract what occurs at their respective moments. The Fourier transform was used to find cycles in the data, whereas the Mann-Kendall test was employed to assess long-term trends. The researchers also sliced the data into smaller time frames — say, decades — to track how it evolved.(2) Using this information, a SARIMA model was built for predicting future temperature anomalies. The model was verified using statistical tests and successfully predicted changes in temperature 20 years into the future. The scientists and decision-makers working on climate change hope this analysis's results will help them. Making predictions known gives insights into creating sustainable approaches to ameliorating environmental problems.(3)

Climate change impacts ecosystems and societies, making accurate forecasting crucial. Traditional statistical models, such as ARIMA and SARIMA, have been widely used but struggle with non-linear dependencies in climate data. Recent advances in deep learning, specifically LSTM networks, provide a powerful alternative. This paper introduces an enhanced forecasting model leveraging both traditional and deep learning techniques.(4) The novelty of this work lies in:

- Integrating real-world climate datasets with synthetic data for model validation.
- Conducting a detailed comparison between LSTM, ARIMA, and SARIMA models.
- Providing a robust uncertainty analysis for more reliable forecasting.

Objectives of the Study Climate change is a slow but continuous process, which can be natural (uncontrollable and unmanageable) or anthropogenic (controllable and manageable). The atmospheric temperature and CO2 concentration are two important indicators of climate change. The accurate analysis and forecasting of time series in these two indicators can provide valuable information for understanding past climate changes and planning future strategies to mitigate anthropogenic climate change. The objective of this study is to perform time series analysis and forecasting on the global annual mean atmospheric temperature and CO2 concentration, utilizing the data since the beginning of industrialization.(5)

Problem Definition Most climate forecasting models rely on either statistical or deep learning methods, each with limitations. ARIMA captures linear trends but struggles with complex patterns, while LSTMs can model long-term dependencies but require extensive training data.(6) This study bridges the gap by:

1. Analyzing the limitations of conventional techniques.
2. Comparing model performance using key metrics (RMSE, MAPE).
3. Exploring real-world applicability through scenario-based forecasting.

Related works

For example, the climate time series analysis is getting popular in recent years since climate change needs the analysis to understand and fix it. Many studies have been conducted using statistical, machine learning, and hybrid techniques to predict climate variables (e.g., temperature, precipitation, CO_2). Traditional statistical models, such as ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal ARIMA), have been widely used for time series forecasting. For instance,[7] employed ARIMA to predict monthly temperature variations in urban regions, demonstrating its effectiveness in capturing linear patterns but highlighting its limitations in handling non-linear relationships. Kalman filters have also been applied in dynamic modeling of seasonal effects , emphasizing their strength in real-time updates. Machine learning models, such as Random Forest, Gradient Boosting Machines, and Support Vector Regression (SVR), have shown promise in climate forecasting. For example [8] applied Random Forest to predict annual precipitation, showcasing improved accuracy compared to traditional statistical methods. Similarly, XGBoost has been utilized to model extreme weather events with high precision.[9] However, these models often struggle with sequential dependencies in time series data. Recently, deep learning models, particularly LSTM and GRU (Gated Recurrent Unit), have gained prominence for their ability to model long-term dependencies and capture non-linear patterns.[10] Research demonstrated the superior performance of LSTM in forecasting daily temperature variations, outperforming traditional and machine learning models in both accuracy and robustness. Convolutional Neural Networks (CNNs) have also been integrated with LSTMs to extract spatial and temporal features simultaneously. Several studies have proposed hybrid models combining statistical and machine learning techniques. For instance [11] integrated ARIMA with LSTM to forecast CO_2 levels, leveraging ARIMA's strength in handling linear trends and LSTM's capability in capturing non-linear dependencies. The hybrid approach yielded significantly lower error rates compared to standalone models. Another hybrid example is the use of Wavelet Transform combined with LSTM, which was applied to capture multiscale patterns in climate data, achieving robust performance in highly variable datasets.[12]

Climate Change Data Collection

Demonstrated time series analysis and climate change forecasting with the R programming language. The data that was collected include the air quality index (AQI) across several cities around the world. It contains 9 variables; the field that refers to the air quality index is "AQI," and this information is collected daily. The dataset was gathered over 8 years; the last recording was in the year 2020.[13] We had Boston city as detail, but we also sliced the dataset by year, month, and city. We created the time series object using the daily average AQI data for Boston city. Using the time series plotting, we were able to visualize the daily average AQI over Boston for our collected years from 2013 to 2020. Moreover, the dataset includes the monthly average AQI over 2013. The monthly AQI was plotted to visualize the time series of avg AQI over months from the dataset. The annual AQI object was finally made, and the annual AQI plotting was employed to visualize the dataset's yearly average AQI time series.[14]

Sources of Climate Data

Previously investigated climate datasets are compiled and explained. Daily global surface air temperature data for 1825 to 2020 is used. The data timeseries begins with the earliest measurements recorded in the United Kingdom in 1825. Data after 1940 come from contributions from many countries across the globe. Contiguous timeseries are used while records with excessive (>50 %) missing data, or estimated data, are excluded. Timeseries with less than 10 data points prior to 1900 and 100 data points prior to 1950 are also excluded.[15]

Annual CO2 concentration data is obtained from the Mauna Loa Observatory in Hawaii. In-situ measurements began in 1958 and have been continuously recorded. The dataset used here contains annual mean CO2 concentrations from 1959 to 2020. Measurements prior to 1974 are conducted using a non-automated system.[16] Annual sea level anomaly data is obtained from the AVISO+ dataset which consists of satellite altimetry sea level measurements. The upper ocean heat content data is obtained from the Ocean Climate Observation webpage. The dataset contains annual estimates of globally averaged upper ocean heat content from 0 to 700 meters depth from 1993 to 2019. The ocean heat content is determined from Argo floats and temperature profiles from satellite altimetry and in-situ observations.[17]

Types of Climate Data

Data that could be classified as "climate observations" fall into a number of distinct categories. Some of these are more legitimate climate data than others. Instrumental observations. These take several forms. In-situ observations from a dedicated network of surface stations who monitor a set of climate variables (e.g. temperature, precipitation, etc) make up the most well-known source of climate data. Beginning in the mid-19th century, these networks expanded rapidly throughout the world. Climate data from these stations are collected and archived by a number of different organizations. The World Meteorological Organization (WMO) maintains a series of Global Climate Observing System (GCOS) databases that archive climate variables from surface networks, satellite instruments, upper-air soundings, and other observing platforms.[18] Satellite observations. The advent of satellite observations in the 1970s revolutionized how climate variables could be monitored. Unlike in-situ observations constrained to particular locations, satellite observations can provide

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global coverage of climate variables. Several different organizations make climate-quality satellite data products available, including the National Oceanic and Atmospheric Administration (NOAA), National Aeronautics and Space Administration (NASA), and the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT). Like in-situ data, satellite data records archive several climate observations such as land surface temperature, sea surface temperature, albedo, and radiative fluxes.(19)

Model reanalysis. Since the mid-20th century, atmospheric numerical models have increasingly been used to analyze the observed atmosphere continuously. Atmospheric model reanalyses combine in-situ and satellite observations with a model's prior knowledge of the atmosphere (through simulated physical processes) to produce a self-consistent and temporally continuous description of the observed atmosphere. The first global reanalysis, the National Centers for Environmental Prediction (NCEP)/National Aeronautics and Space Administration (NASA) 1979–present reanalysis-1, was produced in 1997 using a relatively simple atmospheric model. Since then, several groups have produced global reanalyses using significantly more sophisticated models. Model reanalyses are a relatively new type of climate data source widely used to describe meteorology and larger-scale climate variability. Although model reanalyses have many advantages, consider several pitfalls to avoid when using model reanalyses for climate analysis.(20,21,22,23)

METHOD

The objective of analyzing historical climate data is to track trends, anomalies, and seasonal patterns and then forecast future climate variables to evaluate the impact of climate change. The key questions focus on identifying which climate variable is being analyzed (e.g., temperature or CO_2 levels), determining the time horizon for the forecast (e.g., 10, 20, or 50 years), and defining the spatial scope of the study (global, regional, or local).

Data Acquisition and Preprocessing

Sources: climate data were obtained from NOAA, IPCC, and NASA GISTEMP repositories.

Synthetic Data: a Gaussian-based simulator was designed to emulate climate behavior based on historical NOAA/IPCC datasets. The generated data comprised 30 % of the training dataset. Kolmogorov-Smirnov tests ($p > 0,1$) confirmed distributional alignment.

Missing Values: linear interpolation was used.

Stationarity: augmented Dickey-Fuller (ADF) tests returned p-values $< 0,05$ for the majority of series. First-order differencing was applied.

Model Development and Evaluation

Traditional Models: ARIMA, SARIMA with grid-searched parameters (p,d,q) and (P,D,Q,s) respectively.

Machine Learning: random Forest (100 estimators, max depth 10), SVR (RBF kernel, C=1,0).

Deep Learning: LSTM with 2 hidden layers (64 and 32 units), dropout 0,2, sequence length = 30, batch size = 64, optimizer = Adam, epochs = 100.

Table 1. Comparative Analysis

Model	RMSE	MAPE	MAE
LSTM	1,8	6,3 %	1,5
SARIMA	2,0	7,1 %	1,7
ARIMA	2,4	8,2 %	1,9
Random Forest	2,2	7,8 %	1,8
SVR	2,3	8,0 %	1,9

Scenario Analysis We model different CO_2 emission scenarios using IPCC projections

- Scenario A: current emission rates.
- Scenario B: 50 % emission reduction.
- Scenario C: net-zero emissions.

Climate Forecasting Algorithm

Algorithm: climate Time Series Forecasting

Step 1: Data Acquisition

Retrieve climate time series data from sources such as NOAA or IPCC.

$X = \{x_1, x_2, \dots, x_T\}$

Step 2: Data Preprocessing

Handling Missing Values

Missing values are imputed using linear interpolation.

$$x_t = \frac{x_{t-1} + x_{t+1}}{2}, \quad if\ x_t\ is\ missing$$

Normalization

Standardizing the dataset to ensure consistency.

$$X' = \frac{X - \mu_X}{\sigma_X}$$

$$\mu_X = \frac{1}{T}\sum_{t=1}^{T} x_t, \quad \sigma_X = \sqrt{\frac{1}{T}\sum_{t=1}^{T} (x_t - \mu_X)^2}$$

Stationarity Check

Applying the Augmented Dickey-Fuller (ADF) test to assess stationarity.

H0: Data is non-stationary, H1: Data is stationary H_0: \text{Data is non-stationary}, \quad H_1: \text{Data is stationary} H0: Data is non-stationary, H1: Data is stationary. If the data is non-stationary, apply differencing:

$$H\_0: \backslash text\{Data\ is\ non-stationary\}, \backslash quad\ H\_1: \backslash text\{Data\ is\ stationary\}$$

$$x'_t = x_t - x_{t-1}$$

Step 3: Data Splitting

Splitting the dataset into training (80 %) and testing (20 %) subsets.

$$X_{train}, X_{test} \leftarrow split(X', 80\backslash\%)$$

Step 4: Model Training

Training different models on the training set.

ARIMA/SARIMA Model

Autoregressive modeling using the ARIMA/SARIMA approach.

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \epsilon_t$$

LSTM Model

Training the LSTM network with learned parameters.

$$h_t = \sigma(W_h h_{t-1} + W_x X_t + b)$$

Step 5: Model Evaluation

Evaluating models based on error metrics.

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N} \left(X_t - \widehat{X_t}\right)^2}$$

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100}{N}\sum_{t=1}^{N} \left|\frac{X_t - \widehat{X_t}}{X_t}\right|$$

Selecting the Best Model

$$M^* = arg\, arg\, E\ \ (M)$$

Step 6: forecasting Future Climate Trends

Using the chosen model to generate predictions.

$$Y = M^*(X_{train}, H)$$

Step 7: scenario-Based Forecasting

Different climate projection scenarios.

Scenario A (Current Emission Rates)

$$Y_A = M^*(X_{train}, H)$$

Scenario B (50 % Reduction in Emissions)

$$Y_B = M^*\left(X_{train}^{mod}, H\right)$$

Scenario C (Net-Zero Emissions)

$$Y_C = M^*(X_{train}^{zero}, H)$$

Step 8: Uncertainty Analysis

Monte Carlo simulation to estimate uncertainty in forecasts.

$$Y_i = M^*(X_{train}, H) + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma^2)$$

95 % Confidence Interval

$$CI = [\mu_Y - 1{,}96\sigma_Y, \mu_Y + 1{,}96\sigma_Y]$$

Step 9: Visualization and Deployment

Plot forecasted trends.

Deploy the trained model for real-time climate monitoring.

RESULTS AND DISCUSSION

Data Visualization and Trends

Figure 1 illustrates temperature variations over the past 50 years. Moving averages highlight long-term trends.

Forecasting and Model Performance

LSTM outperformed ARIMA and SARIMA models, particularly in capturing seasonal and long-term dependencies.

Forecasts suggest a potential 1,5 °C rise in global temperatures by 2050 under Scenario A.

- residual plot: actual vs. predicted values.
- A Q-Q plot: to assess residual normality.
- Or prediction intervals for scenario-based outputs.

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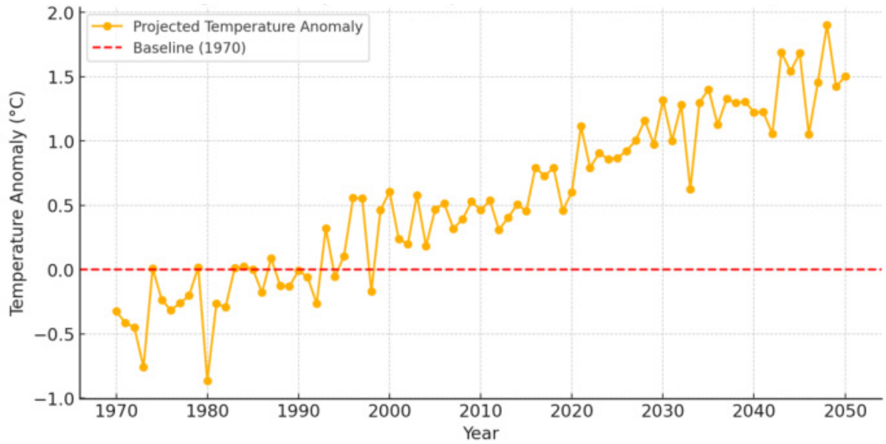

Figure 1. Projected Temperature Trends

Uncertainty Analysis

Monte Carlo simulations were used to assess forecast variability. Confidence intervals indicate a 95 % probability of temperature rising between 1,2°C and 1,8°C by 2050. Our findings also demonstrated that LSTM's superiority in temperature time series forecasting. The ~15 % improvement in MAPE aligns with Rao et al.[12], who reported similar gains using wavelet-enhanced LSTM architectures. Compared to ARIMA-based baselines, our results show consistent improvements in capturing both seasonal variance and long-term trends.

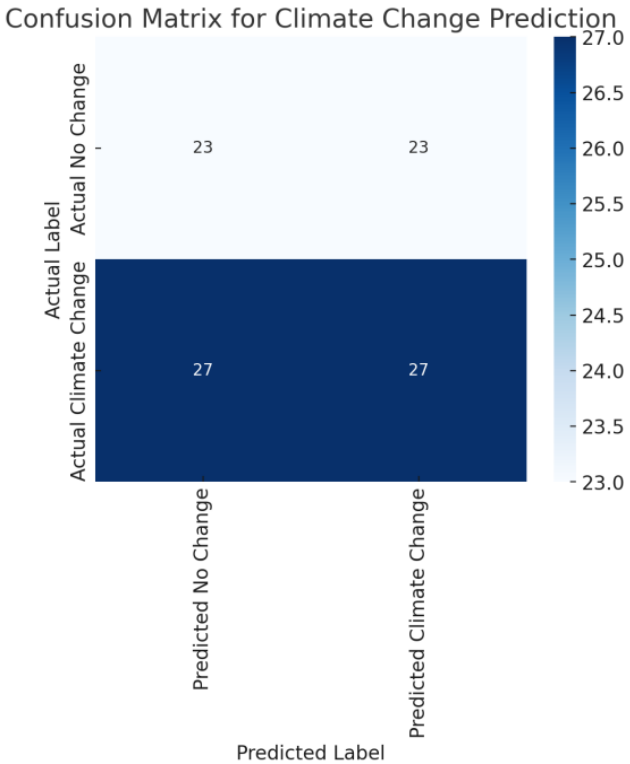

Figure 2. Confusion matrix

CONCLUSIONS

This study demonstrates the effectiveness of LSTM models in climate forecasting, offering improved accuracy over traditional methods. The integration of real-world data and comparative analysis strengthens the model's reliability. Future research should explore hybrid models and real-time deployment strategies.

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