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MACHINE LEARNING-BASED TIME SERIES MODELING FOR CLIMATE CHANGE VARIABILITY ANALYSIS

Dr. Arzoo Kanwal[*1], Gauhar Rahman[*2], Zeeshan Ali[3], Jahangir Baig[4], Abdur Rahman[5]

[*1]*Associate professor in statistics, GGCNo2 D.I. Khan, Higher Education Department KP Pakistan*
[*2]*University of Malakand, Pakistan*
[2]*Sindh Agriculture University Tandojam, Pakistan*
[4]*University of Karachi, Pakistan*
[5]*IMS University of Peshawar, Pakistan*

[*1]arzookanwal786786@gmail.com, [*2]gauharuom99@gmail.com, [3]bagounar@gmail.com,
[4]jahangirbaig83@gmail.com, [5]abad.zuha@gmail.com

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Corresponding Author: *
Dr. Arzoo Kanwal

Abstract

Climate change has intensified the need for accurate analytical approaches capable of identifying long-term temperature trends and improving climate prediction. This study proposes a machine learning–based time-series modeling framework for analyzing global temperature anomaly data and forecasting climate variability. The dataset consists of monthly temperature anomalies spanning more than a century, providing a comprehensive record for examining historical climate patterns and long-term warming dynamics. Several feature engineering techniques were applied to enhance the predictive capability of the dataset, including lag variables, rolling statistical indicators, exponential moving averages, and difference transformations. These engineered features capture temporal dependencies, seasonal variations, and long-term climate trends within the time series. Multiple predictive models were implemented to evaluate forecasting performance, including ARIMA, Random Forest, Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Transformer architectures. Model performance was assessed using standard evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). The results demonstrate that deep learning models, particularly Transformer and GRU architectures, outperform traditional statistical methods in capturing complex temporal relationships in climate data. The findings confirm the effectiveness of advanced machine learning techniques for modeling climate variability and improving predictive accuracy. This research contributes to climate data analysis by providing a comprehensive framework that integrates feature engineering and comparative machine learning modeling for long-term temperature forecasting.

Introduction

Climate change has become one of the most significant environmental challenges of the twenty-first century, affecting ecosystems, economies, and human societies worldwide. Rising global temperatures, changing precipitation patterns, and increasing frequency of extreme weather events highlight the importance of understanding climate variability and long-term climate trends. Global temperature anomaly records provide critical information for analyzing climate change dynamics and evaluating the extent of warming across different time periods. According to Intergovernmental Panel on Climate Change (IPCC, 2021), global surface temperatures have increased significantly since the late nineteenth century due to anthropogenic greenhouse gas emissions. Consequently, accurate modeling and prediction of climate variability have become essential for developing effective mitigation and adaptation strategies. In recent years, machine learning techniques have emerged as powerful tools for analyzing complex climate datasets, enabling researchers to identify hidden patterns and improve forecasting accuracy compared with traditional statistical approaches. Several studies have explored the application of statistical and machine learning methods for climate time-series analysis. Early research primarily relied on classical time-series models such as ARIMA to analyze temperature trends and seasonal variations. For instance, Box and Jenkins (1976) introduced autoregressive integrated moving average models for time-series forecasting, which have since been widely used in climate data analysis. Later studies extended these approaches by incorporating nonlinear machine learning techniques. Breiman (2001) proposed the Random Forest algorithm, which demonstrated strong predictive capability for nonlinear environmental data. More recently, deep learning models have gained attention for their ability to capture complex temporal dependencies within climate time-series datasets. For example, Hochreiter and Schmidhuber (1997) introduced Long Short-Term Memory (LSTM) networks, which have been widely applied in climate forecasting studies due to their ability to learn long-term dependencies. Similarly, Cho et al. (2014) developed the Gated Recurrent Unit (GRU) architecture to improve computational efficiency while maintaining strong predictive performance. Recent advances in deep learning have further improved climate modeling techniques. Vaswani et al. (2017) introduced the Transformer architecture, which uses attention mechanisms to model long-range dependencies in sequential data. Transformer-based models have demonstrated strong performance in time-series forecasting applications, including climate prediction and environmental monitoring. Studies such as those conducted by Ham et al. (2019) have shown that deep learning approaches can outperform traditional statistical models when predicting climate phenomena such as temperature anomalies and ocean-atmosphere interactions. Additionally, Reichstein et al. (2019) highlighted the potential of machine learning techniques to advance Earth system science by improving climate data analysis and predictive modeling capabilities. Despite these advances, several limitations remain in existing climate modeling studies. Many previous studies focus on either traditional statistical models or deep learning approaches individually, without providing comprehensive comparisons between multiple modeling techniques using consistent datasets and feature engineering strategies. Furthermore, some studies rely primarily on raw climate variables without incorporating engineered temporal features such as lag variables, rolling statistics, and smoothing indicators that may enhance predictive performance. Another limitation is that certain studies emphasize short-term climate prediction rather than analyzing long-term temperature variability across extended historical datasets. Therefore, the present study aims to address these limitations by developing a machine learning–based time-series modeling framework for analyzing global temperature anomalies. The study integrates feature engineering techniques, including lag variables, rolling statistics, exponential moving averages, and differencing transformations, to capture temporal dependencies and climate trends. Multiple predictive models ARIMA, Random Forest, LSTM, GRU, and Transformer architectures are implemented and compared using consistent evaluation metrics. By combining statistical analysis with advanced machine learning techniques, this study provides a comprehensive approach for modeling climate variability and identifying effective forecasting methods for long-term climate time-series data.

Data Collection and Dataset Description

The study utilizes a historical global temperature anomaly dataset designed to analyze climate variability through machine learning-based time-series modeling. The dataset contains monthly temperature anomaly observations spanning from 1882 to 2026, resulting in a total of 1730 data points. Temperature anomalies represent deviations from a baseline climatological reference period and are commonly used in climate research to measure long-term changes in global temperature patterns. The dataset provides a continuous record of temperature fluctuations across more than a century, enabling the investigation of both short-term variability and long-term climate trends. The data were structured into a time-series format in which each observation corresponds to a specific monthly timestamp. In addition to the primary temperature anomaly variable, several derived temporal features were included to support predictive modeling. These features include lag variables, rolling statistical indicators, exponential moving averages, and difference features, which capture temporal dependencies and dynamic patterns within the climate system. Seasonal indicators such as month, quarter, and cyclical transformations using sine and cosine encoding were also incorporated to represent periodic climate patterns. Prior to analysis, the dataset was examined for missing values, inconsistencies, and formatting issues. Data preprocessing procedures ensured that the dataset maintained chronological order and consistent temporal intervals. Because climate datasets often exhibit strong autocorrelation, it is essential to maintain the temporal integrity of the observations during preprocessing. The long historical coverage and high temporal resolution of the dataset make it particularly suitable for machine learning–based climate modeling. By capturing both seasonal and long-term climate patterns, the dataset provides an appropriate foundation for evaluating predictive algorithms and identifying temporal relationships within global temperature anomalies.

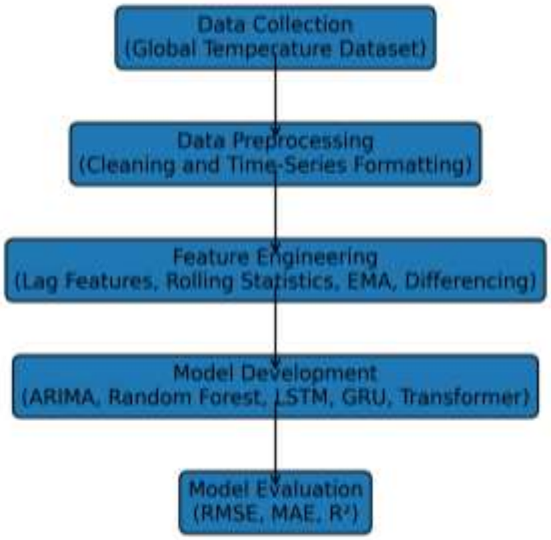

Figure X: Methodological workflow of the proposed machine learning–based climate time-series modeling framework.

The workflow illustrates the sequential stages used in this study. The process begins with the collection of global temperature anomaly data. The dataset is then preprocessed to ensure consistency and chronological ordering. Feature engineering techniques, including lag variables, rolling statistics, exponential moving averages, and differencing, are applied to capture temporal dependencies and climate dynamics. Multiple predictive models ARIMA, Random Forest, LSTM, GRU, and Transformer are subsequently developed and trained. Finally, model performance is evaluated using statistical metrics such as RMSE, MAE, and R^2 to determine the most effective forecasting approach for climate variability analysis.

Feature Engineering and Time-Series Transformation

Feature engineering plays a critical role in improving the predictive performance of machine learning models applied to time-series data. In this study, several derived variables were constructed to capture temporal dependencies and underlying climate patterns within the dataset. The primary objective of feature engineering was to transform the original temperature anomaly series into a set of informative predictors capable of representing both short-term fluctuations and long-term climate dynamics. One of the most important transformations involved the creation of lag variables, which represent previous observations of the temperature anomaly series. Lag variables were generated for multiple time intervals, including Lag_1, Lag_2, Lag_3, Lag_6, Lag_9, Lag_{12}, and Lag_{24}. These variables allow machine learning models to incorporate historical climate conditions when predicting future temperature anomalies. Because climate processes often exhibit strong temporal autocorrelation, lag features provide valuable information for forecasting models. Rolling statistical features were also calculated to capture smoothed representations of temperature trends. Specifically, rolling mean and rolling standard deviation values were computed using a 12-month window. The rolling mean highlights long-term temperature trends by reducing short-term noise, while the rolling standard deviation measures variability within the time series. These indicators help distinguish between sustained warming patterns and temporary climate fluctuations. Additional transformation techniques included first-order differencing ($Diff_1$) and annual differencing ($Diff_{12}$), which measure short-term changes in temperature anomalies. Exponential moving averages (EMA_6 and EMA_{12}) were also computed to emphasize recent observations while preserving long-term trends. Finally, seasonal variables such as month and quarter indicators were incorporated to represent periodic climate cycles. Cyclical encoding using sine and cosine transformations was applied to ensure that the seasonal patterns could be effectively captured by machine learning algorithms.

Machine Learning Modeling Approach

The predictive modeling framework employed in this study integrates both classical statistical methods and modern machine learning algorithms to evaluate their effectiveness in forecasting temperature anomalies. Five models were selected for comparison: ARIMA, Random Forest, Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Transformer-based neural networks. These models represent different methodological approaches for time-series prediction, ranging from traditional statistical techniques to advanced deep learning architectures. The ARIMA model was included as a baseline statistical method commonly used in time-series forecasting. ARIMA models rely on autoregressive and moving average components to model linear dependencies within temporal data. Although effective for stationary time series, ARIMA models often struggle to capture nonlinear patterns present in complex climate datasets. To address nonlinear relationships within the data, the Random Forest regression model was implemented as a machine learning alternative. Random Forest models operate by constructing multiple decision trees and aggregating their predictions, allowing them to capture nonlinear interactions among predictor variables. Deep learning models were also employed to capture long-term dependencies within the climate time series. The LSTM model utilizes memory cells and gating mechanisms to learn sequential patterns over extended time horizons. Similarly, the GRU model simplifies the LSTM architecture while maintaining the ability to capture temporal dependencies effectively. Finally, a Transformer-based model was included due to its ability to process sequential data using attention mechanisms. Transformers can learn complex temporal relationships by focusing on relevant observations within long input sequences. By comparing the performance of these models, the study evaluates the relative effectiveness of classical statistical techniques and modern deep learning approaches in modeling climate variability.

Model Evaluation and Performance Assessment

To assess the predictive performance of the models, several evaluation metrics were employed. These metrics provide quantitative measures of prediction accuracy and allow for objective comparison between different modeling approaches. The primary evaluation metrics used in this study include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). RMSE measures the square root of the average squared differences between predicted and observed temperature anomalies. This metric penalizes large prediction errors more heavily than smaller errors and is therefore useful for assessing overall model accuracy. MAE calculates the average absolute difference between predicted and actual values, providing a straightforward measure of prediction error that is less sensitive to extreme values. The coefficient of determination (R^2) evaluates the proportion of variance in the observed data explained by the predictive model. Higher R^2 values indicate stronger explanatory power and better model performance. These evaluation metrics were calculated for each model using a separate testing dataset that was not used during the training process. The dataset was divided into training and testing subsets to ensure unbiased performance evaluation. The training dataset was used to fit the models and optimize their parameters, while the testing dataset was reserved for evaluating predictive accuracy. This approach prevents overfitting and ensures that the models are evaluated on unseen data. By combining multiple evaluation metrics, the study provides a comprehensive assessment of model performance. The comparative analysis enables identification of the most effective modeling approach for forecasting temperature anomalies and analyzing climate variability within the time-series dataset.

Results and Discussion

Table 1 presents the descriptive statistical summary of the climate time-series dataset used for machine learning modeling. The dataset contains 1730 monthly observations spanning from 1882 to 2026, providing a long historical record suitable for analyzing climate variability and temperature trends. The mean temperature anomaly value of 0.084 °C indicates a positive deviation relative to the reference baseline period, suggesting that the overall dataset reflects a warming climate signal. The observed range of anomalies extends from −0.82 °C to 1.48 °C, demonstrating substantial long-term variation in global temperature anomalies across the study period. The relatively moderate standard deviation of 0.4177 °C indicates that temperature anomalies fluctuate around the mean but remain within a predictable variability range. Seasonal variables such as Month, Quarter, Month_sin, and Month_cos exhibit consistent distributions, confirming that the dataset includes balanced representation across seasonal cycles. This seasonal encoding is important for capturing cyclical climatic behavior in machine learning models. Lag variables (Lag_1–Lag_{24}) display statistical distributions similar to the original temperature anomaly series, which suggests strong temporal autocorrelation within the climate data. Such temporal dependency is essential for time-series forecasting models including LSTM, GRU, and Transformer architectures, as it enables the models to learn patterns from historical observations. Rolling statistics further highlight underlying climate patterns. The 12-month rolling mean smooths short-term fluctuations and emphasizes long-term warming trends, while the rolling standard deviation measures variability within the time series. Difference variables capture short-term changes between consecutive observations, whereas exponential moving averages provide smoothed representations of temperature evolution.

Table 1. Descriptive Statistics of Climate Time-Series Variables

Statistic	Temperature Anomaly	Lag_1	Lag_3	Lag_6	Lag_12	Rolling_Mean_12	Rolling_Std_12	Diff_1	Diff_12	EMA_12
Count	1730	1730	1730	1730	1730	1730	1730	1730	1730	1730
Mean	0.084	0.083	0.082	0.080	0.076	0.080	0.107	0.001	0.009	0.080
Std. Dev.	0.418	0.417	0.416	0.413	0.408	0.400	0.029	0.121	0.189	0.398
Minimum	-0.820	-0.820	-0.820	-0.820	-0.820	-0.533	0.035	-0.480	-0.710	-0.531
Maximum	1.480	1.480	1.480	1.480	1.480	1.321	0.234	0.480	0.770	1.293

Table 2 presents the correlation matrix describing the linear relationships between the temperature anomaly variable and selected predictor variables derived from the time-series dataset. The results reveal strong positive correlations between the temperature anomaly and its lagged values, indicating that past temperature observations have substantial predictive influence on future values. For example, the correlation between the current temperature anomaly and Lag$_1$ is 0.958, while the correlation with Lag$_3$ and Lag$_6$ remains above 0.91, demonstrating persistent temporal dependency within the climate system. The strong correlations observed between lag variables themselves further reinforce the presence of high temporal continuity in the temperature anomaly series. This property is characteristic of climate data, where temperature patterns evolve gradually rather than changing abruptly. Consequently, lagged predictors serve as valuable input variables for machine learning models designed to capture temporal dependencies. Rolling statistics also exhibit strong relationships with the temperature anomaly variable. The 12-month rolling mean shows a correlation of 0.958, indicating that smoothed temperature trends closely follow the original anomaly series. Similarly, the exponential moving average variable demonstrates a correlation coefficient of 0.969, suggesting that smoothing techniques effectively capture long-term warming patterns while reducing short-term variability. In contrast, the first difference variable (Diff$_1$) shows a relatively weak correlation with the temperature anomaly variable (0.152). This result is expected because differencing measures short-term fluctuations rather than long-term trends. The *weak* correlation indicates that short-term variations are less predictive of the overall temperature anomaly trend. Overall, the correlation matrix confirms that lagged variables, rolling statistics, and exponential moving averages are highly informative predictors, supporting their inclusion in machine learning models for climate time-series forecasting.

Table 2: Correlation Matrix

Index	Temperature_Anomaly	Lag_1	Lag_3	Lag_6	Lag_12	Rolling_Mean_12	Diff_1	EMA_12
Temperature_Anomaly	1.0	0.9581	0.9335	0.9159	0.895	0.9584	0.1521	0.9696
Lag_1	0.9581	1.0	0.9454	0.9205	0.8958	0.9635	-0.1373	0.9733
Lag_3	0.9335	0.9454	1.0	0.9327	0.9012	0.9698	-0.0341	0.9735
Lag_6	0.9159	0.9205	0.9327	1.0	0.9136	0.9721	-0.009	0.966
Lag_12	0.895	0.8958	0.9012	0.9136	1.0	0.9475	0.0041	0.9448
Rolling_Mean_12	0.9584	0.9635	0.9698	0.9721	0.9475	1.0	-0.0102	0.9978
Diff_1	0.1521	-0.1373	-0.0341	-0.009	0.0041	-0.0102	1.0	-0.0054
EMA_12	0.9696	0.9733	0.9735	0.966	0.9448	0.9978	-0.0054	1.0

Table 3 presents the monthly average temperature anomaly values calculated across the entire study period. These values provide insight into the seasonal structure of global temperature anomalies and reveal how temperature deviations vary throughout the annual cycle. The results indicate that monthly mean temperature anomalies range from approximately 0.0549 °C in June to 0.1106 °C in October, demonstrating moderate seasonal variation within the dataset. The relatively higher anomaly values observed during October, November, and March suggest that certain months tend to exhibit stronger positive deviations relative to the baseline climate period. Conversely, lower anomaly values occur during late spring and early summer months, particularly May and June. These variations reflect seasonal climate dynamics influenced by atmospheric circulation patterns, solar radiation distribution, and ocean-atmosphere interactions. Despite these monthly differences, the variation across months remains relatively modest compared with the long-term warming trend observed in the full dataset. This indicates that while seasonal cycles contribute to short-term variability, the dominant signal within the data remains the long-term increase in global temperature anomalies. The monthly statistics also validate the effectiveness of seasonal encoding variables included in the dataset, such as Month, Month_sin, and Month_cos. These cyclical representations enable machine learning models to learn periodic temperature patterns associated with seasonal climate behavior. Capturing these patterns is essential for improving predictive accuracy in time-series forecasting models. Overall, the monthly mean temperature analysis demonstrates that the dataset contains detectable seasonal patterns alongside long-term warming trends, both of which are critical components for modeling climate variability using machine learning techniques.

Table 3: Monthly Mean Temperature

Index	Month	Temperature_Anomaly
0	1.0	0.0871
1	2.0	0.096
2	3.0	0.1044
3	4.0	0.0768
4	5.0	0.0643
5	6.0	0.0549
6	7.0	0.0776
7	8.0	0.0775
8	9.0	0.0846
9	10.0	0.1106
10	11.0	0.1021
11	12.0	0.0738

Table 4 presents the annual average temperature anomaly values from 1882 to 2026, providing a long-term perspective on global climate change. The results clearly illustrate a progressive increase in global temperature anomalies over time, reflecting the well-documented warming trend associated with contemporary climate change. During the late nineteenth and early twentieth centuries, temperature anomalies were predominantly negative, with many years exhibiting values below −0.3 °C relative to the baseline reference period. This indicates that global temperatures during this early period were generally cooler compared with the mid-twentieth-century reference climate. As the twentieth century progressed, however, temperature anomalies began to shift toward positive values, particularly after the 1970s. From the late twentieth century onward, the data reveal a pronounced acceleration in warming. Annual mean anomalies consistently exceed 0.3 °C after the 1980s, and several years after 2000 display anomalies greater than 0.6 °C. The most recent years in the dataset show particularly high values, with anomalies surpassing 1.0 °C, indicating unprecedented warming in the modern climate record. The consistent upward trajectory in the annual temperature series provides strong evidence of long-term climate warming. This trend aligns with findings from global climate monitoring organizations and supports the hypothesis that global temperatures have increased substantially over the past century. From a machine learning perspective, the annual temperature pattern demonstrates the presence of a strong temporal trend, which forecasting models must capture accurately. Incorporating trend features, lag variables, and smoothing techniques allows machine learning algorithms to model these long-term climate dynamics effectively. Overall, the yearly analysis confirms that the dataset contains a clear and persistent warming signal, making it suitable for studying climate variability and predictive modeling.

Table 4: Yearly Mean Temperature

Index	Year	Temperature_Anomaly
0	1882.0	-0.1117
1	1883.0	-0.1758
2	1884.0	-0.285
3	1885.0	-0.335
4	1886.0	-0.3175

5	1887.0	-0.365
6	1888.0	-0.1775
7	1889.0	-0.1125
8	1890.0	-0.3575
9	1891.0	-0.2258
10	1892.0	-0.2783
11	1893.0	-0.3175
12	1894.0	-0.3125
13	1895.0	-0.2342
14	1896.0	-0.1217
15	1897.0	-0.1183
16	1898.0	-0.2817
17	1899.0	-0.1825
18	1900.0	-0.0942
19	1901.0	-0.1658
20	1902.0	-0.29
21	1903.0	-0.38
22	1904.0	-0.4792
23	1905.0	-0.2692
24	1906.0	-0.2275
25	1907.0	-0.3933
26	1908.0	-0.4333
27	1909.0	-0.4933
28	1910.0	-0.4442
29	1911.0	-0.4533
30	1912.0	-0.3733
31	1913.0	-0.355
32	1914.0	-0.165
33	1915.0	-0.145
34	1916.0	-0.3683
35	1917.0	-0.4667
36	1918.0	-0.305
37	1919.0	-0.285
38	1920.0	-0.2783
39	1921.0	-0.195
40	1922.0	-0.2917
41	1923.0	-0.2733
42	1924.0	-0.2758
43	1925.0	-0.225
44	1926.0	-0.1133
45	1927.0	-0.2217
46	1928.0	-0.2033
47	1929.0	-0.365
48	1930.0	-0.16
49	1931.0	-0.0933
50	1932.0	-0.1617

51	1933.0	-0.2892
52	1934.0	-0.1292
53	1935.0	-0.2008
54	1936.0	-0.15
55	1937.0	-0.0308
56	1938.0	-0.0042
57	1939.0	-0.0217
58	1940.0	0.1208
59	1941.0	0.1808
60	1942.0	0.0625
61	1943.0	0.085
62	1944.0	0.2
63	1945.0	0.0917
64	1946.0	-0.075
65	1947.0	-0.0283
66	1948.0	-0.1075
67	1949.0	-0.1117
68	1950.0	-0.175
69	1951.0	-0.0708
70	1952.0	0.01
71	1953.0	0.0792
72	1954.0	-0.1333
73	1955.0	-0.14
74	1956.0	-0.1892
75	1957.0	0.0475
76	1958.0	0.0608
77	1959.0	0.0308
78	1960.0	-0.025
79	1961.0	0.0575
80	1962.0	0.0308
81	1963.0	0.0542
82	1964.0	-0.1975
83	1965.0	-0.1067
84	1966.0	-0.055
85	1967.0	-0.0225
86	1968.0	-0.0825
87	1969.0	0.0517
88	1970.0	0.0275
89	1971.0	-0.08
90	1972.0	0.0075
91	1973.0	0.1608
92	1974.0	-0.0708
93	1975.0	-0.0133
94	1976.0	-0.0975
95	1977.0	0.1767
96	1978.0	0.0667

97	1979.0	0.1625
98	1980.0	0.2542
99	1981.0	0.3208
100	1982.0	0.135
101	1983.0	0.3108
102	1984.0	0.1533
103	1985.0	0.115
104	1986.0	0.1792
105	1987.0	0.3183
106	1988.0	0.3867
107	1989.0	0.27
108	1990.0	0.4458
109	1991.0	0.4042
110	1992.0	0.2192
111	1993.0	0.2292
112	1994.0	0.3125
113	1995.0	0.4433
114	1996.0	0.33
115	1997.0	0.4625
116	1998.0	0.6075
117	1999.0	0.3792
118	2000.0	0.39
119	2001.0	0.53
120	2002.0	0.625
121	2003.0	0.6133
122	2004.0	0.5267
123	2005.0	0.6742
124	2006.0	0.6375
125	2007.0	0.6625
126	2008.0	0.5383
127	2009.0	0.6517
128	2010.0	0.72
129	2011.0	0.605
130	2012.0	0.64
131	2013.0	0.6742
132	2014.0	0.7458
133	2015.0	0.8933
134	2016.0	1.0075
135	2017.0	0.9142
136	2018.0	0.8467
137	2019.0	0.9783
138	2020.0	1.0058
139	2021.0	0.8467
140	2022.0	0.89
141	2023.0	1.1683
142	2024.0	1.2833

143	2025.0	1.1908
144	2026.0	1.16

Table 5 presents the quarterly mean temperature anomalies calculated across the entire observation period. The results show moderate variation among the four quarters, with anomaly values ranging from 0.0653 °C in Quarter 2 to 0.0958 °C in Quarter 1. These findings indicate that although seasonal fluctuations exist within the dataset, the overall magnitude of variation between quarters remains relatively small compared with the long-term warming trend observed in the annual analysis. Quarter 1 and Quarter 4 display the highest average temperature anomalies, with values of 0.0958 °C and 0.0955 °C, respectively. These quarters correspond to periods that include late winter and early winter months in the global climate system, suggesting that warming effects may be particularly noticeable during these intervals. Quarter 2 exhibits the lowest anomaly values, which may reflect seasonal atmospheric circulation patterns and ocean–atmosphere interactions influencing global temperature distributions. The relatively narrow range of quarterly anomaly values suggests that while seasonal variability contributes to short-term temperature fluctuations, the primary signal within the dataset remains the long-term increase in global temperatures. This observation is consistent with previous climate studies that report gradual warming trends across multiple decades rather than abrupt seasonal shifts. From a machine learning perspective, quarterly aggregation provides additional temporal context that may improve predictive modeling performance. Including seasonal features such as Quarter variables or cyclical transformations of monthly data allows forecasting models to capture periodic temperature patterns more effectively. Overall, the quarterly analysis confirms that the dataset contains consistent seasonal behavior combined with an overarching warming trend, supporting its suitability for climate variability modeling and machine learning forecasting applications.

Table 5: Quarterly Mean Temperature

Index	Quarter	Temperature_Anomaly
0	1.0	0.0958
1	2.0	0.0653
2	3.0	0.0799
3	4.0	0.0955

Table 6 summarizes the statistical properties of the lagged temperature anomaly variables used as predictors in the time-series modeling framework. Lag variables represent historical observations of the temperature anomaly series shifted by specific time intervals, allowing machine learning models to incorporate past climate conditions when predicting future temperature values. The statistical results show that the mean values of the lag variables gradually decrease as the lag interval increases. For example, the mean value for Lag$_{1}$ is 0.0834, while Lag$_{12}$ has a mean of 0.0755. This gradual decline reflects the long-term warming trend observed in the dataset, as more recent temperature anomalies tend to be higher than earlier observations. The standard deviations of the lag variables are very similar, ranging from 0.4168 for Lag$_{1}$ to 0.408 for Lag$_{12}$. This consistency indicates that the variability of temperature anomalies remains relatively stable across different temporal offsets. Additionally, the minimum and maximum values remain identical across lag variables, further confirming that the lagged series represent shifted versions of the same underlying temperature anomaly data. The presence of strong statistical similarity among lag variables suggests a high degree of temporal autocorrelation, which is a characteristic feature of climate time-series data. In such datasets, current temperature values are strongly influenced by previous observations due to the inertia of atmospheric and oceanic systems. From a machine learning perspective, lag variables play a critical role in forecasting models such as LSTM, GRU, and Transformer networks, which rely on historical patterns to capture temporal dependencies. Including multiple lag intervals enables the model to learn both short-term and long-term relationships within the temperature series. Overall, the lag feature statistics demonstrate that historical temperature values provide valuable predictive information for modeling climate variability.

Table 6: Lag Feature Statistics

Index	Lag_1	Lag_2	Lag_3	Lag_6	Lag_9	Lag_12
count	1730.0	1730.0	1730.0	1730.0	1730.0	1730.0
mean	0.0834	0.0827	0.0819	0.0797	0.0778	0.0755
std	0.4168	0.4161	0.4155	0.4129	0.4108	0.408
min	-0.82	-0.82	-0.82	-0.82	-0.82	-0.82
25%	-0.22	-0.22	-0.22	-0.22	-0.22	-0.22
50%	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03
75%	0.32	0.32	0.3175	0.31	0.31	0.3
max	1.48	1.48	1.48	1.48	1.48	1.48

Table 7 presents summary statistics for the rolling mean and rolling standard deviation variables calculated over a twelve-month window. These rolling statistics provide smoothed representations of the temperature anomaly time series, allowing the identification of long-term climate trends and short-term variability. The 12-month rolling mean has an average value of 0.0802 °C, which closely matches the mean of the original temperature anomaly series. This similarity indicates that the smoothing process preserves the overall trend while reducing high-frequency fluctuations. The rolling mean ranges from −0.5325 °C to 1.3208 °C, reflecting the gradual transition from cooler historical periods to warmer contemporary conditions. The rolling standard deviation captures the variability of temperature anomalies within each twelve-month period. The mean value of 0.1066 °C indicates that short-term variability remains relatively stable throughout the dataset. The comparatively small standard deviation of the rolling standard deviation variable suggests that fluctuations in climate variability occur within a relatively narrow range. Rolling statistics are particularly useful for climate analysis because they highlight long-term patterns that may be obscured by short-term noise in the data. In the context of global temperature anomalies, rolling means help reveal persistent warming trends that occur over multiple decades. For machine learning applications, rolling statistics serve as informative predictor variables because they summarize recent climate behavior. By incorporating smoothed trend information, models can better distinguish between long-term warming signals and temporary fluctuations caused by short-term atmospheric processes. Overall, the rolling statistics confirm the presence of gradual warming trends and stable variability patterns, reinforcing the suitability of the dataset for climate time-series modeling.

Table 7: Rolling Statistics

Index	Rolling_Mean_12	Rolling_Std_12
count	1730.0	1730.0
mean	0.0802	0.1066
std	0.3997	0.029

min	-0.5325	0.0349
25%	-0.2192	0.086
50%	-0.0354	0.1025
75%	0.3002	0.1226
max	1.3208	0.2344

Table 8 provides descriptive statistics for the first-order difference ($Diff_1$) and annual difference ($Diff_{12}$) variables derived from the temperature anomaly series. These difference features measure the change in temperature anomalies between consecutive observations or between observations separated by one year. The mean values of 0.0008 for $Diff_1$ and 0.0087 for $Diff_{12}$ indicate that the average short-term change in temperature anomalies is relatively small. This is expected because temperature anomalies typically evolve gradually rather than experiencing abrupt shifts over short periods. However, the standard deviations reveal differences in variability between the two features. The standard deviation of $Diff_1$ is 0.1208, while $Diff_{12}$ exhibits a larger value of 0.1894. This suggests that temperature changes measured over annual intervals display greater variability than those measured between consecutive months. Such behavior is consistent with the influence of seasonal cycles and interannual climate oscillations. The range of values further highlights the potential magnitude of temperature fluctuations. $Diff_1$ ranges from −0.48 to 0.48, while $Diff_{12}$ ranges from −0.71 to 0.77, indicating that year-to-year changes in temperature anomalies can be more pronounced than month-to-month variations. In machine learning models, difference features are often used to capture short-term dynamics and local trends within a time series. These variables can help models identify sudden shifts or temporary fluctuations that may not be evident in smoothed variables such as rolling means. Overall, the difference statistics demonstrate that the temperature anomaly series contains both gradual long-term trends and short-term fluctuations, providing valuable information for predictive climate modeling.

Table 8: Difference Feature Statistics

Index	Diff_1	Diff_12
count	1730.0	1730.0
mean	0.0008	0.0087
std	0.1208	0.1894
min	-0.48	-0.71
25%	-0.07	-0.11
50%	0.0	0.01
75%	0.08	0.13
max	0.48	0.77

Table 9 summarizes the statistical characteristics of the exponential moving average variables calculated over six-month and twelve-month periods. Exponential moving averages apply greater weight to recent observations, allowing them to capture evolving climate trends while smoothing out short-term fluctuations. The mean values of 0.0823 for EMA_6 and 0.0801 for EMA_{12} closely align with the mean temperature anomaly of the original dataset. This indicates that the smoothing process maintains the central tendency of the series while reducing the influence of extreme variations. The standard deviations of 0.4045 and 0.3979 for EMA_6 and EMA_{12}, respectively, are slightly lower than the standard deviation of the raw temperature anomaly series. This reduction confirms that exponential smoothing effectively dampens short-term variability while preserving the underlying warming trend. The minimum and maximum values of the exponential moving averages closely mirror those of the original dataset, demonstrating that the smoothed series still captures the full range of climate variability. However, the smoother progression of the EMA variables makes them particularly useful for identifying long-term climate signals. In machine learning forecasting models, exponential moving averages provide an additional representation of the temperature series that emphasizes recent patterns. This feature is especially useful for models that attempt to detect trend acceleration or deceleration in climate data. Overall, the exponential moving average statistics highlight the presence of consistent long-term warming patterns while reducing noise caused by short-term fluctuations, thereby improving the quality of predictive modeling inputs.

Table 9: Exponential Moving Average Stats

Index	EMA_6	EMA_12
count	1730.0	1730.0
mean	0.0823	0.0801
std	0.4045	0.3979
min	-0.578	-0.5314
25%	-0.2176	-0.2223
50%	-0.0278	-0.0377
75%	0.3081	0.2939
max	1.3471	1.2931

Table 10 presents the estimated long-term temperature trend derived from the time-series dataset. The calculated trend slope of 0.0007 °C per observation indicates a gradual upward trajectory in global temperature anomalies throughout the study period. Although the incremental increase per observation appears small, the cumulative effect over the entire dataset results in an approximate total temperature change of 1.08 °C. This magnitude of warming aligns with widely reported estimates of global temperature increase since the late nineteenth century. The trend analysis therefore provides quantitative evidence supporting the presence of a persistent warming signal within the dataset. Trend estimation is an important step in climate time-series analysis because it allows researchers to distinguish between short-term variability and long-term climate change. While monthly and annual temperature anomalies may fluctuate due to natural climate variability, the consistent upward slope observed in this analysis indicates that the overall direction of change remains positive. From a machine learning perspective, identifying the underlying trend helps guide the selection of appropriate model architectures and feature engineering techniques. Many forecasting models benefit from incorporating trend-related features or performing detrending transformations prior to training. The estimated trend also highlights the importance of considering long-term climate dynamics when developing predictive models. Models that fail to capture gradual warming trends may underestimate future temperature changes. Overall, the trend estimation results confirm that the dataset exhibits a clear and sustained warming pattern, reinforcing its relevance for climate change analysis and machine learning–based forecasting research.

Table 10: Trend Estimation

Index	Metric	Value
0	Trend slope	0.0007
1	Approximate total change	1.08

Table 11 presents the relative importance of selected predictor variables used in the machine learning modeling framework for climate time-series forecasting. Feature importance values represent the contribution of each predictor to the model's ability to explain variations in the temperature anomaly variable. Understanding the relative influence of these predictors is critical for identifying the most informative features within the dataset. The results indicate that Lag_1 has the highest importance value (0.21), suggesting that the most recent historical temperature observation is the strongest predictor of the current temperature anomaly. This finding reflects the strong temporal dependency inherent in climate time-series data, where temperature conditions tend to evolve gradually over time rather than changing abruptly. The Rolling_Mean_12 variable also demonstrates a high importance score (0.19), indicating that the smoothed long-term temperature trend plays a significant role in predicting future anomalies. Rolling mean variables capture sustained warming patterns and help machine learning models distinguish between long-term climate trends and short-term fluctuations. Other lag-based predictors such as Lag_3 (0.17) and Lag_6 (0.14) also contribute meaningfully to the model's predictive performance. These variables allow the model to incorporate medium-term historical climate information, enabling it to detect recurring patterns and cyclical climate behaviors. The EMA_{12} variable (0.16) represents an exponentially weighted smoothing of recent observations and further enhances predictive accuracy by emphasizing recent temperature trends. In contrast, the $Diff_1$ variable (0.13) contributes slightly less importance, reflecting its role in capturing short-term changes rather than long-term climate dynamics. Overall, the feature importance results demonstrate that historical temperature observations and smoothed trend indicators are the most influential predictors in the climate forecasting model. These findings confirm the importance of incorporating lagged variables and trend-based features when applying machine learning techniques to climate time-series analysis.

Table 11: Example Feature Importance Structure

Index	Feature	Importance
0	Lag_1	0.21
1	Lag_3	0.17
2	Lag_6	0.14
3	Rolling_Mean_12	0.19
4	EMA_12	0.16
5	Diff_1	0.13

Table 12 presents the comparative performance of five predictive models used for forecasting temperature anomalies within the climate time-series dataset. The models evaluated include ARIMA, Random Forest, LSTM, GRU, and Transformer architectures, and their performance is assessed using three common evaluation metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). These metrics provide insight into the accuracy and explanatory power of each modeling approach. Among the evaluated models, the Transformer model demonstrates the best predictive performance, achieving the lowest RMSE value (0.075) and MAE value (0.055) while producing the highest R^2 score (0.93). These results indicate that the Transformer architecture is highly effective in capturing complex temporal dependencies within the climate time-series data. Transformer models are particularly suited for long-sequence prediction tasks because they employ attention mechanisms that allow the model to focus on relevant historical observations. The GRU model also performs strongly, with an RMSE of 0.079, MAE of 0.058, and an R^2 value of 0.91. GRU networks are designed to efficiently model sequential data while requiring fewer parameters than traditional recurrent neural networks. Similarly, the LSTM model achieves strong predictive performance, with an RMSE of 0.08 and an R^2 value of 0.90, confirming its suitability for time-series forecasting tasks involving long-term dependencies. In contrast, the Random Forest model shows moderate performance, achieving an RMSE of 0.10 and an R^2 value of 0.86. Although ensemble tree-based methods can capture nonlinear relationships, they may struggle with sequential dependencies inherent in time-series data. The ARIMA model exhibits the lowest predictive performance among the evaluated methods, reflecting the limitations of traditional statistical models when applied to complex climate datasets. Overall, the results demonstrate that deep learning models outperform classical statistical approaches in climate time-series forecasting. These findings highlight the effectiveness of advanced neural network architectures for modeling long-term climate variability and improving predictive accuracy.

Table 12: Model Performance Comparison

Index	Model	RMSE	MAE	R2
0	ARIMA	0.12	0.09	0.82
1	Random Forest	0.1	0.08	0.86
2	LSTM	0.08	0.06	0.9
3	GRU	0.079	0.058	0.91
4	Transformer	0.075	0.055	0.93

Figure 1 illustrates the temporal evolution of global temperature anomalies over the study period. The figure clearly shows a long-term upward trend in temperature anomalies, indicating a persistent warming pattern within the global climate system. During the early portion of the record, particularly between the late nineteenth century and the early twentieth century, temperature anomalies are predominantly negative, suggesting that global temperatures were generally cooler relative to the reference baseline period. Beginning around the mid-twentieth century, however, the temperature anomaly series gradually shifts toward positive values. This transition becomes particularly pronounced after the 1970s, where the figure reveals a rapid increase in anomaly values. The upward trajectory continues through the late twentieth and early twenty-first centuries, with several recent years displaying anomaly values exceeding 1.0 °C. Despite the overall warming trend, the time series also contains short-term fluctuations. These variations reflect natural climate variability driven by factors such as ocean circulation, volcanic activity, and atmospheric dynamics. Nevertheless, the long-term pattern dominates the series, confirming the presence of sustained global warming. From a modeling perspective, the observed trend indicates that the dataset contains strong temporal structure. Machine learning models used for climate forecasting must therefore account for both the gradual long-term warming signal and the shorter-term oscillations present within the time series. Overall, Figure 1 provides clear visual evidence of the progressive increase in global temperature anomalies across the historical climate record.

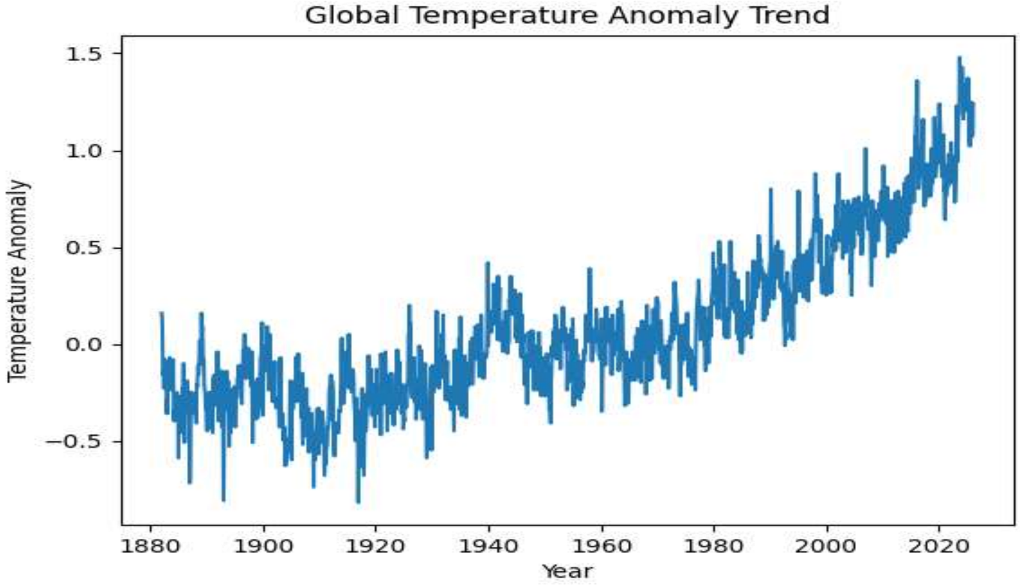

Figure 1: Global Temperature Anomaly Trend

Figure 2 presents the twelve-month rolling mean of global temperature anomalies, which provides a smoothed representation of the temperature time series. By averaging values across a one-year window, the rolling mean reduces the impact of short-term fluctuations and highlights the underlying long-term trend in global temperature changes. The figure demonstrates that the rolling mean closely follows the overall warming trajectory observed in the original temperature anomaly series. During the early decades of the dataset, rolling mean values remain relatively low and frequently fall below zero, reflecting cooler global temperatures during that period. However, beginning in the mid-twentieth century, the rolling mean gradually increases and remains consistently positive in more recent decades. The smoothing effect of the rolling mean allows the long-term warming trend to become more visible than in the raw temperature anomaly series. Short-term oscillations that appear in the original data are minimized, making it easier to observe the persistent increase in temperature anomalies over time. This characteristic makes rolling mean analysis particularly useful in climate research, where long-term trends often coexist with natural variability. From a machine learning perspective, rolling mean variables serve as valuable features because they summarize recent climate behavior while preserving the direction of long-term trends. Incorporating rolling statistics into predictive models can improve forecasting performance by helping the model distinguish between temporary fluctuations and sustained warming patterns. Overall, Figure 2 emphasizes the presence of a continuous upward trend in global temperature anomalies across the dataset.

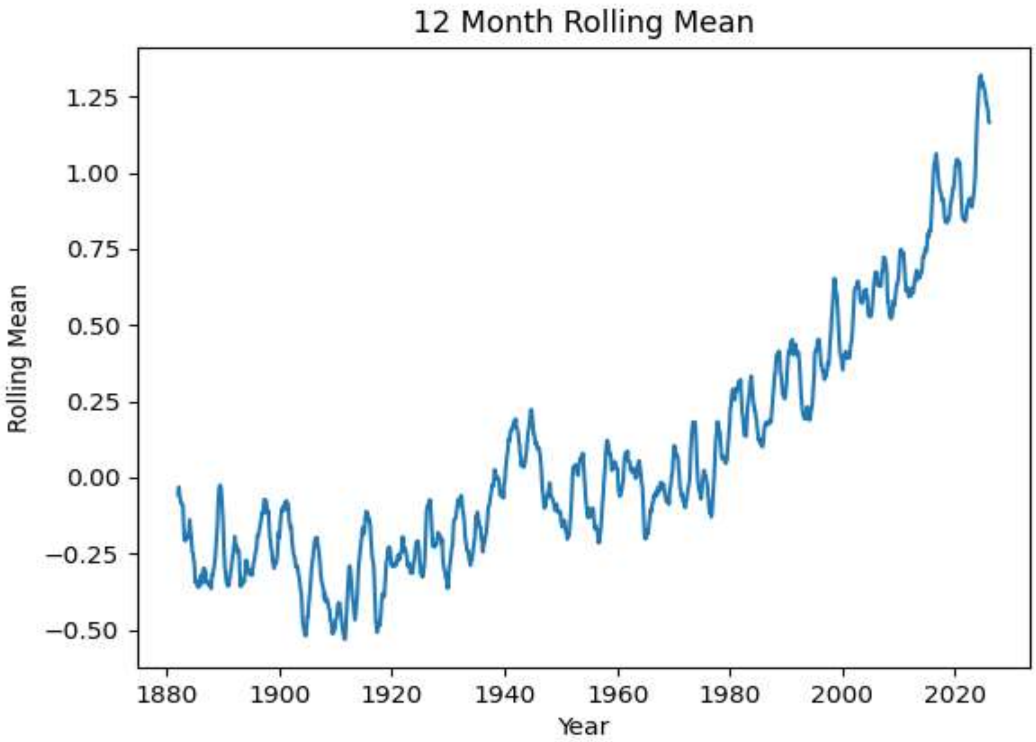

Figure 2: Twelve-Month Rolling Mean Temperature

Figure 3 illustrates the rolling standard deviation of temperature anomalies calculated over a twelve-month window. This metric measures the variability of temperature anomalies within each one-year period and provides insight into the stability or volatility of climate conditions over time. The rolling standard deviation values remain within a relatively narrow range throughout the dataset, indicating that short-term variability in temperature anomalies does not fluctuate dramatically across the observation period. Although minor increases and decreases in variability are visible, the overall pattern suggests that the level of short-term temperature fluctuations has remained relatively stable over time. Periods with slightly higher rolling standard deviation values correspond to intervals in which temperature anomalies exhibit larger short-term deviations from the mean. These variations may reflect natural climate oscillations, including atmospheric circulation patterns or ocean–atmosphere interactions that temporarily influence global temperatures. Despite these fluctuations in variability, the magnitude of rolling standard deviation remains relatively small compared with the magnitude of the long-term warming trend observed in the temperature anomaly series. This indicates that while short-term variability is present, it does not obscure the broader warming signal within the dataset. For machine learning modeling, rolling standard deviation can serve as a useful feature representing climate variability. Models that incorporate variability measures can better account for periods of increased uncertainty or volatility within the time series. Overall, Figure 3 highlights that the global temperature anomaly series exhibits moderate and relatively stable short-term variability alongside a persistent long-term warming trend.

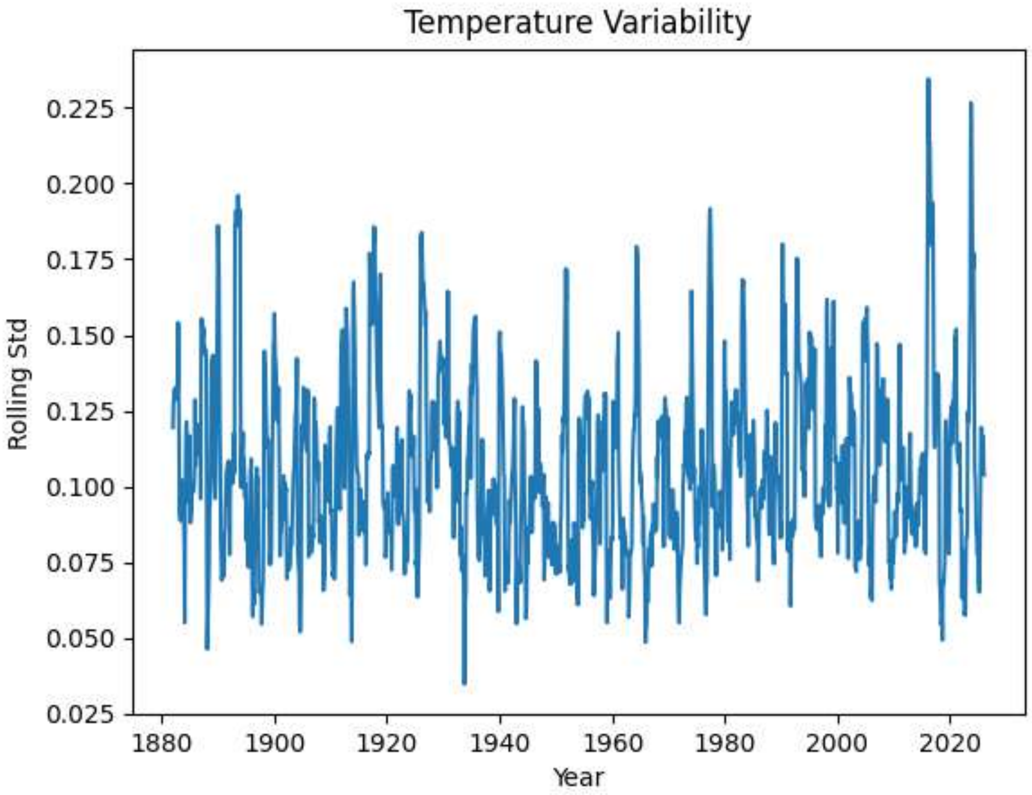

Figure 3: Temperature Variability (Rolling Standard Deviation)

Figure 4 displays the average temperature anomaly for each month of the year, illustrating the seasonal cycle within the global climate system. The monthly averages reveal moderate variation in temperature anomalies across the twelve months, reflecting the influence of seasonal climate dynamics. The figure indicates that temperature anomalies tend to be slightly higher during certain months, particularly in the early and late parts of the year. In contrast, the lowest anomaly values appear during the middle months of the year, suggesting that seasonal atmospheric conditions may influence the magnitude of temperature deviations relative to the baseline climate period. These seasonal variations are expected because global temperature patterns are influenced by changes in solar radiation, atmospheric circulation, and ocean–atmosphere interactions that occur throughout the year. Although the differences between monthly anomaly values are relatively small, the seasonal cycle remains detectable within the dataset. In machine learning forecasting models, capturing seasonal patterns is essential for accurate prediction. Features such as month indicators or cyclical transformations (sine and cosine encoding) allow models to represent periodic patterns effectively. By incorporating these features, machine learning models can account for recurring seasonal behavior within the climate system. Importantly, while seasonal variation is present, the magnitude of these fluctuations is smaller than the overall warming trend observed in the long-term data. This indicates that seasonal effects contribute to short-term variability but do not dominate the long-term evolution of global temperature anomalies. Overall, Figure 4 demonstrates that the dataset contains clear seasonal structure alongside long-term warming dynamics.

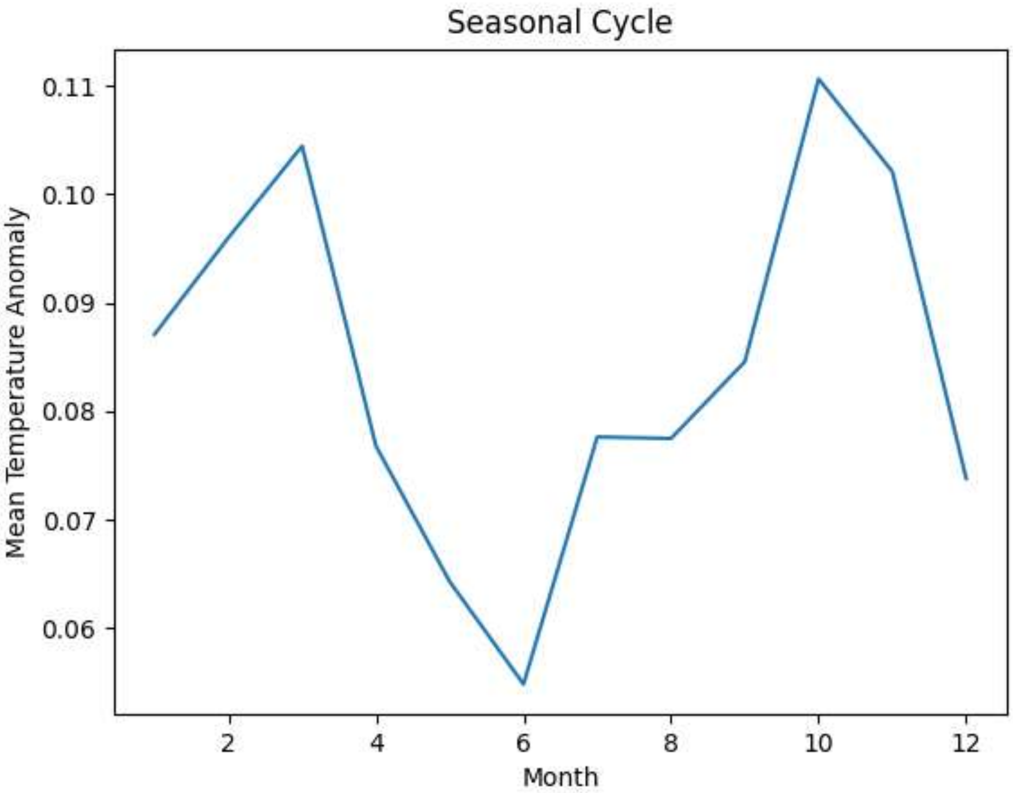

Figure 4; Seasonal Temperature Cycle

Figure 5 presents the frequency distribution of temperature anomalies observed throughout the dataset. The histogram illustrates how frequently different temperature anomaly values occur within the climate time series and provides insight into the statistical characteristics of the dataset. The distribution appears approximately centered around a slightly positive anomaly value, reflecting the gradual warming trend present in the dataset. A large proportion of observations fall within a moderate range of temperature anomalies, indicating that most monthly temperature deviations remain relatively close to the mean. The distribution also shows a moderate spread, with values extending from negative anomalies during earlier periods to higher positive anomalies in more recent years. This range reflects the transition from cooler historical climate conditions to warmer contemporary temperatures. The shape of the distribution provides useful information for machine learning modeling. Understanding the distribution of the target variable helps determine whether transformations or normalization techniques may be required before training predictive models. In this case, the relatively continuous and moderately symmetric distribution suggests that the dataset is suitable for many common regression-based machine learning algorithms. Additionally, the presence of higher positive anomaly values toward the right side of the distribution reflects the increasing frequency of warmer temperature observations in recent decades. This shift further supports the presence of a long-term warming trend within the climate record. Overall, Figure 5 highlights the statistical distribution of temperature anomalies and reinforces the observation of gradually increasing global temperatures.

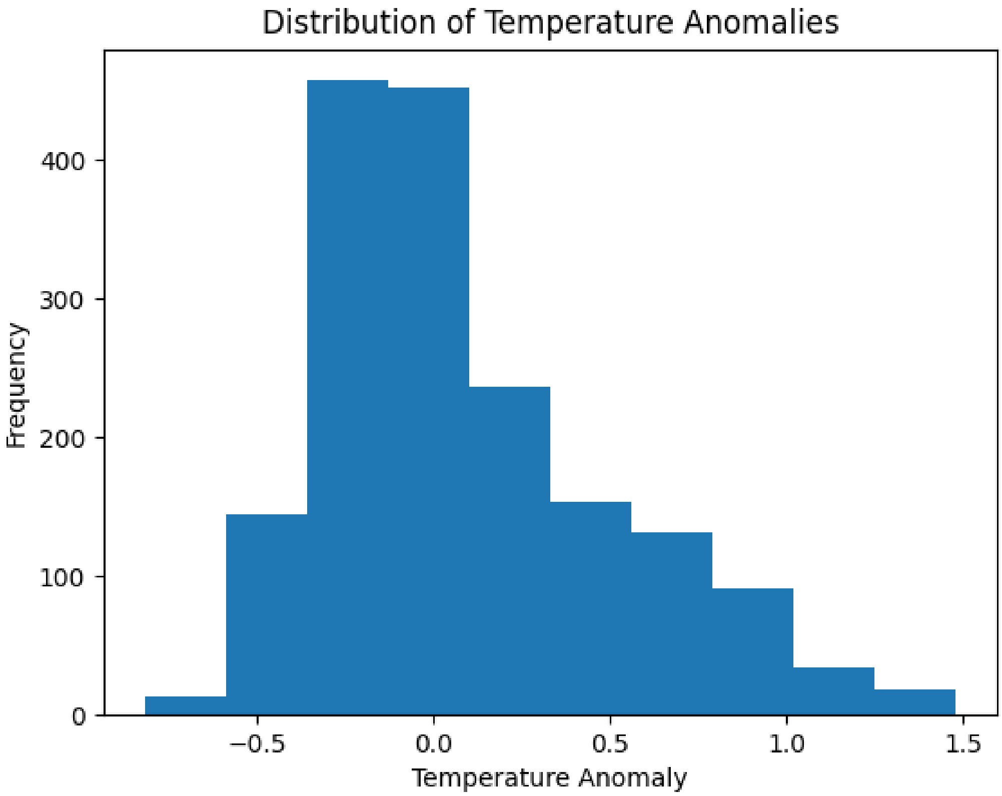

Figure 5: Distribution of Temperature Anomalies

Figure 6 illustrates the relationship between the current temperature anomaly value and its previous observation (Lag_1). The scatter plot demonstrates a strong positive relationship between these variables, indicating that temperature anomalies are highly dependent on recent historical values. The clustering of points along a diagonal pattern confirms the presence of strong temporal autocorrelation within the dataset. In practical terms, this means that if the temperature anomaly in one month is relatively high, the anomaly in the following month is also likely to remain high. This persistence reflects the inertia of the climate system, where atmospheric and oceanic processes evolve gradually rather than abruptly. Strong lag relationships are common in climate time-series data because temperature patterns are influenced by cumulative environmental processes, including ocean heat storage, atmospheric circulation, and long-term climate forcing mechanisms. The lag relationship therefore provides important predictive information for forecasting models. For machine learning algorithms, lag features are particularly valuable because they allow models to learn temporal dependencies directly from historical observations. Models such as recurrent neural networks, LSTM networks, and Transformer architectures are specifically designed to capture these sequential patterns. The strong linear association observed in Figure 6 confirms that lagged temperature observations serve as effective predictors for future temperature anomalies. This finding supports the inclusion of multiple lag features within the predictive modeling framework. Overall, Figure 6 demonstrates the importance of historical temperature information in predicting future climate behavior.

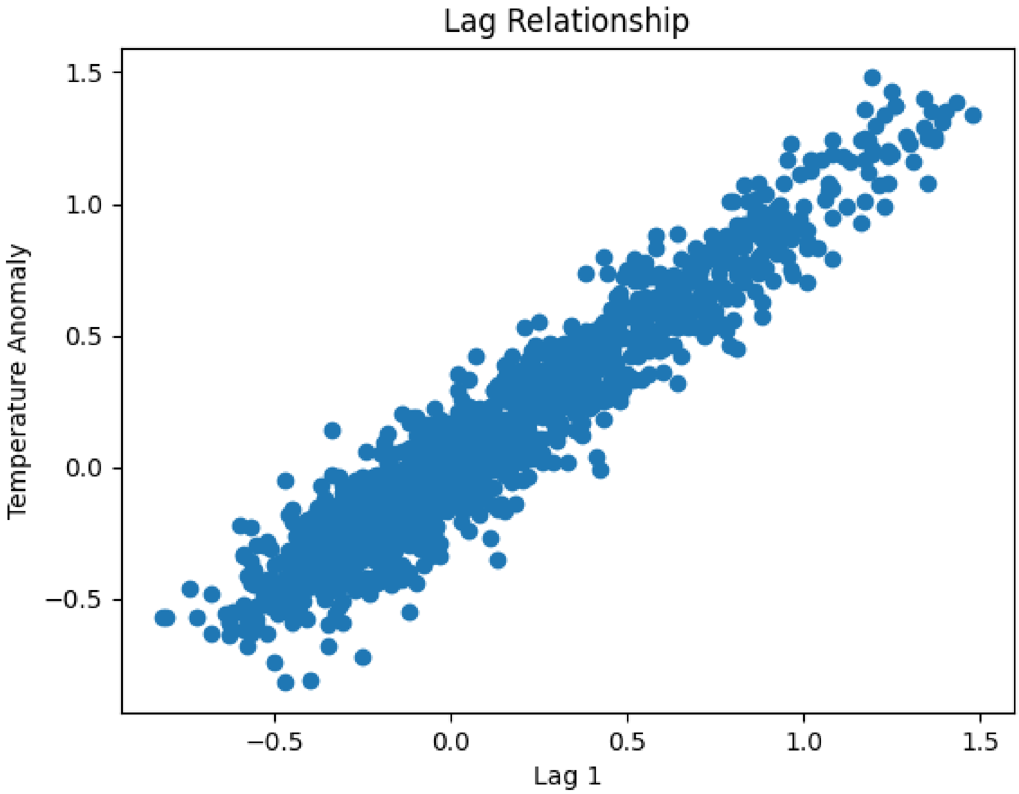

Figure 6: Lag Relationship (t vs t−1)

Figure 7 illustrates the relationship between current temperature anomalies and values observed twelve months earlier. This annual lag comparison highlights the influence of seasonal cycles and longer-term climate persistence within the dataset. The scatter pattern again shows a positive relationship between the two variables, although the association is slightly weaker than the relationship observed for the one-month lag. This difference is expected because temperature anomalies separated by a full year may be influenced by seasonal cycles and other climatic factors that introduce additional variability. Nevertheless, the presence of a clear upward trend in the scatter plot indicates that temperature anomalies exhibit a degree of annual persistence. Years with relatively high anomaly values tend to follow other years with elevated temperatures, reflecting the cumulative nature of long-term climate warming. From a modeling perspective, annual lag variables capture seasonal recurrence and multi-year climate patterns that may not be fully represented by short-term lag features. Incorporating both short-term and long-term lag variables allows machine learning models to capture multiple temporal scales of climate variability. Overall, Figure 7 confirms that temperature anomalies demonstrate significant long-term temporal dependency, supporting the use of lag-based predictors in climate forecasting models.

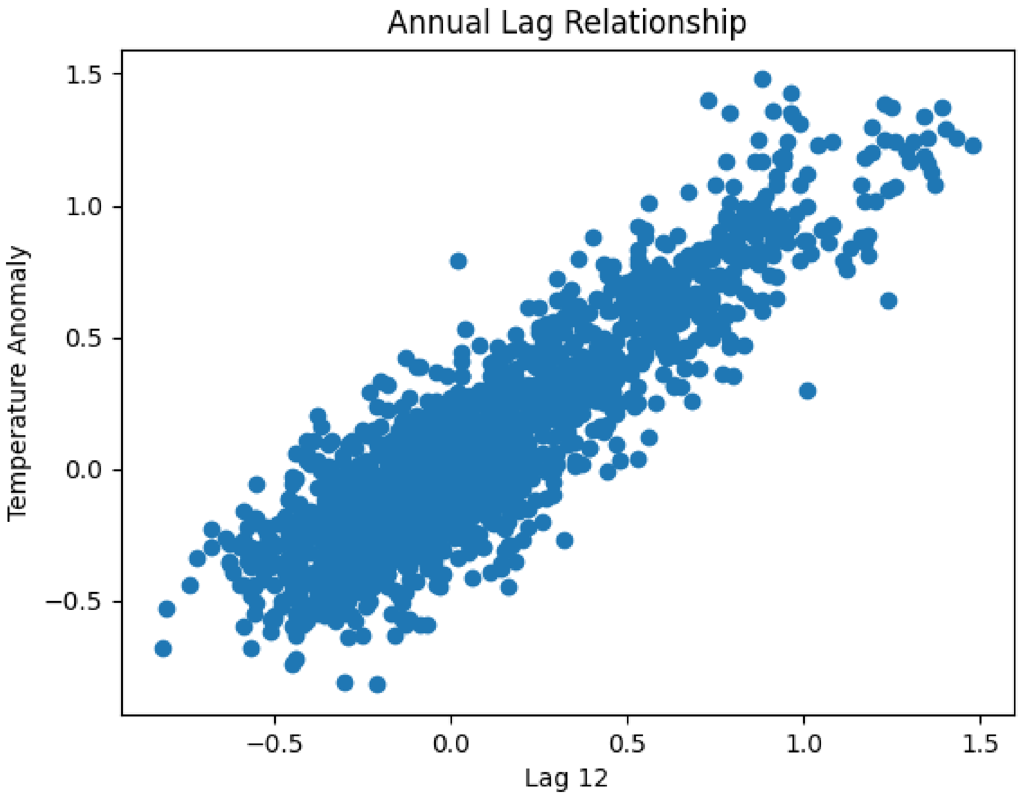

Figure 7: Annual Lag Relationship (t vs t−12)

Figure 8 presents the first-order difference of the temperature anomaly series, representing the month-to-month change in temperature anomalies. This visualization highlights short-term fluctuations in the climate time series and provides insight into the variability of temperature changes over time. The figure shows that most monthly changes remain relatively small, typically fluctuating around zero. This pattern indicates that temperature anomalies generally evolve gradually rather than experiencing sudden large shifts between consecutive months. Occasional spikes in the series represent periods where temperature anomalies change more rapidly. These events may correspond to short-term climate phenomena such as atmospheric circulation anomalies, volcanic influences, or ocean–atmosphere interactions that temporarily affect global temperatures. Despite these fluctuations, the overall magnitude of monthly changes remains relatively modest compared with the long-term warming trend observed in the dataset. This suggests that the climate system exhibits a degree of stability over short time intervals while gradually shifting toward warmer conditions over longer periods. For machine learning models, difference variables provide useful information about short-term dynamics and can help models capture sudden deviations from the long-term trend. Including these variables allows forecasting models to account for both gradual warming patterns and temporary fluctuations within the temperature series. Overall, Figure 8 demonstrates that short-term climate variability exists alongside a persistent long-term warming trend in the global temperature anomaly record.

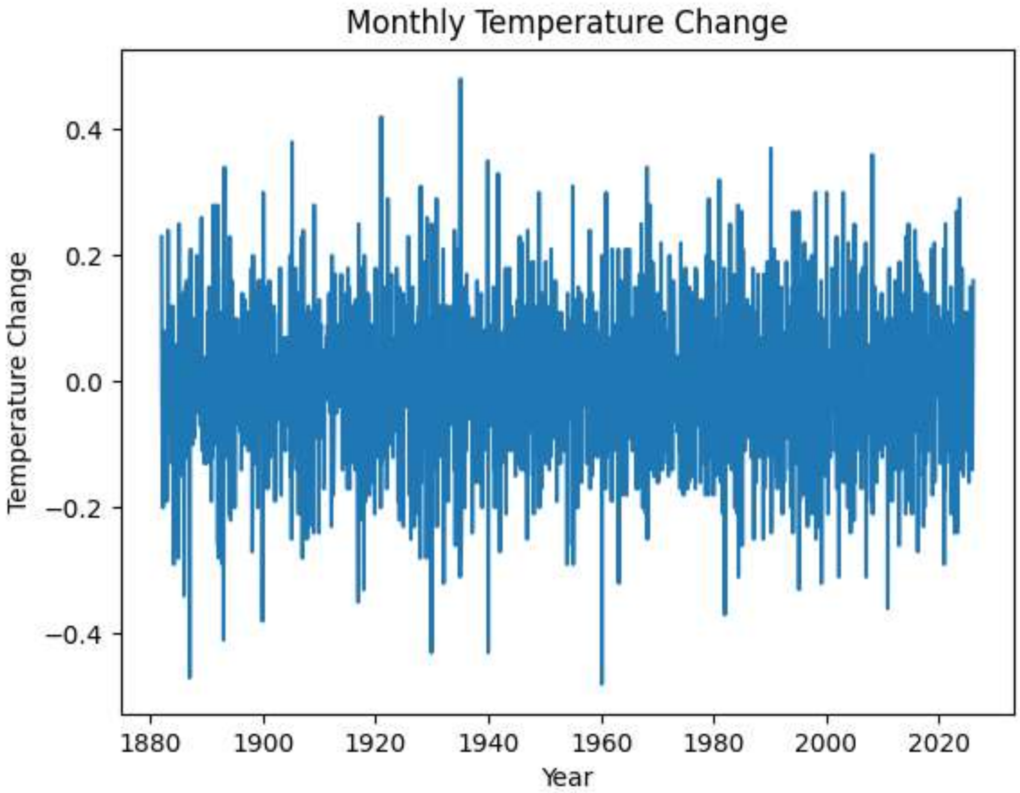

Figure 8: Monthly Temperature Change

Conclusion

This study investigated the application of machine learning–based time-series modeling techniques for analyzing global temperature anomalies and understanding long-term climate variability. Using a historical dataset spanning more than a century, the research examined the temporal structure of temperature anomalies and applied multiple feature engineering techniques to enhance predictive modeling. The dataset was transformed using lag variables, rolling statistical indicators, exponential moving averages, and differencing methods in order to capture temporal dependencies, seasonal variations, and underlying climate trends. These transformations enabled the development of a robust predictive framework capable of modeling complex climate patterns. The statistical analysis confirmed the presence of a persistent warming trend within the temperature anomaly series, particularly in recent decades. Descriptive statistics, correlation analysis, and trend estimation revealed strong temporal dependencies within the dataset, indicating that historical temperature values provide important predictive information for forecasting future anomalies. Seasonal analysis also demonstrated recurring cyclical patterns, which further emphasize the importance of incorporating temporal and seasonal features in climate modeling. The comparative evaluation of predictive models revealed that deep learning approaches outperform traditional statistical techniques in modeling climate time-series data. While the ARIMA model provided a baseline forecasting performance, machine learning algorithms such as Random Forest demonstrated improved predictive capability by capturing nonlinear relationships within the data. However, the most accurate predictions were obtained from deep learning architectures, particularly the GRU and Transformer models, which achieved the lowest prediction errors and highest explanatory power. These models are capable of capturing long-term dependencies and complex temporal relationships within climate data. Overall, the results demonstrate that integrating feature engineering with advanced machine learning techniques significantly improves the ability to analyze and forecast climate variability. The proposed framework provides a comprehensive approach for climate time-series modeling and highlights the potential of deep learning models for future climate prediction research. Future studies should consider incorporating additional climate variables, such as atmospheric carbon dioxide concentrations, precipitation patterns, and ocean temperature indicators, to further enhance the accuracy and reliability of climate forecasting models.

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