Analysis of temperature anomalies using machine learning, numerical methods and statistical techniques in global and Nepal datasets.

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Abstract: This study analyzes temperature anomalies to compare Nepal's local trends with global patterns using Berkeley Earth data. Techniques like regression, Gaussian fitting, interpolation, moving averages, Rossler attractors, and spiral graphs revealed cyclical and chaotic climate behaviors. Results show a strong link between Nepal's climate trends and global patterns, influenced by its unique geography and monsoon-driven climate. Attractor modeling provided new insights into underlying dynamics. The research highlights the importance of integrating local and global perspectives for understanding climate variability, offering valuable insights for regional adaptation and global climate policy, particularly for vulnerable regions like Nepal**.**

Keyword: Anomalies; Climate; Dynamics; Trends.

Introduction

Temperature anomalies, defined as deviations from long-term average temperatures, are key indicators of climate variability and change. They help distinguish between natural fluctuations and anthropogenic influences like greenhouse gas emissions[1]. By examining these deviations, patterns and trends shaping global and regional climates can be identified. This is particularly relevant for Nepal, where diverse climates from subtropical lowlands to alpine highlands result in localized impacts that differ from global trends[2]. This approach is particularly relevant for regions like Nepal, which exhibit diverse climatic conditions due to their unique topography. Ranging from subtropical lowlands to alpine highlands, Nepal's varied landscapes lead to localized climate impacts that can differ significantly from global trends. For instance, the Himalayan region is experiencing rapid glacial melt due to rising temperatures, affecting freshwater resources and Himalayan region is experiencing rapid glacial melt due to rising temperatures, affecting freshwater resources and increasing the risk of glacial lake outburst floods. Meanwhile, the Terai lowlands are witnessing more often increasing the risk of glacial lake outburst floods. Meanwhile, the Terai lowlands are witnessing more frequent and intense heatwaves, impacting agriculture and public health. Therefore, studying temperature anomalies is essential for understanding localized climatic changes in Nepal. It enables a more detailed examination of how different regions are responding to global warming, offering valuable insights for climate adaptation and mitigation strategies. The figure 1 below shows the trend of global temperature anomalies from 1880 to 2022. The upward trend indicates a consistent increase in temperature anomalies over the years, reflecting the impact of anthropogenic climate change.

Temperature anomalies

Temperature anomalies are calculated as the difference between observed temperatures and a reference baseline: Positive anomalies indicate warmer than average conditions while negative anomalies indicate cooler than average conditions[3]. Global anomalies provide a broad view of climate trends, whereas regional anomalies

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capture localized variations influenced by geographical features like altitude and mountain ranges. Figure 2 shows global and Nepal trends.

$$\text{Anomaly} = T_{\text{observed}} - T_{\text{baseline}}$$

Regression analysis

Regression analysis models the relationship between temperature anomalies and influencing factors, enabling trend prediction and impact assessment[4]. It helps understand how anomalies respond to variables like time and greenhouse gas concentrations[5].

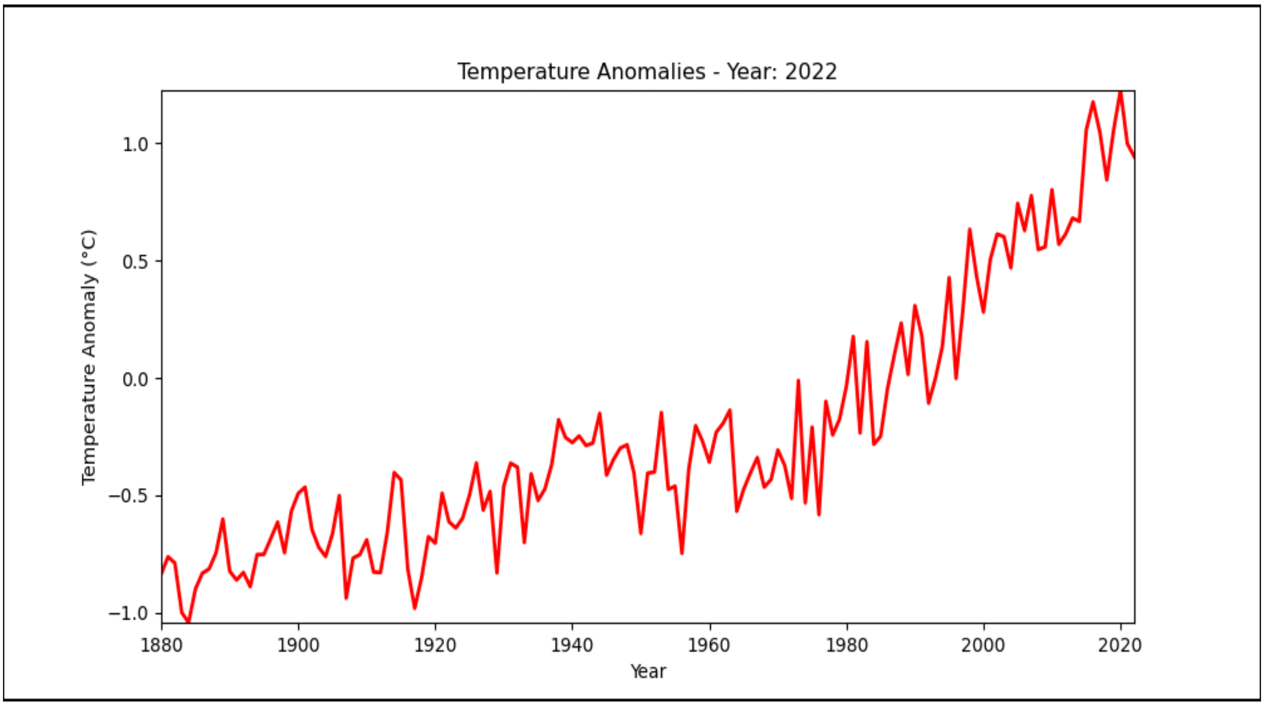


Figure 1: Global temperature increase over the years.

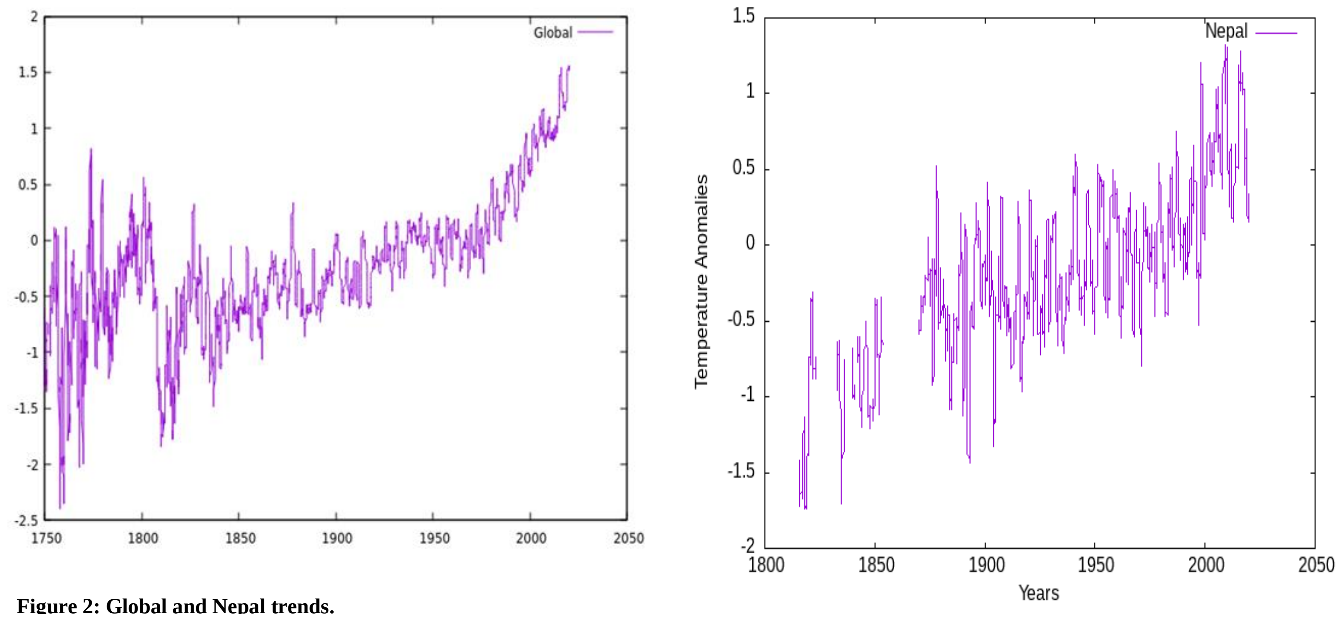


Figure 2: Global and Nepal trends.

Histogram and gaussian fit

Histograms and Gaussian fitting analyze the distribution of temperature anomalies, helping identify trends and extreme events[6]. Gaussian fitting estimates the mean μ and standard deviation σ to model the data's probability distribution.

Interpolation

Interpolation estimates intermediate values between known data points. Linear Interpolation assumes a straight line change between points

$$y(x) = y_1 + \frac{(x - x_1)}{(x_2 - x_1)} \cdot (y_2 - y_1)$$

Spline interpolation uses piecewise cubic polynomials for smoother transitions, ensuring continuity in value and derivatives[7].

The rossler attractor

The Rossler system models chaotic behavior using three nonlinear differential equations[8]:

$$\frac{dx}{dt} = -y - z,$$
$$\frac{dy}{dt} = x + ay,$$
$$\frac{dz}{dt} = b + z(x - c),$$

where a, b, c control system dynamics. Phase portraits and bifurcation analysis reveal transitions from periodic to chaotic behavior[9].

Moving averages

Moving averages smooth time series data, revealing trends and reducing noise[10].

Simple moving average (SMA) averages a fixed number of consecutive data points:

$$SMA_t = \frac{1}{N} \sum_{i=t-N+1}^{t} x_i$$

It eliminates random noise but may not capture rapid trend changes.

Spiral graphs

Spiral graphs visualize cyclical data, effectively showing seasonal or yearly temperature patterns[11]. Data points are plotted along a spiral curve:

$$r(\theta) = A + B\theta$$

where $r(\theta)$ is the radial distance, θ represents time, and A, B control the spiral's start and winding. This method highlights periodic cycles and long-term trends[12].

Discussion and Conclusion

Descriptive statistics

The descriptive statistics for both Nepal and Global datasets provide valuable insights into the temperature anomalies over time. These statistics summarize the distribution and central tendency of the data, which are

Table 1: Descriptive statistics of Nepal.

Count	2132
Mean	-0.187700
Std. Dev.	0.900619
Min	-4.261000
25%	-0.733250
Median (50%)	-0.167000
75%	0.369500
Max	4.056000

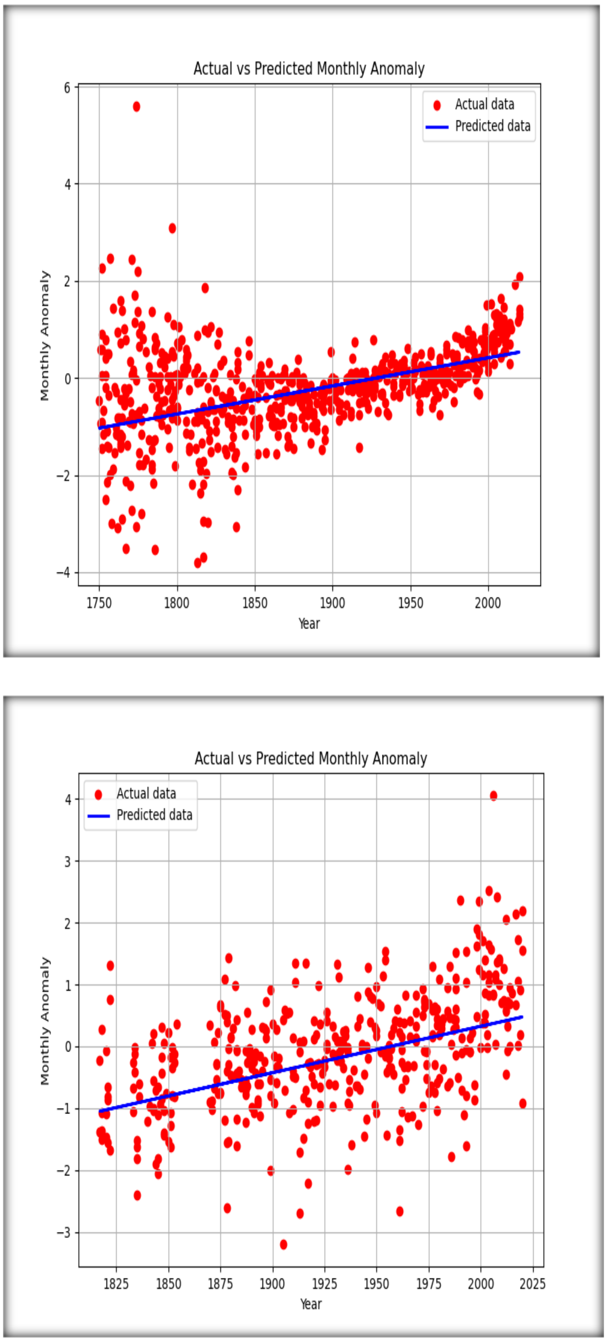


Figure 3: Regression: Global and Nepal monthly.

Table 2: Descriptive statistics of Global.

Count	3251
Mean	-0.235522
Std. Dev.	0.946474
Min	-5.988000
25%	-0.672000
Median (50%)	-0.166000
75%	0.245500
Max	5.599000

crucial for understanding the underlying trends and variations in temperature anomalies. Below Table 1 and Table 2 is a detailed summary of the key statistical measures for each dataset, highlighting the similarities and differences between Nepal and global trends

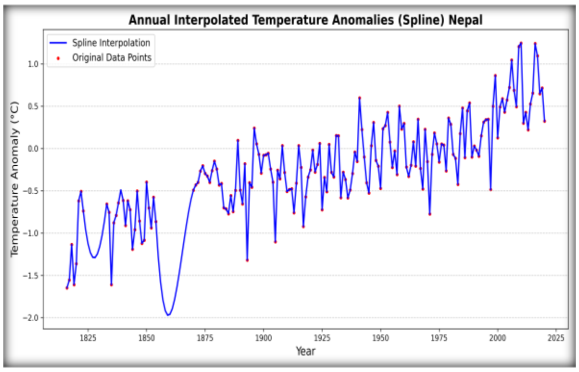
Modeling and predictions

Regression

Linear Regression estimator from sklearn.linear model is implemented to splitting the data for that the model is tested using the data Xtest and it generates the prediction throughout the datasets by displaying the predicted values[13].Training and Testing. Monthly Anomalies of Global and Nepal are plotted using Matplotlib library[13]shown in figure 3. The coefficient and intercept values are used to predict future temperature is

$$y = mx + b$$

For Global and Nepal, the values of the coefficient and intercepts are:



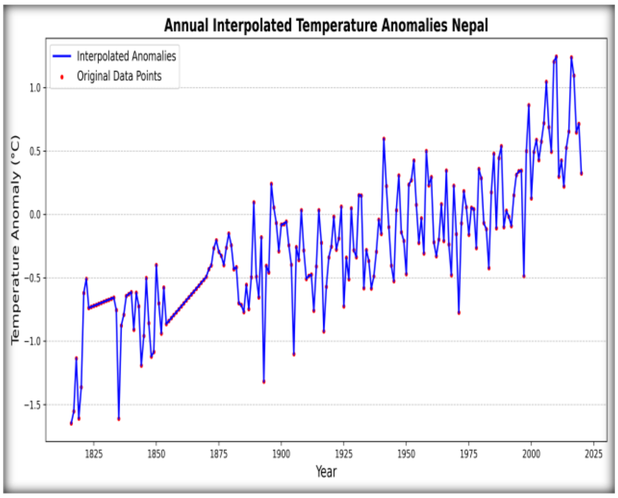


Figure 4: Linear and spline interpolation.

Global

Coefficient(Slope),m:0.01

Intercept, b: = -11.17

Nepal

Coefficient(Slope),m:0.01

Intercept, b: -14.68

Interpolation:Nepal

Nepal datasets have missing anomalies in various years. Linear interpolation and cubic spline technique is used to derive missing years anomalies[7].

The analysis of annual temperature anomalies in Nepal was conducted using two interpolation methods.

Global and Nepal predicted temperature anomalies

Global

Year: 2021	Predicted Anomaly: 0.54
Year: 2022	Predicted Anomaly: 0.54
Year: 2023	Predicted Anomaly: 0.55
Year: 2024	Predicted Anomaly: 0.55
Year: 2025	Predicted Anomaly: 0.56
Year: 2026	Predicted Anomaly: 0.56
Year: 2027	Predicted Anomaly: 0.57
Year: 2028	Predicted Anomaly: 0.58
Year: 2029	Predicted Anomaly: 0.58
Year:2030	Predicted Anomaly: 0.59

Nepal

Year: 2021	Predicted Anomaly: 0.48
Year: 2022	Predicted Anomaly: 0.49
Year: 2023	Predicted Anomaly: 0.50
Year: 2024	Predicted Anomaly: 0.50
Year: 2025	Predicted Anomaly: 0.51
Year: 2026	Predicted Anomaly: 0.52
Year: 2027	Predicted Anomaly: 0.53
Year: 2028	Predicted Anomaly: 0.53
Year: 2029	Predicted Anomaly: 0.54
Year: 2030	Predicted Anomaly: 0.55

linear interpolation and spline interpolation is dipic in fig 4. Both methods effectively reveal long-term trends in temperature anomalies from the early 19th century to the present.

The linear interpolation method connects the original data points with straight lines, resulting in a piecewise representation. The anomalies range from approximately $-1.5°C$ in the early 19th century to nearly $+1.0°C$ in recent years. Between 1825 and 1900, anomalies fluctuated predominantly between $-1.5°C$ and $-0.5°C$, indicating cooler periods. A gradual warming trend is observed from the early 20th century, with anomalies rising from $-0.5°C$ to $+0.5°C$ by the 1950s, and peaking at about $+1.0°C$ in the 2000s. However, this method introduces abrupt transitions between data points, which may oversimplify natural variability[14].

In contrast, spline interpolation generates a smooth curve, providing a more realistic representation of temperature trends. It captures significant negative anomalies in the early 19th century, reaching as low as $-2.0°C$, which are lower than those represented by the linear method. Between 1850 and 1900, anomalies remain within the range of $-1.5°C$ to $-0.5°C$, with smoother transitions. From 1900 to 1950, anomalies gradually increase from $-0.5°C$ to $+0.5°C$, followed by a consistent rise, peaking around $+1.0°C$ in recent decades. The smoothness of spline interpolation highlights finer details and gradual transitions, making it more suitable for climate studies.

Both methods confirm a significant warming trend in Nepal, with anomalies increasing from approximately $-2.0°C$ in the 19th century to $+1.0°C$ in the 21st century. These findings align with global warming patterns and emphasize the need for climate adaptation measures in Nepal to address the impacts of rising temperatures.

Histogram and gaussian fit

The histogram is plotted with the number of bin counts 20. The histogram shows the distribution of temperature anomalies $°C$. A red curve represents a Gaussian (normal) distribution fit to the data.

Global

The Gaussian fit is annotated with the mean ($\mu = -0.24$) and standard deviation ($\sigma = 0.95$). is shown in Fig 5 where Gaussian fit is done on histogram.

Nepal

The Gaussian fit is annotated with the mean ($\mu = -0.19$) and standard deviation ($\sigma = 0.90$).

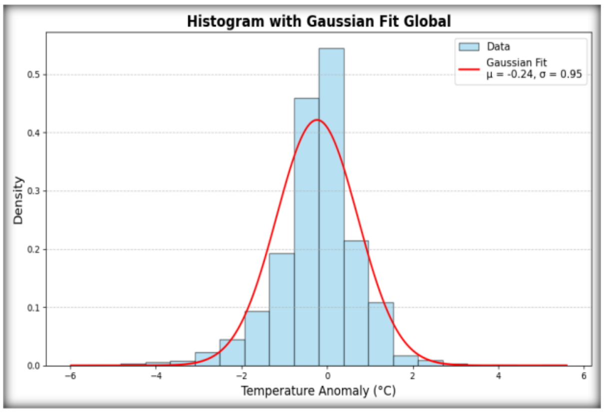


Figure 5: Histogram and gaussian fit: Global.

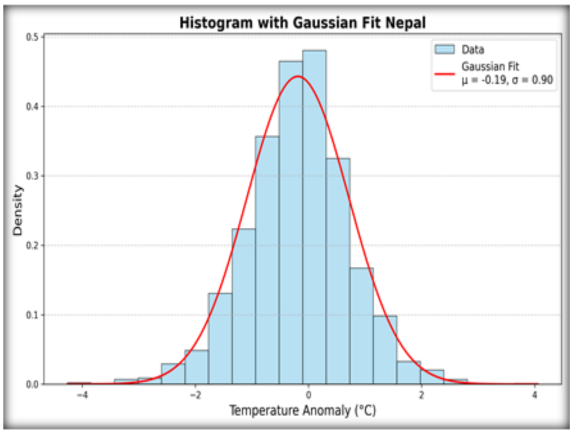


Figure 6: Histogram and gaussian fit: Nepal.

Moving average: Global and Nepal

The graphs represent temperature anomalies over time, with one focusing on global trends and the other on Nepal trends. In Graph, the Xaxis depicts the year span and the Yaxis depicts deviations from the baseline temperature, with positive values (yellow) indicating warmer years and negative values (blue) indicating cooler years. Nepal trends have more fluctuation than Global trends.

Non-linear dynamics and chaos in temperature data

Rossler system explored the chaotic attractor using the parameter values $a = 0.1$, $b = 0.1$, and $c = 14$ for stability graph analysis. Bifurcation graph is examined through topological analysis, focusing on $b = 2$, $c = 4$, with a selected as the bifurcation parameter[8]in Global and Nepal system.

Global

Stability analysis Graph

The stability graph figure 8 Global consists of five vertically aligned subplots, each representing the Rossler attractor in phase space ($x(t)$ vs. $y(t+\tau)$)

The variation in the parameter c is depicted across the subplots with the following values: $c = 4.0$, $c = 6.0$, $c = 8.5$, $c = 12.0$, and $c = 15.0$

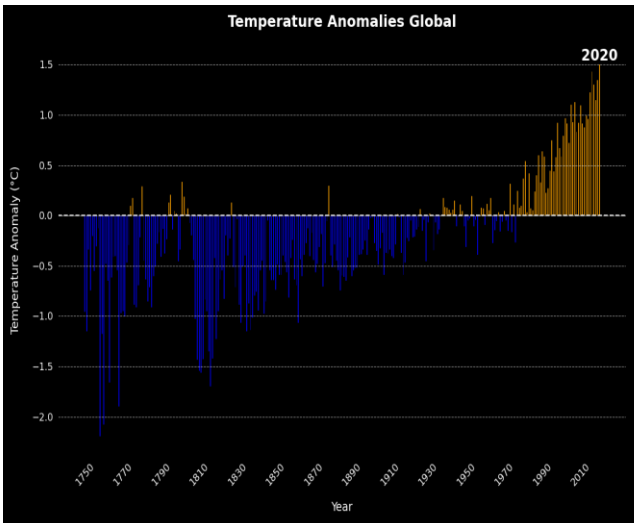
Observation

1. For lower values of c, the trajectories form tight, elliptical spirals, indicating more stable behavior

2. As c increases, the trajectories expand, reflecting increased complexity or divergence in the dynamics. Global system is more stable attractor due to the large scale averaging.

Bifurcation diagrams

- The figure 9 contains ten panels arranged in a 2x5 grid, each showing the attractor in phase space (x vs. y).
- The parameter c increases across the panels with the following values: $c = 4.0$, $c = 5.6$, $c = 7.1$, $c = 8.7$, $c = 10.2$, $c = 11.8$, $c = 13.3$, $c = 14.9$, $c = 16.4$, and$c = 18.0$.



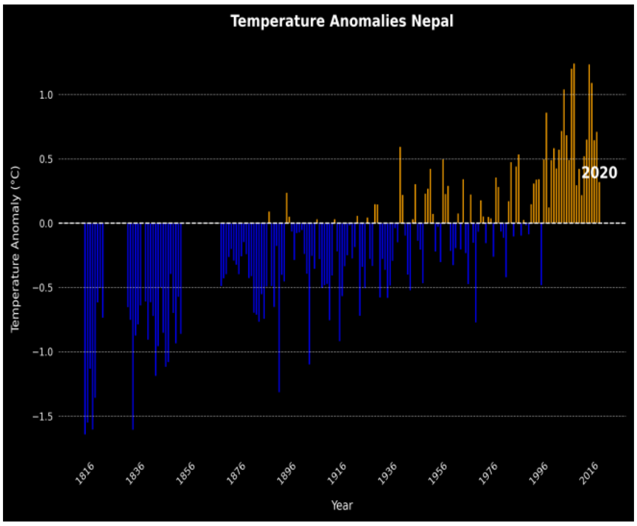


Figure 7: Moving average: Global and Nepal.

Observation

- Similar to the first graph, lower c values result in tightly coiled spirals, indicating regular dynamics.
- As c increases, the system transitions to more complex patterns, suggesting a progression toward chaotic dynamics.Global system is more stable than Nepal counterpart[16].

Nepal

Stability analysis Graph

- The figure 10 consists of five vertically aligned subplots, each representing the Rossler attractor[17] in phase space ($x(t)$ vs. $y(t+\tau)$). as describe in Global system.
- The variation in the parameter c is depicted across the subplots with the following values: $c = 4.0$, $c = 6.0$, $c = 8.5$, $c = 12.0$, and $c = 15.0$.

Observation

- For lower values of c, the trajectories form tight, elliptical spirals, indicating more stable behavior.

  As c increases, the trajectories expand, reflecting increased complexity or divergence in the dynamics. The spread of trajectories in the Nepal dataset is smaller in magnitude compared to the Global dataset

Bifurcation diagrams

- The figure 11 contains ten panels arranged in a 2x5 grid, each showing the attractor[18] in phase space (x vs. y) like global system.

- The parameter c increases across the panels with the following values: $c = 4.0$, $c = 5.6$, $c = 7.1$, $c = 8.7$, $c = 10.2$, $c = 11.8$, $c = 13.3$, $c = 14.9$, $c = 16.4$, and $c = 18.0$.

Observations

- Similar to the first graph, lower c values result in tightly coiled spirals, indicating regular dynamics.
- As c increases, the system transitions to more complex patterns, suggesting a progression toward chaotic Nepal datasets exhibit more localized fluctuations

Implications for climate change

The results of this study suggest that both global and Nepal temperatures are experiencing significant warming. The faster rate of warming observed in Nepal highlights the importance of considering local climatic factors when addressing climate change. The chaotic nature of the temperature anomaly data underscores the challenge of making precise long-term climate predictions. However, the increasing trends in temperature anomalies across both global and Nepal datasets provide strong evidence that climate change is an ongoing and pressing issue, which calls for urgent action in mitigation and adaptation strategies[19] .

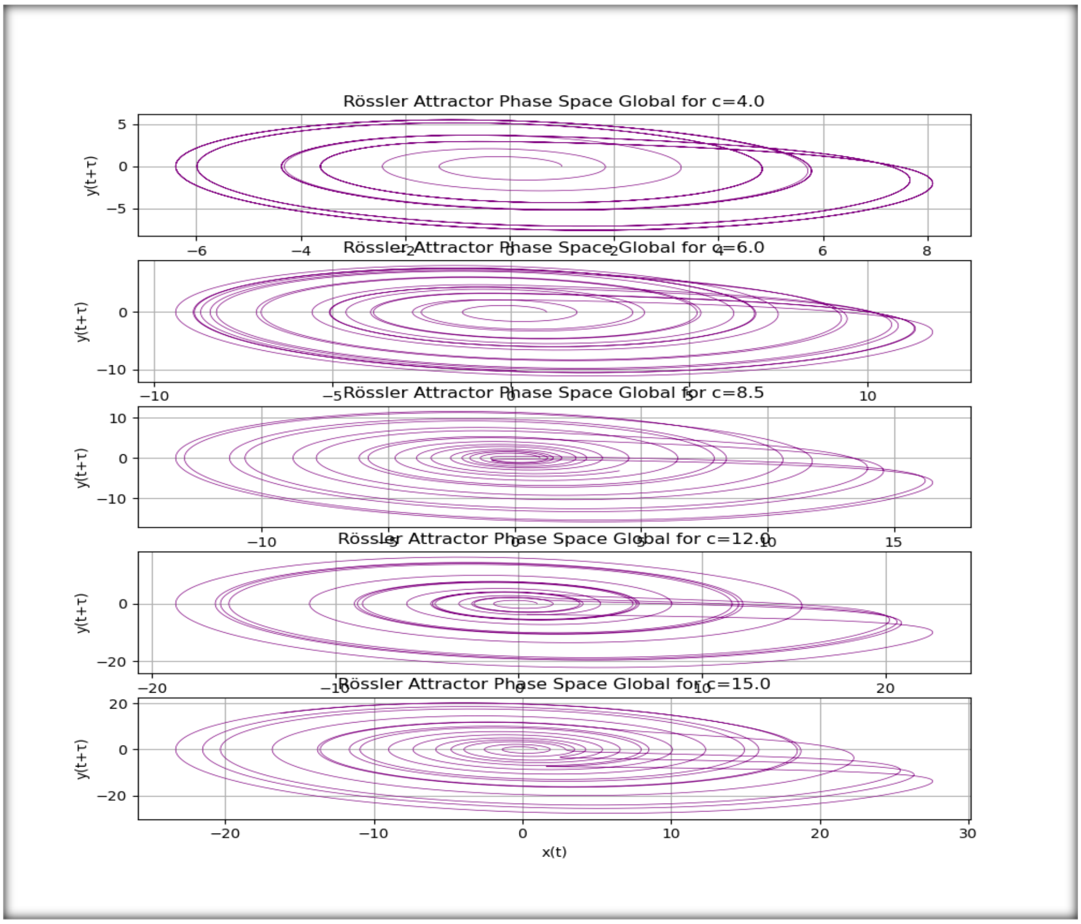


Figure 8: Stability graph: Global.

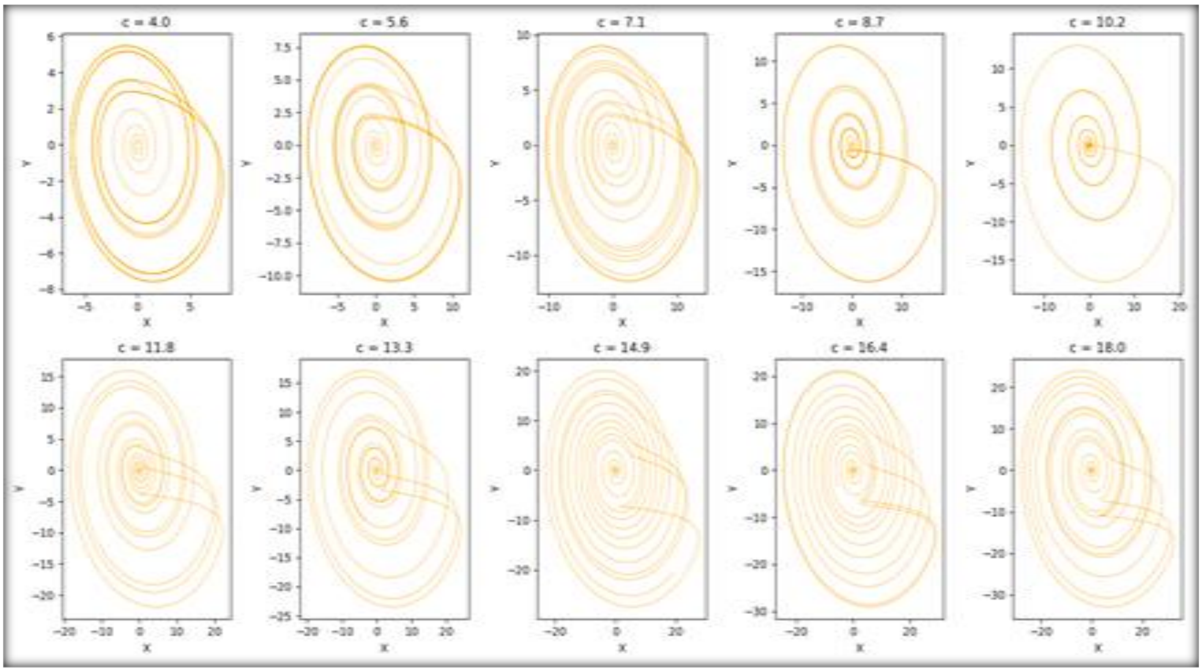


Figure 9: Bifurcation diagrams: Global.

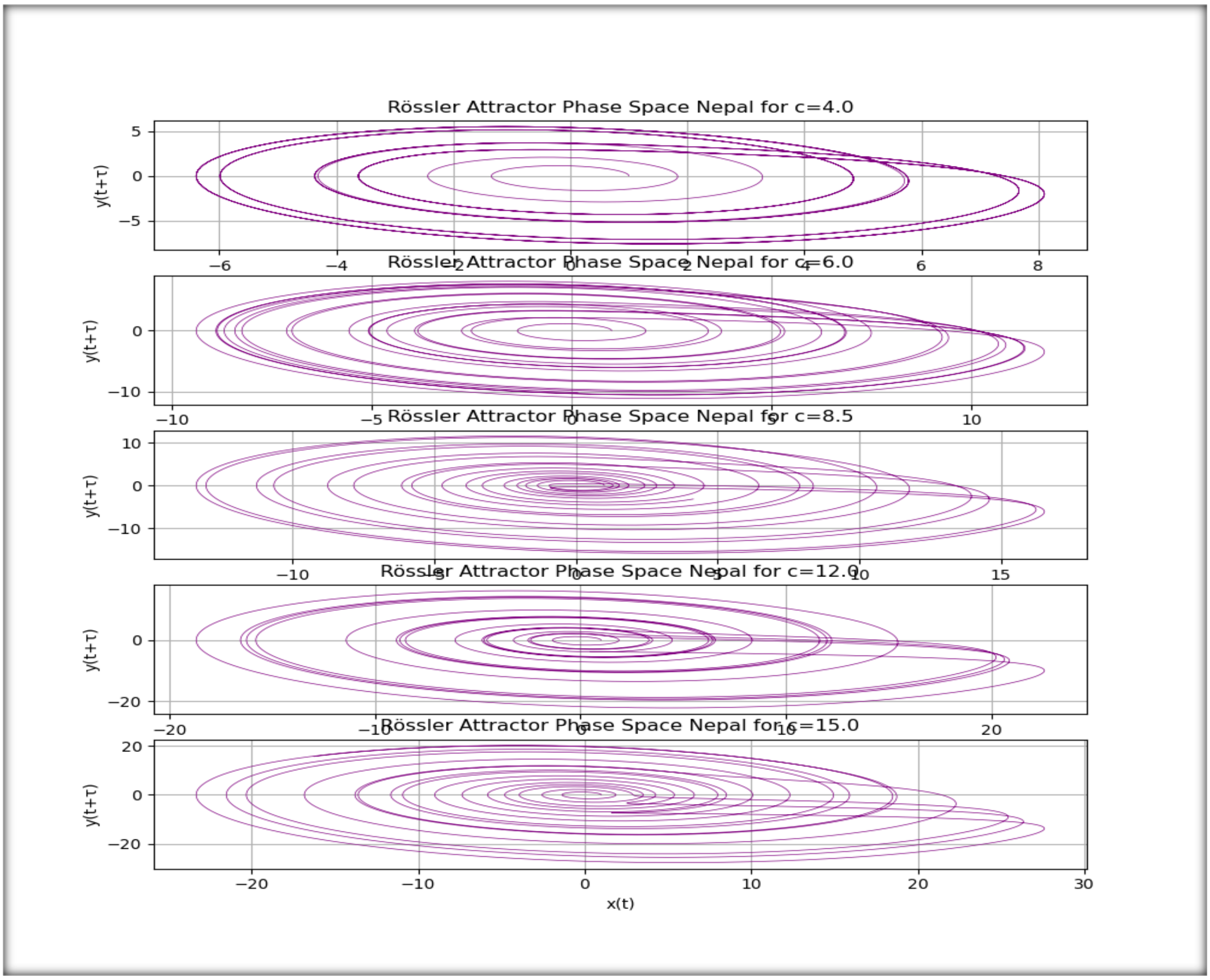


Figure 10: Stability graph : Nepal.

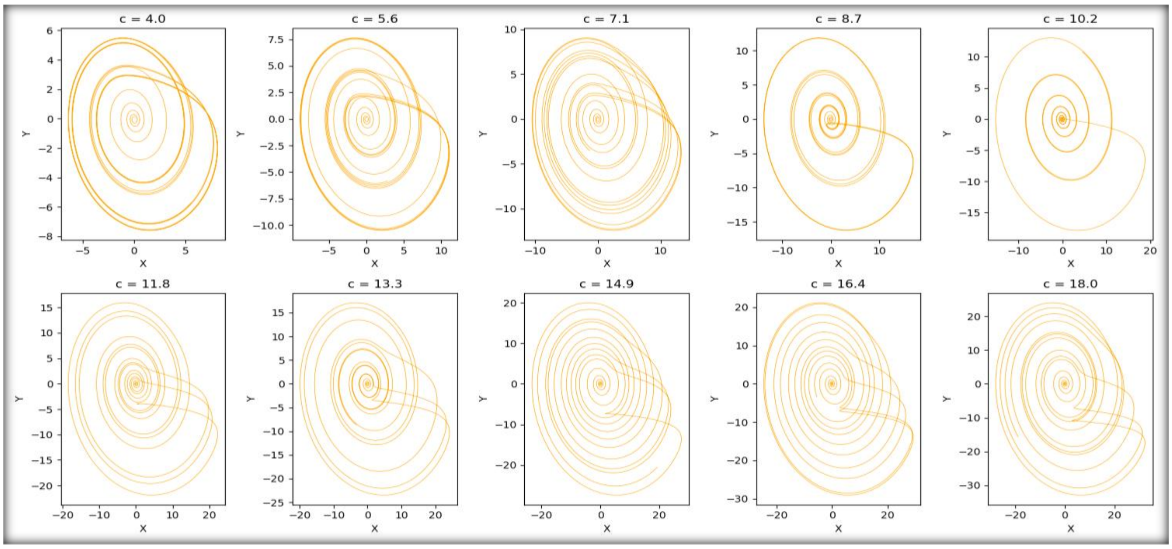


Figure 11: Bifurcation diagrams: Nepal.

For perspective, the spiral graph of Global temperature anomalies is plotted in Fig 12 using the matplotlib's function animation. The spiral grows outward from the center, with months distributed radially around the circle. The years are displayed in the center, and temperature anomalies are plotted relative to a baseline (often 0C).

Spiral graph observations

- **Year Annotation:** The year is prominently displayed at the center, indicating the data's progression over time.
- **Threshold markers:** Red and yellow dashed circles likely mark significant thresholds, such as 1.5C and 2C, associated with global warming targets.

Conclusion

Using Berkeley Earth as the primary data source, this study presents a comprehensive analysis of temperature anomalies, comparing Nepal's local trends with global patterns. Advanced analytical techniques—including regression analysis, Gaussian-fitted histograms, linear and spline interpolation,moving averages, Rossler attractor modeling, and spiral graph visualization were employed to capturethe complexity of climate variations.

The findings reveal a persistent rise in temperature anomalies, aligning with recent global studies[20] (e.g., Cheng et al., 2017; Rashed & Hafez, 2022; Hwang et al., 2020).

Key insights from this study indicate

- A statistically significant warming trend, with Nepal experiencing similar anomaly patterns as global datasets.
- Nonlinear regression models and Rossler attractor analysis highlight chaotic but predictable fluctuations in climate behavior

- Spiral graph visualizations demonstrate an accelerating rise in temperature anomalies over the decades.

Comparing our results with recent literature, we find strong agreement with global oceanic warming trends (Cheng et al., 2017) and increasing regional temperature variations linked to anthropogenic influences[21] (Rashed & Hafez, 2022). Furthermore, our findings align with Hwang et al. (2020), emphasizing the role of urbanization and land-use changes in amplifying local temperature anomalies.The global impact of rising temperature anomalies is profound, contributing to more frequent and severe climate-related disasters such as heat waves, floods, , and glacier melt, which have direct consequences for Nepal's fragile ecosystem. Additionally, health risks associated with prolonged heat exposure, vector-borne diseases, and food security challenges necessitate urgent mitigation strategies. This study underscores the importance of integrating advanced numerical techniques with climate modeling to better inform adaptation policies and sustainable development efforts, particularly in climate-sensitive regions like Nepal.

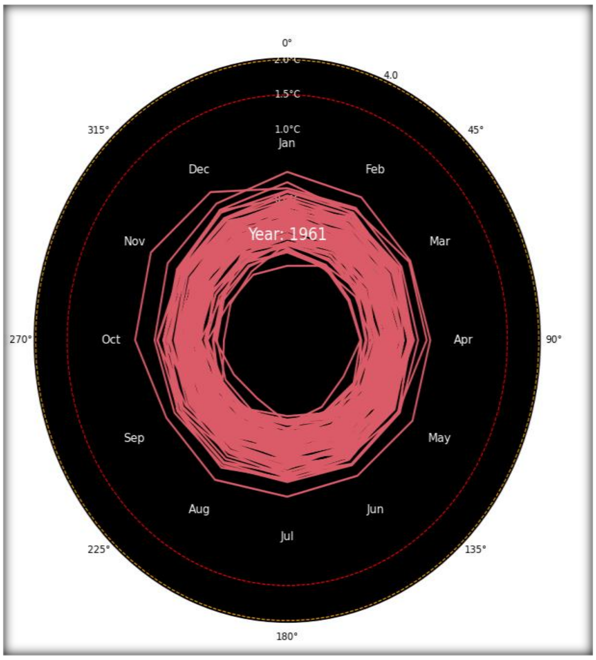


Figure 12: Spiral graph.

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