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FROM TEMPERATURE ANOMALIES TO EL NIÑO - USING MACHINE LEARNING TO PREDICT EL NIÑO INDEX

ABSTRACT

This presentation explores the intersection of climate science and machine learning by analyzing global temperature anomalies and predicting El Niño events. The primary objective is to study long-term trends and patterns in global temperature anomalies to better understand the shifts occurring in Earth's climate system.

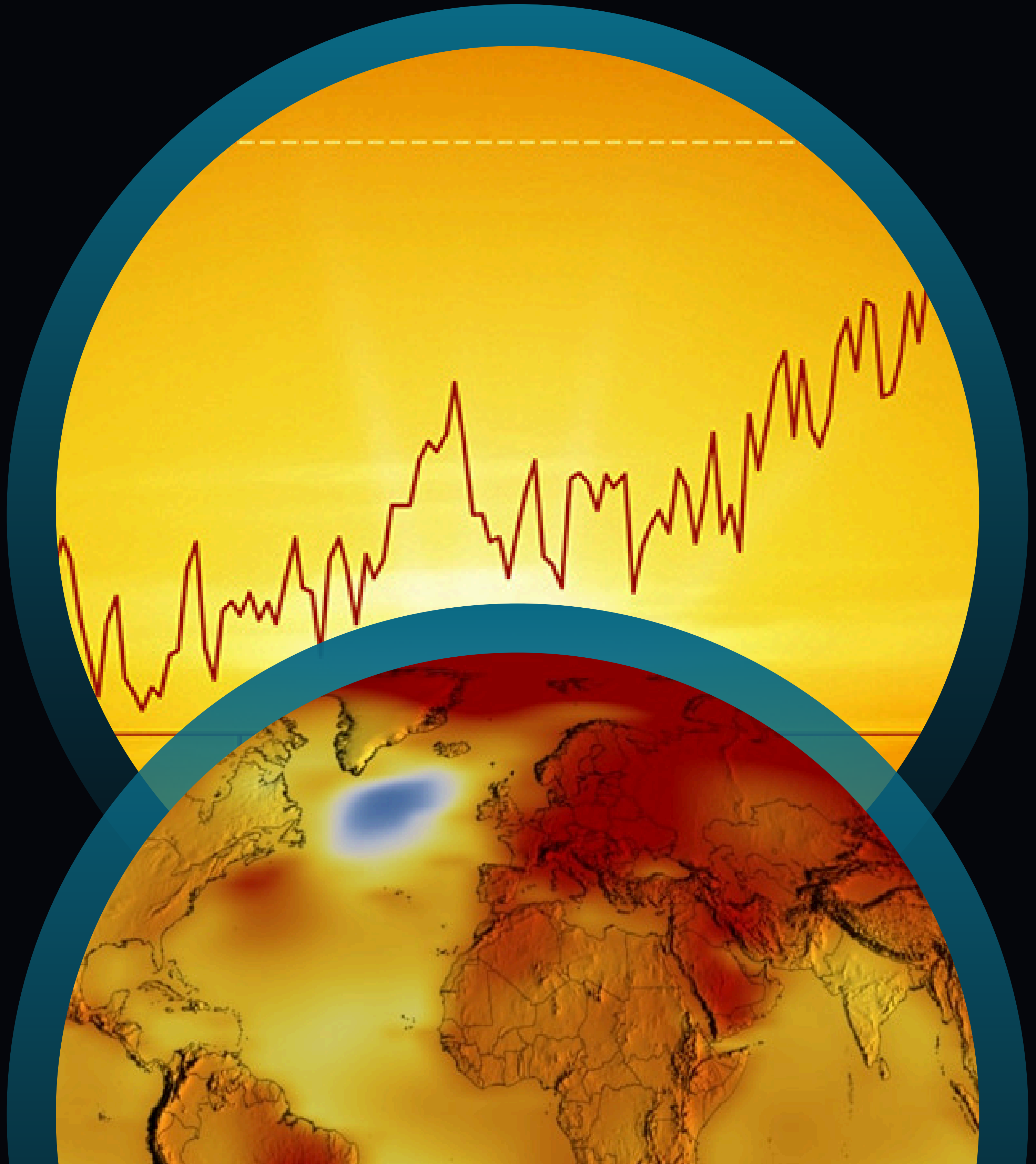
Building on this analysis, we apply machine learning techniques to forecast the El Niño Southern Oscillation (ENSO) by predicting the El Niño index. Our approach combines data-driven insights with predictive modeling to contribute to early warning systems and improved climate forecasting.

WHY STUDY GLOBAL TEMPERATURE ANOMALIES ?

- **WHAT ARE TEMPERATURE ANOMALIES ?**

  Temperature anomalies are deviations from a baseline or reference temperature; usually the average temperature over a specific time period.

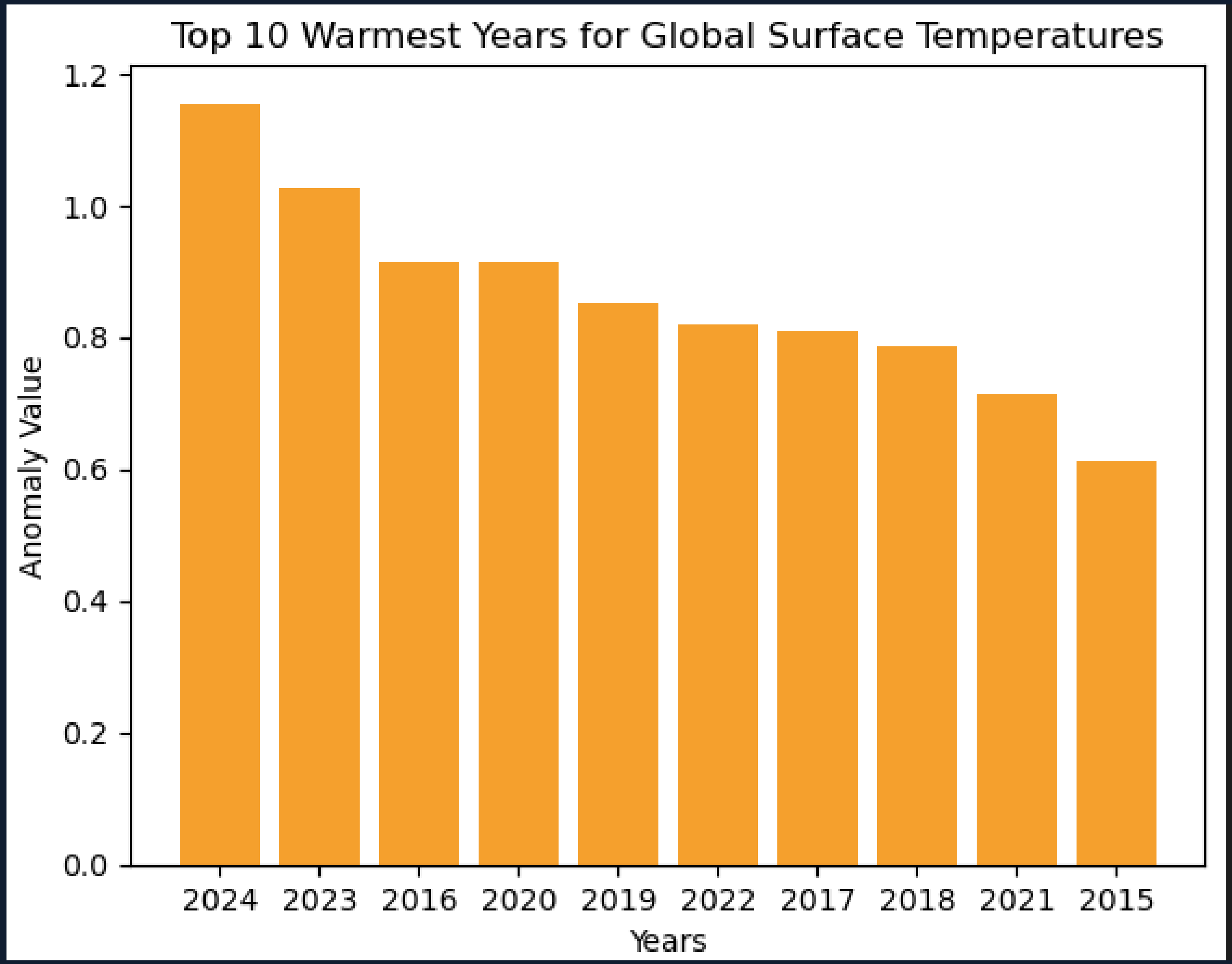
- **WHY ARE ANOMALIES IMPORTANT ?**
  - **Climate change indicator** - Temperature anomalies reveal long term climate trends and deviations from historical norms
  - **Predictive power** - Anomalies helps improve weather forecasting , agricultural planning , and disaster preparedness
  - **Scientific Foundation** - Temperature anomalies are fundamental to climate science research

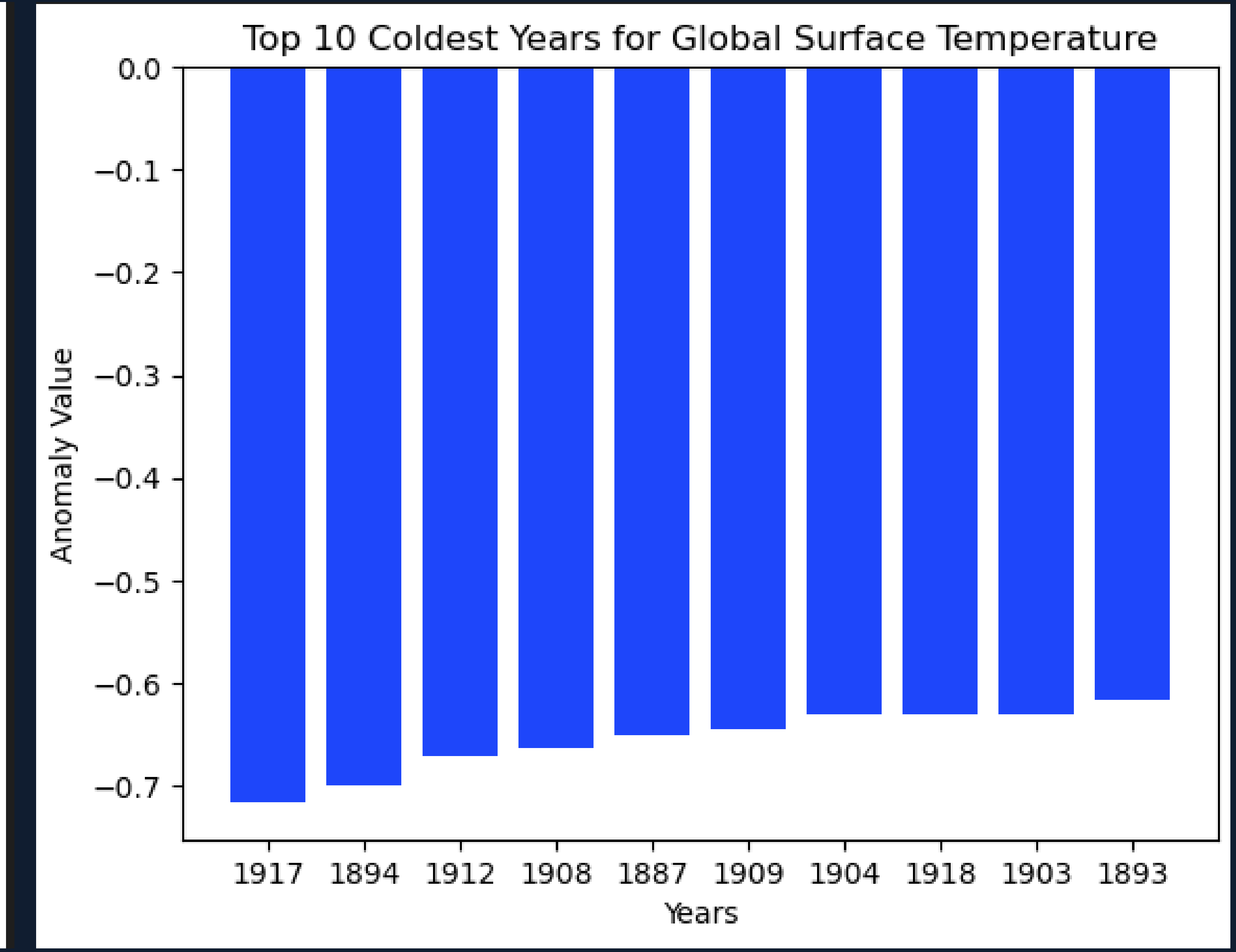


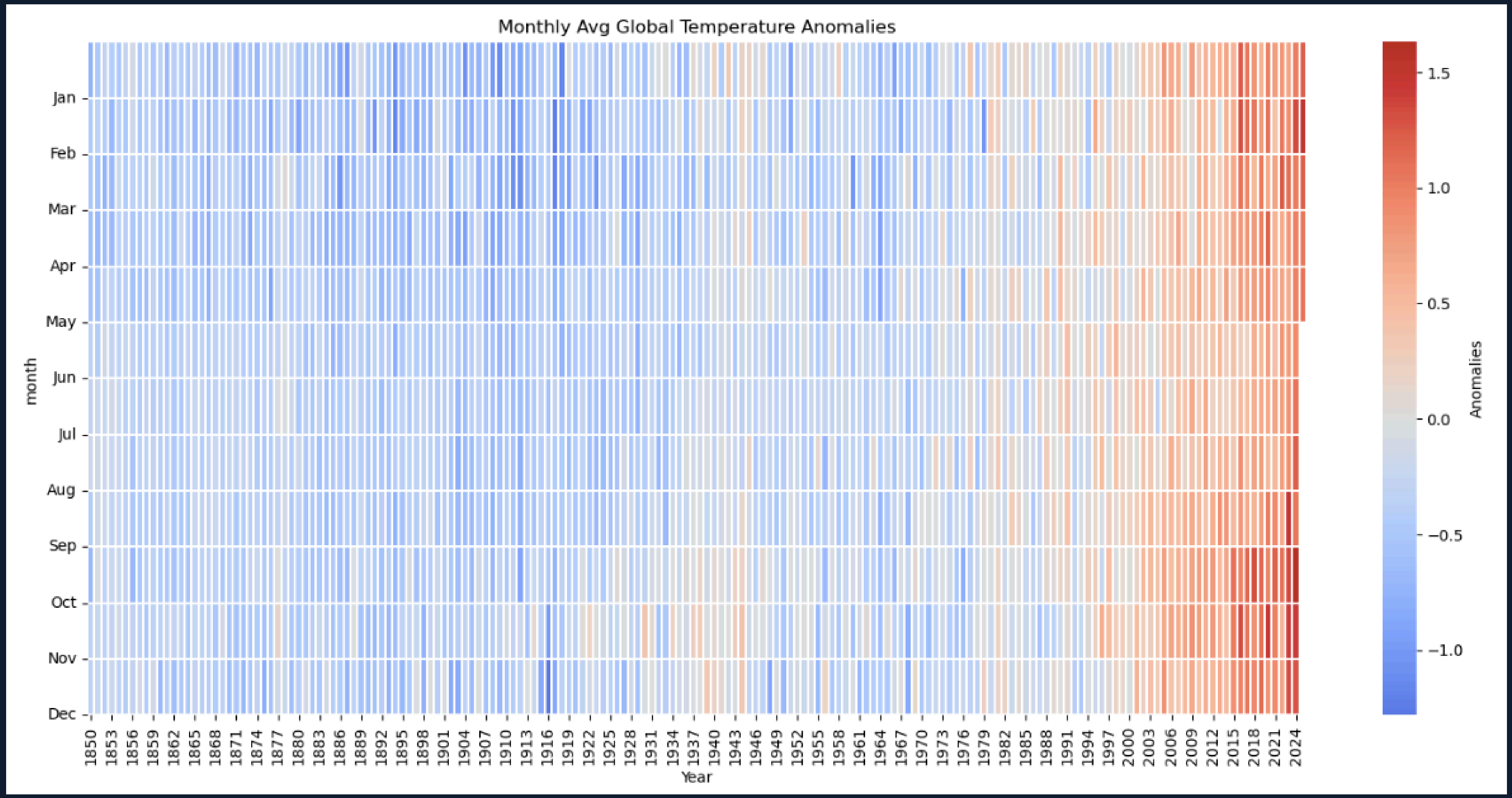
METHODOLOGY: VISUALIZING TEMPORAL DYNAMICS

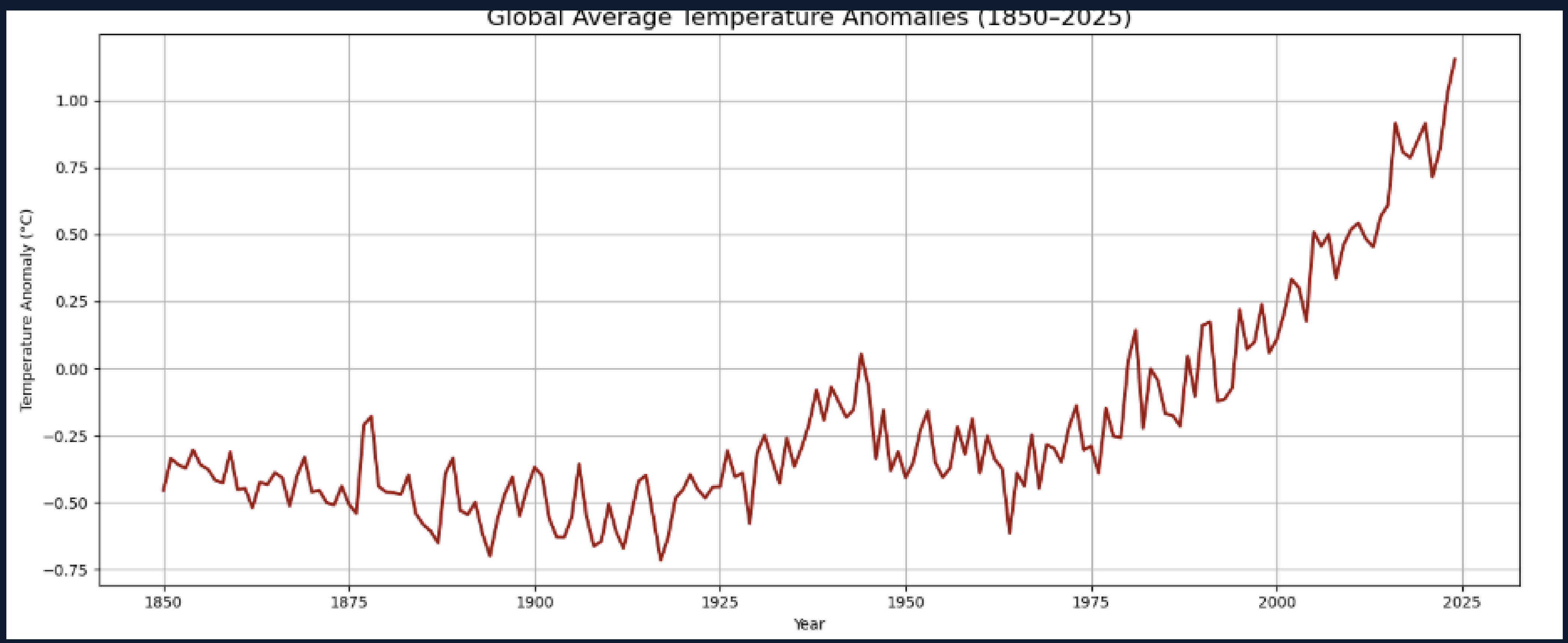
- **EXTREME EVENT IDENTIFICATION**

To quantify the most significant anomalies, we systematically **ranked all anomaly values to identify the top 10 warmest and top 10 coldest years within the dataset**. A notable finding was **the concentrated occurrence of warmest years within recent decades, underscoring the rapid progression of global warming.**









Methodology: Visualizing Temporal Dynamics

Raw Data Plotting

We began by plotting raw annual and monthly temperature anomaly data to illustrate short-term fluctuations and long-term shifts. This initial visualization clearly delineated a period of relative climatic stability prior to the mid-20th century, followed by a pronounced and accelerating warming trend evident from the 1970s onwards.

SMOOTHING FOR TREND ANALYSIS

To effectively distinguish underlying long-term climate trends and annual variability, we employed three distinct data smoothing techniques:

MOVING AVERAGE

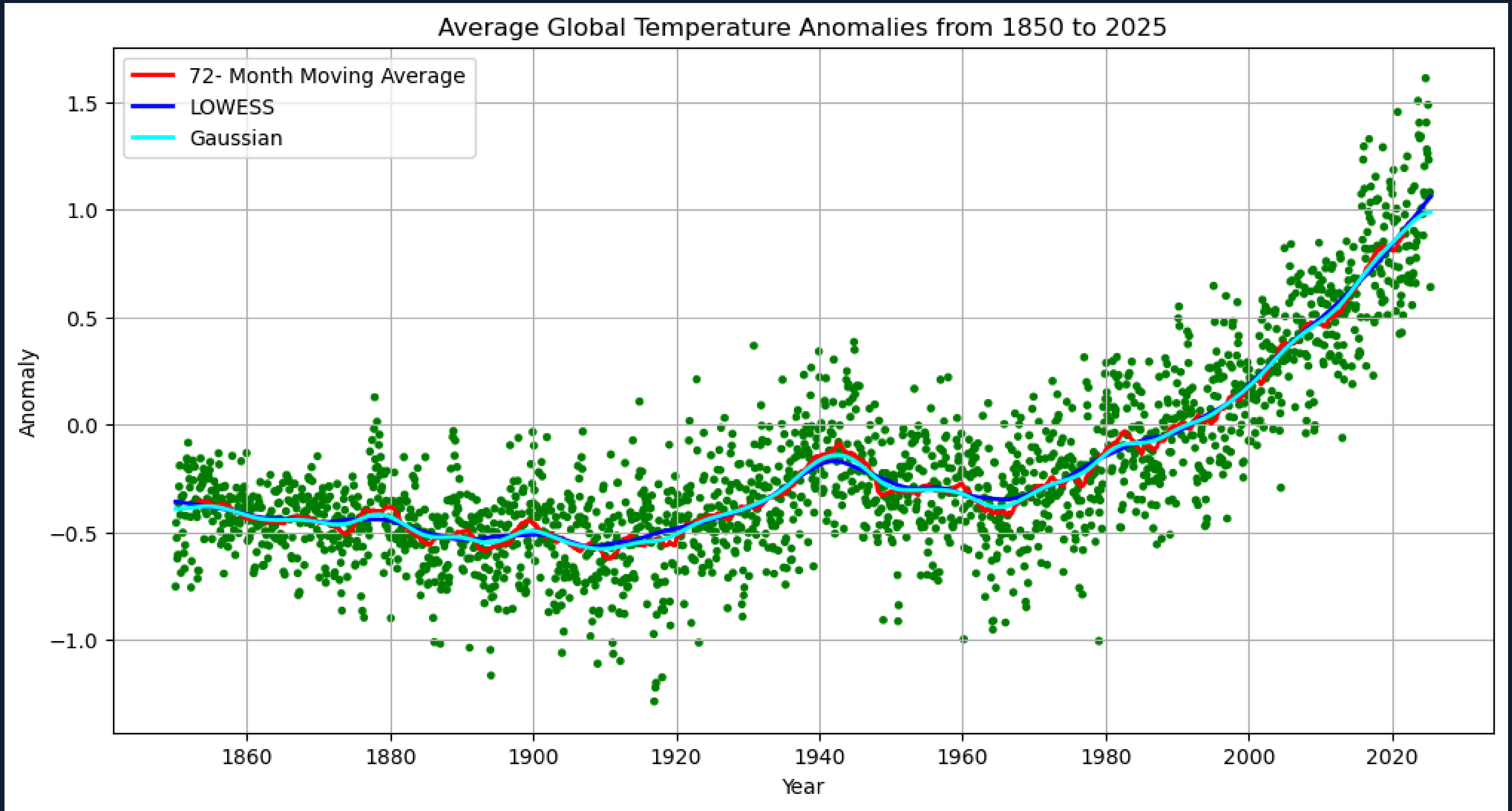
Averaging anomaly values over fixed temporal windows (70-month periods) to highlight patterns and dampen high-frequency oscillations.

GAUSSAIN SMOOTHING

Applying a Gaussian kernel to assign weighted averages, giving more emphasis to data points closer to the central value, thus providing a smoother, more continuous representation of the trend. (Sigma = 36)

LOWESS (LOCALLY WEIGHTED SCATTERPLOT SMOOTHING)

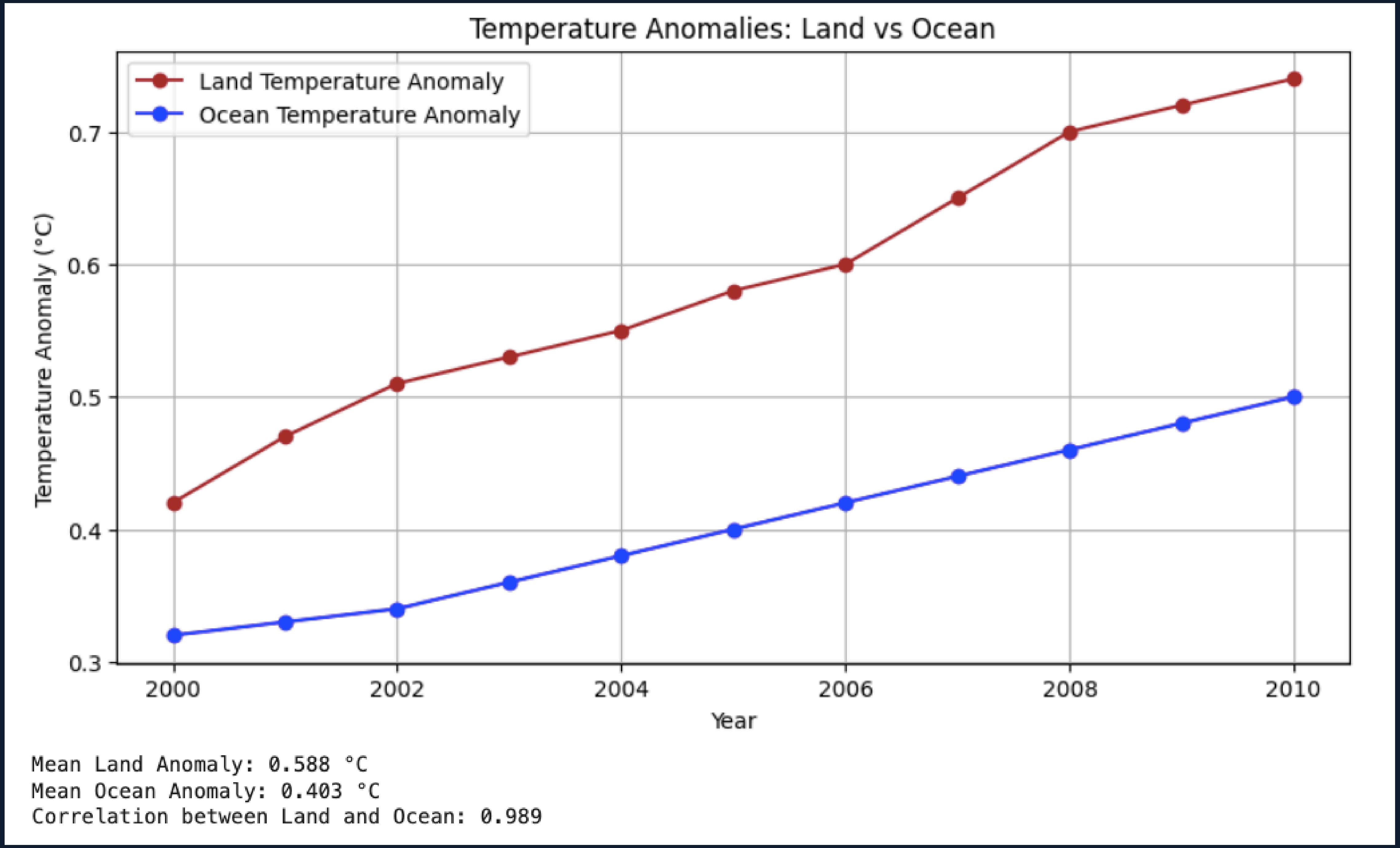
A non-parametric regression method that fits local polynomial models to subsets of the data. This approach offers enhanced flexibility in trend detection, particularly useful for non-linear progressions, by adapting to local data structures. (LOWESS = 0.1)



This graph reveals Earth's rising temperature trend since 1850. Smoothing methods cut through natural noise to expose a clear, accelerating warming pattern—driven by human activity. The post-1975 spike leaves no doubt: climate change is here.

Gaussian and LOWESS methods smooth the trend better than the Moving Average Method

Methodology: Geophysical Differentiations



Ocean vs. Land Comparison: The NOAA dataset was further bifurcated into land and ocean components to facilitate a comparative analysis of anomaly trends. This revealed that land areas consistently exhibited greater temperature variability and more extreme anomalies compared to oceanic regions, a finding attributed to the significantly lower heat capacity of terrestrial surfaces relative to large bodies of water.

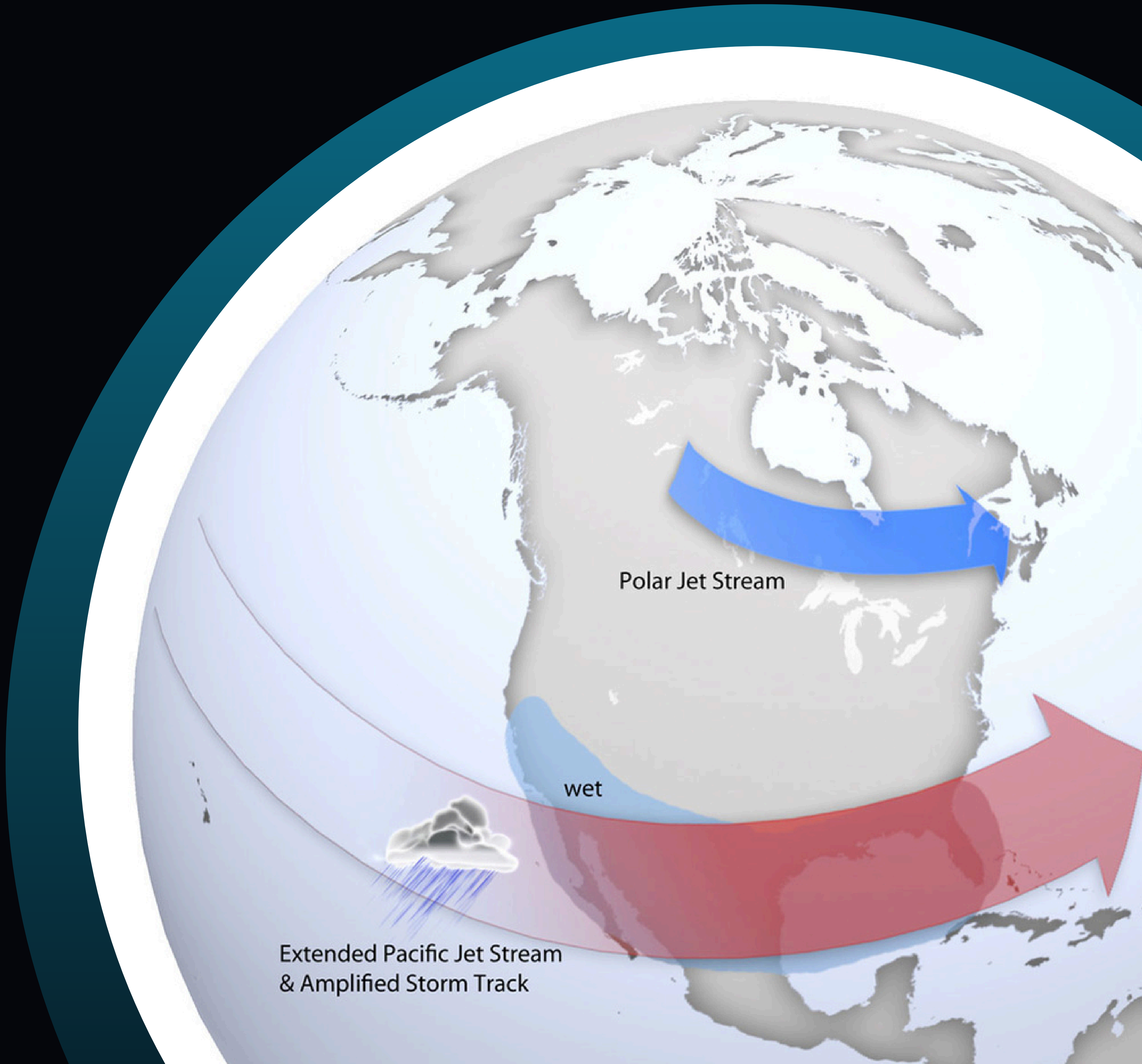
UNDERSTANDING EL NIÑO & ENSO

What is ENSO ?

- El Niño - Southern Oscillation - climate pattern in the - Pacific Ocean.
- Irregular cycle occurring every 2-7 years
- Most influential climate science phenomenon affecting global weather patterns

The Three Phases:

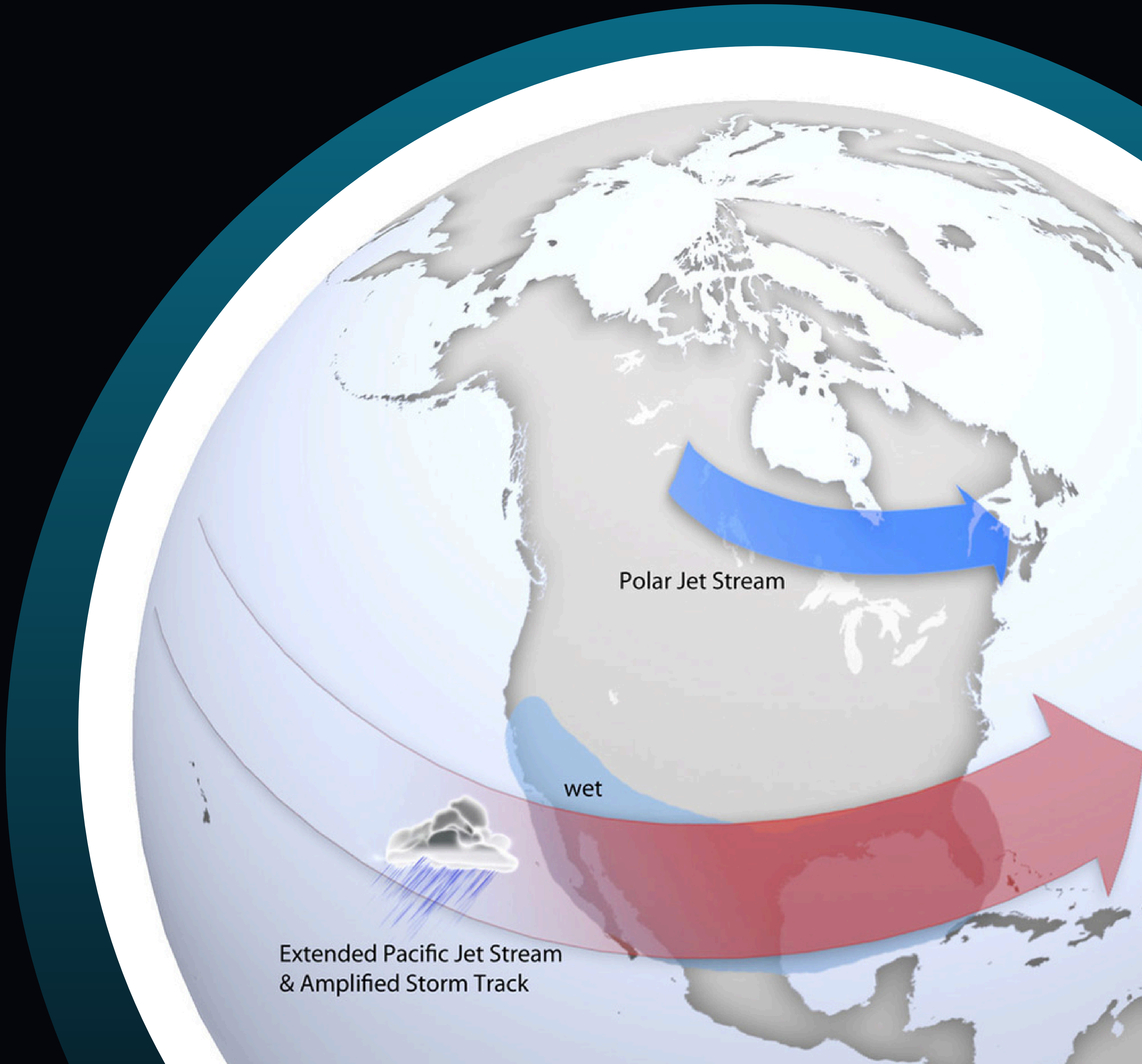
- **El Niño - Warming phase (warmer than normal sea surface temperatures)**
- **La Niña - Cooling phase (cooler than normal sea surface temperatures)**
- **Neutral - Normal conditions**



UNDERSTANDING EL NIÑO & ENSO

El Niño 3.4 Index - Our focus:

- **Geographic Region**: Central tropical Pacific (5°N-5°S, 170°W-120°W)
- **What it measures**: Sea Surface Temperature (SST) anomalies in this region
- **Why this region**: Best represents the core of ENSO variability
- **Calculation**: 3-month running mean of SST anomalies from 30-year baseline



El Niño Prediction

Preprocessing and Methology

- Using ENSO indices (SOI, Niño 3.4 anomalies), global temperature anomaly data, and additional predictors like sea surface temperatures and atmospheric variables
- **Three inputs used**: SST-only, global anomaly-only, combined data with SST and global anomalies

3 Neural Network Models:

Convolutional Neural Network (CNN)

CNNs are great at recognizing spacial-temporal patterns and are generally faster to train and scalable.

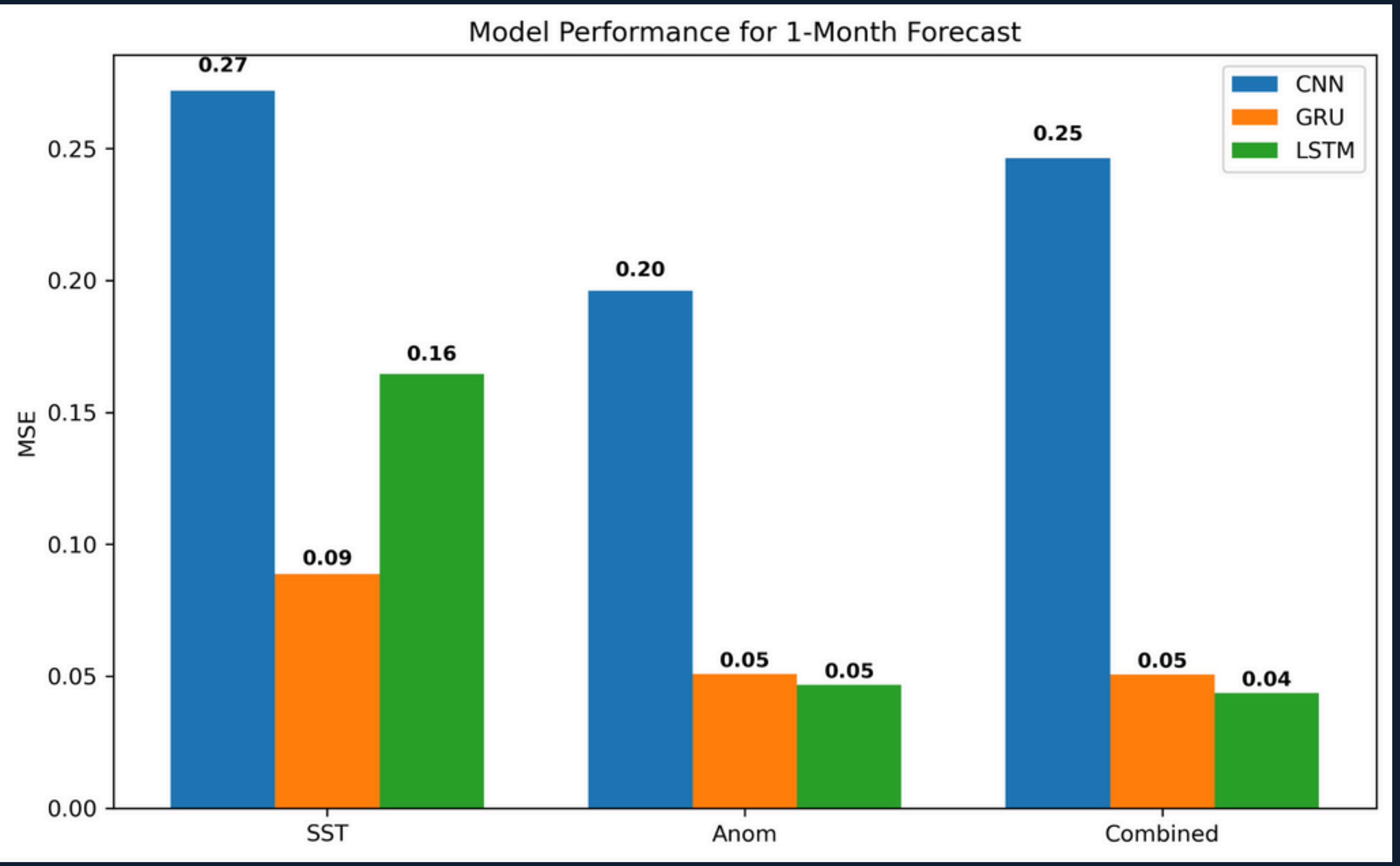
Long-Short-Term Memory Neural Network (LSTM)

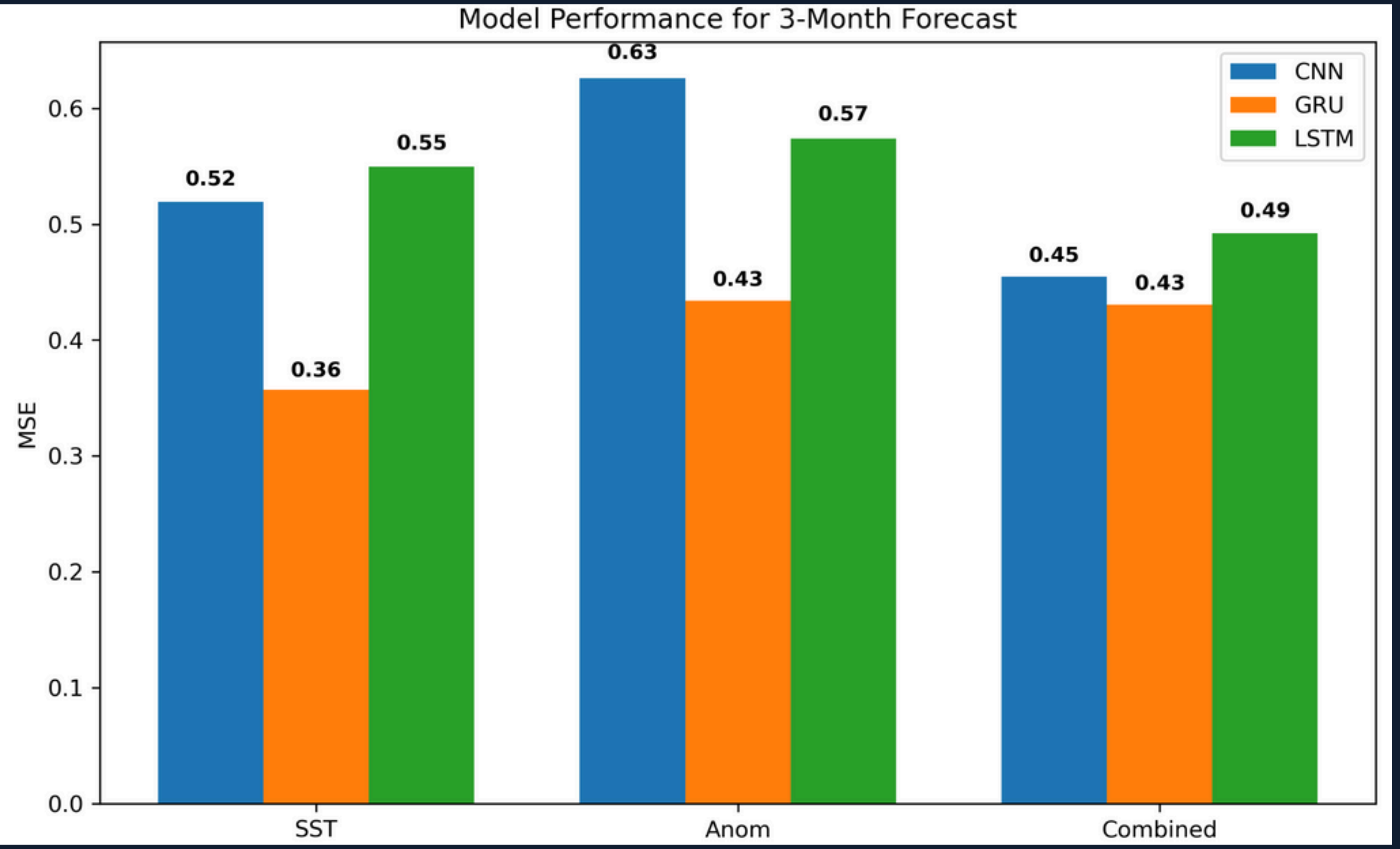
LSTM is well-suited for this task because it captures long-term dependencies in sequential data, making it effective for predicting climate patterns like El Nino, which evolve over months or years

Gated Recurrent Units (GRUs)

GRUs are great at recognizing temporal dependencies as well and handle vanishing gradients better. It also offers a more efficient alternative than employing an LSTM model.

RESULTS





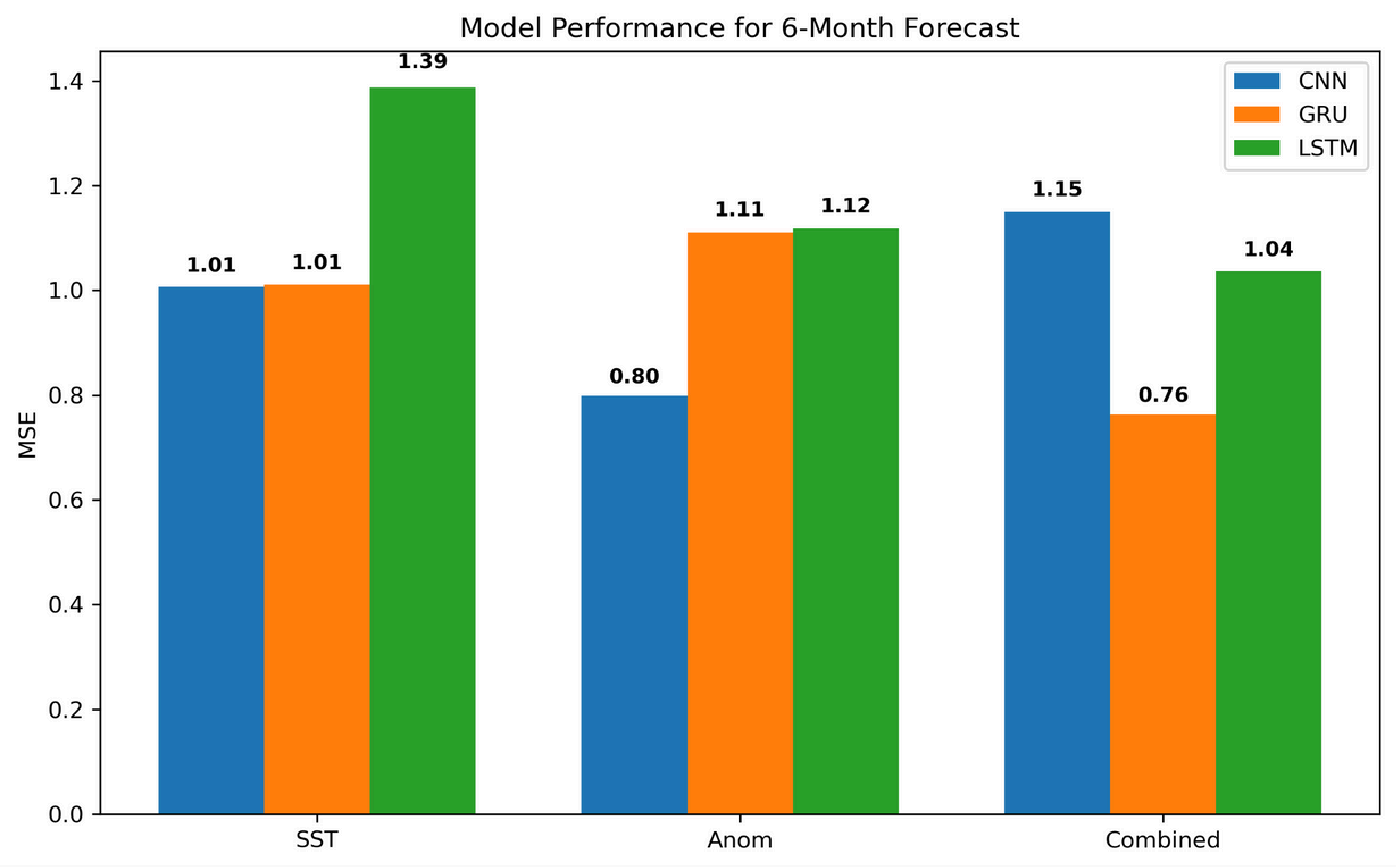
1 Month Forecast

- Shows least amount of errors across all 3 horizons
- **Best performance**: **LSTM** model on **combined** dataset (MSE = 0.04)

3 Month Forecast

- More errors begin to occur, showing decline in performance
- **Best performance**: **GRU** model on **SST** dataset (MSE = 0.36)

RESULTS



6 Month Forecast

- As the horizons increased to 6 months, errors increased substantially.
- **Best performance**: The **GRU** model with the **combined** dataset produced the most accurate results (MSE = 0.76)

KEY OBSERVATIONS

1

Accelerated Historical Warming

A unequivocal **warming trend emerged post-mid-20th century,** with global **anomalies consistently positive since the 1980s**, signaling a rapid shift in baseline temperatures.

2

Concentration of Extreme Warm Years

Analysis showed **coldest anomalies predominantly in the late 19th century**, while the **warmest years were heavily clustered after 2010**, indicating a recent intensification of warming.

3

El Niño Prediction with Neural Networks

Based on the model performance for El Niño, **combined datasets** that included SOI, SST, and global anomaly data **consistently improved forecast accuracy** compared to others. **LSTM and GRU models both outperformed CNN** approach at all horizons

CONCLUSION

Our internship research project demonstrates the transformative potential of integrating advanced machine learning methodologies with robust climate datasets for enhanced analysis and forecasting of El Nino events.

By systematically visualizing historical trends, precisely identifying extreme events, and applying machine learning techniques, we have established a solid foundation for more accurate and nuanced predictive modeling and detection of major climate events.

These integrated methods significantly deepen scientific understanding of climate dynamics and provide critical, data-driven insights essential for informing strategic climate adaptation policies.

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