

# ENSOcast

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Decoding El Niño–Southern Oscillation

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## ENSO: The Pulse of the Pacific

This natural cycle, called the **El Niño–Southern Oscillation (ENSO)**, is driven by fluctuations in sea surface temperature and atmospheric pressure in the Pacific Ocean. It moves through three phases:

# The ENSO Challenge

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# The ENSO Challenge

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1999	-1.55	-1.30	-1.07	-0.98	-1.02	-1.04	-1.10	-1.11	-1.16	-1.26	-1.46	-1.65
2000	-1.66	-1.41	-1.07	-0.81	-0.71	-0.64	-0.55	-0.51	-0.55	-0.63	-0.75	-0.74
2001	-0.68	-0.52	-0.44	-0.34	-0.25	-0.12	-0.08	-0.13	-0.19	-0.29	-0.35	-0.31
2002	-0.15	0.03	0.09	0.20	0.43	0.65	0.79	0.86	1.01	1.21	1.31	1.14
2003	0.92	0.63	0.38	-0.04	-0.26	-0.16	0.08	0.21	0.26	0.29	0.35	0.35
2004	0.37	0.31	0.23	0.17	0.17	0.28	0.47	0.64	0.70	0.67	0.66	0.69
2005	0.64	0.58	0.45	0.43	0.29	0.11	-0.06	-0.14	-0.11	-0.29	-0.57	-0.84
2006	-0.85	-0.77	-0.57	-0.37	-0.14	-0.03	0.10	0.30	0.54	0.77	0.94	0.94
2007	0.66	0.22	-0.12	-0.32	-0.38	-0.47	-0.56	-0.81	-1.07	-1.34	-1.50	-1.60
2008	-1.64	-1.52	-1.29	-1.01	-0.84	-0.61	-0.37	-0.23	-0.24	-0.35	-0.55	-0.73
2009	-0.85	-0.79	-0.61	-0.33	0.01	0.28	0.45	0.58	0.71	1.01	1.36	1.56
2010	1.50	1.22	0.84	0.35	-0.17	-0.66	-1.05	-1.35	-1.56	-1.64	-1.64	-1.59
2011	-1.42	-1.19	-0.93	-0.73	-0.55	-0.44	-0.48	-0.62	-0.83	-1.01	-1.09	-1.04
2012	-0.86	-0.72	-0.59	-0.47	-0.26	-0.01	0.25	0.37	0.37	0.27	0.05	-0.21
2013	-0.43	-0.43	-0.34	-0.30	-0.36	-0.41	-0.40	-0.32	-0.26	-0.18	-0.17	-0.27
2014	-0.42	-0.46	-0.27	0.04	0.21	0.16	0.05	0.07	0.23	0.49	0.64	0.66
2015	0.55	0.47	0.53	0.70	0.93	1.18	1.52	1.86	2.16	2.42	2.57	2.64
2016	2.48	2.14	1.58	0.94	0.39	-0.07	-0.36	-0.54	-0.63	-0.69	-0.67	-0.56
2017	-0.34	-0.16	0.05	0.20	0.30	0.31	0.14	-0.11	-0.38	-0.65	-0.84	-0.97
2018	-0.92	-0.85	-0.70	-0.50	-0.22	-0.01	0.09	0.23	0.49	0.76	0.90	0.81
2019	0.75	0.72	0.71	0.66	0.54	0.45	0.28	0.14	0.19	0.35	0.51	0.55
2020	0.50	0.48	0.40	0.19	-0.08	-0.30	-0.41	-0.57	-0.89	-1.17	-1.27	-1.19
2021	-1.05	-0.93	-0.84	-0.66	-0.48	-0.38	-0.40	-0.49	-0.67	-0.81	-0.98	-0.98
2022	-0.97	-0.93	-0.99	-1.06	-0.99	-0.85	-0.81	-0.91	-1.01	-0.99	-0.92	-0.83
2023	-0.68	-0.43	-0.15	0.16	0.48	0.77	1.07	1.32	1.56	1.78	1.92	1.95
2024	1.78	1.48	1.14	0.71	0.39	0.15	0.04	-0.11	-0.21	-0.26	-0.37	-0.53

# The ENSO Challenge

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## El Niño

Warmer ocean temps, weaker trade winds, heavy rainfall



## Neutral

Normal conditions, stable weather patterns



## La Niña

Cooler ocean temps, stronger trade winds, droughts

Cycles every 2-7 years, impacts weather worldwide

# The ENSO Challenge

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## 2023-2024 El Niño

5th most powerful ENSO event on record



**Massive Wildfires**



**California Floods**



**Amazon Droughts**

Climate change is intensifying ENSO frequency and severity



# The ENSO Challenge

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**Research Goal:** Develop machine learning models to accurately predict ENSO phases using historical climate indicators.



# Data & Methodology

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## Dataset Overview

- **Temporal Coverage:** 1982-2024 (42+ years of monthly data)
- **Primary Indicators:** Sea Surface Temperature (SST) anomalies, Southern Oscillation Index (SOI)
- **Target Classes:** El Niño, Neutral, La Niña phases based on Oceanic Niño Index (ONI)
- **Spatial Focus:** Niño 3.4 region (5°N-5°S, 170°W-120°W)

# Data & Methodology

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## **Sea Surface Temperature (SST)**

Deviations from long-term averages in Niño 3.4 region (5°N-5°S, 170°W-120°W)

## **Southern Oscillation Index (SOI)**

Atmospheric pressure differences between Tahiti and Darwin, Australia

## **Oceanic Niño Index (ONI)**

Gold standard: 3-month moving average of SST anomalies

ONI held back during training — it directly corresponds to ENSO labels

# Data & Methodology

## Capturing temporal dependencies and patterns:



### Lagged Variables

1-3 month delays for SST & SOI



### Seasonal Encoding

Sine/cosine transformations



### Rolling Averages

Smooth short-term variability



### Trend Calculations

Month-to-month changes



### Interaction Terms

Combined ocean-atmosphere effects

Result: Rich feature set that captures complex climate dynamics

# Machine Learning Models

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# Machine Learning Models

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## **Random Forest**

Baseline: 82% accuracy

Captures non-linear interactions

## **XGBoost**

Gradient boosting optimization

Handles noise & missing data

## **1D CNN**

Temporal pattern recognition

Detects short-term transitions

## **LSTM**

Long-range dependencies

Models multi-month trends

## **Ensemble Learning**

Combines Random Forest + XGBoost for robust predictions

Up to 90% accuracy on specific configurations

# ENSOcast Platform

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# ENSOcast Platform

## An Interactive ML Platform for ENSO Forecasting

Making climate science accessible through data-driven predictions



### 40+ Years of Data

NOAA oceanographic records since 1982



### Interactive Dashboard

Built with Streamlit for hands-on exploration



### 5 ML Models

Random Forest, XGBoost, CNN, LSTM, Ensemble



### 82-90% Accuracy

Reliable ENSO phase classification

# ENSOcast Platform

## Narrative-Driven Learning Experience

From basic ENSO concepts → data exploration → hands-on training



### Global SST Maps

Explore historical temperatures



### Time Series

SST, SOI, ONI relationships



### Seasonal Patterns

Monthly phase distributions



### Confusion Matrix

Model performance breakdown



### Feature Importance

What drives predictions?



### Custom Training

Experiment with parameters


# Conclusions

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# Conclusions

## Lagged SST Anomalies Dominate



 Ocean temperature changes precede atmospheric responses by 2-3 months

# Conclusions

## Focused Training Wins

Models trained on specific time periods often outperform full-dataset training

**Why?** Climate variability changes across decades

## Phase Predictability

Not all phases are equally predictable:

**Neutral:** Most predictable ✓

**La Niña:** More uncertainty

**El Niño:** Intermediate

La Niña's longer persistence and gradual transitions make it harder to classify

# Conclusions



## ENSO Phases Show Distinct Seasonal Preferences



### El Niño

Clusters in late fall/winter months

Nov-Dec-Jan-Feb



### Neutral

Common during spring/summer transitions

Mar-Apr-May-Jun



### La Niña

Strengthens in winter, persists longer

Dec-Jan-Feb-Mar

This asymmetry helps predict when phase changes are most likely

# Conclusions

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## **Current Limitations**

- ✓ Simplified approach to complex climate system
- ✓ Limited to surface-level indicators (SST, SOI)
- ✓ No real-time operational forecasting
- ✓ Requires integration with physics-based models

**ENSOcast bridges the gap between climate expertise and public understanding**





# ENSOcast

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Oscillation



## PREDICTING EL NIÑO WITH MACHINE LEARNING



<https://ensocast.streamlit.app/>

*Thank You!*