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Article

# Explainable AI in Assessing Multi-Year ENSO Predictability from the Western North Pacific Precursor

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**Abstract:** The application of Explainable AI (XAI) to improve understanding of complex non-linear SST teleconnections and gain predictive skills is at the frontier of climate research. In this study, we attempt to refine the applications of XAI advancements to ENSO prediction by including SSTA in the western North Pacific (WNP) as a precursor. Our analyses indicate that the baseline accuracy increases from the 60% threshold previously reported for ENSO to >85% for moderate warm, cold, and neutral ENSO states one year in advance when WNP SSTA is included. Precision increases to over 90% for higher magnitude El Niños and La Niñas. Experiments conducted at 4-year lead times yield a strong WNP SSTA signal. A moderate SSTA signal is observed at 3-year lead time with no predictability; however, predictability spikes to over 80% when stratospheric zonal winds are included with WNP SSTA. While additional scientific work is required to make robust connections between XAI and dynamical processes, our results demonstrate a potential to improve long term predictability of ENSO through the ability of XAI in capturing SST patterns evolving at extended spatial and temporal scales.

**Keywords:** ENSO Predictability; Machine Learning; Explainable AI; Western North Pacific

## 1. Introduction

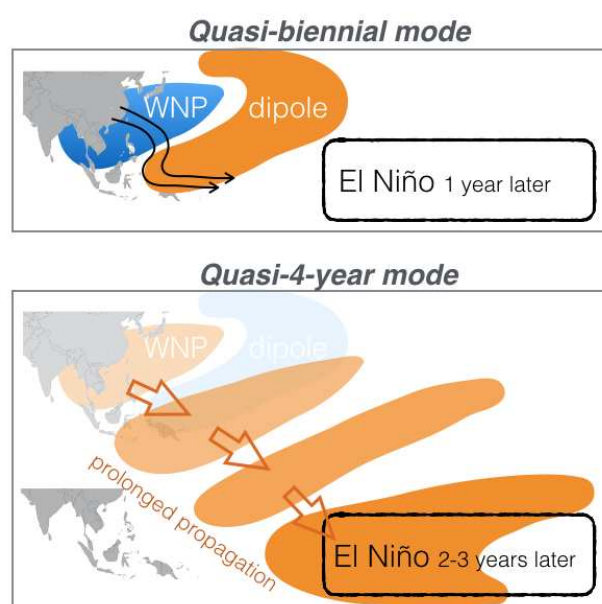
Recent advancements in artificial intelligence (AI)-based prediction of the El Niño-Southern Oscillation (ENSO) using sea surface temperature (SST) have marked significant progress, yet gaps remain in the field. The introduction of a hidden Markov model by [1] and [2] development of a self-attention-based neural network, the 3D-Geoformer, have pushed the boundaries of prediction lead times. [3] employed explainable deep learning to enhance understanding of global SST influences, while [4] and [5] introduced models like MIMO and Unet-LSTM for multi-scale SST prediction with high accuracy. Despite these strides, challenges persist in integrating subsurface ocean information and generalizing these models across different ocean basins. Meanwhile, explainable Artificial Intelligence (XAI) is a rapidly evolving field that focuses on making machine learning models more transparent and understandable to humans.

The landscape of ENSO prediction methodologies is diverse, ranging from traditional statistical models such as Canonical Correlation Analysis (CCA) and Empirical Orthogonal Functions (EOFs) to intricate dynamical simulations grounded in General Circulation Models (GCMs). Recently, the advent of XAI has added a new dimension to this field, offering nuanced approaches to model complex climatic systems. XAI techniques aim to provide insights into how AI systems make decisions, especially in complex tasks like spatial drought prediction. One such study emphasizes the development of explainable deep learning models to shed light on ENSO prediction [6].

Despite significant advancements in understanding ENSO, the field has reached a plateau regarding prediction accuracy, especially concerning long-term forecasts. Warm and cold sea surface temperature (SST) anomalies propagate from the western North Pacific (WNP) to the central–eastern

equatorial Pacific over 1–3 years, culminating in the development of El Niños and La Niñas. As illustrated in Figure 1, the WNP is defined as a specific SSTA pattern depicting an opposite signed dipole located in the east of Taiwan and northeast of Papua New Guinea, which forms one year before a full-fledged El Niño/La Niña [7]; a later analysis by [8] found that the same-signed SSTA east of Taiwan can propagate southeastward to the Niño-3 region over a duration up to 4 years and, under favorable conditions, can connect to ENSO development [9]. These anomalies are influenced by a complex interplay of factors such as the Kuroshio current, the North Pacific Subtropical Gyre, and wind stress curl [10].

This study aims to bridge the gap between advancements in XAI and the dynamics of ENSO specific to the WNP region. Employing machine learning and XAI techniques, we focus on ENSO prediction within the WNP area, as depicted in Figure 1. Our preliminary research [10,11] has unveiled dynamic insights into previously unexplored aspects of 1-year and 3-year ENSO predictability, as illustrated in the top and bottom of Figure 1, respectively; these insights draw on the foundational work of [7] and [8]. Building on the XAI methodology established by [6], our study delves deeper into these novel facets of ENSO predictability, emphasizing the unique characteristics of the WNP region.



**Figure 1.** Schematic diagram of the WNP precursor that manifests in two modes, one involving the WES feedback-Kelvin wave forcing (top) and the other with North Pacific anticyclone's low-frequency variability (bottom). The former mode can trigger El Niño a year later [7] and the latter could propagate across the subtropical Pacific and then connect to El Niño about 3 years later [8].

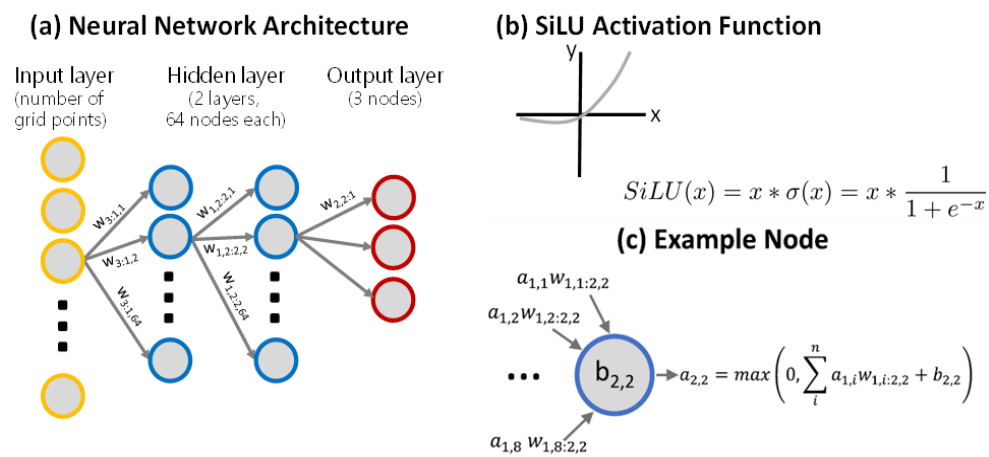
## 2. Data and Methodology

All observational and model data utilized in this study are monthly averages. Specifically, we rely on Sea Surface Temperature (SST) reanalysis data from the Japanese Meteorological Center (JMA) COBE-SST v2, with a  $1^\circ$  resolution [12–14]. Zonal wind data are from ERA5 reanalysis with a  $0.25^\circ$  resolution [15]. Data from 1940 to 2019 are used in this study. The long-term average of each month from 1940 to 2019 and the linear trend are both removed. The data from 1940 to 2000 were used as a training set, and the data from 2001 to 2019 were used as a testing set. Input data is normalized to the scale between -0.5 and 0.5.

Our research methodology draws significant inspiration from [6], which leveraged Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for climate prediction. The neural network architecture we employ closely adheres to the specifications in [6], but with some modifications to serve the purpose of this study. The main structure of this model is a fully connected classification deep learning model (Figure 2a). The number of nodes in the input layer is the same as the number of grid points. There are two connected layers in the hidden

layer structure, each contains sixty-four nodes. Three nodes in the output layers since this model is applied to identify an El Nino (warm), La Nina (cold), or normal month. The SiLU (Sigmoid Linear Unit) is adopted as an activation function (Figure 2b) because SiLU keeps features from the negative value region. Adaptive moment estimation (ADAM) is adopted as an optimizer.

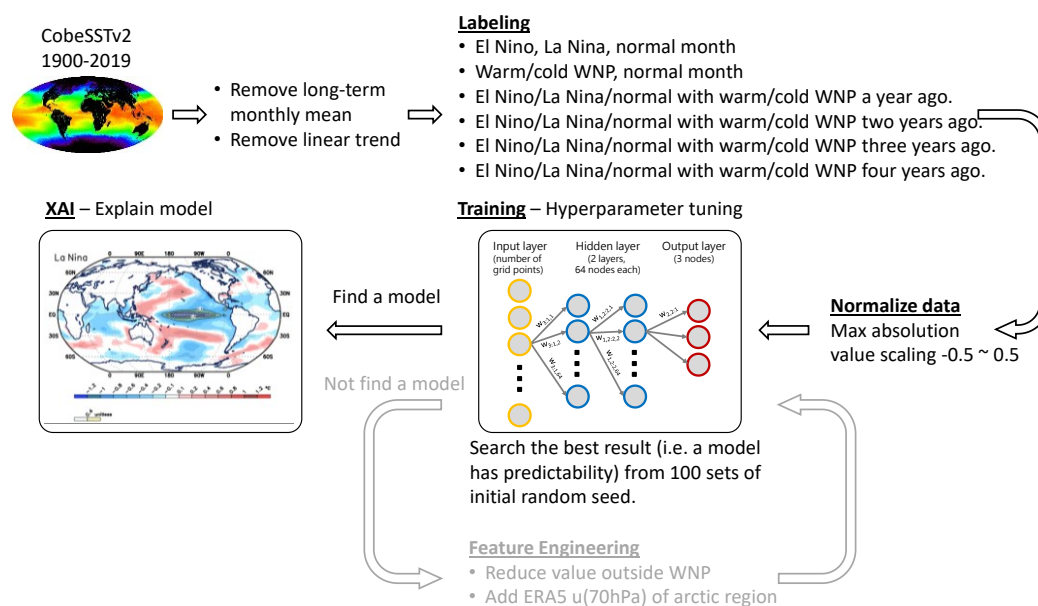
There were three labels in the data, El Nino (warm), La Nina (cold), and normal. With normal years often having more than five times the quantity compared to El Nino or La Nina, resulting in a data imbalance issue. Therefore, in selecting the loss function, this study uses the Cross Entropy Loss method, which allows the adjustment of weights. When calculating the loss function, we added weights inversely proportional to the quantity of data for each category. This imposed a higher penalty when the category with fewer data was misclassified. Batch size is equal to the total input data, allowing the neural network to review all the data at once for parameter adjustment. With this adjustment, the loss function could gradually and stably decrease during training, resulting in a more robust model.



**Figure 2.** (a) The neural network architecture used in this study, (b) a schematic and equation for the SiLU activation function, (c) an illustration of data processing through neurons, with 'a' representing the activation function, 'w' indicating weights, and 'b' representing biases."

In order to build a model with good performance and robustness, hundred sets of randomly generated initial parameters are prepared for each training. A model with high accuracy on both training and testing datasets is selected. If there are no suitable models, two attempts are made: 1) Reduce the values outside the WNP region, allowing the neural network to focus on identifying relationships within the WNP region. 2) Incorporate zonal wind from the 70hPa level of ERA5 data in the polar region (explained later).

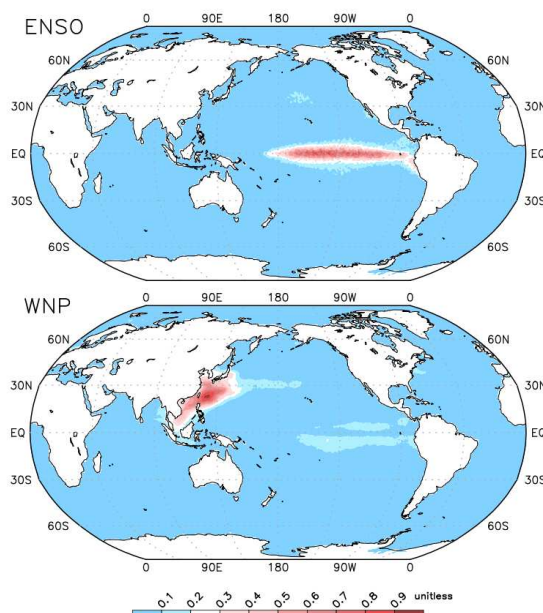
Integrated Gradients (IG) [16] was used in this study for XAI. IG is similar in spirit to LPR but uses integration along the entire gradient path to determine the importance of input features in making a classification decision, addressing some of LPR's shortcomings. IG does not require modifications to the original neural network architecture and provides a feature importance distribution of the input data. The flow of data preparation, model training, and explanation processes is depicted in Figure 3.



**Figure 3.** Flow of data preprocessing, labeling, normalization, model training, hyperparameter tuning, and using XAI.

### 3. Results

In a comparative analysis with [6], who achieved a 60% accuracy rate in predicting ENSO events one year in advance, our model sets this "0.6" as a baseline for performance. Figure 4 demonstrates that our XAI model can fully replicate the methodology of [6], identifying the relationship between ENSO and the WNP's SST conditions (highlighted in red). By incorporating the state of the WNP, we can further discern the warm, cold, and neutral states of ENSO one year in advance. Our model was trained on data from 1940-1999 and tested on data from 2000-2020. The results, compared to those of [6] who did not consider the WNP, are significantly improved.



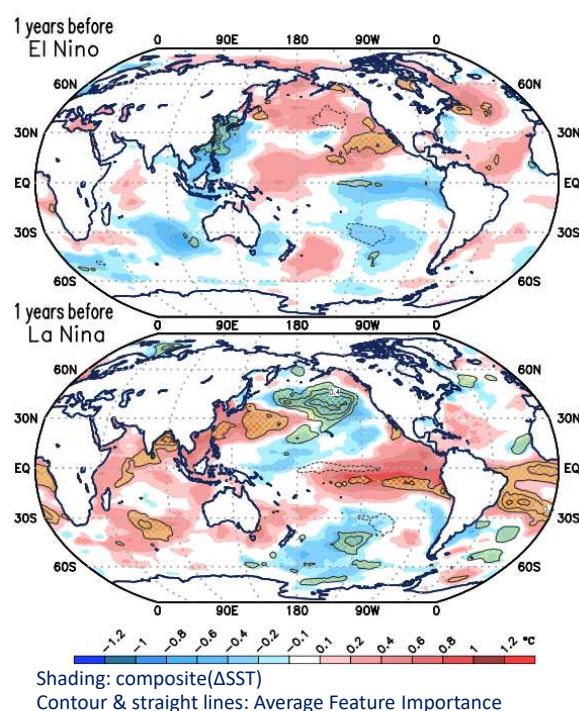
**Figure 4.** XAI as used in Toms et al. [6] was able to depict the ENSO source region (top; 100% accuracy) and the WNP source region (bottom; 99% accuracy) in a diagnostic manner.

### 3.1. One-Year Predictability

The outcomes after incorporating the WNP are illustrated in Figure 5. The map section displays the composite sea surface temperature anomalies for warm and cold ENSO events one year prior (colored regions), along with the strength of stratified correlations (contour lines and light yellow shading). The accompanying coefficient table and consolidated results are also provided (Table 1). Notably, the accuracy indicates that the neural network effectively captures the sea temperature signals in the WNP region. After accounting for these WNP signals, the neural network elevates the ENSO prediction accuracy to 85%' as shown in Table 1 alongside other statistics. This model is particularly effective in capturing strong El Niño and La Niña cases, lending significant implications for seasonal prediction.

The WNP region serves as a critical precursor for ENSO events, affecting them primarily through zonal advection and thermocline feedback mechanisms. The model's success in this area is noteworthy given the increasing amplitude and frequency of summer westerly anomalies in a warming climate. These anomalies imply stronger and more frequent El Niños under WNP influence. The intensification of westerlies induces stronger westerly wind stress, amplifying Kelvin wave activity in the western equatorial Pacific. This leads to stronger downstream effects related to the Bjerknes feedback, facilitating an easier transition to an amplified El Niño [17–19].

The XAI methods inspired by Toms et al. [6] were instrumental in achieving this level of predictability. XAI's ability to provide insights into the model's decision-making process allowed us to understand why the model was particularly effective in picking up the WNP's 1-year lead for ENSO development. The model's XAI features revealed that the key variables contributing to this high level of accuracy were related to the documented strengthening effects of both Ekman and geostrophic heat advection and entrainment of subsurface water in the equatorial Pacific [9,10].



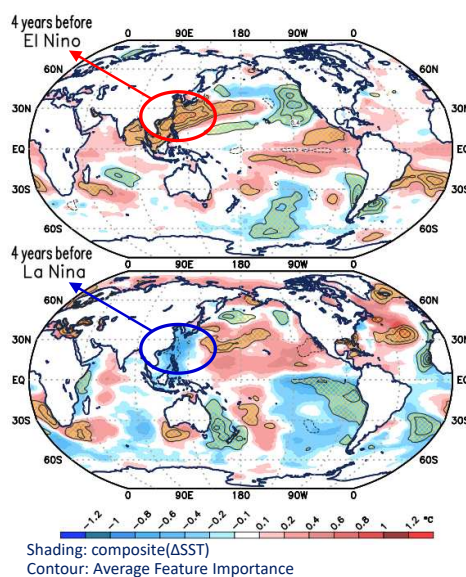
**Figure 5.** On 1-year lead ENSO prediction: Reconstructed composite SST anomalies with significance areas hatched in light yellow showing WNP-based XAI prediction for one year before DJF-season El Niño (top) and La Niña (bottom).

**Table 1.** The statistics of training set and the testing set.

<b>Training Set</b>		precision	Recall	f1-score
Predict El Nino	El	0.90	0.90	0.90
Predict La Nina	La	1.00	0.75	0.86
Predict normal	normal	0.62	1.00	0.77
accuracy				0.85
<b>Testing Set</b>		precision	Recall	f1-score
Predict El Nino	El	1.00	0.50	0.67
Predict La Nina	La	1.00	1.00	1.00
Predict normal	normal	0.80	1.00	0.89
accuracy				0.88

### 3.2. Three-Plus Years of Predictability

In an effort to extend the frontiers of ENSO predictability, we conducted additional tests focusing on the beyond-one-year lead times. The analyses revealed significant but varying ENSO predictabilities for both different years in advance, with a marginal WNP signal three years before ENSO and, counterintuitively, a robust WNP signal four years prior. Figure 6 shows that four years before an ENSO event, the WNP exhibits significant feature strength. Unlike the anti-phase relationship one year before, as shown in Figure 5, the long-lead WNP signal to ENSO is in-phase four years prior, meaning that warm WNP could coincide with an El Niño event four years later. In essence, and as observed in [8] and explained in [10], warm WNP conditions would appear to propagate to equatorial eastern Pacific linking to El Niño events four years later, and vice versa for cold WNP conditions. We avoid the term "caused" because the physical mechanisms driving these SST anomalies and their influence on ENSO events are still under investigation, while the role of air-sea coupling is difficult to isolated from the coupled ENSO dynamics. However, the focus here is on predictability, and with an estimated predictability rate of 0.75 (Table 2), we believe that leveraging this phenomenon of WNP could offer a viable pathway for advancing seasonal ENSO forecasts.



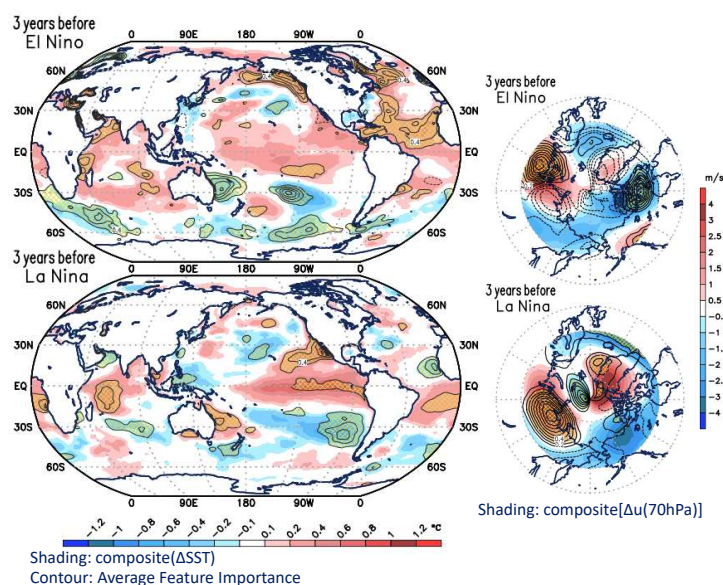
**Figure 6.** Composite of sea temperature and ML feature strength four years before ENSO. The in-phase WNP signal occupies a large proportion, contributing to a predictability of 0.75.

**Table 2.** The statistics of training set and the testing set at 4-year lead.

Training Set	precision	Recall	f1-score
Predict El Nino	1.00	1.00	1.00
Predict La Nina	1.00	1.00	1.00
Predict normal	1.00	1.00	1.00
accuracy			1.00
Testing Set	precision	Recall	f1-score
Predict El Nino	0.75	1.00	0.86
Predict normal	0.00	0.00	0.00
accuracy			0.75

Recent research has continued to unravel the intricate relationship between ENSO and the Arctic polar vortex. Kumar et al. [20] assessed the structure and evolution of polar vortex during different ENSO phases, revealing significant impacts on polar vortex behavior. Furthermore, the work of [21] on stratosphere-troposphere coupling in the Southern Hemisphere provided insights into the predictability of surface climate, underlining the global reach of ENSO-polar vortex interactions. These studies underscore the complex and far-reaching influence of ENSO on Arctic circulation dynamics, adding to our understanding of climate teleconnection and predictability.

Recognizing the established relationship between ENSO, the North Pacific, and Arctic winter stratospheric circulation, we attempt next to examine whether incorporating polar vortex behavior would help the relatively low skill at 3-year lead. Thus, we incorporated 70hPa polar u-wind within 65°N as an additional predictor to examine this association with tropical low-frequency variability. The results, illustrated in Figure 7, are intriguing. Despite the relatively low signal strength of SST three years before an ENSO event, the inclusion of 70hPa 65°N u-wind alongside the WNP signal led to a predictability rate as high as 0.9 for ENSO events three years in advance, based on data from 2000-2019 (Table 3). This polar circulation signal was significant only three years prior to an ENSO event, lacking notable features at other times.

**Figure 7.** Composite of sea temperature anomalies and feature strength three years before ENSO (left), along with 70hPa winter u-wind anomalies and feature strength three years before ENSO (right).

This result suggests that the state of polar vortex three years before an ENSO event, when juxtaposed with the right WNP condition, could influence the North Pacific Oscillation (NPO), subsequently affecting the East Asian winter monsoon. These, in turn, impact the WNP-triggered development of ENSO in the following year. A strong polar vortex keeps cold air contained at the poles. However, shifting of the jet stream and development of wave trains during El Niños can warm and weaken the polar vortex and release outbreaks of cold winds towards the mid-latitudes [22–24]. This sudden stratospheric warming (SSW) may adjust ENSO impacts on regional climates [25]. In the Pacific, a disrupted polar vortex may contribute to sea level pressure anomalies characteristic of both positive and negative NPO phases [26], making the timing of the polar vortex weakening 3 years before ENSO in Figure 7 potentially significant in ENSO development.

**Table 3.** The statistics of training set and the testing set.

<b>Training Set</b>	precision	Recall	f1-score
Predict El Nino	1.00	1.00	1.00
Predict La Nina	1.00	1.00	1.00
Predict normal	1.00	1.00	1.00
accuracy			1.00
<b>Testing Set</b>	precision	Recall	f1-score
Predict El Nino	1.00	1.00	1.00
Predict La Nina	1.00	1.00	1.00
Predict normal	0.00	0.00	1.00
accuracy			0.75

#### 4. Discussion

While the model seemed to have achieved a high accuracy rate for three-to-four-year predictions of ENSO, it's crucial to approach these findings with scientific caution. Our analyses suggest that the four-year WNP SSTA propagation is consistent with the reshaping of an SSTA along the southeastern quadrant of the North Pacific Subtropical Gyre as it shifts in and out of equilibrium. The SSTA's propagation is influenced by geostrophic flow dynamics, and the sea surface height gradient is most pronounced to the southeast [10]. This ensures that any SSTA originating from the WNP moves downslope towards the central–eastern equatorial Pacific. On the polar vortex's role in enhancing the three-year ENSO prediction via the WNP pattern, the same dynamics apply; that is, the Arctic circulation modulates the NPO or North Pacific Subtropical Gyre leading to slight changes in the otherwise pan-four-year propagation of WNP that links to ENSO development 3-4 years later. While these findings are encouraging, they are subject to the limitations of the model and the quality of the input data.

In theory, the gradual movement of warm and cold SSTAs from the WNP to the central–eastern equatorial Pacific could potentially extend ENSO prediction lead times up to 3–4 years [8]. However, it's important to consider that these results are based on a single model and a specific set of conditions. Further research is needed to validate these findings and to explore how they might generalize to other models and conditions. This study serves as a preliminary step in understanding how deterministic relationships between extratropical precursors and ENSO through subtropical gyres can contribute to advancements in longer lead time (>1 year) ENSO predictions.

Long-term predictability has been a complex and often elusive goal in ENSO research. This level of long-term predictability has been a challenging frontier in ENSO research. The presented XAI model's relative success is attributed to its ability to capture slow-moving, large-scale oceanic and

atmospheric patterns in the WNP region. These patterns are pivotal in ENSO development and are illustrated in Figure 1. The neural network architecture of the model, inspired by [6], appears to be effective in capturing these slow-moving patterns. However, it is also important to note that while the XAI model outperforms many traditional forecasting methods, further validation is needed to confirm these results.

## 5. Concluding Remarks

Traditional empirical forecasts and regression analyses have shown that using WNP sea surface temperatures to predict ENSO one year in advance yields a predictability of only around 0.6 (correlation coefficient). This is consistent with the findings of [6], who also achieved a predictability of 0.6 using machine learning. Even using the so-called Pacific Meridional Mode (PMM) concept to predict winter ENSO nine months in advance only reaches a predictability of 0.6. Our experiments demonstrate that by integrating advanced machine learning methods with physical mechanisms (i.e., using XAI with the WNP precursor), one can elevate the accuracy of one-year ENSO predictions to 0.85—a significant improvement from 0.6. The application of XAI further substantiates the physical relationship between WNP and ENSO, reinforcing the findings of [7,8] that there are indeed predictive signals in the WNP region one year before ENSO events.

Moreover, our study reveals unprecedented interannual predictability by leveraging quasi-four-year modal characteristics, as shown in Figure 4 and [8]. Specifically, sea surface temperature anomalies move from the WNP region southeastward to the equatorial eastern Pacific. Using XAI methods, we achieved a predictability as high as 0.75 for ENSO events four years in advance, post-2000. This opens up a new frontier in ENSO forecasting that warrants further in-depth and theoretical investigation.

While these results are promising, it's crucial to approach them with scientific caution. The complex relationships captured by machine learning methods between oceanic and atmospheric variables are still not fully understood and require further scrutiny to assess their physical significance. Nonetheless, the advancements in predictability achieved in this study mark a noteworthy step forward in the realm of ENSO research.

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