Proceedings of ICMMGH 2026 Symposium: Cell and Molecular Biology: Understanding Immune Cell Functions
DOI: 10.54254/2753-8818/2026.PJ30146

Application of Artificial Intelligence in ENSO Prediction Research

Tao Wen

School of Economics and Management, Beijing Institute of Petrochemical Technology, Beijing, China
Id.taowen@gmail.com

Abstract. The El Niño-Southern Oscillation (ENSO) is basically an air-sea interaction phenomenon of the tropical Pacific capable of initiating global extreme weather events by modifying atmospheric circulation and ocean temperature distribution, with profound impacts on society and economy. While the basic mechanisms of ENSO are fairly well-appreciated, accurate prediction remains a big challenge in climate science. Traditional dynamical and statistical models are limited in long-term predictions and addressing issues such as the "spring predictability barrier." This article highlights how artificial intelligence (AI) is revolutionizing ENSO prediction research through three key areas: direct application of deep learning models, development of hybrid forecasting strategies, and overcoming key scientific challenges. Building on this foundation, this article proposes that future research trends will further deepen the integration of AI and physical dynamics, leveraging interpretable AI to improve forecast accuracy while simultaneously uncovering new dynamical mechanisms underlying ENSO, thereby advancing climate science to new levels of sophistication.

Keywords: El Niño-Southern Oscillation, Artificial intelligence, Deep learning

1. Introduction

The El Niño-Southern Oscillation (ENSO) is a periodic phenomenon in the tropical Pacific Ocean. It is caused by the interaction between the ocean (El Niño/La Niña) and the atmosphere (Southern Oscillation). It is characterized by alternating periods of abnormally high and low sea temperatures [1]. This phenomenon influences global weather in the redistribution of rainfall and potential emergence of extreme weather events like droughts, floods, and heat waves. These phenomena have an impact on agricultural crop production and water resource management as well as energy demand and the economy at large. Therefore, a better understanding of its causes together with improved prediction accuracy remain(intensify) core challenges in climate science [2]. The mechanisms of ENSO are complex. While a basic consensus and theoretical foundation have been established regarding their causes, predicting their specific behavior remains a work in progress, and its increasing instability complicates research. The well-established theoretical cornerstone is the ocean-air positive feedback hypothesis, which describes a self-reinforcing cycle that is crucial to the growth phase of El Niño events. However, to explain the quasi-periodicity of ENSO, negative

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2753-8818/2026.PJ30146

feedback mechanisms are also required which would terminate the growth of El Niño events in the form of delayed and charge-discharge oscillators. Past research on ENSO has largely depended on two paradigms: dynamical and statistical models [3, 4]. Dynamical models attempt, based on physics, to simulate the whole process of ocean-air interactions. They are very expensive to run and suffer from large systematic errors. Statistical models are built by analyzing historical data. Although they are computationally efficient, they cannot explain the nonlinear characteristics of ENSO.

Against this backdrop, big data technologies and artificial intelligence (AI) have put ENSO research on the fast track. The sixth phase of the Coupled Model Intercomparison Project (CMIP) has released huge datasets which include for example the fifth generation reanalysis data from European Centre for Medium-Range Weather Forecasts (ECMWF), and Argo Global Ocean Observing System among others. This big data is analyzed by big data technologies and stored thereby creating conditions in which an artificial intelligence model can be trained. With their powerful nonlinear fitting and feature extraction capabilities, AI algorithms such as deep learning can uncover underlying patterns in this data that are difficult to detect using traditional methods [5].

Based on this, the article organizes and speculates on the research methods of the main literature review and will discuss the following core perspectives: (1) it will thoroughly analyze how the “direct application of deep learning models” has evolved from initial model transplantation to specific algorithms targeting the pain points of ENSO prediction, (2) it will detail the emergence process of “hybrid forecasting strategies” in an organized manner, displaying the development route from “shallow result combination” to “deeper mechanism symbiosis” while exploring a possible new positioning process for artificial intelligence in this work - transforming from a “leader” into a “collaborator,” and (3) telling about and showing how artificial intelligence helped academic society beat spring predictability barrier, Through these analyses, this article aims to demonstrate the revolutionary impact of artificial intelligence on ENSO research, improving forecasting skills and fostering a new scientific paradigm that deeply integrates physical and data laws.

2. Reasons of ENSO

Before describing how artificial intelligence can be used to enhance ENSO research, its original cause must be described-a natural phenomenon discovered before the artificial intelligence era began. ENSO contains a self-sustained periodic mode of coupled oscillation between the ocean and atmosphere in the tropical Pacific. The key result enabling such a mode turns out to be what has become known as "Bjerknes feedback." [6]. It shows that under normal conditions, the trade winds blow warm surface water to the western Pacific, keeping the eastern Pacific cool due to the upwelling of deep cold water. When the trade winds weaken, the warm water in the western Pacific will flow back eastward, causing the sea temperature in the eastern Pacific to rise abnormally. This warming in turn heats the upper atmosphere, further weakening the trade winds' strength, forming a powerful positive feedback loop and ultimately promoting the formation and development of El Niño events. Scientists established this basic theoretical framework for the cause of ENSO through decades of field observations, physical theory derivation and traditional numerical simulations. Its discovery and establishment rely almost entirely on modern artificial intelligence or deep learning technology, but on the research results of physical oceanography and atmospheric science, laying a solid theoretical foundation for the subsequent application of AI in fields such as ENSO prediction.

DOI: 10.54254/2753-8818/2026.PJ30146

3. Artificial intelligence revolutionizes ENSO prediction research

ENSO has always been a challenge to predict. The main approach in forecasting ENSO comes from physically dynamical models and statistical models based on historical data. Long-term forecast accuracy, with issues like the spring predictability barrier problem [7], has not been very successful through this method. Artificial intelligence is, however, changing the research of ENSO prediction. With its powerful nonlinear data mining and pattern recognition capabilities, AI has significantly improved prediction accuracy, fostered new hybrid forecasting strategies, and demonstrated great potential in addressing classic scientific challenges.

3.1. Direct application of artificial intelligence and deep learning models

Allow deep learning models to train themselves on historical climate observation and simulation data both in regards with ENSO precursor signals and those aspects difficult or impossible to capture explicitly by traditional methods. The most advanced academic research presently shows empirically that deep learning models have successfully extended the technical forecast lead time of ENSO far beyond 17 months, even up to 20 months under certain conditions. This achievement far exceeds the forecast limit of most traditional dynamic models [8, 9]. For extreme events with significant impacts, such as strong El Niño or strong La Niña, the "weighted loss function" and other methods have effectively improved the model's prediction accuracy for low-frequency, high-impact events, compensating for the forecast bias of traditional models caused by imbalanced training data [10]. When training the model, this method requires more attention to rare but highly influential extreme events, and specific factors must be refined to solve them. This shows that the academic community is no longer satisfied with directly applying existing artificial intelligence models, but is innovating at the algorithm level to address specific pain points in ENSO prediction.

The heart of attaining the above results is in applying several advanced deep learning architectures-for instance, convolutional neural networks (CNNs) [11]. CNNs were initially designed for image recognition. They can efficiently extract spatial features and local patterns from climate data, such as sea surface temperature (SST) and ocean heat content (OHC), and automatically identify abnormal signals in key areas (such as the equatorial western Pacific warm pool) [12,13]. Another example is long short-term memory networks (LSTMs) [14], a recurrent neural network (RNNs) widely used to process time series data. LSTMs can effectively capture the long-term dependencies of ENSO indices (such as the Niño 3.4 index) in the time dimension, thereby simulating their complex evolution process [15]. The more cutting-edge research works use large model architectures such as Transformer [16]. Transformer can simultaneously capture long-range dependencies in space and time through the self-attention mechanism. A technological evolution path has been described from CNN and LSTM to the more cutting-edge Transformer architecture, which shows a possible future: ENSO prediction models will develop in a more integrated and global direction, better understanding the complex interactions between different regions and time points, thereby further building a more complete dynamic understanding of the ENSO system.

3.2. The rise of hybrid forecasting strategies

While deep learning models have achieved great success, relying solely on data-driven methods may overlook the prerequisite of geophysical principles. Therefore, hybrid forecasting strategies integrating deep learning models with traditional dynamic models that include atmosphere-ocean

DOI: 10.54254/2753-8818/2026.PJ30146

interactions have become an important research direction. Cutting-edge research results show that the final forecasting skill can stably surpass any single model by simply linearly combining the forecast results of deep learning models with the ensemble average of multiple dynamic models [17]. This strategy not only improves the accuracy of forecasts but also significantly enhances the robustness of the forecast system. Another, more in-depth integration method is to use AI to "correct the deviation" of the output of the dynamic model. The AI systematically learns the error pattern of a dynamic model from past forecast histories and intelligently corrects future forecast results thus “taking the essence and removing the dregs” [18, 19]. This is an example of further integration between artificial intelligence and skilled models.

In the hybrid forecasting strategy, AI technology is an “optimizer” for correcting deviations. Neural network models (such as multi-layer perceptrons) are trained to learn a complex nonlinear mapping function. The input of this function is the original forecast field of the dynamic model and the relevant initial conditions, and the output is the forecast result after correction, which can be closer to the actual situation. This method is a complex statistical post-processing technology, but its nonlinear modeling ability far exceeds the traditional linear regression method. Another framework is “model residual learning” where AI models (such as LSTM) are specifically trained to predict the forecast error of the dynamic model. During actual forecasting, simply subtract the error indicated by AI from the original estimates of the dynamic model to get a more accurate result. This enables AI to focus on learning those parts which the dynamic model is “not good at”. Thus, it realizes deep complementarity between physical and data laws [20]. Compared with what was mentioned in the previous paragraph, the role played by artificial intelligence has changed - from "protagonist" to "key collaborator". This collaborator can be a balancer to improve the system's overall stability, or a calibrator to correct the systematic deviations of the physical model. This has guided a new development direction for artificial intelligence research.

3.3. Overcoming the “Spring Predictability Barrier” and new model progress

The "Spring Predictability Barrier" (SPB) is an obstacle to ENSO prediction - the forecasting skill of almost all prediction models decreases significantly during the Northern Hemisphere spring (March to May). AI offers a new approach to the solution by enabling it to pick up weak signals. State-of-the-art research demonstrates that deep learning models are capable of detecting nonlinear precursor signals associated with the formation of ENSO from the ostensibly noisy global climate system several months before spring-initiated development [9,21]. Interpretable artificial intelligence technology makes it possible to trace which variables are the key basis for making predictions and visualize them, thereby identifying the sources of these important precursor signals [22, 23].

In addressing the challenges of SPB, AI's nonlinear pattern recognition forms the basic technological edge. Spring is the ENSO cycle transition time; therefore, an extremely low signal-to-noise ratio exists within the tropical Pacific. Clues are quite weak. However, deep CNNs extract features at multiple levels such that some hidden-and-out-of-sight patterns can be amplified and recognized inside this complex background. The deep learning model integrates information at different spatial and temporal scales to construct a more complete 'blueprint’ of the pre-ENSO state than possible by traditional statistical methods. For example, a model might discover that a slight anomaly in the distant Southern or Indian Ocean during the winter months can exert a decisive early influence on the subsequent transition in the tropical Pacific in the spring through teleconnections in the atmospheric circulation. This provides a traceable basis for predicting the future course of ENSO before the "chaotic" spring signal arrives. This capability allows AI models to rely on other, more stable climate cues even during an SPB, overcoming this major challenge in traditional forecasting.

DOI: 10.54254/2753-8818/2026.PJ30146

4. Conclusion

This article first briefly introduces the causes of the ENSO phenomenon and then reviews how artificial intelligence technology has promoted research on its causes, demonstrating the importance of artificial intelligence technology in this field. By directly applying deep learning models such as convolutional neural networks (CNNs) and long short-term memory networks (LSTMs), researchers have successfully extended the effective forecast period of ENSO to over 18 months and significantly improved the accuracy of predictions for extreme events such as strong El Niño. The use of AI has enabled powerful hybrid schemes for prediction, combining the nonlinear information of data-based models with the physical content provided by traditional dynamical models. Even in an approach aimed at enhancing forecast stability through linear combinations or AI-driven bias correction and residual learning on top of a dynamical model, deep complementarity between physical laws and data laws is achieved. The potential ability of AI to overcome the classical "spring predictability barrier" problem involving highly non-linear weak precursor signals not easily captured by conventional methods appears very optimistic.

A key focus for ENSO research will be further deepening the integration of AI and physical dynamics. By leveraging explainable AI techniques to improve forecast accuracy and trace the underlying model decisions, we can uncover new climate dynamics and feed data-driven insights into physical theory. This marks the beginning of a new era in ENSO research, moving from simple predictions to a new AI-assisted era focused on deeper mechanistic understanding and scientific discovery.

References

[1] National Weather Service Climate Prediction Center. (n.d.). Frequently asked questions about El Niño and La Niña. Retrieved from https: //www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensofaq.shtml
[2] Dijkstra, H. A., Petersik, P., Hernández-García, E., & López, C. (2019). The application of machine learning techniques to climate prediction and analysis. Nonlinear Processes in Geophysics, 26(1), 87–105.
[3] Zebiak, S. E., & Cane, M. A. (1987). A model El Niño–Southern Oscillation. Monthly Weather Review, 115(10), 2262–2278.
[4] Saha, S., Moorthi, S., Wu, X., Wang, J., Nadiga, S., Tripp, P., ... & Becker, E. (2014). The NCEP climate forecast system version 2. Journal of Climate, 27(6), 2185–2208.
[5] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444.
[6] Bjerknes, J. (1969). Atmospheric teleconnections from the equatorial Pacific. Monthly Weather Review, 97(3), 163–172.
[7] Webster, P. J., & Yang, S. (1992). Monsoon and ENSO: Selectively interactive systems. Quarterly Journal of the Royal Meteorological Society, 118(507), 877–926.
[8] Ham, Y. G., Kim, J. H., & Luo, J. J. (2019). Deep learning for skillful El Niño forecasts. Nature, 573(7775), 568–572.
[9] Chen, Q., Cui, Y., Hong, G., Ashok, K., Pu, Y., Zheng, X., Zhang, X., Zhong, W., Zhan, P., & Wang, Z. (2025). Towards long-range ENSO prediction with an explainable deep learning model. arXiv preprint arXiv: 2503.19502.
[10] Kim, D.H., Lim, C., & Kug, J.-S. (2024). Improved prediction of extreme ENSO events using an artificial neural network with weighted loss functions. Frontiers in Marine Science, 10, 1309609.
[11] LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278–2324.
[12] Geng, H., & Wang, T. (2021). Spatiotemporal model based on deep learning for ENSO forecasts. Atmosphere, 12(7), 810.
[13] Zhou, J., & Zhang, R. (2023). A graph-based approach for ENSO predictability analysis and forecast. Advances in Atmospheric Sciences, 40, 2191–2204.
[14] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780.
[15] Mu, B., Qin, B., & Yuan, S. (2021). ENSO-ASC 1.0.0: ENSO deep learning forecast model with a multivariate air–sea coupler. Geoscientific Model Development, 14(11), 6977–6999.

DOI: 10.54254/2753-8818/2026.PJ30146

[16] Ye, M., Yan, J., Jia, X., Ge, Q., & Fan, X. (2021). A Transformer-based artificial neural network for ENSO forecasting. Expert Systems with Applications, 184, 115589.
[17] Chen, Y., Jin, Y., Liu, Z., et al. (2025). Combined dynamical-deep learning ENSO forecasts. Nature Communications, 16, 3845.
[18] Kuang, Z., Song, Y., Song, Z., et al. (2023). A Hybrid ENSO Prediction System Based on the FIO-CPS and XGBoost Algorithm. Remote Sensing, 15(7), 1728.
[19] Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 785–794.
[20] Schlör, J., Newman, M., Thuemmel, J., Alvanos, A. J. P., & Chapman, W. (2024). A Hybrid Deep-Learning Model for El Niño Southern Oscillation in the Low-Data Regime. arXiv preprint arXiv: 2412.03743.
[21] Ludescher, J., Gozolchiani, A., Bogachev, M. I., et al. (2020). Complexity-based approach for El Niño magnitude forecasting before the spring predictability barrier. Proceedings of the National Academy of Sciences, 117(1), 133–138.
[22] Toms, B. A., Barnes, E. A., & Ebert-Uphoff, I. (2020). Deep learning for multi-year ENSO forecasts. Journal of Advances in Modeling Earth Systems, 12(8), e2019MS002002.
[23] Ham, Y.G., & Kug, J.-S. (2012). How well do current climate models predict the La Niña state? Climate Dynamics, 39, 2061–2074.