ESSO-Indian National Centre for Ocean Information Services (ESSO-INCOIS)

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INCOIS/ENSO/Bull/2026/01 **5th February 2026**

Outlook of NINO 3.4 index for the period February 2026 - October 2026

Highlights:

- **The sea surface temperature anomaly signature in the eastern and central Pacific shows the development of La Niña conditions in January.**
- **Probability of ENSO-neutral conditions over the Pacific is dominant from March 2026 onwards, with probabilities of 50–65% throughout the forecast period. From March to July 2026, La Niña remains the second most likely ENSO phase with probabilities of 20-55%, shifting to El Niño during August to October 2026 with probabilities of 20-45%.**

Introduction

El Niño refers to the warm eastern Pacific Ocean warming associated with the positive phase of the El Niño Southern Oscillation (ENSO). A prevailing El Niño condition in the Pacific Ocean has an adverse effect on the Indian summer monsoon rainfall and, thereby on the economic well-being of the country. El Niño is also found to cause stronger and prolonged marineheatwaves in the northern Indian Ocean, damaging the ecological balance, coral reefs and causing significant losses to the fishery industry. Thus, monitoring the El Niño condition and predicting its further evolution with sufficient lead time is of prime importance for better preparedness and policymaking. This bulletin outlines the current state of the Pacific Ocean and an outlook on the evolution of El Nino/La Nina conditions in the subsequent seasons.

Details of the datasets and methodology used to prepare this bulletin is given in Annexure-I.

Evolution of Nino 3.4 Sea Surface Temperature Anomaly

Monthly evolution of Nino 3.4 SST anomaly in the past two years is shown in Fig. 1. The El Nino conditions, which were prevailing in the Pacific until March/April 2024, turned to near neutral conditions by May 2024 (Fig. 1). Fig. 2 shows that strong negative subsurface temperature anomalies (~4°C) developed in the central and eastern equatorial Pacific from January 2025 to July 2025, indicating subsurface cooling typical of La Niña development. However, SST anomalies remained weak and near-neutral during most of this period, with patchy warming and cooling (Fig. 2). By October 2025, subsurface warming (>3°C) emerged in the western Pacific while eastern cooling intensified, along with mostly La Niña SST anomalies (Fig. 2). As seen in Fig. 3, by January 2026, significant negative SST anomalies persisted across the central and eastern equatorial Pacific, along with notable subsurface cooling in the east and strong warming in the west, indicating a developing La Niña pattern. Hence, ENSO was in its La Niña phase over the central Pacific by January 2026.

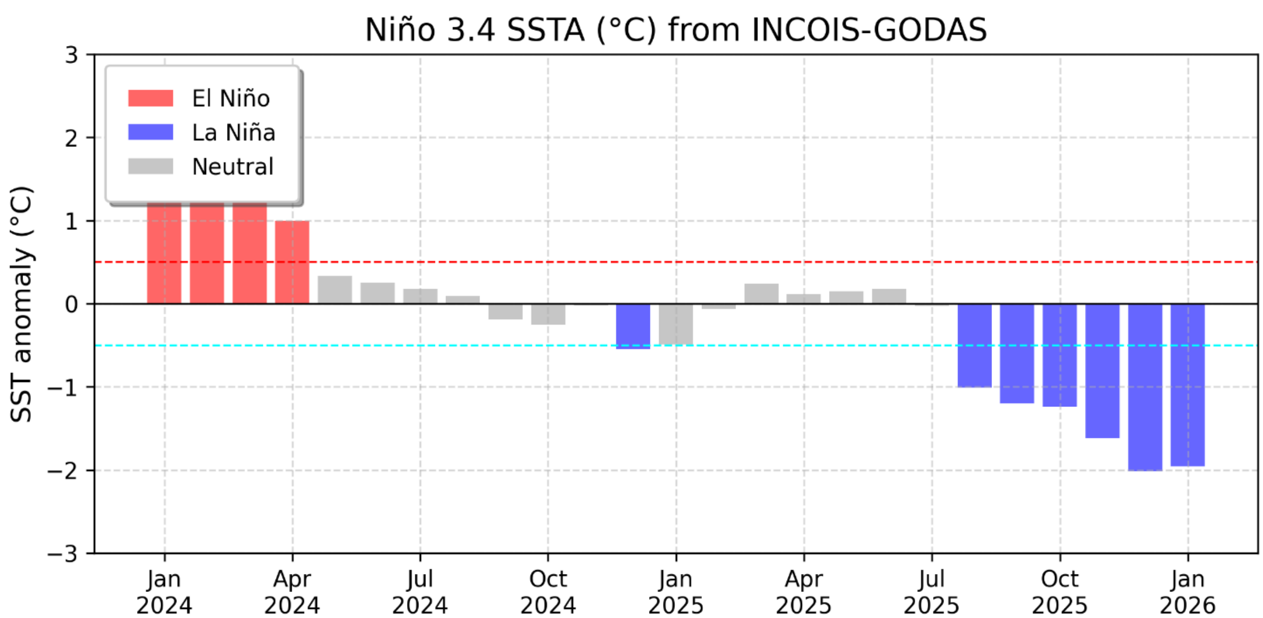

Fig. 1: Evolution of Sea Surface Temperature anomalies (°C) in the Niño 3.4 (5°S-5°N, 170°W-120°W) region in the period January 2024 - January 2026. The RED and CYAN horizontal lines represent 0.5°C SST anomaly

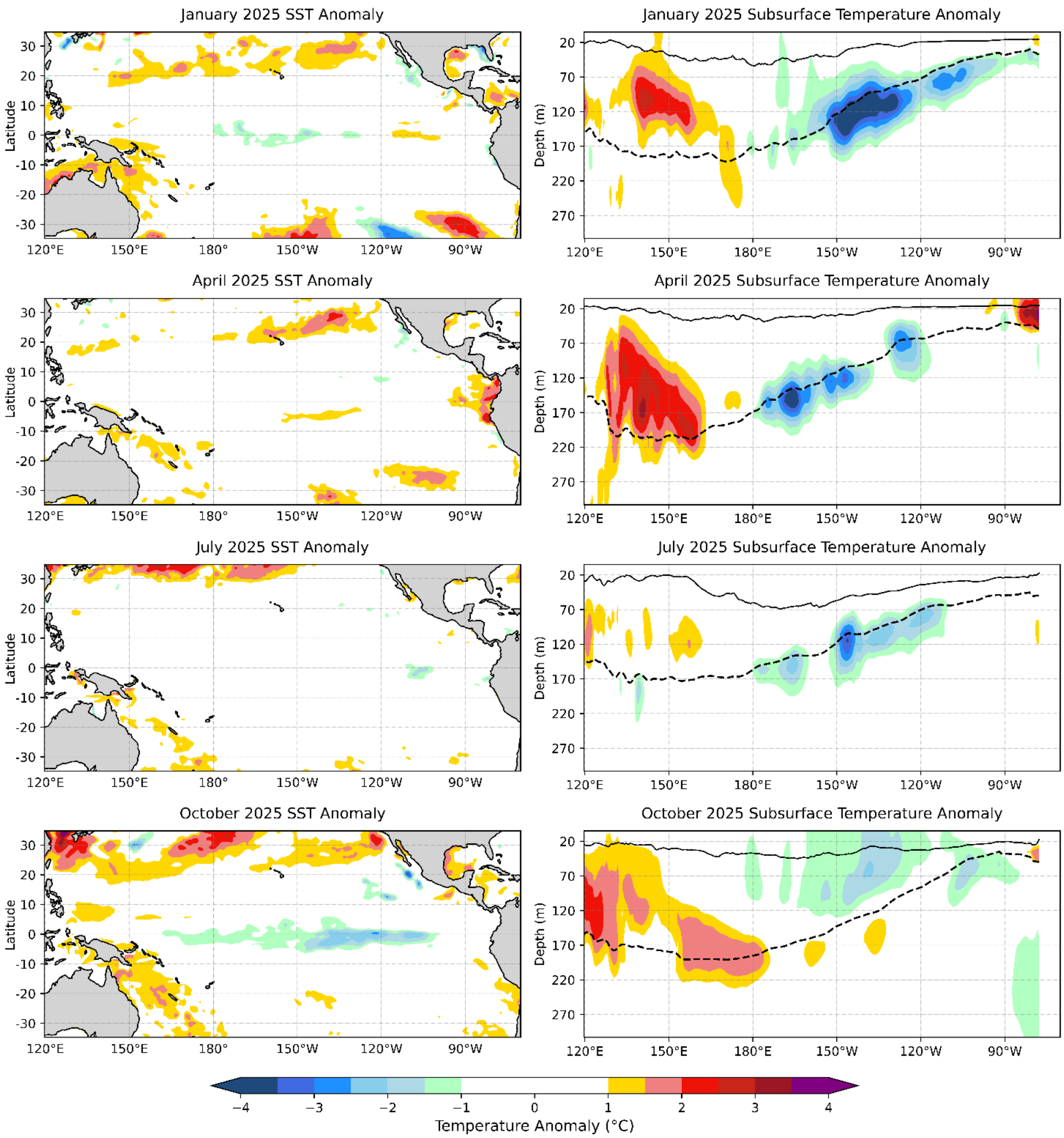

Fig. 2: (left) Monthly SST anomaly for the tropical Pacific. (Right) Subsurface temperature anomaly averaged over 5º S-5º N for the corresponding months.

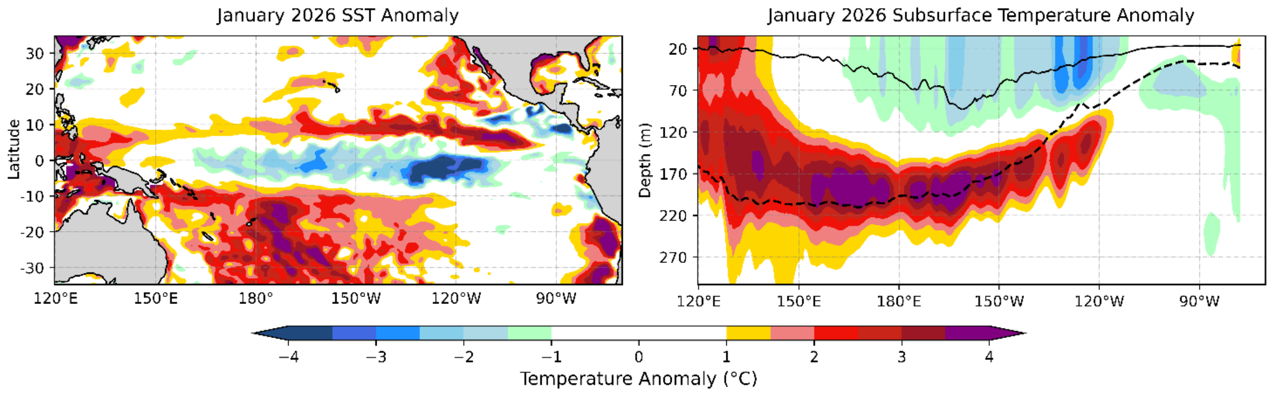

Fig. 3: (Left) Monthly SST anomaly for the tropical Pacific in January 2026. (Right) Subsurface temperature anomaly averaged over 5º S-5º N for January 2026.

INCOIS Outlook for NINO 3.4 index

INCOIS devised a deep learning-based Bayesian Convolutional Neural Network (BCNN) model to have probabilistic outlooks of the future evolutionof Nino 3.4 index. The model provides skillful prediction of Nino 3.4 index up to a lead-time of 15 months [See Annexure-I for more details of the model and its skill levels]. Median values of Nino 3.4 SST anomalies predicted by the model based on the November 2025 – January 2026 initial conditions extracted from INCOIS- GODAS are shown in Fig. 4. However, the model forecasts La Niña conditions in February. From March 2026 onwards, ENSO-neutral conditions emerge as the dominant phase throughout the forecast period, with probabilities ranging from 50% to 65%. During March to July 2026, La Niña conditions represent the second most likely ENSO phase, with probabilities of 20-55%, whereas from August to October 2026, El Niño becomes the second most likely phase, with probabilities of 20-45%.

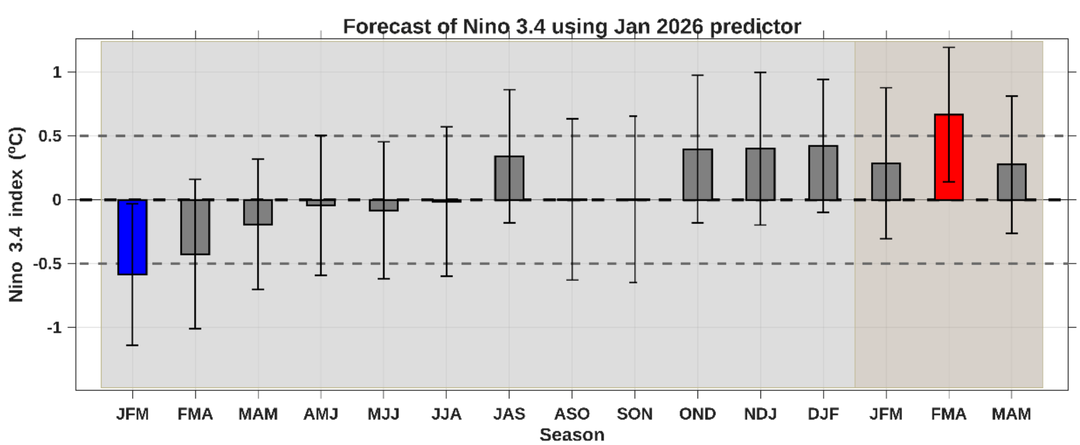

Fig. 4: Median prediction of Nino 3.4 index using November 2025-January 2026 predictors for the upcoming seasons.

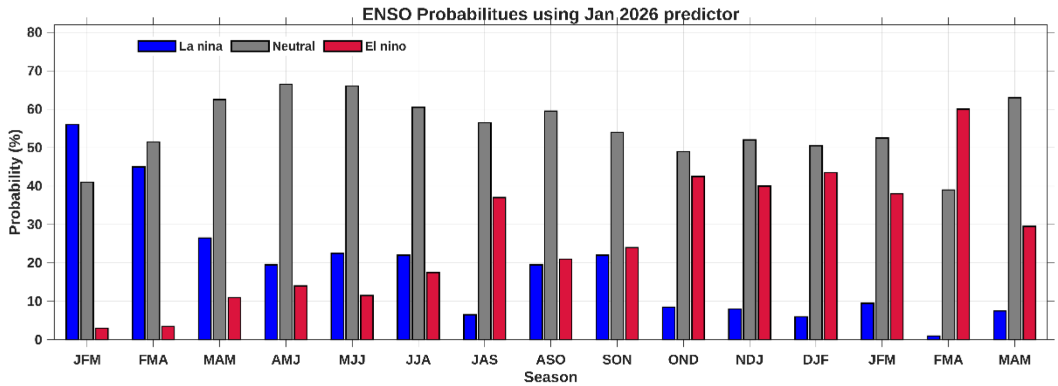

Fig. 5. Forecast of El Nino/La Nina conditions using November 2025-January 2026 predictors.

DISCLAIMER: This bulletin is based on numerical ocean model and ML method being run at INCOIS and the conclusions are based on the scientific understanding of those who prepared the bulletin. The predictions are evaluated routinely with available observational datasets. Individuals/groups/organizations are advised to be cautious while taking any decisions based on this bulletin.

Annexure-1

Data and Methodology

INCOIS-GODAS

INCOIS-GODAS is an ocean analysis system based on the Modular Ocean Model (MOM4p0) with 0.5° uniform zonal and varying (0.25 ° at the equator) meridional resolution and 40 vertical z-coordinate levels. It assimilates in-situ temperature and salinity profiles using 3DVAR assimilation scheme. Additionally, the model SST is relaxed to OISST with a 5-day timescale andthe surface salinity is relaxed to World Ocean Atlas at a monthly timescale. The model is forced with 6-hourly atmospheric fluxes from GFS v13 (provided by NCMRWF). The analysis is available from 1999 to date.

Bayesian Convolutional Neural Network (BCNN) model that provides probabilistic predictions for El Nino/La Nina conditions

The advent of deep learning-based approaches marks a transformative era in climate and weather prediction. Here, we introduce a deep learning-based Bayesian Convolutional Neural Network (BCNN) model that provides probabilistic predictions for El Nino/La Nina with a lead time of up to 24 months. The Bayesian layers within the CNN maintain the capability to predict a distribution of learned parameters. The inherent capacity for uncertainty modelling enhances the reliability of BNNs, making them particularly valuable in operational services. Validation of the all-season correlation skillof the Nino3.4 index from the BCNN model demonstrates significantly higher accuracy up to 16 months leads compared to current state-of-the-art dynamical forecast systems.

Data & Methods:

This work is inspired by the recent study of Ham et al., 2019, in which El Nino/La Nina prediction was carried out using a CNN network and ocean predictors with a lead time of 2 years in advance. A significant drawback of their system wasthe absence of model uncertainty quantification and confidence in prediction, which has been addressed here using BCNN.

BCNN Model Predictors and training

The prediction approach relies on the fact that El Nino/La Nina is connected to slow oceanic variations and their atmospheric coupling, indicating the potential for early forecast. Here, global, gridded monthly sea surface temperature (SST) data and upper 300 m integrated ocean potential temperature (T0-300)data (at a resolution of 2.5^0x2.5^0) spanning from 0°-360°E and 55°S-60°N for three consecutive months (n, n-1, n-2) are employed as plausible predictors of El Nino/La Nina, while the predictand or target is the Nino3.4 index, representing the area-averaged SST anomaly over 170°–120°W and 5°S to 5°N, predicted upto 24 months in advance.

One challenge in applying deep learning to El Nino/La Nina prediction is the scarcity of sufficient training data due to the limited observation period. Since global oceanic temperature records have only been accessible since 1871, fewer than 150 monthly samples are typically available to date. To overcome this limitation, we augment the training dataset by incorporating historical runs (1850-2014 period) from the Coupled Model Intercomparison Project phases5 (CMIP5) and 6 (CMIP6). CMIP models that exhibit good skill in reproducing historical ENSO characteristics are selected based on previous literature.

The initial training of the model incorporates 11 CMIP5 and 14 CMIP6 models, resulting in a substantial dataset of about 3200 samples. To mitigate systematic errors in the BCNN reflecting those of the CMIP samples, a learning transfer technique was employed, where the fine-tuning of the CMIP pre-trained model was conducted through another training approach utilising Simple Ocean Data Assimilation (SODA) reanalysis predictors spanning from 1871 to 1980. Details of data listed in table 1.

Separate BCNN models were set up for each season and each lead time. The BCNN predicted Nino 3.4 index was validated using NCEP-GODAS from 1991- 2020. The results show high predictability accuracy, with an all-season correlation skill exceeding 0.8 for the first six months, decreasing to 0.5 after only a 16-month lead (see Fig. 7.

Table 1. Details of data used for the BCNN model.

	Data	Period
Training dataset	CMIP5 historical run (11 models)	1850-2005
	CMIP6 historical run (14 models)	1850-2014
Training dataset (Transfer Learning)	Reanalysis (SODA)	1871-1980
Validation dataset	Reanalysis (GODAS)	1990-2020
Operational forecast dataset	INCOIS GODAS	2024 onwards

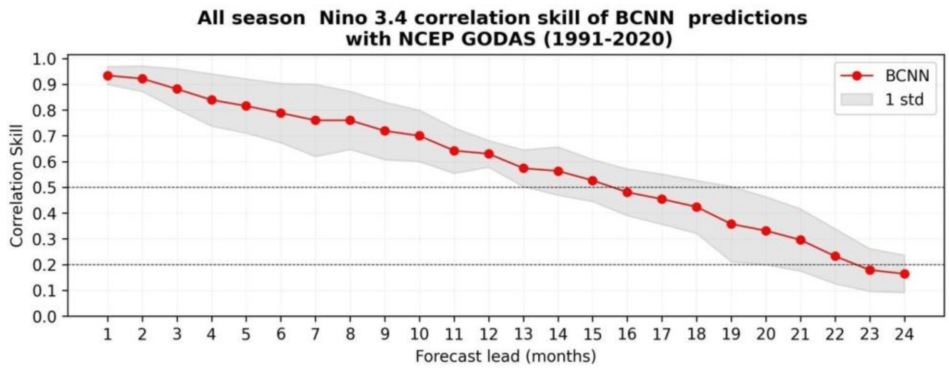

Fig 1. All-season correlation skill of BCNN-based El Nino/La Nina prediction compared with NCEP GODAS reanalysis for 1991-2020. The red line represents the median predicted El Nino/La Nina, with the 1 standard deviation of prediction shown in gray shades.