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Research Paper

Retrospective ENSO predictions using an intermediate ocean-atmosphere coupled model by integrating deep-learning sea surface wind stress*

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Abstract Various physics-based dynamical and data-based statistical models have been developed for uses in predicting sea surface temperature (SST) evolution in relation to the El Niño-Southern Oscillation (ENSO) over the tropical Pacific. At present, clear limitations remain in their ENSO predictions, with predicted SST anomalies (SSTAs) being widely spread across diverse models and considerable inter-model uncertainty. Fortunately, deep learning (DL)-based modeling has recently made promising advances in ENSO prediction tasks; numerous neural networks (NNs) have been constructed for ENSO predictions. However, most NNs themselves are purely data-driven and lack constraints of the necessary physical processes in the coupled system; there are few studies in which DL models are directly integrated with physics-based dynamical models. Previously, such a new type of intermediate coupled models (ICMs) was developed by directly integrating U-Net-derived sea surface wind stress models with an intermediate ocean dynamical model (denoted as ICM-UNet), with demonstrated success in simulating ENSO evolutions in freely coupled runs. It is thus natural to take a step further for prediction applications. In this study, this new ICM-UNet is applied for retrospective ENSO predictions, the first time that such a fusion of DL atmospheric model and dynamical oceanic model with different architectures can be achieved to make ENSO predictions. The overall evaluations indicate that the ICM-UNet yields valid retrospective predictions during the period 1995–2023, confirming that the ICM-UNet is a credible ocean-atmosphere coupled model for ENSO predictions. In case studies during 2020–2023, the ICM-UNet predictions reveal that SSTAs over the equatorial Pacific evolved into a second-year cooling in late 2021 and a warming tendency in 2023, forming a three-year La Niña and an El Niño event thereafter, which is consistent with the reality. The ICM-UNet successful fusion, taking advantage of both the physical constraints due to dynamical oceanic models and nonlinear representations of wind responses due to DL capacity, further underscores the high adaptability of integrating data-driven NNs into the ocean-atmosphere coupled modeling for ENSO-related studies.

Keyword: El Niño-Southern Oscillation (ENSO) prediction; intermediate coupled model; deep learning (DL); an integration of DL model with an ocean model; intermediate coupled model (ICM)-UNet

1 INTRODUCTION

The spatio-temporal evolution of sea surface temperature (SST) over the tropical Pacific plays an

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important role in global atmospheric and oceanic circulation, influencing weather and climate conditions as represented in precipitation, air temperature, wind fields, and others (Ropelewski and Halpert, 1987; Diaz et al., 2001; McPhaden et al., 2006). Among these influences, the El Niño-Southern Oscillation (ENSO) is a principal climate phenomenon that reflects interannual SST variability over the tropical Pacific, exhibiting a quasi-periodic oscillation (Chen and Cane, 2008; Capotondi et al., 2013). Beyond its role in atmospheric and oceanic variability, ENSO exhibits property changes and diversities under the warming climate condition (Zhang et al., 1998), and thus it is also central to global climate change assessments and the mitigation of natural disasters associated with its impacts (Scaife et al., 2024). Consequently, accurately predicting and projecting ENSO events is a fundamental challenge in physical oceanography and climate science, with both scientific and societal significance (Latif et al., 1998; Adams et al., 1999; Yang et al., 2018).

Basic exploration on ENSO prediction began in the mid-1980s (Cane and Zebiak, 1985; Cane et al., 1986). In the preceding few decades, significant advancements have been made in ENSO modeling, enabling real-time predictions up to 6–12 months in advance (Tang et al., 2018). The foundation of ENSO dynamics and predictions lies in the Bjerknes feedback mechanism, which describes the systematic ocean-atmosphere interactions that contribute to the formation and maintenance of ENSO events (Bjerknes, 1969). Since then, various state-of-the-art theories have been developed to explain ENSO dynamics, including the delayed action oscillator (Schopf and Suarez, 1988), the recharge-discharge oscillator (Jin, 1997), and the western Pacific paradigm (Weisberg and Wang, 1997). These theories have shaped ENSO research, transitioning from simple statistical analyses to more sophisticated dynamical modeling and predicting.

ENSO prediction models are broadly categorized into data-based statistical models and physics-based dynamical models, each with distinct advantages and limitations. Statistical models can be further classified into linear and nonlinear approaches. While linear models provide robust relationships and simplified structures, they often lack physical constraints. Nonlinear statistical models, on the other hand, incorporate complex mappings among variables, improving predictive capability. Meanwhile, physics-based ocean-atmosphere coupled models leverage geophysical fluid dynamics to represent ENSO evolution. These models exhibit various complexities, ranging from simple intermediate coupled models (ICMs; Zebiak and Cane, 1987; Zhang et al., 2003, 2005) to hybrid coupled models (HCMs; Barnett et al., 1993; Zhang, 2015) and fully coupled general circulation models (CGCMs; Ji et al., 1994; Jin et al., 2008). While CGCMs offer comprehensive simulations of ENSO evolution, they are computationally intensive. In contrast, ICMs provide efficient and effective modeling tools while keeping essential physical processes. One notable ICM, developed at the Institute of Oceanology, Chinese Academy of Sciences (IOCAS), has been successfully applied for real-time SST anomaly (SSTA) predictions (Gao et al., 2016, 2018; Zhang and Gao, 2016).

Historical observations highlight the complexity and diversity of ENSO, as no two events follow an identical evolutionary pattern (Timmermann et al., 2018). This inherent diversity makes ENSO prediction one of the most challenging problems in physical oceanography (An and Jin, 2004; Yeh et al., 2009; Zhang et al., 2022). Multiple climatic factors contribute to ENSO's complexity (Xie et al., 2018; Tian et al., 2021), and recent years have witnessed a decline in ENSO predictability due to decadal climate changes in a warming world (Yu and Kao, 2007; Horii et al., 2012; Cai et al., 2018). Both statistical and dynamical models have struggled with configuration limitations (Hu et al., 2014; Zhang et al., 2020). For instance, most statistical models fail to capture nonlinear relationships effectively (Barnston et al., 2012), this may explain why linear atmospheric models in ICMs produce overly regular simulations that overlook ENSO's inherent complexity (Zhang et al., 2008). These challenges underscore the need for new techniques to overcome the limitations of traditional linear atmospheric models and develop new types of modeling capabilities for ENSO representations and predictions.

Deep learning (DL) has emerged as a state-of-the-art method in physical oceanography and ocean-atmosphere interactions in recent years (Dong et al., 2022; Zhao et al., 2024). Early efforts, such as Tangang et al. (1997), applied basic neural networks (NNs) for SST predictions over the equatorial Pacific. More recently, Ham et al. (2019) illustrated that convolutional neural networks (CNNs) could outperform traditional dynamical models by accurately predicting Niño3.4 SST index up to

17 months in advance. Various deep learning architectures have since been explored for ENSO prediction, including CNNs (Ham et al., 2021), graph neural networks (GNNs; Cachay et al., 2021), and recurrent neural networks (RNNs; Guo et al., 2020). More recently, transformer-based models, known for their self-attention mechanisms, have been applied to ENSO predictions. For example, Zhou and Zhang (2023) constructed self-attention-based NNs primarily for predicting upper-ocean three dimensional temperature and wind stress anomalies, and it has been applied for ENSO real predictions (Gao et al., 2023; Zhang et al., 2024a, b; Zhou and Zhang, 2024, 2025). These advancements illustrate how ENSO prediction has evolved from simple single-index predicting to more representative, interpretable three-dimensional modeling (Hu et al., 2021; Ye et al., 2021; Zhou and Zhang, 2022; Zhou et al., 2023; Qin et al., 2024). Moreover, the advent of big-data-based meteorological models such as Fuxi and Pangu has ushered in a remarkable new era of data-driven weather forecasting (Bi et al., 2023; Chen et al., 2023).

Increasingly complex neural networks are also being integrated with physical models to leverage the strengths of both approaches and capture underlying dynamical processes (Rivera Tello et al., 2023; Lyu et al., 2024; Sreeraj et al., 2024). A promising direction involves the direct fusion of deep learning models with dynamics frameworks, a hybrid architecture consisting of different components of the ocean-atmosphere coupled system. For instance, Kochkov et al. (2024) developed a general circulation model (GCM) that integrates differentiable atmospheric dynamics solvers with deep learning components for ensemble weather forecasts. Note that although similar methods have been adopted to make weather forecasts and ocean predictions by using NN-based or physics-based models, they are either the atmosphere or ocean only without their coupling, and their forecast applications are short time (e.g., up to 10 d in time interpolation). Currently, there exists no coupled model that has integrated NN atmosphere with dynamical ocean in a fusion manner to successfully reproduce interannual oscillation for the tropical Pacific climate system.

More recently, a breakthrough was made by Du and Zhang (2024) who introduced U-Net-based ICM (named ICM-UNet) that combines a deep learning-based atmospheric wind stress model derived from the U-Net technique with an intermediate dynamical ocean model to form a novel coupled ocean-atmosphere model. Specifically, ICM-UNet employs UNet-derived wind stress models to capture the nonlinear relationship between monthly SST anomalies (SSTAs) and sea surface wind stress anomalies over the tropical Pacific from historical data. This ICM-UNet has been quietly extensively tested for its ability to represent oceanic and atmospheric interannual variabilities over the tropical Pacific, including atmosphere-only, ocean-only, and coupled simulations, respectively. Building upon these activities, a refined model—ICM-RCUNet—was also developed to incorporate multi-day time sequences into the wind stress component to represent the effects of atmospheric processes on multiple time scales, further enhancing ENSO simulations (Du and Zhang, 2025). These advances underscore the potential of DL to enhance ENSO predictions when integrated into dynamical models. While ICM-UNet has been validated for simulating ENSO spatio-temporal evolution, it has yet to be tested for retrospective predictions.

The principal objective of this study is to make a first attempt to use such a deep learning (U-Net)-based ICM-UNet and evaluate its feasibility and reliability for retrospective ENSO predictions. The ICM-UNet, which integrates UNet-derived wind stress models with an intermediate-complexity ocean model, has already demonstrated its capability in simulating ENSO events. This study assesses whether it can be successfully used for retrospective predictions spanning 1995–2023. Case studies during 2020–2023 reveal that ICM-UNet can adequately capture key ENSO features, including a second-year surface cooling event in late 2021 and a warming trend in 2023 over the equatorial tropical Pacific. It is worth noting that the predictions are obtained directly from the ICM-UNet without data assimilation techniques implemented, and no model output statistics corrections. These outcomes suggest that integrating deep learning atmospheric models with physics-based ocean models enhances the prediction of complex ENSO behaviors. Ultimately, this study reinforces the benefits of hybrid approaches that merge deep learning with traditional ocean-atmosphere coupled models, offering a promising avenue for future ENSO predicting research. As a first step, some preliminary results are provided in subsequent sections, and further improvements using the integrated DL-physics modeling approach are necessary in the future.

The remainder of the paper is structured as follows: the data and prediction methodology are presented in Section 2. Then, Section 3 describes an evaluation of ICM-UNet predictions, including overall assessment during the period 1995–2023 and case studies for 2020–2023, respectively. Finally, conclusion and discussion are given in Section 4.

2 DATA AND PREDICTION METHODOLOGY

2.1 Data

This study employs a variety of data sets for mainly two purposes: one for initializing the ICM-UNet and the other for constructing the UNet-derived atmospheric models. For example, the observed SSTAs used for initialization were derived from the ECMWF Reanalysis v5 (ERA5) data (Hersbach et al., 2020). Specifically, the downloaded monthly-averaged SSTAs covering the tropical Pacific (31.5°S–31.5°N, 123.5°E–77.5°W) from January 1982 to April 2024 were interpolated into 1°×1° horizontal grids. These ERA5 reanalysis SSTAs served as the observed data to initialize the ICM-UNet. Also, the UNet-derived sea surface wind stress models were trained and validated using extensive monthly-averaged reanalysis data and historical simulations from ECMWF Ocean Reanalysis System 5 data (ORAS5; Zuo et al., 2017) spanning from 1958 to 1994 and Coupled Model Intercomparison Project Phase 6 products (CMIP6; Eyring et al., 2016) spanning from 1850 to 2014. More details about the CMIP6 and ORAS5 data used to train the UNet-derived atmospheric models can be seen in Du and Zhang (2024).

2.2 Prediction methodology

As displayed on the right part of Fig.1 (inside the dashed box), the ICM-UNet consists of a UNet-derived atmospheric component and an intermediate-complexity dynamical ocean model, which performs retrospective predictions after initialization (the left part of Fig.1). As an atmospheric component of the ICM-UNet, UNet-derived sea surface wind stress models are built based on the original U-Net structure with a standard encoder-decoder configuration (Ronneberger et al., 2015). The original U-Net model, initially designed for semantic segmentation, is a variant of fully convolutional networks and has evolved into more sophisticated models such as UNet++ (Zhou et al., 2018). The UNet-derived atmospheric models in this study are adapted from the original U-Net framework (Supplementary

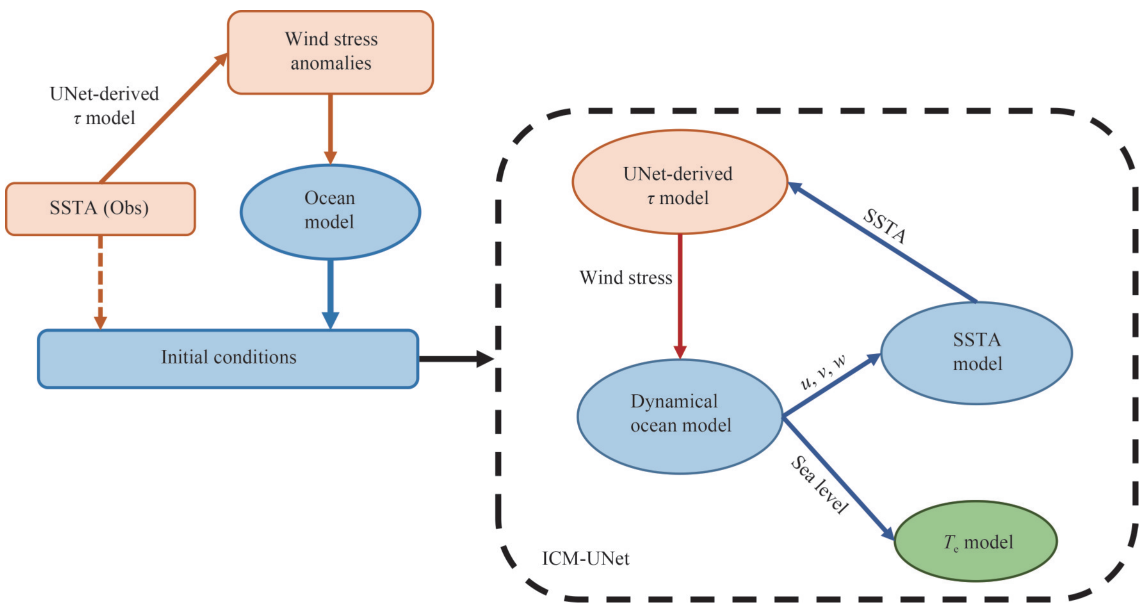

Fig.1 A schematic diagram showing the prediction system of ICM-UNet

The left part (outside the dashed box) represents the initialization procedure. Observed interannual sea surface temperature anomalies (SSTAs) are the only fields considered in the initialization procedure for real-time predictions. First, observed SSTAs are used to derive wind stress anomalies using the UNet-derived wind stress (τ) model. Subsequently, initial conditions necessary for the prediction model are generated from the ocean model forced by the derived wind stress fields. The right part (inside the dashed box) represents the structure of the ICM-UNet. The ICM-UNet is comprised of the UNet-derived wind stress model and an intermediate ocean model consisting of a dynamical ocean model (u and v represent the zonal and meridional velocities in the surface mixed layer; w denotes the vertical velocity at the mixed layer bottom), an SSTA model, and an empirical anomaly model for T_e. For real-time predictions, the initial conditions (from the left part outside the dashed box) are used to initialize the ICM-UNet (the right part inside the dashed box).

Fig.S1). It has been demonstrated that the trained and validated U-Net models can effectively produce wind stress anomalies based on input SSTAs in ocean-atmosphere coupled modeling (Du and Zhang, 2024). In addition, the ICM-UNet adopts an identical ocean component as the IOCAS ICM with modifications (Keenlyside and Kleeman, 2002; Zhang et al., 2003; Zhang and Gao, 2016).

Predicting atmospheric and oceanic interannual variabilities using the ICM-UNet involves several considerations. In particular, initial fields, the performance of each component, and their coherence at the initial time are crucial for accurate SSTA predictions. The main prediction procedures for the ICM-UNet are shown in Fig.1. Currently, the ICM-UNet applies a simple initialization using observed SSTAs (Zhang and Gao, 2016). Taking the 12-month prediction made on 1 January 2020 as an example, the UNet-derived atmospheric models first calculate interannual wind stress anomalies using the observed SSTAs from January 1982 to December 2019; these derived wind stress fields are then applied to force the ocean model for generating initial conditions on the first day of each month (i.e., 1 January 2020). In the initial conditions, the simulated SSTAs are directly replaced by observed SSTAs, ensuring that both simulated dynamical ocean fields and observed SSTAs serve as initial conditions. As an ocean-atmosphere coupled model, the initialized ICM-UNet produces retrospective ENSO predictions directly without additional modifications or corrections. Generally, the ICM-UNet produces predictions for SSTAs and other oceanic and atmospheric anomalies covering the tropical Pacific.

In prediction experiments, each component in the ICM-UNet exchanges variable information once a day, and the atmospheric and oceanic models are coupled with text-file interactions. At each time step, oceanic variables are first calculated using the dynamical ocean model, such as sea level. Subsequently, the temperature of subsurface water entrained into the mixed layer (T_e) anomalies are calculated from sea level anomalies through the T_e model and serve as the interface between SSTAs and dynamical components. Next, the SSTA model produces the SSTAs from the calculated T_e anomalies, oceanic fields, observed SST climatologies, and vertical temperature gradients. The saved SSTAs are then input into the UNet-derived atmospheric models to obtain zonal and meridional wind stress anomalies, and they are applied to force the dynamical ocean model. To generate predictions with different lead times, the ICM-UNet requires iterative updating following these procedures (Zhang et al., 2005).

3 PREDICTION EVALUATION BASED ON THE ICM-UNET

3.1 An overall assessment during the period 1995–2023

This section evaluates the overall retrospective prediction performances through error and correlation analyses to justify the credibility of subsequent case studies. The ICM-UNet is employed to perform retrospective experiments on SSTAs in the tropical Pacific from 1995 to 2023, starting on the first day of each month. It is worth mentioning that the UNet-derived atmospheric models were fine-tuned and validated using ORAS5 data from 1958 to 1994, indicating that the model training periods are independent of the prediction periods, ensuring that the prediction is independently made and its accuracy is not overestimated. To present a quantitative validation of the prediction performance, the Root Mean Square Error (RMSE) and Correlation coefficient (Corr) between observed and predicted Niño3.4 SSTAs are calculated. In particularly, the RMSE provides the discrepancy estimates between observed and predicted Niño3.4 SSTAs, while the Corr quantifies their linear correlation, which can be defined as:

$$\mathrm{RMSE}_t = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(\tilde{X}_{t,j}-X_j\right)^2}, \tag{1}$$

$$\mathrm{Corr}_t = \frac{\sum_{j=1}^{N} X_j \tilde{X}_{t,j}}{\sqrt{\sum_{j=1}^{N} X_j^2 \sum_{j=1}^{N} \tilde{X}_{t,j}^2}}, \tag{2}$$

where $\tilde{X}_{t,j}$ and X_j indicate the predicted and reanalysis Niño3.4 SSTAs; N shows the number of months representing the predicting duration (N=1, 2, $\cdots$, 12); the predictions are obtained from the ICM-UNet with t=1, 2, $\cdots$, j months in advance.

As shown in Fig.2, the ICM-UNet produces reliable retrospective ENSO predictions (i.e., Corr> 0.5) up to 7 months in advance, while the RMSE remains within an acceptable range. Furthermore, the ICM-UNet exhibits high prediction skills at relatively short lead times, with the Corr remaining above 0.8 and RMSE below 0.5 °C at 3 months in advance. These results ensure the feasibility of

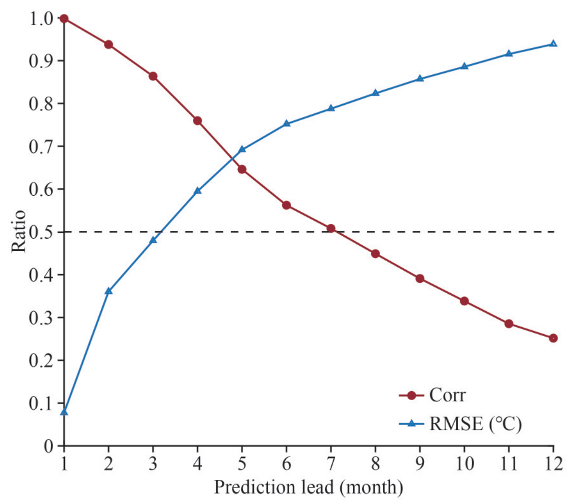

Fig.2 Correlation coefficient (Corr, red) and root mean square error (RMSE, blue) curves are calculated as a function of prediction lead months for the Niño3.4 sea surface temperature (SST) anomalies

The results are obtained for all predictions made during the period 1995–2023.

subsequent case studies for 2020–2023. For longer lead times, the prediction accuracy drops gradually. At a 12-month lead time, for example, the RMSE remains below 1 °C, but the Corr decreases to 0.25. This is likely due to the ICM-UNet's simple fusion of UNet-derived wind stress models with the intermediate ocean model, without taking advanced data assimilation in this experiment (i.e., the initial oceanic state is not adequately adjusted). It suggests that the ICM-UNet still has considerable potential for improvement in predicting ENSO events over longer timescales.

To evaluate the spatial structure of retrospective predictions, Fig.3 demonstrates the horizontal distribution of Corr and RMSE between observed and predicted SSTAs at lead times of 3 and 6 months. As seen in Fig.3a–b, the distribution of Corr exhibits a V-shaped pattern. High Corr regions are concentrated in the central-eastern tropical Pacific, accompanied by two low-value regions in the northwest and southwest. The Corr exceeds 0.8 in the central Pacific and remains above 0.6 in the east for 3-month lead time predictions (Fig.3a). Meanwhile, the RMSE exceeds 1 °C only in the eastern equatorial Pacific and North American coastal regions (Fig.3c). From a spatial perspective, the overall retrospective predictions are reasonable and performances in the central basin are significantly better. The Corr remains above 0.5 in the central Pacific at 6-month lead time predictions, but decreases below 0.5 over most regions east of 120°W (Fig.3b), and the RMSE exceeds 1 °C near the equator (Fig.3d).

In summary, as a promising prediction model that integrates the UNet-derived atmospheric model with

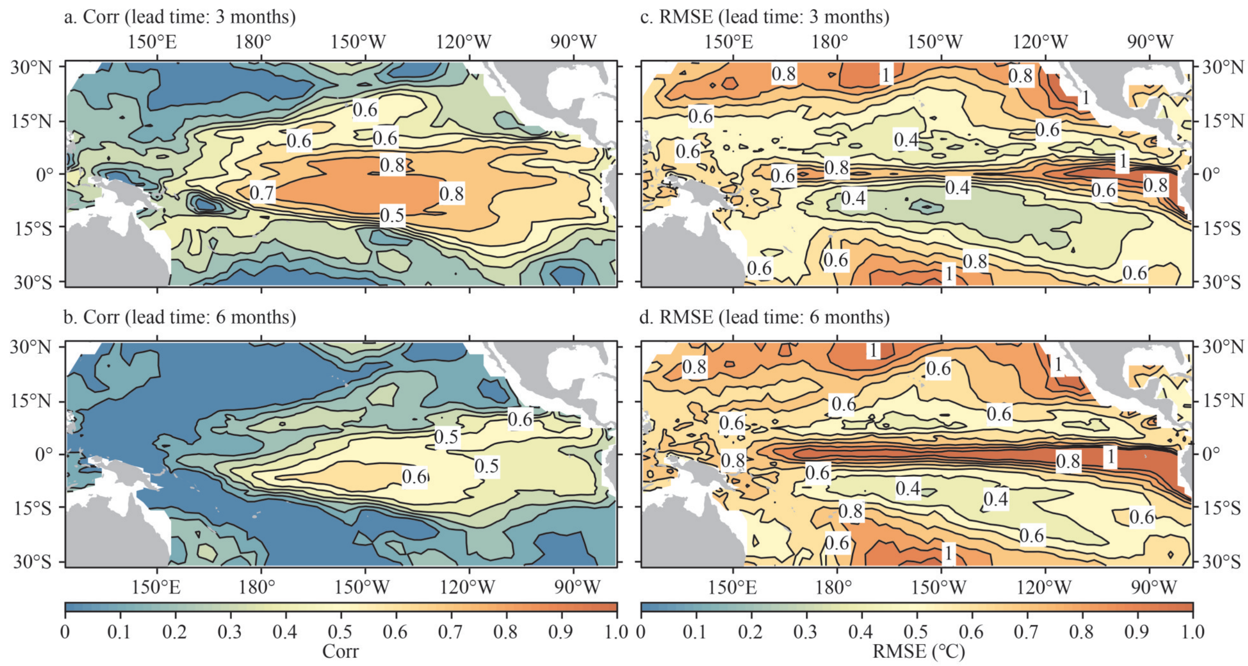

Fig.3 Horizontal distributions of Corr (a–b) and RMSE (c–d) for observed and predicted SSTAs for 3- and 6-month lead times, respectively

The results are obtained for all predictions made during the period 1995–2023. The contour intervals are both 0.1.

the physics-based dynamical oceanic model, the ICM-UNet provides reasonably well retrospective ENSO predictions with reliable and stable performances, laying the foundation for subsequent case studies during 2020–2023.

3.2 A case study for 2020–2023

ENSO has exhibited diversity and complexity in recent years due to the effects of global warming, which has continuously caused a decrease in ENSO predictability using traditional dynamical and statistical models. For example, five multi-year La Niña events have occurred during this century, including 1998–2000, 2007–2008, 2010–2011, 2016–2017, and 2020–2022 La Niña events (Hu et al., 2014; Feng et al., 2015; Gao et al., 2022; Wang et al., 2023). As seen in observations (Supplementary Fig.S2), a three-year La Niña event occurred during 2020–2022 and developed into a typical El Niño condition in 2023. More specifically, a moderate La Niña condition occurred in late 2020, accompanied by strong easterly wind anomalies prevailing in the western-central equatorial Pacific. In mid-2021, the SST in the eastern equatorial Pacific was close to normal state, but cooling conditions reoccurred in August and September, and the turning point appeared in June. These cooling conditions then evolved into a second-year La Niña event in late 2021. In early 2022, the cold SSTAs exhibited a lingering evolution signature over the central-eastern tropical Pacific. Moreover, the cold SSTAs reappeared and enhanced again from February to April 2022, leading to a third-year La Niña in late 2022 (Hasan et al., 2022; Li et al., 2022; Fang et al., 2023; Chen et al., 2024). Following this three-year La Niña condition, significant warm SSTAs emerged over the equatorial Pacific in early 2023. By spring 2023, warm SSTAs were intensified rapidly in the southeast and propagated westward along the equator, and finally evolved into a typical El Niño event (Iwakiri and Watanabe, 2021; Lian et al., 2023; Hu et al., 2024).

Indeed, some distinct features of the three-year La Niña event during 2020–2022 and the El Niño event in 2023 pose significant challenges to predictions. Figure 4 displays the 2020–2024 Niño3.4 SSTAs predicted by the ICM-UNet from different initial times. Overall, the temporal evolution of Niño3.4 SSTAs predicted by the ICM-UNet is close to the ERA5 reanalysis, capturing the general cooling and warming tendencies during the period 2020–2024. In particular, the ICM-UNet

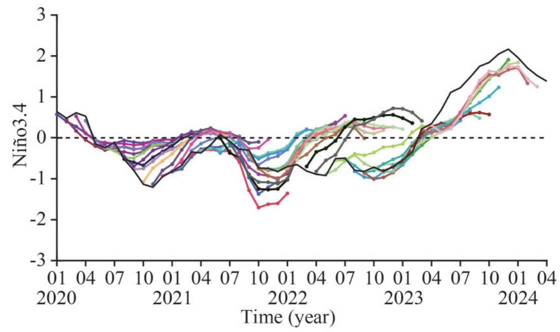

Fig.4 ERA5 reanalysis (black lines) and predicted (colored lines) Niño3.4 SST anomalies during 2020–2024

Each colored line represents a 12-month prediction made using ICM-UNet from different initial conditions.

provides more realistic retrospective predictions of the second-year surface cooling condition in late 2021 and the warming trend in 2023, especially the phase transition in February 2023. The success in retrospective ENSO predictions is partly attributed to the enhanced representation of ocean-atmosphere interactions, demonstrating the potential of integrating UNet-derived wind stress models with the physics-based dynamical oceanic model for ENSO representations. However, the ICM-UNet still has biases in the underestimation of SSTAs, leading to the spring predictability barrier (SPB), so the predictions for 2022 are considerably inaccurate.

The 12-month atmospheric and oceanic anomaly predictions made from January 2021 as the initial condition are shown in Figs.5–7. The cooling condition that reappeared in late 2021 is consistent with observations, illustrating that the ICM-UNet can successfully predict the second-year La Niña condition 12 months in advance, which is challenging for several other prominent dynamical and statistical models (Supplementary Figs.S2–S3). As reflected in Fig.5, the ICM-UNet reasonably captures the key relationships among SSTAs, zonal wind stress anomalies, and SL anomalies. When cold SSTAs emerged in the eastern equatorial Pacific, the western Pacific exhibited easterly wind anomalies. Moreover, the ICM-UNet captures the turning point of SSTAs in June, with the resulting SSTAs evolving again into a La Niña condition afterward. The spatio-temporal distributions of relevant atmospheric and oceanic variables provide additional evidence that the ocean-atmosphere coupled system over the equatorial Pacific sustained a cooling state in late 2021 (Figs.6–7).

The ICM-UNet predictions made with January 2023 as the initial condition are shown in Figs.8–10.

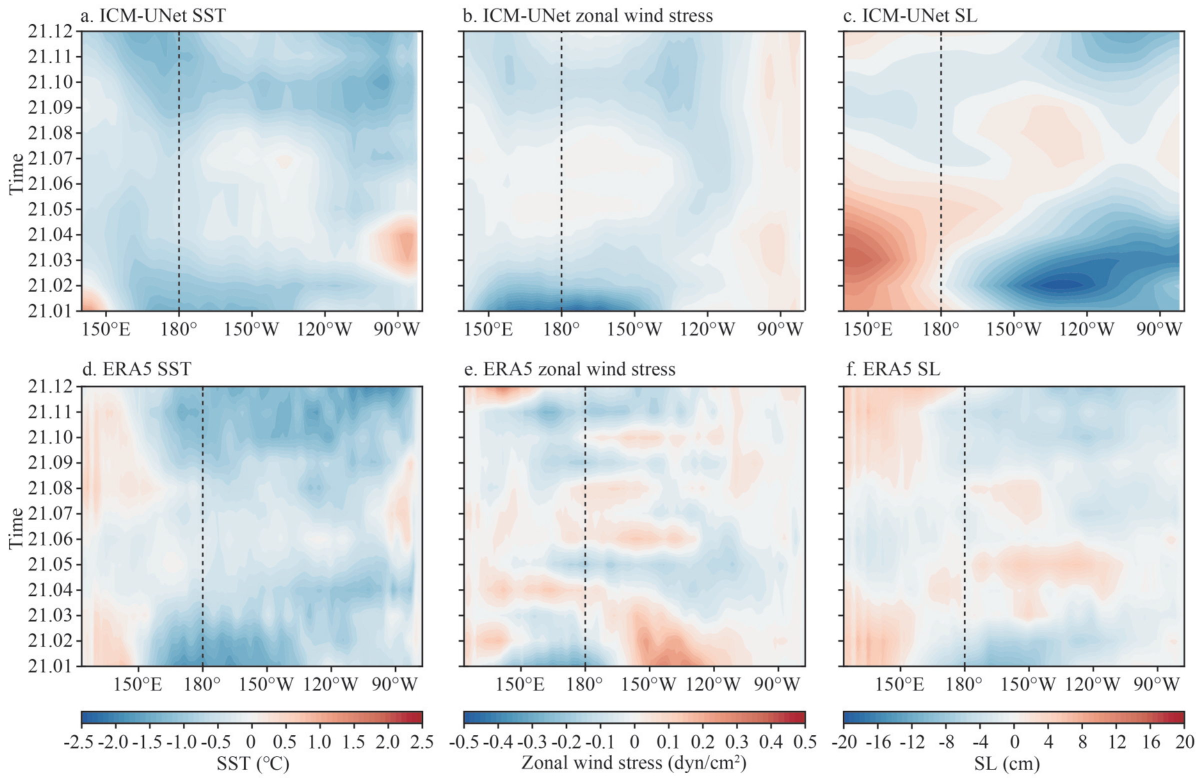

Fig.5 Zonal-time sections along the equator for anomalies of SST (left column), zonal wind stress (middle column), and sea level (SL, right column), calculated from ERA5 reanalysis data (d, e, f) and predicted (a, b, c) using the ICM-UNet from the initial conditions in January 2021

These retrospective predictions indicate that the tropical Pacific experienced a typical El Niño event in 2023 (Fig.8), with SSTAs shifting rapidly to a warm condition in mid-2023. Meanwhile, their horizontal distributions depict different phases of the 2023 El Niño event (Figs.9–10). When warm SSTAs over the equatorial eastern Pacific are predicted to emerge in late spring, they are associated with robust westerly wind anomalies, and the SL anomalies gradually intensify when propagating eastward. Since spring 2023, the interaction between the SSTAs and wind stress anomalies has been further enhanced, leading to warm SSTAs in the tropical Pacific, which aligns with observations (Supplementary Fig.S2). However, the ICM-UNet underestimates the warming intensity of SSTAs when predicted from spring. These biases between predicted SSTAs and observations in early 2023 are seasonally dependent, suggesting that the ICM-UNet still has potential for improvement in accurately representing the ocean-atmosphere coupled processes.

As seen evidently, the ICM-UNet retrospective predictions represent the critical assessments for ENSO features during the period 2020–2023, including a second-year La Niña condition in late 2021 and an El Niño state in 2023. It is indicated that the direct fusion of the DL-based model with the physics-based dynamic oceanic model can enhance the prediction of complex ENSO behaviors.

4 DISCUSSION AND CONCLUSION

In the climate communities, the primary objective of ENSO-related studies is to provide reliable ENSO predictions through mechanism understanding and process representations. The complexity and diversity of ENSO make it challenging to depict complicated evolution patterns, leading to difficulties in accurately predicting and projecting ENSO events. For instance, a three-year La Niña event occurred over the tropical Pacific after 2020 and evolved into a typical El Niño condition in 2023. Many physics-based models failed to predict the spatio-temporal evolution of these complex events due to their inherent configuration limitations. Consequently, there is an urgent need to develop novel types of modeling capabilities for ENSO process

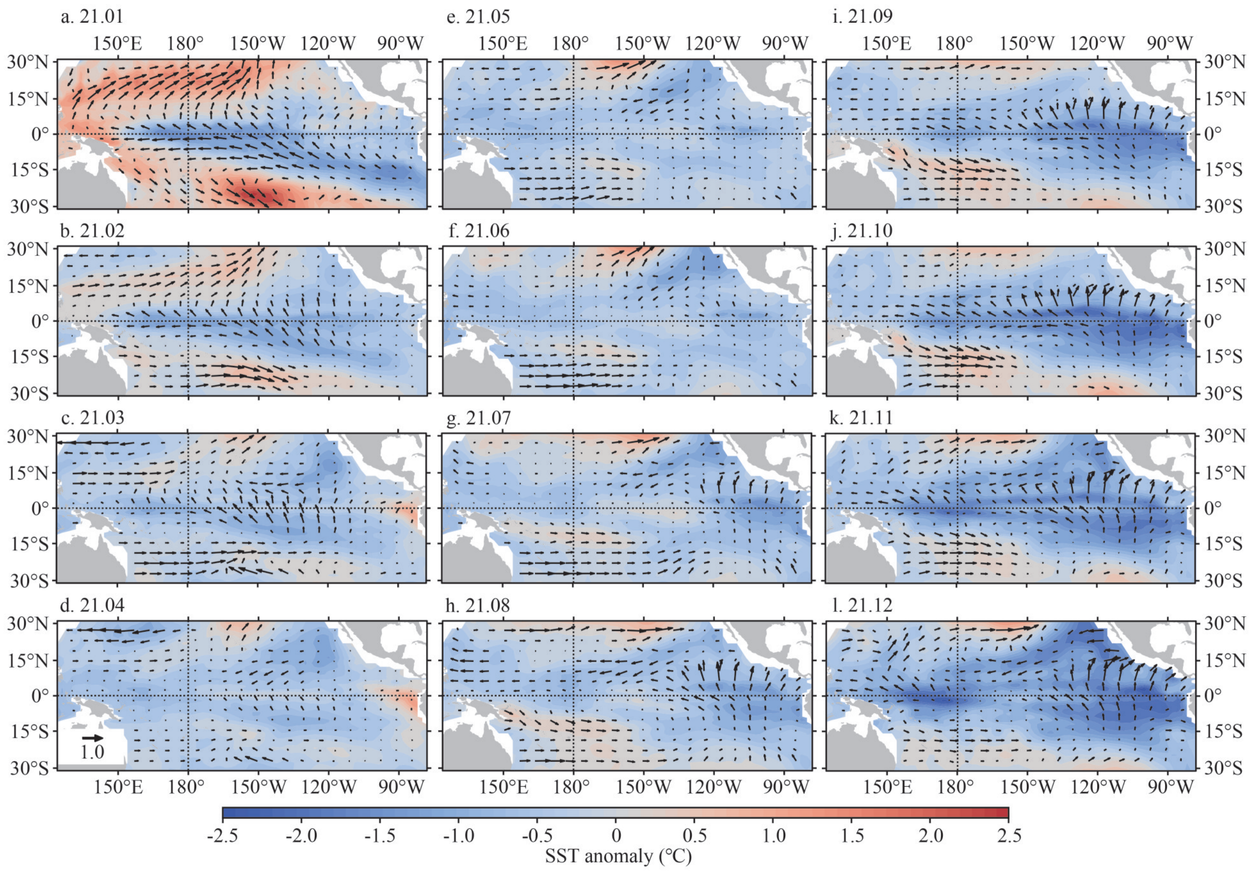

Fig.6 Horizontal distributions of SST anomalies (color shading; unit: °C) and wind stress anomalies (vectors; unit: dyn/cm^2) predicted using the ICM-UNet from the initial conditions in January 2021

The scale for wind stress vectors given by the black arrow in the lower left corner indicates 1.0 dyn/cm^2.

representations and thus to improve their predictions.

With the profound applications of DL techniques in physical oceanography and meteorology, increasingly complex NNs provide promising avenues for accurate ENSO representations and predictions. Differing from simplified NNs that perform sequence predictions, directly integrating deep learning models with dynamics frameworks is a new technique to leverage the strengths of both approaches. Previously, Du and Zhang (2024) directly integrated UNet-derived wind stress models with an intermediate ocean model to form the ICM-UNet, which was then employed to simulate the atmospheric and oceanic interannual variabilities over the tropical Pacific. While the ICM-UNet was used to simulate ENSO events, no attempt has been made to perform retrospective predictions.

Therefore, this study extends previous work by making the first attempt to use the ICM-UNet to make retrospective ENSO predictions independent of the UNet models' training period. The results suggest that the ICM-UNet yields credible retrospective ENSO predictions during the period 1995–2023, proving that the ICM-UNet is a feasible ocean-atmosphere coupled model capable of both simulating and predicting the spatio-temporal evolution of SSTAs over the tropical Pacific without data assimilation. In case studies, the ICM-UNet makes reliable predictions of atmospheric and oceanic interannual variabilities during the period 2020–2023. Specifically, the ICM-UNet successfully captures key ENSO features, including a second-year La Niña condition in late 2021 and an El Niño event in 2023. These outcomes indicate that predictions starting in January 2021 reflect a persistent cooling condition over the equatorial Pacific and a second-year surface cooling in late 2021. Moreover, the warming tendency in predicted SSTAs was depicted for the 2023 El Niño event, which initiated in the spring, developed rapidly in the fall, and matured in the winter. Thus, these results clearly illustrated that integrating deep learning atmospheric models with physics-based ocean models enhances the prediction of complex ENSO behaviors.

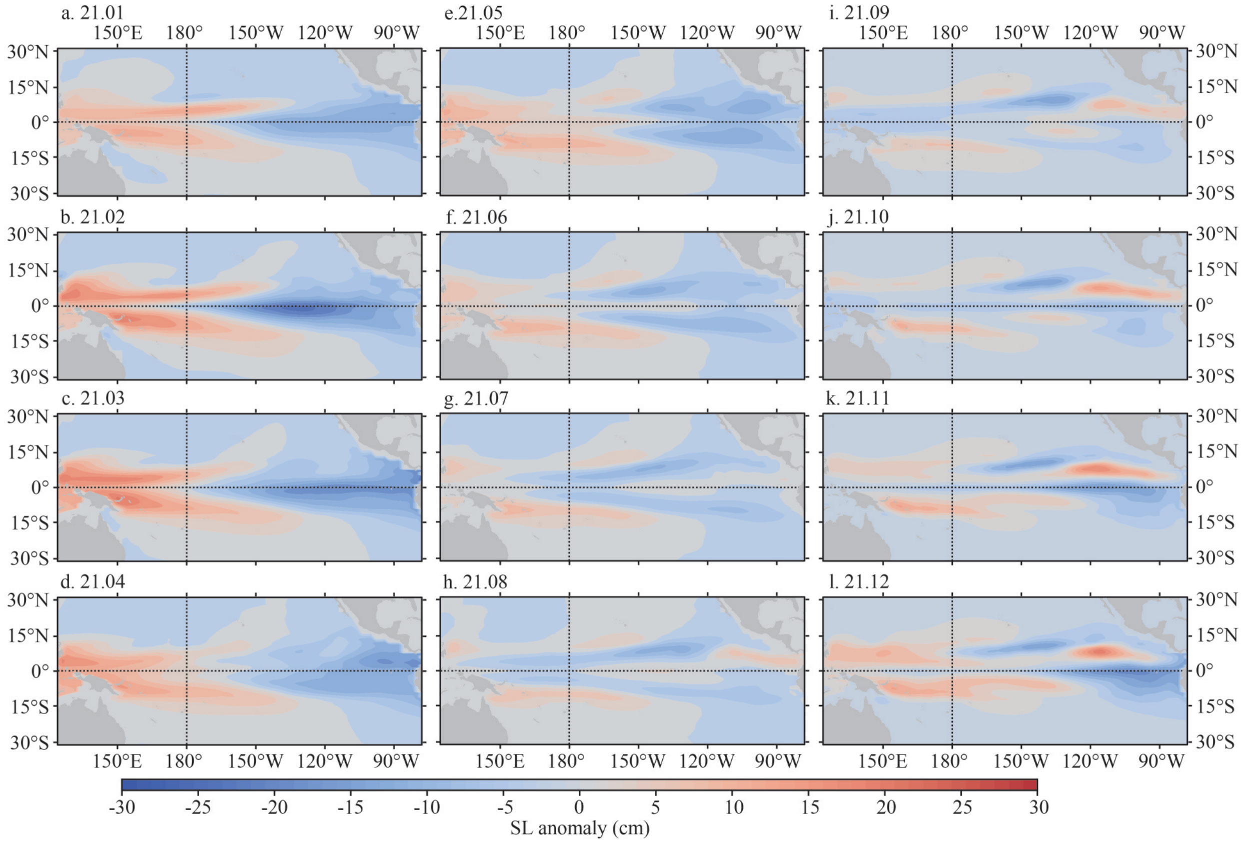

Fig.7 Horizontal distributions of SL anomalies (unit: cm) predicted using the ICM-UNet from initial conditions in January 2021

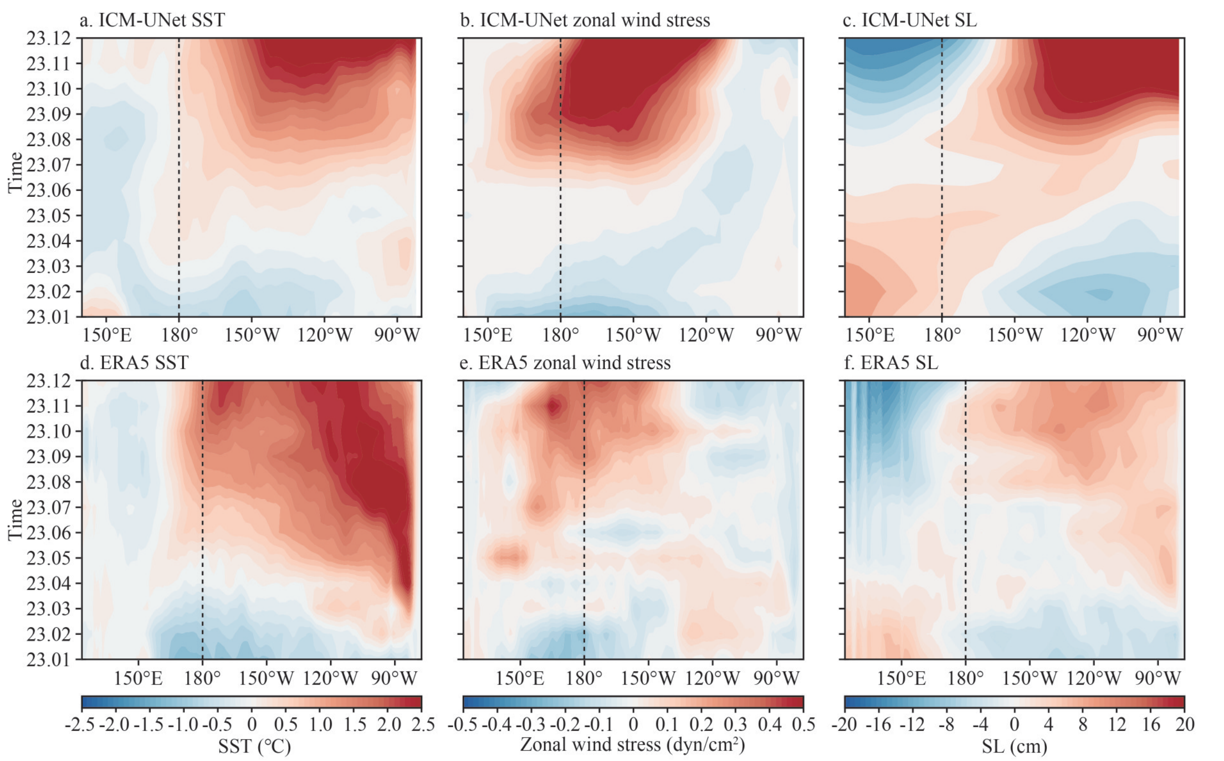

Fig.8 As in Fig.5 but for predictions from initial conditions in January 2023

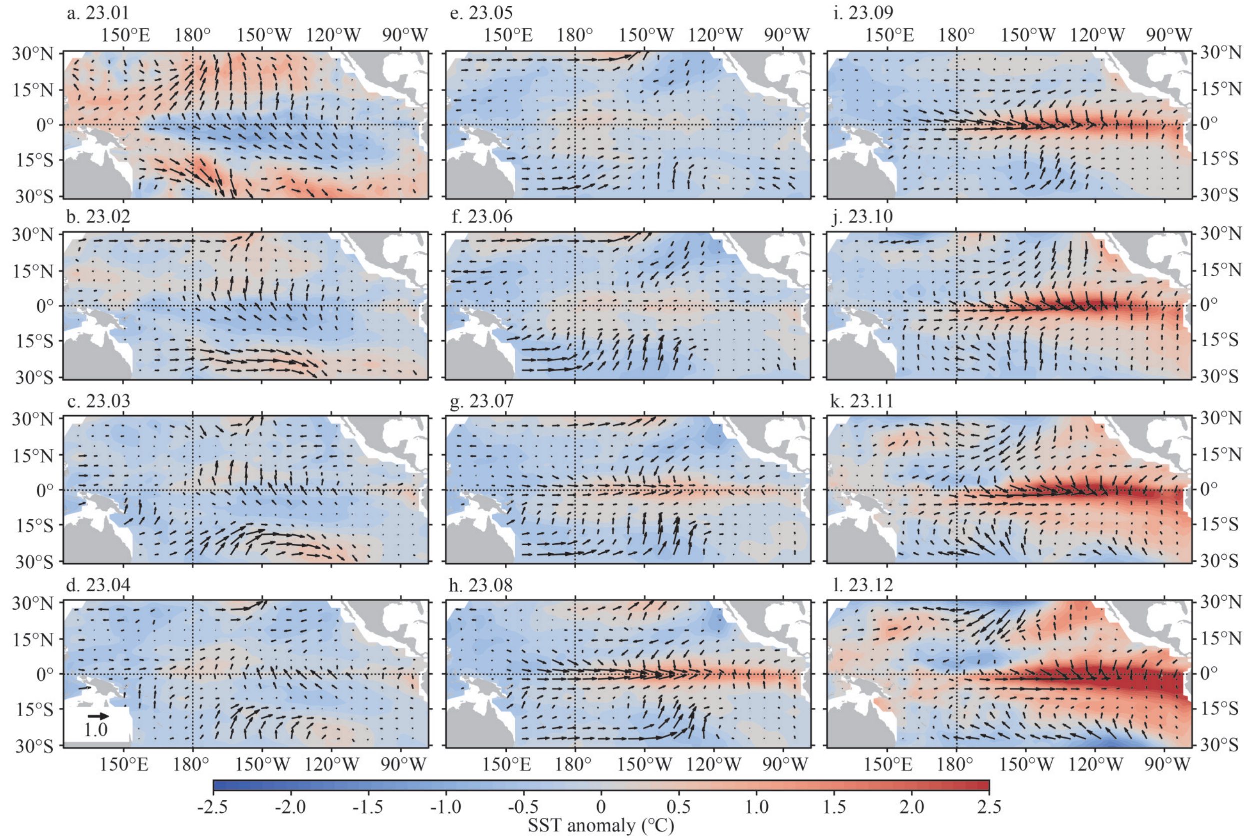

Fig.9 As in Fig.6 but for predictions from initial conditions in January 2023

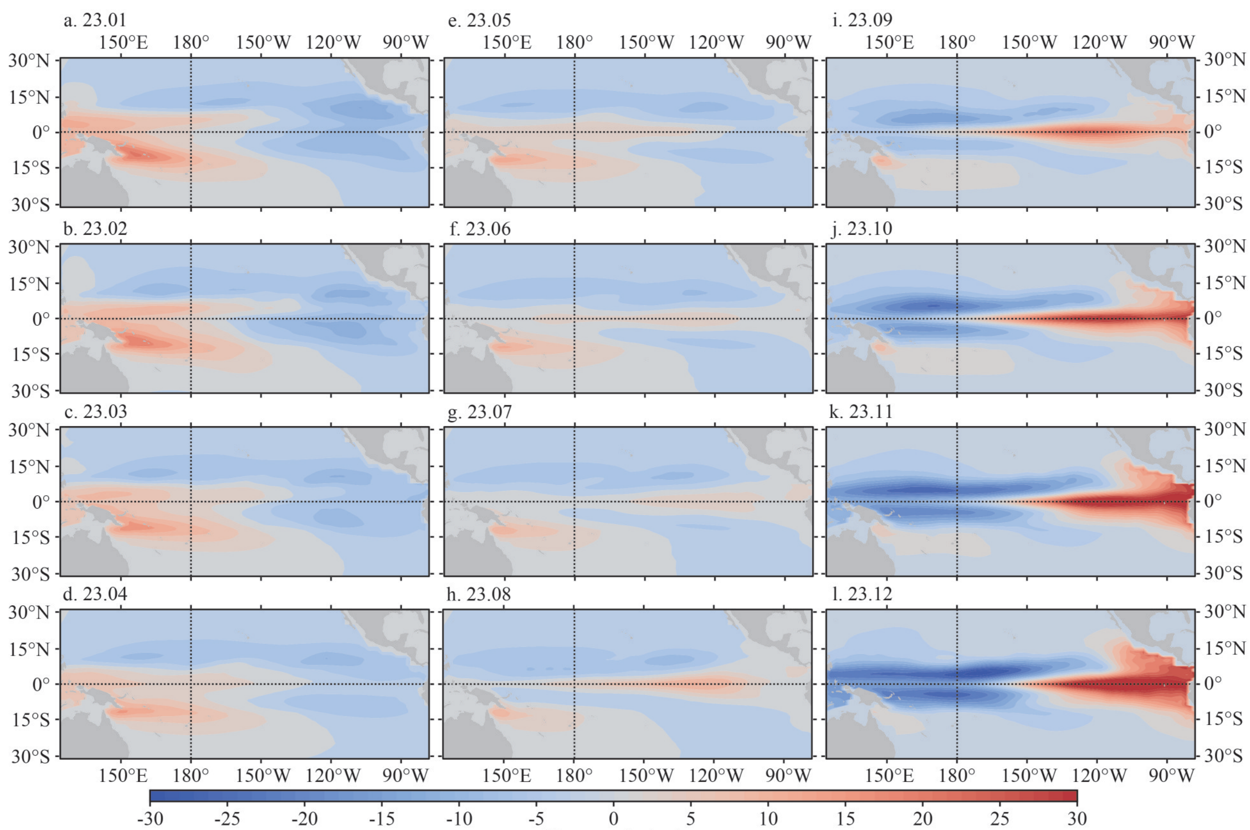

Fig.10 As in Fig.7 but for predictions from initial conditions in January 2023

However, the intensity of cold SSTAs is overestimated when it is predicted from January 2021, and the intensity of warm SSTAs is underestimated when it is predicted from January 2023. These biases highlight the necessity for more sophisticated representations of ocean-atmosphere interactions during the corresponding periods.

Thus, there are several issues to be addressed in the future. First, the UNet-derived wind stress models themselves are purely data-driven and lack the physical interpretability of corresponding ocean-atmosphere interactions. Future work should incorporate other geophysical fluid dynamical models to provide more verification of underlying physical processes and enhance the interpretability of NNs. Next, the existing ICM-UNet predictions lack a comprehensive representation of ENSO diversity, such as central Pacific El Niño. This is because the DL-based atmospheric model is used only to replace the original atmospheric model without adjusting the other oceanic components in the IOCAS ICM. Subsequent studies will focus on developing DL techniques to represent ocean-atmosphere interactions at multiple time scales and update the dynamical oceanic model, further improving the simulation and prediction capabilities over longer timescales. Moreover, it is feasible to categorize all ENSO cases to calculate and improve their prediction accuracy separately. Overall, such a direct fusion of data-driven NNs with physics-based dynamical models reinforces the benefits of hybrid approaches, providing a practical example for diverse applications of DL techniques in the ocean-atmosphere coupled modeling for ENSO predictions, which will become a high-potential integration approach in physical oceanography and climate communities.

5 DATA AVAILABILITY STATEMENT

The CMIP6 simulations can be obtained from the Centre for Environmental Data Analysis at https://esgf-node.llnl.gov/search/cmip6/. ERA5 and ORAS5 data can be obtained from the Copernicus Climate Change Service, Climate Data Store.

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Electronic supplementary material

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