# Physics-informed neural networks help to strongly reduce uncertainty in ocean state forecasting

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Complex cross-scale interactions render the ocean highly nonlinear, making accurate prediction of future ocean states a long-standing scientific challenge. Although traditional numerical models have served as the principal tools for addressing this problem over recent decades, they remain limited by major theoretical and computational constraints. High computational cost and dependence on sub-grid parameterizations continue to contribute to persistent uncertainty in future ocean prediction.

Physics-informed neural networks (PINNs) provide a foundational paradigm by combining deep learning with physical laws in scientific prediction. Such as the partial differential equations, it directly embeds the governing equations and initial/boundary constraints into the loss function, then enabling unified forward and inverse problems. Building on this idea, a broader family of physics-aware learning frameworks has emerged, in which physical knowledge can be incorporated not only through equation-based loss functions, but also through dynamical guidance, architecture design, latent-state evolution, and end-to-end forecasting strategies. In ocean prediction, these developments can be viewed as methodological extensions of the original PINNs philosophy rather than as a single uniform class of models. Recent studies have shown their potential across a wide range of marine applications, including sea surface temperature and sea surface height reconstruction, extreme-event detection, and deep-ocean evolution modelling.[1] They have also shown advantages in computational efficiency and dynamical stability during temporal integration. Collectively, these advances indicate that PINNs can improve predictive skill across timescales and help reduce uncertainty in future ocean states (Figure 1).

## SHORT TO SUBSEASONAL FORECASTING

In short-term ocean forecasting, small initial errors can grow rapidly because of the ocean's strong nonlinearity. When physical constraints are absent, this growth often manifests as dynamic inconsistency, causing predicted trajectories to drift away from plausible physical evolution. Purely data-driven autoregressive models are therefore prone to cumulative error and progressive over-smoothing, which reduces their capacity to represent high-frequency variability.

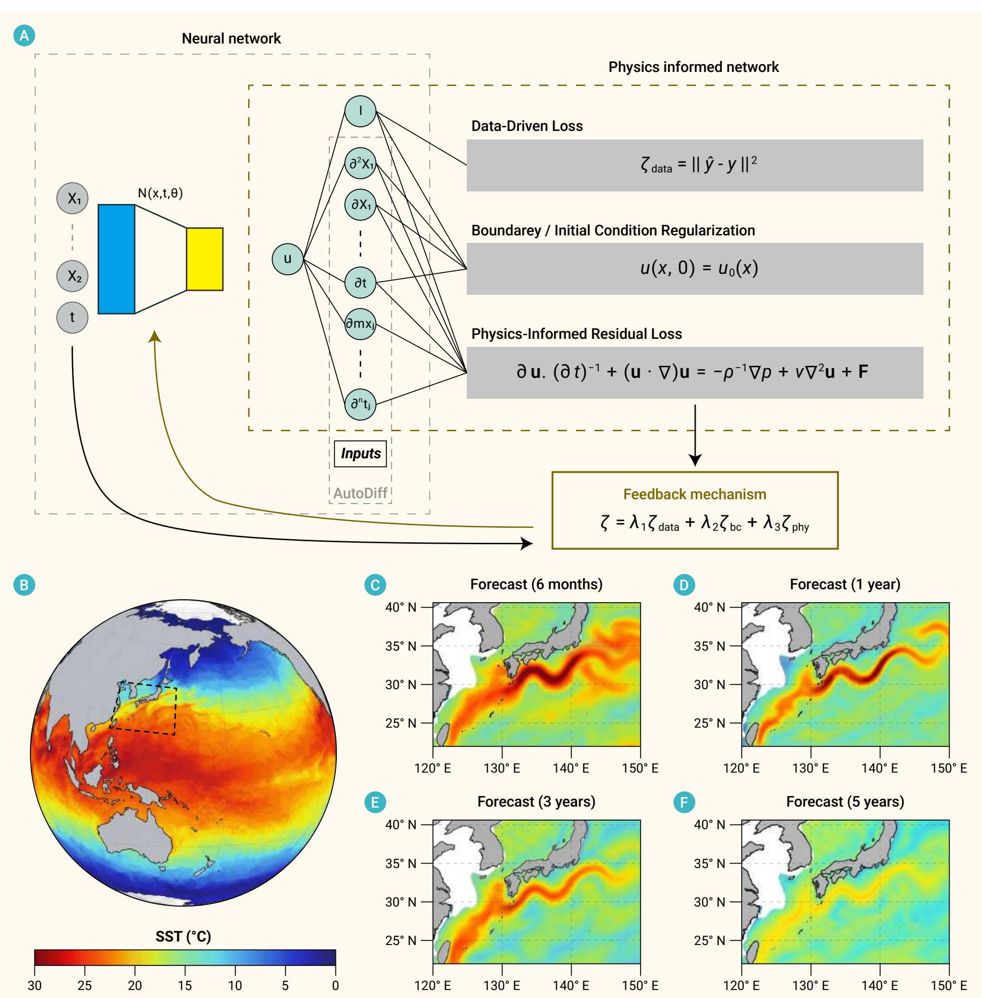


**Figure 1. Schematic of the physics-informed neural network (PINN) framework and ocean-state prediction results at different lead times** (A) Workflow of the PINN framework. The model takes spatiotemporal variables as inputs and is jointly optimized using data-driven loss, initial/boundary condition constraints, and residuals of the governing physical equations. (B) Global sea surface temperature (SST) distribution, with the black box indicating the study area used for subsequent predictions. (C)-(F) Predicted Ocean temperature fields in the study area at lead times of 6 months, 1 year, 3 years, and 5 years, respectively, demonstrating the model's ability to capture the evolution of ocean temperature fields across different prediction horizons.

Accordingly, short-range forecasting frameworks have moved toward more flexible physics-guided designs, in which physical knowledge is introduced through auxiliary dynamical information rather than only through explicit equation residuals. In this context, SSTFormer exemplifies how ocean-current guidance can extend the PINN philosophy to improve short-lead SST prediction while retaining high-frequency variability. In frameworks such as SSTFormer, a physics-guided deep learning framework for sea surface temperature forecasting, these constraints help suppress unphysical error growth and enhance the stability of high-frequency forecasts. In particular, SSTFormer achieved RMSE values of 0.17°C for daily SST forecasts and 0.60°C for monthly forecasts, while the inclusion of ocean-current guidance improved forecast accuracy by up to 0.20°C at 1-6 day leads, relative to baseline configurations.[2] By introducing explicit dynamical guidance, such models are encouraged to learn physically meaningful spatiotemporal relationships among variables, thereby mitigating the distortions that often arise in purely data-driven evolution. At relatively low computational cost, these approaches can better capture short-timescale variability in key ocean states. Their main advantage at short lead times lies in suppressing rapid error growth and autoregressive drift, thereby helping preserve physically plausible high-frequency variability that is often lost in purely data-driven forecasts. However, their skill at this timescale still depends strongly on the quality of initial conditions and on how well fine-scale dynamical guidance can be represented.

## SEASONAL TO INTERANNUAL FORECASTING

On seasonal to interannual timescales, ocean variability is governed largely by internal dynamics. Traditional numerical models often struggle in this regime because empirical parameterizations limit their ability to represent complex internal processes, leading to increasing uncertainty at longer lead times. These approximations may cause bias, noise accumulation, and loss of key climate signals.

As prediction lead times increase, developments beyond classical PINNs increasingly emphasize how physical consistency is maintained throughout state evolution and forecasting, rather than relying only on equation-based residual constraints in the loss function. In this sense, end-to-end physics-aware forecasting systems can be viewed as a further extension of the PINN philosophy, with physical principles embedded more deeply into representation learning and predictive evolution. By integrating physics-based model with the ocean prediction process, these end-to-end approaches can represent global ocean states more efficiently. For example, GLONET was benchmarked against both the operational physical forecasting system GLO12 and the neural baseline Xihe. In a trajectory-based evaluation, GLONET reduced the 10-day Euclidean distance error by approximately 25 km relative to Xihe, while also being assessed with validation metrics extending beyond traditional point-wise error measures.[3] Specifically, incorporating core physical laws such as mass and energy conservation into training helps constrain latent-state inference within known hydrodynamical frameworks. This mechanism mitigates the over-reliance of purely data-driven algorithms on surface observations, facilitating a critical transition from the correlative learning of superficial data features to the causal modelling of deep physical mechanisms. As a result, these frameworks move beyond purely black-box fitting by better representing the longer-term memory and internal adjustment processes that govern seasonal-to-interannual variability. Their main value at these lead times lies in preserving physically consistent state evolution across large-scale climate modes, although forecast skill remains limited by accumulated model error and the difficulty of generalizing to unprecedented anomalies.

## DECADAL TO LONG-TERM PREDICTION

On decadal and longer timescales, traditional numerical models remain limited by sparse deep-ocean observations and the gradual accumulation of parameterization errors, both of which can contribute to climate drift during extended integrations. Such systematic biases not only distort the background mean state of the ocean but also undermine confidence in projections of long-term trends.

On the basis of the PINN framework, in which physical equation constraints are explicitly enforced through the loss function, physical laws are further incorporated into network architecture, data assimilation, state estimation, and time integration, thereby forming a unified physics-informed framework that spans model construction, training, and prediction. Physics-informed approaches provide a promising route to addressing these limitations. By incorporating physically based constraints into long-term integration, such models can compensate in part for the scarcity of deep-ocean observations and help restrict the solution space to more dynamically plausible trajectories. This is particularly important in abyssal regions, where purely data-driven models may drift in the absence of observational anchoring. Frameworks such as ORCA-DL exemplify this strategy by embedding physical constraints directly into the time-integration scheme. In doing so, they can improve consistency with fluid dynamics, preserve mass and momentum conservation over long simulations, and better represent sub-grid nonlinear processes in the deep ocean. Quantitatively, ORCA-DL retained significant ENSO prediction skill, with a Niño 3.4 correlation skill of 0.75 at 12-month lead and skillful prediction extending to 20 months, surpassing several dynamical models as well as other data-driven models at longer leads. In decadal prediction experiments, it also maintained a correlation skill of 0.77 between predicted and observed global-mean SST anomalies despite a slight cold bias.[4] At decadal and longer timescales, the main strength of PINN-inspired frameworks lies in constraining long-horizon drift and maintaining physically consistent trajectories under sparse observational coverage. They are suitable for long-term stable prediction, but remain limited by incomplete physics, sparse observations, and unresolved cross-scale feedbacks.

## CHALLENGES AND FUTURE DIRECTIONS

Despite recent progress across multiple timescales, PINNs have not fully resolved uncertainty in future ocean state prediction. A key limitation is that the physical constraints embedded in these models remain incomplete descriptions of ocean dynamics.[5] Existing governing equations and empirical sub-grid parameterizations reflect only part of present knowledge, while many nonlinear interactions, cross-scale energy transfers, and deep-ocean feedback remain insufficiently understood. Even with physical constraints, models may still incompletely represent ocean variability where unresolved processes dominate.

This challenge points to a deeper tension between physical prescription and data-driven discovery. In many current frameworks, physical constraints are treated as fixed rules,[4,5] which can limit neural networks' ability to learn emergent nonlinear features that existing theory has not yet captured. Yet the ocean is a complex dissipative system whose evolution is shaped by processes that are only partly represented in current parameterization schemes. Rigid physical constraints may reduce predictive skill and limit models from learning unresolved dynamics.

Future models should balance physical consistency with data-driven flexibility. They should be guided by established laws, such as mass and energy conservation, while retaining the ability to learn unresolved processes from observations, thereby improving the stability, interpretability, and reliability of ocean state prediction.

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## AUTHOR CONTRIBUTIONS

All authors contributed to the manuscript and approved the final version.

## DECLARATION OF INTERESTS

The authors declare no competing interests.