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Advancing Ocean Forecasting in the Russian Arctic: A Performance Analysis of MariNet Model in Comparision to FourCastNet and PhyDNet

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Abstract

Marine forecasts are essential for safe navigation, efficient offshore operations, coastal management, and research, especially in areas with a such harsh conditions as the Arctic Ocean. They require accurate predictions of ocean currents, wind-driven waves, and other oceanic parameters. However, physics-based numerical models, while precise, are computationally demanding. Consequently, data-driven methods, which are less resource-intensive, may offer a more efficient solution for sea state forecasting. This paper presents an analysis and comparison of three data-driven models: our newly developed convLSTM-based MariNet, FourCastNet and the PhydNet, a physics-informed model for video prediction. Using metrics such as RMSE, Bias and Correlation, we demonstrate the areas where our model surpasses the performance of the prominent prediction models. Our model achieves improved accuracy in forecasting ocean dynamics compared to FourCastNet and PhyDNet. We also find that our model requires significantly less training data, computing power, and consequently provides less carbon emmisions. The results suggest that data-driven models should be further explored as a complement to physics-based models for operational marine forecasting. They have the potential to enhance prediction accuracy and efficiency, enabling more responsive and cost-effective forecasting systems.

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Key Points:

- We developed a new data-driven model called MariNet for the short-term ocean state predictions.
- MariNet outperformed two other prominent data-driven forecasting models in accuracy and the carbon emissions rate on the training phase.
- Data-driven models can complement physics-based models for marine forecasting. They provide advantages in accuracy and cost-effectiveness.

Abstract

Marine forecasts are essential for safe navigation, efficient offshore operations, coastal management, and research, especially in areas with a such harsh conditions as the Arctic Ocean. They require accurate predictions of ocean currents, wind-driven waves, and other oceanic parameters. However, physics-based numerical models, while precise, are computationally demanding. Consequently, data-driven methods, which are less resource-intensive, may offer a more efficient solution for sea state forecasting. This paper presents an analysis and comparison of three data-driven models: our newly developed convLSTM-based MariNet, FourCastNet and the PhydNet, a physics-informed model for video prediction. Using metrics such as RMSE, Bias and Correlation, we demonstrate the areas where our model surpasses the performance of the prominent prediction models. Our model achieves improved accuracy in forecasting ocean dynamics compared to FourCastNet and PhyDNet. We also find that our model requires significantly less training data, computing power, and consequently provides less carbon emmisions. The results suggest that data-driven models should be further explored as a complement to physics-based models for operational marine forecasting. They have the potential to enhance prediction accuracy and efficiency, enabling more responsive and cost-effective forecasting systems.

Plain Language Summary

Accurate forecasts of conditions like winds, waves, and currents are important for safe ocean travel and coastal management, especially in harsh areas like the Arctic. Complex physics-based computer models can make good forecasts, but take a lot of computing power. We developed a new artificial neural network called MariNet that makes forecasts directly from data, which uses less resources. We tested MariNet against two other prominent data-driven models. MariNet was more accurate at predicting ocean conditions, needed less computing power, and produced less carbon emissions. Overall, AI systems like MariNet complement physics-based models and have advantages in efficiency and responsiveness. They should be explored further to enhance marine forecasts in a cost-effective way, enabling better decisions on the oceans.

1 Introduction

Machine Learning is the process of making computer systems learn without explicit instructions by analyzing and drawing inferences from data patterns using algorithms and statistical models. One of the major limitations of Artificial Intelligence and Machine Learning has always been computational power, which has been a cause of concern for researchers. CPUs were not as powerful and efficient a few decades ago when it came to running large computations for machine learning. Hardware manufacturers have worked hard to create a processing unit capable of performing any AI operation.

Though CPUs are no longer viable sources of computational power, they were the pioneers. Today, those CPUs are rightfully replaced by GPUs and AI accelerators, specifically designed for large computing. The main features considered while purchasing an AI accelerator are cost, energy consumption, and processing speed.

The study of ocean circulation is crucial for many reasons, including the climate research, determining marine life distribution, shaping human activity, and more. Accurate prediction of currents can help forecast weather, estimate energy transfer rates in the ocean, predict the spread of oil spills and drift of the sea ice and icebergs. Sediment transport is another important correlated aspect correlated with the water circulation, affecting marine economic activities such as fishing, transport, logistics, and tourism. Therefore, in the seas, especially in the high latitudes, the prediction of currents is crucial for port, pipeline, and logistics development, as well as for the analysis of sea ice drift for safe logistics. In this context, the development of a machine learning model for the prediction of sea water movement and sea level variations is essential.

Sea currents and sea surface level prediction have a long history of development, starting with traditional empirical methods and evolving into modern AI methodologies. The early efforts held in the 17^{th} -19^{th} centuries (e.g. Halley, 1686; Maury, 1855) and relied on accindental in situ observations. With the transition from single observations to systematic measurements, the emergence of scientists specializing in hydrodynamics and ocean studies, the development of a network of observation stations and scientific equipment, analytical methods of describing observed phenomena were formed in (Navier, 1822; Stokes, 1845) and numerically solved in (V. Bjerknes, 2023; Vilhelm Bjerknes, 1903). In the early 20th century, V. Walfrid Ekman's research on wind-driven surface currents laid important groundwork for understanding ocean transport mechanisms. It laid the foundation of geophysical fluid dynamics and led to the pioneering work of numerical weather forecasting of (Richardson, 1922). The first numerical forecasts in oceanography were developed for the wind-driven waves by (Sverdrup & Munk, 1947). Development of numerical methods based on solving the Navier-Stokes equations continued in the ocean simulations with the first models (Bryan, 1969) and succeded in mesoscale ocean circulation forecasting by 1983 (A. R. Robinson, 1983). Over time, increased computational power and improved mathematical representations of ocean processes have enabled more sophisticated forecasting models. The satellite remote sensing era, that began nearly at the same time, provided massive volume of data for observing and assimilating sea surface height data into models.

All it made the global ocean reanalysis and forecasting projects available. Operational forecasting centers like the European Centre for Medium-Range Weather Forecasts (ECMWF) and the National Oceanic and Atmospheric Administration (NOAA) began running global ocean prediction systems to support weather, climate and marine applications (Storto et al., 2019), while regional models with finer resolutions also emerged for areas like the Arctic (Chen et al., 2009).

With the availability of petabytes of oceanographic and remote sensing observations, with the outputs of numerical model simulations, with the growth of computational power, artificial intelligence (AI) tools are increasingly being leveraged in a variety of applications in oceanography (Dong et al., 2022). The high energy efficiency of the AI models (e.g. (Pathak et al., 2022) also contributes to their spreading.

Various AI algorithms are now being used for the identification of mesoscale eddies (Du et al., 2019; Duo et al., 2019; Franz et al., 2018; Lguensat et al., 2018; Santana et al., 2020; Xu et al., 2019, 2021), forecasting surface waves (Buinyi et al., 2022; Fan et al., 2020; Gao et al., 2021; Mandal & Prabaharan, 2006; Zhou et al., 2021), prediction of features, like the Indian Ocean Dipole, with a multi-task deep learning model in (Ling et al., 2022), that outpermormed traditional numerical multiseasonal prediction.

The topics of sea surface heights and currents forecasting are also covered with the AI methods. One approach is the use of deep learning methods such as ConvLSTMP3, which extracts spatial-temporal features of sea surface heights using convolutional operations and long short-term memory (LSTM) (Song et al., 2021). One more paper (Zulfa et al., 2021) uses LSTM to predict sea surface velocity and direction, achieving good results with low Mean Absolute

Percentage Error (MAPE) values in Labuan Bajo waters. In the paper (Ning et al., 2021) an optimized Simple Recurrent Unit (SRU) deep network was develped for short-to-medium-term sea surface height prediction with AVISO data.

There are a lot of promising results in geosciences now. We have created MariNet, the ML architecture, and compared its output with two state-of-art ML models of different architectures to test their ability in the Arctic region forecasting. In the current work, we test the algorithms on the surface currents data and sea surface heights.

2 Materials and Methods

In the initial stages of our research, we harnessed PhyDNet and FourCastNet, two of the most promising machine learning architectures applicable to the ocean state forecasting available at the time, for the comparison with MariNet, our Neural Network. The neural networks are described below.

2.1 MariNet neural network

MariNet is an artificial neural network (ANN) based on the parallel encoder-decoder architecture within which ConvLSTM modules are embedded in latent space (Buinyi et al., 2023). The ConvLSTM itself is introduced by (Shi et al., 2015) and described as a type of neural network architecture that combines convolutional and LSTM layers. Due to the successful architecture design it is used for spatiotemporal data analysis and prediction, such as a precipitation nowcasting (Shi et al., 2015), a temperature (Lin et al., 2019) or flood (Moishin et al., 2021) forecasting, predicting the arctic sea ice concentration (Liu et al., 2021) and seismic events (Fuentes et al., 2021) with relatively high reliability.

The architecture of our model is shown on the Figure 1. MariNet consists of several interconnected encoder-decoder blocks, within which ConvLSTM modules are embedded between the encoder and the decoder. Each ConvLSTM module contains several parallel ConvLSTM cells connected in such a way that the sum of their outputs forms the resulting forecast of time series in the latent space. This design allows the neural network to simultaneously detect temporal dependencies at various frequencies without assumptions about frequency distribution and a priori defined data distributions.

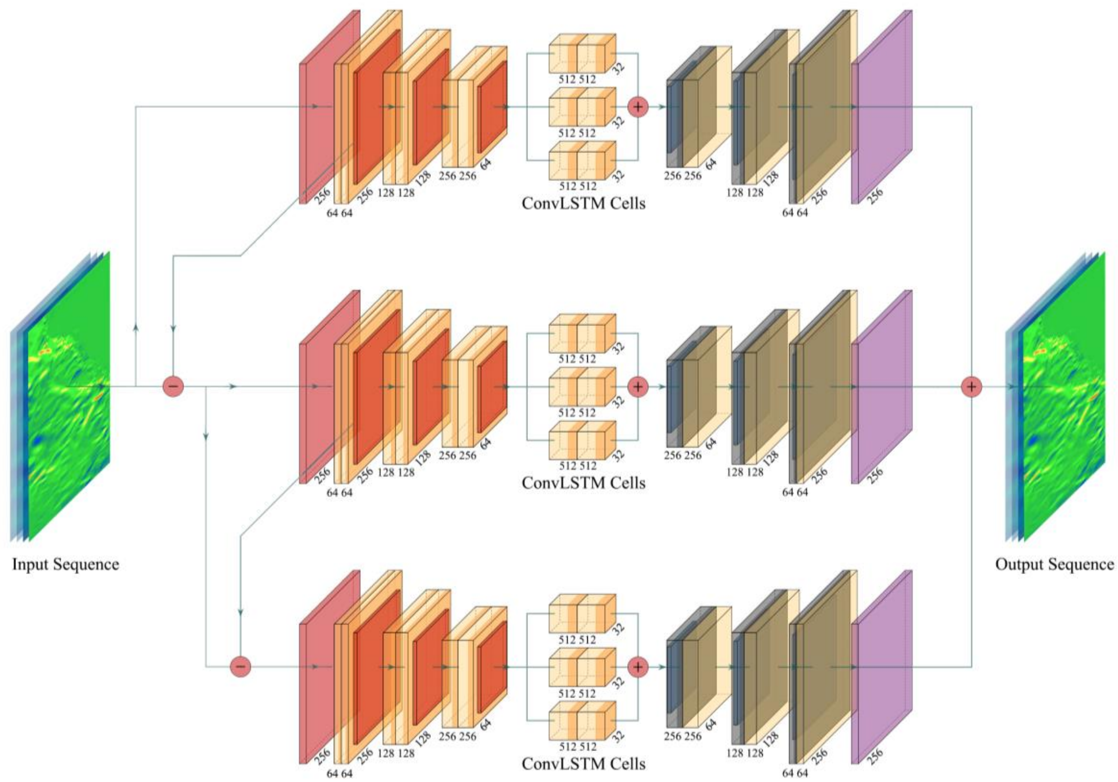

Figure 1. The architecture of MariNet

The encoder-decoder blocks are interconnected in such a way that the input to each subsequent block is the result of subtracting the original data from the original data passed through the first convolutional layer in the block, which produces average pooling. Moreover, the size of the convolution in the first layer of the block varies for each block. This solution helps to hierarchically highlight patterns in images: first, the neural network is trained to work with larger patterns. Then it analyzes smaller patterns and their conditional dependencies on larger ones.

A key feature of the model's operation is the forecasting algorithm. Here, we don’t use a typical recursive algorithm, where the forecast from the previous step is cyclically fed into the neural network to form a forecast for the next steps. Our neural network sequentially receives several previous values for the water velocity and sea surface heights. Therefore, instead of getting a single array for one time point, our neural network is initialized by the dynamics of such arrays, which allows for a more accurate assessment of the state of the forecasted values, and consequently, ensures a more precise forecast.

2.2 Phydnet neural network

PhyDNet is a deep learning model introduced in (Le Guen & Thome, 2020) and designed for unsupervised video prediction. Due to its architecture, the model integrates physical knowledge into the learning process, making it effective for tasks such as weather forecasting, fluid dynamics, and other physical phenomena prediction. The model leverages physical knowledge on dynamics and disentangles it from other unknown factors. To achieve this goal, authors introduced a PhyDNet disentangling architecture, and PhyCell physically-constrained recurrent cell. The recurrent block projects input video frames into a latent space. This projection is achieved through a deep convolutional encoder, which transforms the input video into a lower-dimensional representation. The latent space is where the disentanglement of physical dynamics and residual information occurs. Two parallel neural networks are responsible for it: PhyCell and ConvLSTM. PhyCell is a recurrent cell that models and solves Partial Differential Equations (PDE) with internal physical predictor computing and combining partial derivatives with convolutions. PhyCell allows exploiting prior physical knowledge to improve prediction of a model, add explainability and leverages physical constraints to limit the number of model parameters. The ConvLSTM network is trained to learn the residuals, or errors, of the physical model's predictions. By learning these residuals, the network can correct the physical model's predictions and improve the overall accuracy of the system. Learned physical and residual representations are summed before decoding to predict the future video frame. As a result, PhyDNet generates one-step-ahead prediction that can be extended by recursive feeding predicted frame into the model. It's important to note that predictions are reinjected as the next input only for the ConvLSTM branch, and not for PhyCell. This is because the PhyCell is designed to capture the deterministic physical dynamics, which should not be influenced by the predictions.

In (Le Guen & Thome, 2020) PhyDNet has been compared with PredRNN, ConvLSTM, Causal LSTM, Memory in Memory (MIM), outperformed them and showed itself as one of the state-of-the-art model of its time. Therefore, we have chosen PhyDNet to compare with our model.

2.3 FourCastNet neural network

FourCastNet, or Fourier ForeCasting Neural Network is first described in (Pathak et al., 2022). It is a data-driven global weather forecasting model that provides short to medium range predictions. It is trained with an ERA5 reanalysis from the European Centre for Medium-Range Weather Forecasts (ECMWF), which has hourly estimates of atmospheric variables at a 0.25° resolution. FourCastNet utilizes a Fourier transform-based token-mixing scheme (Guibas et al., 2021) which is complemented with a vision tranformer (ViT) backbone (Dosovitskiy et al., 2021). This method is grounded in the recent advancements in the Fourier neural operator, or Adaptive Fourier Neural Operator (AFNO) that has demonstrated success in modeling challenging partial differential equations (PDE), including fluid dynamics, in a resolution-invariant manner (Li et al., 2020).

According to (Pathak et al., 2022) the use of ViT backbone is preferred due to its ability to effectively model long-range dependencies. The combination of ViT and Fourier-based token mixing produces a high-resolution model that effectively resolves fine-grained features and scales well with the size and resolution of the dataset, leading to the training of high-fidelity data-driven models at an unprecedented resolution.

The original version of FourCastNet models 20 variables at five vertical levels, that are: surface air pressure, mean sea level pressure, air temperature at 2m from the surface, zonal and meridional wind velocity 10m from the surface; zonal and meridional wind velocity at 1000, 850, and 500 hPa; air temperature at 850 and 500 hPa; geopotential at 1000, 850, 500, and 50hPa; relative humidity at 850 and 500hPa, and Total Column Water Vapor. Authors use the model to predict such variables as the surface wind speed, precipitation, and atmospheric water vapor. They propose FourCastNet to be implied for planning wind energy resources, predicting extreme weather events such as tropical cyclones, extra-tropical cyclones, and atmospheric rivers. FourCastNet matches the forecasting accuracy of the ECMWF Integrated Forecasting System (IFS), a state-of-the-art Numerical Weather Prediction (NWP) model, at short lead times for large-scale variables, while outperforming IFS for small-scale variables, including precipitation.

According to (Pathak et al., 2022), the FourCastNet uses such metrics as Root Mean Squared Error (RMSE), Anomaly Correlation Coefficient (ACC) at lead times of up to three days and gives results comparable to the ECMWF Integrated Forecasting System (IFS), one of the best to the moment classical numerical model used by ECMWF to construct reanalyses and make weather forecasts.

2.4 Metrics for the model output quality estimation

We trained all three netwoks with the data on the surface water currents and the sea surface heights, started the inferences and compared their outputs with several metrics: Root Mean Squares Error (RMSE), Bias and Correlation. They are defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2},$$

$$Bias = \frac{1}{N}\sum_{i=1}^{N} y_i - \frac{1}{N}\sum_{i=1}^{N} x_i ,$$

$$Correlation = \frac{S_{xy}}{\sqrt{S_{xx}S_{yy}}}, \text{ with}$$

$$S_{xy} = \sum_{i=1}^{N} x_i\, y_i - \frac{\sum_{i=1}^{N} x_i \sum_{i=1}^{N} y_i}{N},$$

$$S_{xx} = \sum_{i=1}^{N} x_i^2 - \frac{\left(\sum_{i=1}^{N} x_i\right)^2}{N},$$

$$S_{yy} = \sum_{i=1}^{N} y_i^2 - \frac{\left(\sum_{i=1}^{N} y_i\right)^2}{N},$$

where x_i is the original data value for a given timestep, y_i is a predicted value for a given timestep, N – the length of the timeseries.

In scholarly terms, the Root Mean Square Error (RMSE) quantifies the divergence in magnitude between the model's predictions and the actual observations. It is preferable for the RMSE to be smaller as this signifies a better alignment between predicted and actual values.

Bias, on the other hand, signifies the systematic deviation of the approximated quantifier from the real value and can be interpreted as a consistent overestimation or underestimation of an output. It is desirable for the bias to be closer to zero, indicating that the estimates are nearer to the actual data.

The correlation, in contrast, is a statistical measure that sheds light on the degree to which two variables share a linear relationship. This relationship is frequently deployed to depict the linear association between two contingent factors. Greater values of correlation denote a stronger relationship between the two variables.

3 Data

The Copernicus Marine Environment Monitoring Service (CMEMS) offers a comprehensive global ocean analysis and forecast system through its Global Ocean Physics Analysis and Forecast (CMEMS-GLO-PUM-001-024) product. The system operates at a high-resolution scale of 1/12°, updated daily, and provides global ocean forecasts for a 10-day period (Operational Mercator Global Ocean System). The dataset employs a combination of the numerical ocean model NEMO 3.6 with LIM3 Multi-categories sea ice model, ECMWF IFS HRES atmospheric forcing, and several data assimilation techniques, like SAM2 (SEEK Kernel) 4D, allowing for seamless integration of in-situ and satellite observations.

For our needs we choose the region bounded by 60°N-90°N and 5°E-150°W and obtain the hourly surface data of zonal sea water velocity (u), meridional sea water velocity (v), and sea surface height above geoid (zos) for 2019-2022. We interpolate them to the 6-hour temporal resolution and 0.25°x0.25° spatial resolution and feed the data to the ML models.

4 Results

MariNet model shows promising results. The figures representing metrics of FourCastNet model have artifacts. The average metrics are shown in Table 1. According to the table, MariNet model has minimal RMSEs for the sea surface heights and components of surface sea water velocities. The bias of the MariNet model is also the closest to zero among the mentioned models. Mean correlation between models in average is not significantly high. Nevertheless, the PhyDNet and MariNet demonstare here the highest correlation, that is about 0.5 for the sea surface velocities and 0.4 for the sea surface heights.

Table 1

Metrics of MariNet, FourCastNet and PhyDNet for zonal and meridional components of surface water velocities and Sea Surface Heights

	Model	**RMSE (m/s)**	**Bias (m/s)**	**Correlation**
u	MariNet	**0.027**	**-0.001**	0.507
	FourCastNet	0.051	0.003	0.432
	PhyDNet	0.043	0.004	**0.519**
v	MariNet	**0.028**	**0**	0.515
	FourCastNet	0.051	0.002	0.428
	PhyDNet	0.044	**0**	**0.524**
ssh	MariNet	**0.027**	**-0.001**	0.430
	FourCastNet	0.082	-0.050	0.367
	PhyDNet	0.046	0.003	**0.451**

Figure 3 demonstrates the temporal evolution of the RMSE for the sea surface velocity and the sea surface heights for the chosen models through the prediction time. As we see, all RMSEs monotonically grow. According to the plots, MariNet and PhyDNet demonstrate close results, their RMSEs grow from the 0.01 m/s and 0.01 m to about 0.04 m/s and 0.045 m for sea water velocity and sea surface heights respectively.

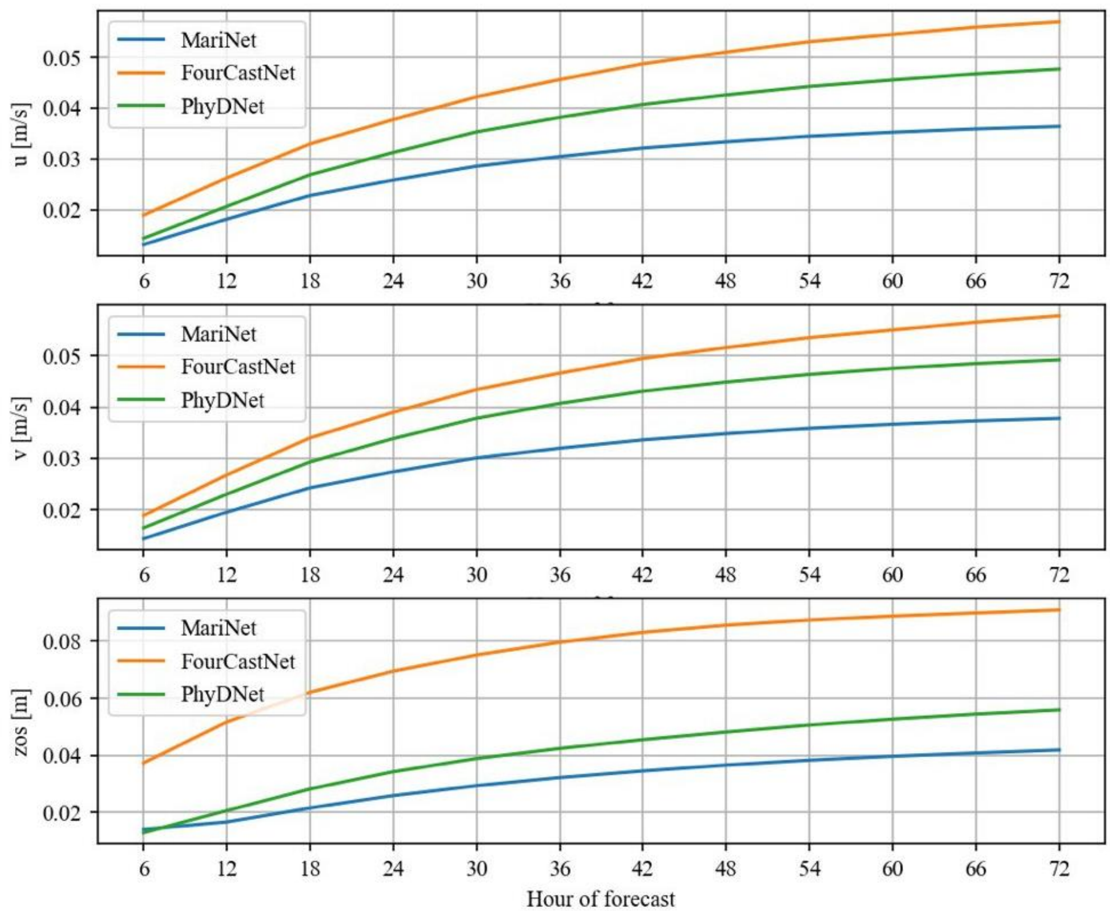

Figure 2. Plots of temporal evolution of RMSE for Zonal (upper image), Meridional (middle image) Components of Surface Water Velocity (m/s), and the Sea Surface Heights (m) above geoid for MariNet (blue line), PhyDNet (green line), and FourCastNet (orange line) models.

Figures 3-5 show maps of RMSE for zonal components of surface water velocity for the research area. All three models have similar spatial distribution of RMSEs, with the high values in the areas with more active ocean circulation and the low values in the eastern offshore areas. In average, MariNet results with a twice less RMSE compared with other two neural networks.

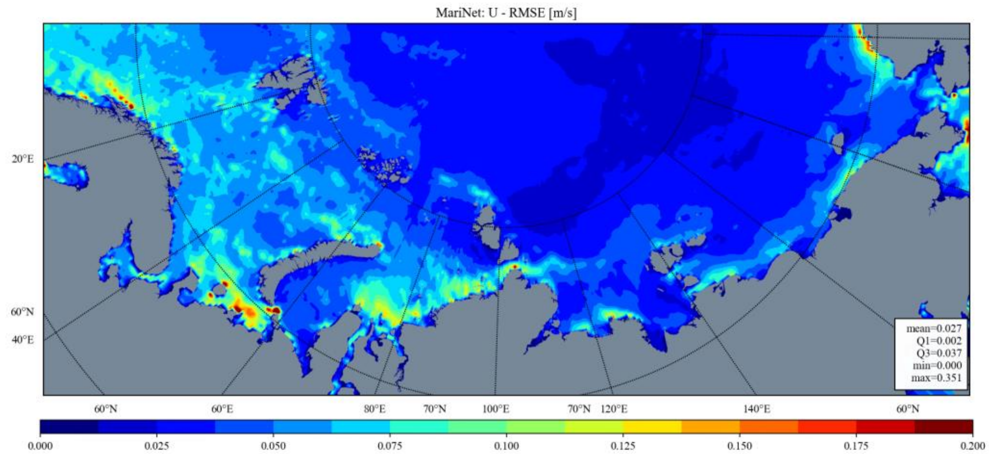

Figure 3. RMSE (in m/s) for Zonal Component of the Surface Water Velocity for MariNet model

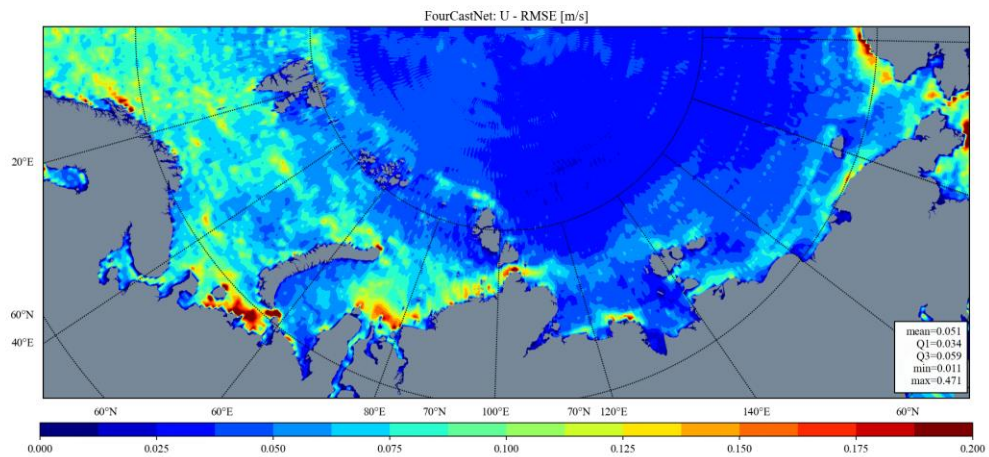

Figure 4. RMSE (in m/s) for Zonal Component of the Surface Water Velocity for FourCastNet model

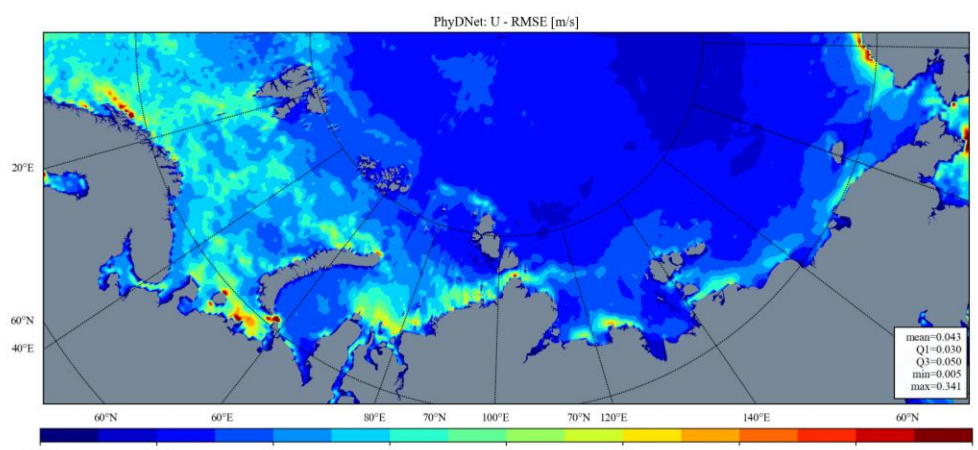

Figure 5. RMSE (in m/s) for Zonal Component of the Surface Water Velocity for PhyDNet model

Computational Cost of MariNet

With the CodeCarbon software package, we have calculated the carbon emissions and the energy consumption of the MariNet, FourCastNet and the PhyDNet for our calculations. Results are shown in the Table 2. Training of the MariNet model has the least carbon emission rate, but, due to the relatively large time of training, it takes the most energy. At the same time, PhyDNet wins the energy consumption and the emission rate challenges.

Table 2
Comparison of the carbon emissions and energy consumption during the models training and inference

	Model Training			**Model Inference**		
	Emissions Rate (g/s)	**Energy Consumed (kW)**	**Time (hrs)**	**Emissions Rate (g/s)**	**Energy Consumed (W)**	**Time (sec)**
FourCastNet	0.100	**103.356**	**103.30**	0.104	0.431	1.997
PhyDNet	0.116	103.734	119.06	**0.02353**	**0.001097**	**0.0224**
MariNet	**0.083**	214.788	257.90	0.0908	0.0973	0.515

5 Conclusions

In the study, we proposed a forecast model MariNet model, based on the encoder-decoder architecture, and compared it with FourCastNet and PhyDNet, the most promising ML models in the field weater prediction of their time. We have chosen the Arctic region, one of the hottest spots of the modern climate science research and obtained the hourly data on zonal and meridional velocities of the surface sea water and sea surface heights above geoid from the Copernicus Marine Data Store. We switched temporal resolution from 1 hour to 6 hours and fed the datasets to the MariNet model, PhyDNet and FourCastNet.

In comparison with the other mentiones ML models, the RMSE and bias of the MariNet model are significantly lower. At the same time, the mean correlations of all three models with the original data are moderate and located between 0.4-0.5.

The above experimental results all show that the MariNet model has great potential in the mid-term predictions of the ocean dynamics. The further development of the model incudes imroving the efficiency of computational operations, expanding the number of parallel running modules of our model to capture more temporal and spatial features of data variability, and increase the number of variables used in training.

Acknowledgments

The study has been conducted using E.U. Copernicus Marine Service Information; https://doi.org/10.48670/moi-00016. We would like to acknowledge the use of the GitHub repository https://github.com/nvlabs/fourcastnet for providing the FourCastNet code, https://github.com/vincent-leguen/PhyDNet for providing the PhyDNet code used in our experiments, and https://github.com/mlco2/codecarbon for the CodeCarbon package.

Data and Software Availability Statement

The Operational Mercator global ocean analysis and forecast data for the sea water velocity and the sea surface height used for the ML models training and validation in the study are available on the Copernicus Marine Service Data Store via DOI https://doi.org/10.48670/moi-00016. The data may be obtained after on-site registration.
The FourCastNet model is described in (Pathak et al., 2022) and can be obtained via the link https://github.com/nvlabs/fourcastnet. The PhyDNet model (Le Guen & Thome, 2020) is stored in https://github.com/vincent-leguen/PhyDNet.

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