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Deep Learning Ensemble Approach for Predicting Significant Wave Height Using N-BEATS

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Abstract: Accurate prediction of the physical parameters of the ocean, like wave height, wave period, etc., is of paramount importance when forewarning the coastal community of imminent threats. The forecast of wave heights is presently being generated using state-of-the-art numerical wave models like Mike 21SW, Wave Watch III, Swan, etc. The study leverages a pure deep learning architecture (N-BEATS) to generate more accurate wave height predictions for the multi-model ensemble. For the ensemble process, the observation data collected by the coastal open ocean buoys and the forecast generated by various models for one year have been considered. Performance investigation using Brier Skill Score (BSS) and Taylor diagrams has indicated that the N-BEATS Ensemble forecast has outperformed not only the numerical weather predictions (NWP) but also other neural engines such as temporal convolution networks (TCN), long short-term memory networks (LSTM), and multi-layer perceptron models. The performance of the N-Beats Ensemble Forecast approach during cyclonic events in the Bay of Bengal and the Arabian Sea in 2021 indicated an improved correlation with minimal RMSE

Keywords: *N-BEATS, TCN, LSTM, MLP, deep learning, multi-model ensemble, Numerical Weather Predictions*

1. Introduction

Ocean General Circulation Models (OGCM) are used to make accurate and timely predictions about the physical properties of the ocean, such as wave height, wave period, etc. Running on a high-performance computer, the models require restart files, boundary conditions, and, most importantly, ground level winds. Any uncertainty in the forcing fields will be propagated to the wave models, resulting in deviations from the actual observations. Over time, these uncertainties accumulate, and the meticulous consideration of potential wave-causing parameters proves arduous without ensuring optimal outcomes. Several attempts have been made to reduce the uncertainty in generating wave forecasts. Various endeavours have been undertaken to enhance the precision of wave forecasts, involving enhancements in forcing fields and assimilating observations ([1, 2]). Although improving the accuracy of the modes is a constant endeavour, several attempts are being made in this regard. Mike's forecasts with the observations of satellite data and the observatories resulted in a good agreement [3]. The forecast generated by the fine-tuned third-generation Wave Watch III developed by NOAA/NCEP suggests that the error rate of wave forecasts during the monsoon season is significantly less; a study was proposed to improve the accuracy during the non-monsoon season ([4]). Global studies have been conducted to analyse wave propagation with the help of the Simulation of Waves Near Shore model (SWAN), Mike 21 Spectral Wave Model, and Wave Watch III ([5]) and have stated that the mesh resolutions (near the coast) and wind (offshore) are of paramount importance for generating accurate forecasts.

Identifying gaps, this study emphasizes improvements concerning wave models ([6, 7]) and observational techniques ([8–10]). Solutions, considering the statistical approaches of Bayesian model averaging, multiple linear regression, seem promising in the initial phases, as suggested by ([11–13]). Subsequently, quick attention is drawn towards deep learning architectures that are capable of better learning complex features than traditional machine learning or statistical models. studies carried out by [14–17] Predicting the weather parameters like winds and waves is prone to errors as the seasonality, global weather conditions, climatology of the region of interest, extreme weather events, etc. play a major role. Training pure deep learning architectures can sometimes be cumbersome and exceedingly challenging. Considering the fact that there is no one perfect forecasting system, the fusion (referred to as ”ensemble”) of predictions from diverse models is not a novel approach. The simplest of ensembles are Ensemble Voting Regression ([18, 19], Model Averaging ([20]), and Weighted Model Averages ([21, 22]). Cawood et. al. (2022)

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[23] have summarized and explored many ensemble models and meta-learning strategies, during which he has recommended research on stacked ensembles, which is primarily our approach.

Due to the dynamic characteristics of ocean waves, machine learning algorithms struggle to achieve precise forecasts for extended periods beyond 10 days. Most state-of-the-art ensemble methods provide forecasts for a shorter period, and the outcomes have yielded notable success. As demonstrated by [24, 25] multi-model ensembling has potential in a variety of scenarios, including wind prediction. [26–28] and others have conducted a survey on ensemble learning, delving into the approaches of blending and super learner ensembles and offering specific insights. Abdelmigid et al. [29] accomplished an impressive correlation of 0.998 for ensemble forecasting with a lead time of 1 hour. Notably, Gao et al.'s experimentation with N-Beats, LSTM, and Extreme Learning Machines (ELM) revealed that ensemble forecasting for one, two, and four hours ahead led to minimal RMSE values [30]. Additionally, a reduction in the correlation coefficient was observed as the forecasting horizon increased, as evidenced in [31]. Meanwhile, Karan et al. [32] achieved correlations of 0.96 and 0.99 in wave height forecasting, particularly in scenarios involving sudden changes, by utilizing a range of LSTM architectures. In our current study, we achieved a correlation of at least 0.9 with minimal RMSE at most buoy locations, surpassing the mentioned performance. A comprehensive discussion of the proposed system's performance is elaborated upon in the results section. The primary focus of this study involves extracting valuable insights by correlating the outcomes of physics-based numerical weather predictions with observational data. Although ensembling is the study's focus, the concept is to combine wave model forecasts with observations. This method yields accurate predictions with adjustable forecast lengths. Also, our study aims at

1. Establishing a two level (base learning and meta learning) learning framework for enhancing the accuracy of wave height predictions, where the base learners are the wave models, and the meta learner is a deep-learning ensemble technique
2. Conducting a large-scale inspection of the proposed system at various geographical locations where observations are available
3. Enhancement of operational forecast accuracy during exceptional events such as cyclones

Looking at the broader context of issuing alerts to the coastal community, Points 2 and 3 are pivotal in instilling confidence among officials before disseminating alerts, which can save lives in case of imminent threats.

2. Dataset Description

The dataset utilized for ensemble prediction is amalgamated from the physics-based ocean models and the observation data at various locations, which are detailed below.

2.1. Observation Data

The primary sources of observational data are the coastal wave rider buoy and open ocean-moored buoy measurements. These buoys are equipped with sensors that calculate wave heights at regular intervals. The sensor data is stored locally and transmitted through INSAT communication. In this research, we focused on buoys with a minimum of six months of continuous operation at sea. Validation studies conducted by James et al. (2022) affirm the accuracy of sensor-derived wave heights at various depths in British waters, enhancing our confidence in the data.

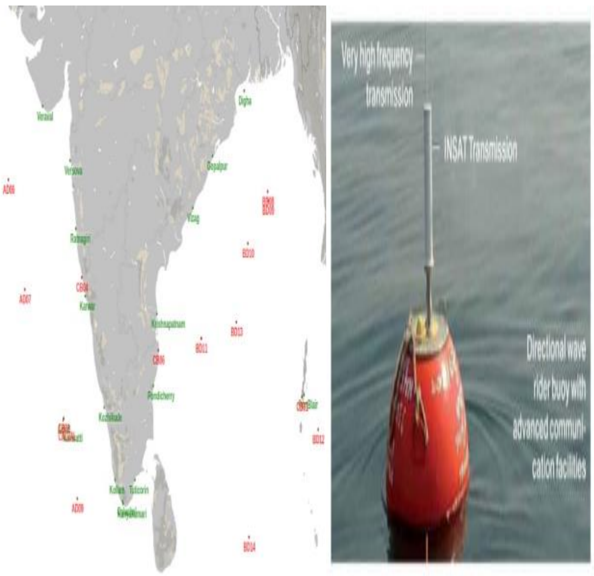


Fig. 1. (a) Location of Wave Rider Buoys (green) and Moored Buoys (red) for observations; (b) Deployed Wave Rider Buoy and a brief description of communication channels.

The performance of the datawell's directional WRB for the Indian region has been verified by T. M. Balakrishnan Nair et al. (2013)[1], P. Sirisha et al. (2022)[2] and V. Sanil Kumar et al. (2022)[9] to the Arabian Sea. Harikumar et al.(2016)[8] have stressed the importance of observational data stations along India's coastline and the effect of assimilation into ocean-met forecasting models.

2.2. Numerical Weather Prediction Models (Base Learners)

A suite of wave models, which run on a High-Performance Computing platform (AADITYA & MIHIR HPC) to generate 3 hourly forecasts for the coming 5–7 days, as mentioned in table 1, were considered for the study. The wave forecast is generated by forcing the low-level winds from the European Centre for Medium-Range Weather

Forecast (ECMWF) or from the National Centre for Medium-Range Weather Forecast (NCMRWF) using the physical wave equations. The details of the models are mentioned in table 1.

Table 1: Details of operational models with domain and forcing fields

Model	Domain	Assimilation	Forcing
Mike	IO[3]	NO	ECMWF[1]
Mike High Resolution	NIO[4]	NO	ECMWF[1]
SWAN	NIO[4]	Yes	ECMWF[1]
SWAN	NIO[4]	NO	ECMWF[1]
SWAN	NIO[4]	NO	NCMRWF[2]
WW III	NIO[4]	Yes	ECMWF[1]
WW III	NIO[4]	NO	ECMWF[1]
WW III	NIO[4]	NO	NCMRWF[2]

[1]Wind forecasts generated by the European Centre for Medium-Range Weather Forecasts
[2]Wind forecasts generated by the National Centre for Medium Range Weather Forecasting
[3]Indian Ocean
[4]North Indian Ocean

2.2.1. Mike 21 SW

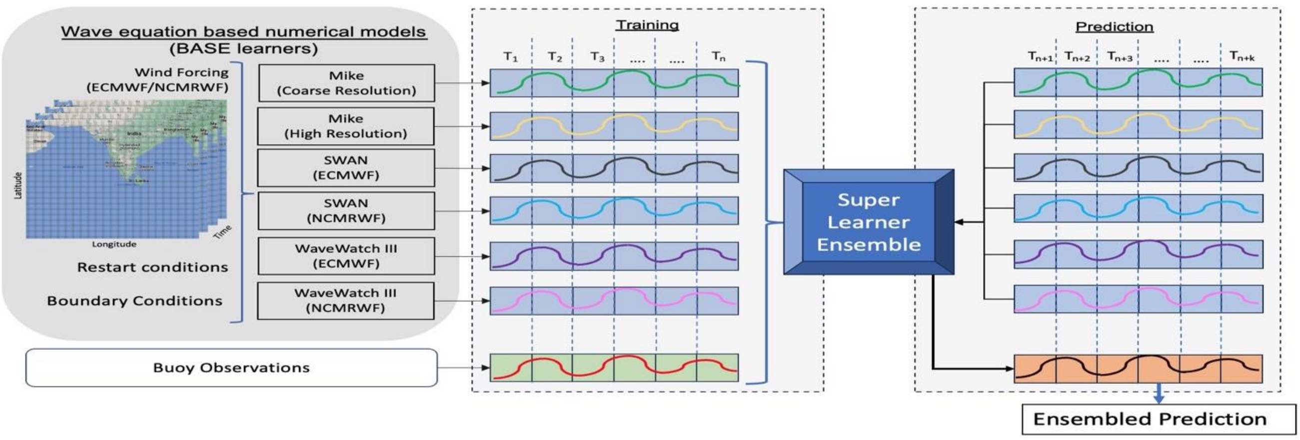


Fig. 2. An architectural representation showing how NWP (base learners) and observational data are used in the training process and how ensemble predictions are made.

Mike 21 spectral wave model for modelling wind-generated wave swells for 7 days ahead. A high-resolution setup for accurate predictions using a smaller grid size was used. Studies conducted by Zhipeng Zhou et al. (2021)[33] stated that the mike model predictions of waves were reasonable and promising along the Ghana coast. Muhammed Naseef T et al. (2022)[7] conducted the sensitivity analysis of wave hindcasts using the Mike 21 setup and provided crucial statistical measures of the performance of the model in the Indian Ocean region.

2.2.2. SWAN

Delft University of Technology has developed the third generation SWAN model to better predict wind-generated waves. Zed et al. (2022)[34] for the Mediterranean Sea have concluded that the SWAN model has performed on par with the competing wave models and provided accurate forecasts.

2.2.3. Wave Watch III

Developed at the NOAA/NCEP, the multi grid Wave Watch III model is an advanced wave modelling system for predicting wind waves. The model has been validated for the Northern Indian Ocean region by forcing ground-level winds from the ECMWF or NCMRWF. The results of the studies have been published by Remya et al. (2020)[6] and have concluded with the reliable performance of the model.

3. Proposed Super Learner Ensemble

The research introduces a novel ensemble strategy that amalgamates the predictions from physics-based ocean models with observed data, effectively merging the advantages of both numerical models and real-world observations. This hybrid approach harnesses the power of neural network architectures, specifically the innovative N-BEATS architecture, which introduces a new perspective to the methodology. Utilising the available time-series data from various locations along the Indian coastline, the objective is to determine the optimal ensemble technique. The precision of the ensemble prediction is assessed through the root mean square error (RMSE) and the Pearson correlation coefficient. Model training involves employing one year's worth of forecast and observation data and generating an ensemble forecast for the subsequent 128 timestamps, equivalent to a 16-day forecast period. The system's architecture is illustrated in Figure 2 mentioned below.

Every wave model in a high-performance computing environment has initial and boundary conditions, and ground-level winds are the driving force. Consequently, the forced model generates a spatial wave distribution within the specified domain. Wave forecasts are then extracted at the buoy locations indicated in Figure 1a.

Algorithm 1 Super Learner Ensemble

1: *X* ⇐ *UNION*(*XMIKE*,*XSWAN*,*XWWIII*)

2: *Y* ⇐ *Yobservation*

3: *Xtrain*,*Xtest* ⇐
X,*Ytrain*,*Ytest* ⇐ *Y* 4:

$$y = \phi(\sum_{i=1}^{n} w_i x_i + b)$$

while *epoch* <
maxEpochs **do**

7: train the model update weights and optimize $error : \sum_{i=1}^{D}(x_i - y_i)^2$

8: **If** *error* is minimal **then**

9: *break*

10: **end if**

11: **end while**

12: $Y_{pred} \Leftarrow predict(X_{test})$

13: $r = \frac{\sum_{i=1}^{n}(y_{pred_i} - \overline{y_{pred}})(y_{test_i} - \overline{y_{test}})}{\sqrt{\sum_{i=1}^{n}(y_{pred_i} - \overline{y_{pred}})^2 \sum_{i=1}^{n}(y_{test_i} - \overline{y_{test}})^2}}$

For each of the previously mentioned neural architectures, the procedure outlined in Algorithm 1 is adhered to, and the resulting correlations are recorded to determine the most effective architecture. The comprehensive rankings of these architectures are elaborated upon in the results section.

The current proposed meta-learning approach has the benefit of acquiring knowledge from the base models regarding seasonality, climatological variations, the quality of the forcing fields, and global environmental shifts. As an illustration, the base learners have the capacity to react to exceptional oceanic events such as cyclones and tsunamis. Consequently, the meta learner, having observed these occurrences previously, can make predictions regarding such events more accurately. Like a conventional multimodal ensemble approach, the key advantage lies in the fact that even if just one model within the ensemble demonstrates strong performance, the overall ensemble performance is enhanced. Moreover, the ensemble prediction is consistently presumed to exhibit superior accuracy compared to any individual model's prediction.

In the results section, the best super-learner is found, and then its performance is compared to observations and established benchmarked wave models during two cyclone events: Tauktae on India's west coast and Gulab on India's east coast.

3.1. Multi-Layer Perceptron (MLP)

A fully connected network with multiple layers, or simply an MLP, will associate weights and biases for the model values in the training samples to fit the observed values. A dense layer with relu activation is used along with the adam optimizer and mean-squared error as the loss function. The combination of the inputs, corresponding weights, and the activation function can be represented as

Where φ is the activation function (relu in our case), wi is the vector of weights, xi is the input vector, and b is the bias of the forecasting model with respect to the observation.

3.2. Long Short-Term Memory

For sequence-sequence problems, recurrent neural networks, especially the LSTM, are one of the most profound choices as they can learn long-term dependencies. Overcoming vanishing gradient and exploding gradient problems is one of the major advantages of architecture. The input gate, the output gate, and the forget gate are the building blocks of LSTM. It is widely used when the sequences are very long and are like the RNNs. LSTMs learn from input sequences, compute what to forget and what to remember. The output of one LSTM memory cell is fed to the next memory cell along with the computed weights. A brief description of one memory cell can be seen here. This is like predicting the next word when we know all the words so far.

3.3. Temporal Convolution Networks (TCN)

Temporal convolution networks have a very different approach compared to the earlier architectures, where the sequences in the past affect the current value. In a way, if y = y1,y2,y3,y4,y5,... is the time series data for the observed wave heights, convolution will make the y5 get affected by y2,y3,y4 for the drawing relationship between y5and y1. In general, 1D convolution network is shown below During the learning phase, TCN approximates a function that has minimal loss between the actual inputs and the predicted values. To maintain the same length during the process, zero padding is used so that the input length and the hidden layer length are the same.

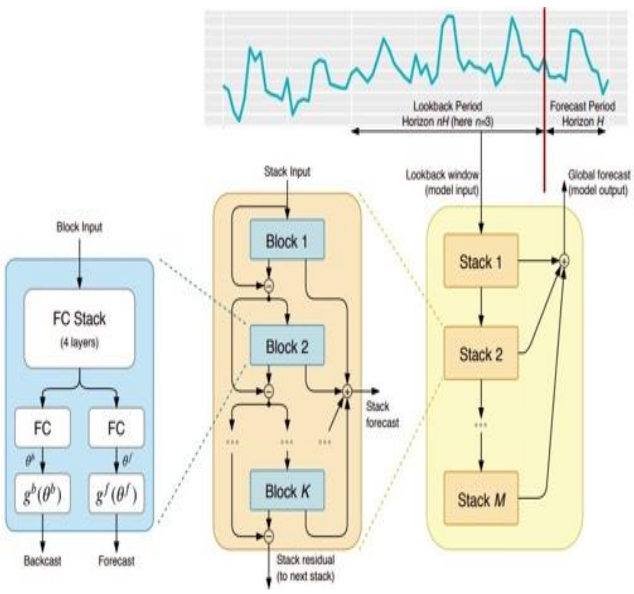


Fig. 3: (a) Stacked Dilated Convolution Layers (b) Details of the TCN Residual Block

The network can look back up to (k-1)d time steps, where k is the kernel size and d is the dilation factor. The number of layers depends on the length of the historic data available. Finally, the residual block ensures the network can learn from a long history of two series of convolution, weight normalisation, activation, and dropout. Element wise addition is carried out, and the result is transmitted for further processing.

3.4. Neural Basis Expansion Analysis for Interpretable Time Series (N-BEATS)

In the recent past, an architecture for time series forecasting was presented by Oreshkin et al. (2019)[35] named Neural Basis Expansion Analysis for Interpretable Time Series (N-BEATS). It is a pure neural engine that has proved its mettle against the M3 and M4 datasets, outperforming classical approaches to statistical + ML models. Studies conducted by Chatigny et al.(2021)[36] for scaling the N-BEATS approach, Stevenson et al.(2021)[37] for solar radio flux forecasting, etc. have achieved a successful performance increase using the N-Beats approach. N-BEATS has a forked architecture, which can be represented below.

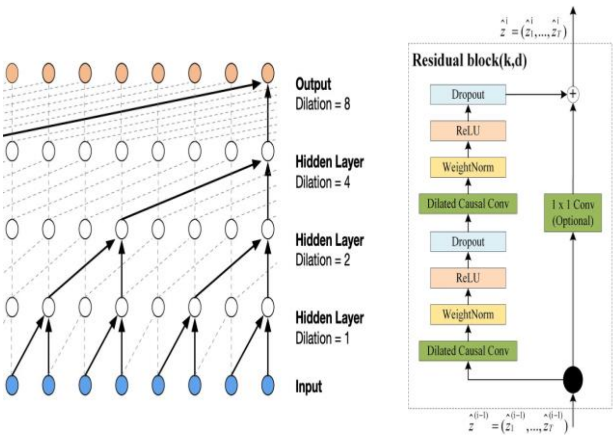


Fig. 4. overall architecture of the N-BEATS model (from the original paper) showing the blocks in double residual stacking fashion and the details of each block

The model relies on the outputs generated by each block, which takes inputs xl and outputs of two vectors $\hat{x}_l$ (best estimate) and $\hat{y}_l$ (block's forward forecast). The length of the input window also needs to be specified, known as the horizon H (generally ranging from 2H to 7H). Each block internally computes the θ_l^b , θ_l^f (backward and forward expansion coefficients) g_θ^f , g_θ^b (basis layers map the expansion coefficients to outputs).

where hl,4 can be computed recursively from the fully connected layers starting from layer 1 and hl,1 = RELU(wl,1 + bl,1). Finally, the forecast and backcast output are computed using the expansion coefficients.

The backcast and forecast outputs run through double residual stacking, correcting the future blocks the approximations much faster and making predictions accurate. The N-BEATS model also deals with standard seasonality and the trend model internally. Stacks and Blocks: The N-BEATS model is organized into stacks, each containing multiple fully connected feedforward blocks. You need to decide the number of stacks and the number of blocks in each stack. For example, you might choose to have 2 stacks with 4 blocks in each stack.

To facilitate effective learning, a lookback value of 7 is employed, implying that the model considers the past 7 days of data to predict the subsequent 7 days' values. This choice enables the model to capture trends and enhance the accuracy of predictions effectively. Modifying the lookback value adversely impacts the model's ability to accurately capture ascending or descending trends, and it hampers the efficiency of minimizing error.

All the models discussed above have been set up to generate ensemble forecasts for wave height prediction. As discussed earlier, the data from the model outputs of WWIII, Mike and Swan, along with the observations at the East Coast (Visakhapatnam, Pondicherry, BD14, BD11) and West Coast (Karwar, Ratnagiri, AD07, AD09), were considered in this study. The specific locations were chosen for the analysis as the data availability is continuous over a period.

4. Results and Discussion

For comparative analysis, the Brier Skill Score (BSS) was employed, where the Brier Score BSref of the model of interest is compared against other forecasting models.

$$BSS = 1 - (BS/BSref)$$

Once the best ensemble forecast is drawn, this study compares the performance of the best neural ensemble models against the traditional ocean forecasting models using the Pearson Correlation Coefficient (PCC) along with Root Mean Square Error and Standard Deviation. For better visual comparison, the Taylor diagrams were used. The Brier Skill Scores for the employed neural engines is presented in Table 2. The skill scores of the NBeats ensemble outperform the other machine learning techniques by a fair margin in many locations. In a few locations, Temporal Convolution Networks performed better at AD09 and Pondicherry, than NBeats but with marginal improvement. In the rest of the locations, the NBeats model has outperformed all the other ensemble models. The highest skill score (green) and the second highest skill score (red) are marked for ease of understanding.

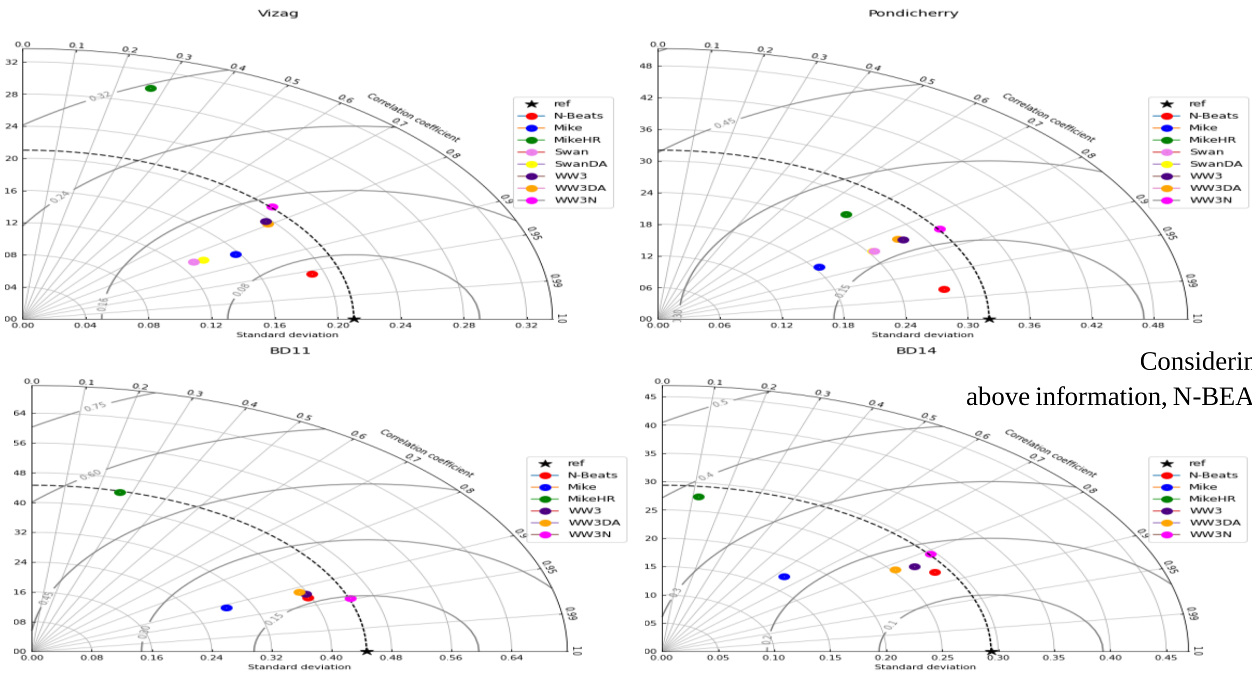


Fig. 5: Taylor diagrams depicting correlation and standard deviation comparison of the NBeats Ensemble prediction against the ocean forecasting models in the Bay of Bengal (East Coast of India)

Table 2: Brier Skill Scores of the ANN Models

	N-Beats	TCN	LSTM	MLP
Visakhapatnam	0.995891	0.994453	0.985016	0.979540
Pondicherry	0.989432	0.990626	0.971691	0.947339
BD14	0.977739	0.97297	0.900757	0.968632
BD11	0.972178	0.913151	0.963948	0.899581
Karwar	0.989637	0.986288	0.986381	0.974400
Ratnagiri	0.995578	0.986544	0.873406	0.954033
AD07	0.941097	0.485050	0.791790	0.649891
AD09	0.985958	0.989880	0.901655	0.496184

Considering the above information, N-BEATS is the best candidate for ensemble. In this study, the N-BEATS ensemble forecast (NEF) is compared with the traditional ocean general circulation models in operational mode and during extreme events like cyclones. Along the east coast of India, the NBeats Ensemble prediction has not only predicted a better correlation but also a lower standard deviation. For the said regions, we can draw the conclusion that when the ocean general circulation models predict with a 0.95 correlation, NBeats Ensemble prediction also produces good results (in the case of BD11), but when the ocean models perform poorly, NBeats Ensemble prediction

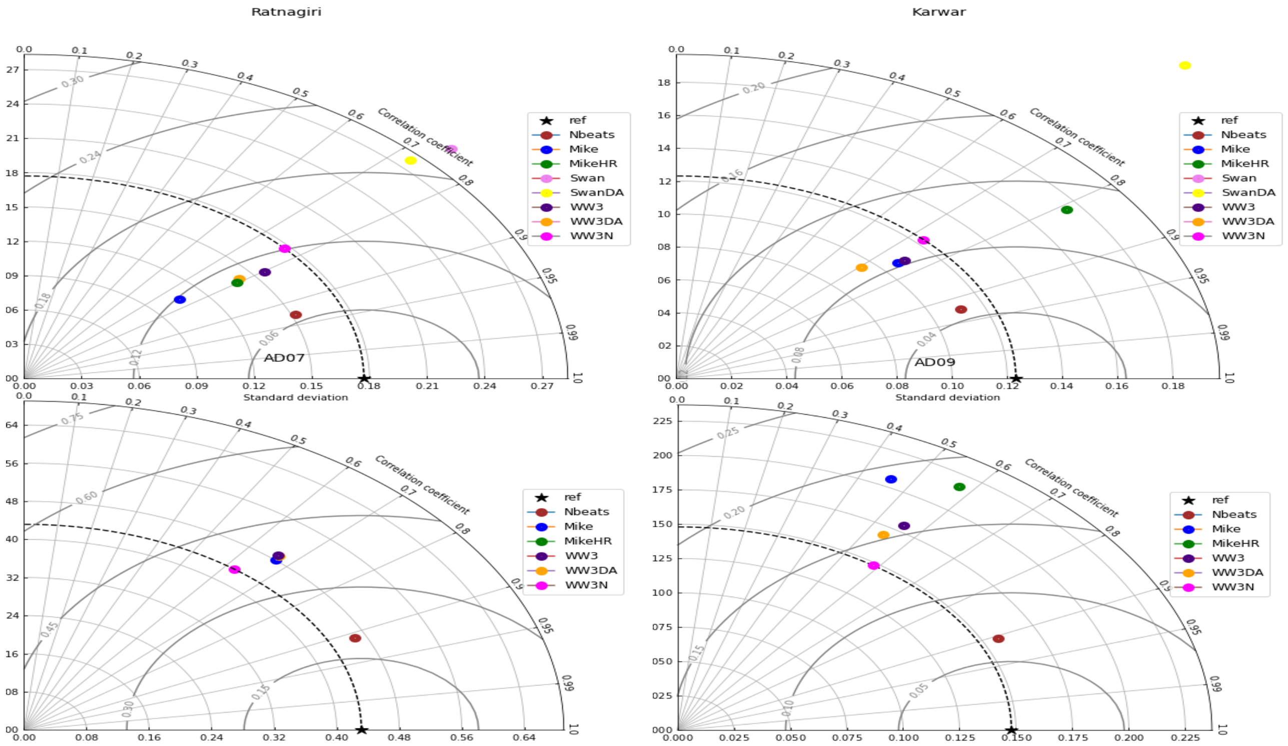


Fig. 6: Taylor diagrams depicting correlation and standard deviation comparison of NBeats Ensemble prediction against the ocean forecasting models in the Arabian Sea (West Coast of India)

provides the best prediction with greater correlation coefficients (in the case of BD14, Vizag, and Pondicherry). Since it is known that predictions vary hugely from the Bay of Bengal to the Arabian Sea because of various environmental conditions, this study focuses on predictions in the Arabian Sea as well.

It can be concluded through this study that NBeats ensemble prediction outperforms the traditional ocean forecasting models as well as other neural network-based ensembles. Since we are dealing with forecasting natural or environmental parameters, the implicit question is whether the forecasting model performs equally well during extreme events. So, in the present work, NBeats Ensemble prediction assessment has been carried out during two cyclone events, namely Gulab and Tauktae, formed in the Bay of Bengal and the Arabian Sea, respectively. Separate models were trained for a period of one year to capture the associations between the OGCM model outputs and observations in the BOB and Arabian Sea.

4.1. Gulab (September 24 to September 27, 2021)

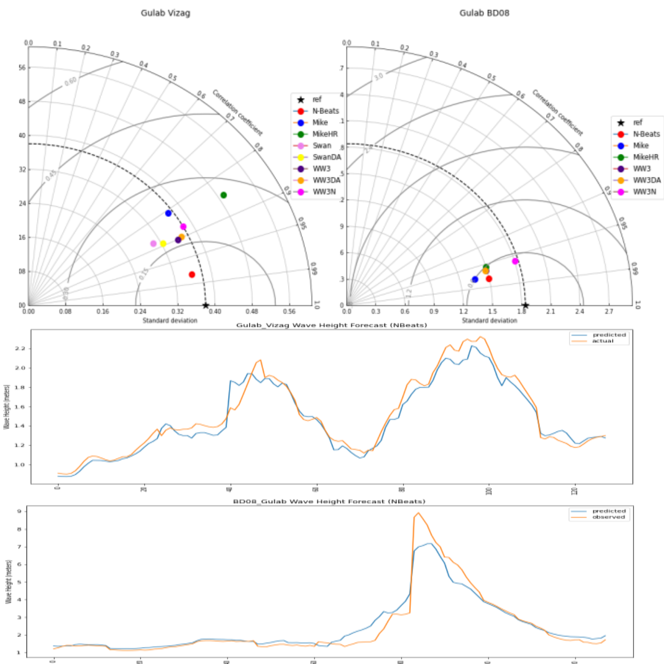
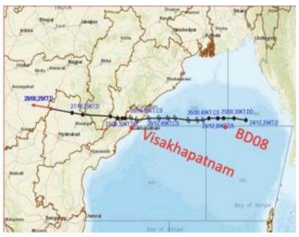


Fig. 7: (a) Comparison of NBeats at Visakhapatnam against other ocean forecasting models and time series comparison against observation (b) Comparison of NBeats at BD08 against other ocean forecasting models and time series comparison against observations



On September 25th, Cyclone Gulab was named when the well-marked low pressure formed in the eastern Bay of Bengal turned into a cyclone. The system moved eastward and made its landfall in Visakhapatnam. Observation stations were available, and reporting along the path, especially by Wave Rider Buoy of Visakhapatnam and Moored Buoy of BD08, helped record and monitor the ocean parameters in real-time. At Visakhapatnam, using NBeats, the forecast accuracy has improved with minimal RMSE. Without Nbeats, the best available forecast is from Wave Watch III, using which all the alerts were issued for the region. There is a notable increase in the correlation for NBeats in the case of Visakhapatnam, which is greater than 0.95, while the maximum correlation achieved by the ocean forecasting models is around 0.9. For the location BD08, there is an increase in the correlation, but with marginal RMSE, and most of the ocean forecasting models, along with the NBeats, have achieved a correlation of around 0.96. Using NBeats as the super learner to generate predictions along the cyclone path, it produces more accurate results. The correlation and RMSE values tested at Tuticorin are 0.8 and 0.13, respectively, and at BD08, they are 0.93 and 0.23, respectively.

4.2. Tauktae (May 14, 2021 to May 18, 2021)

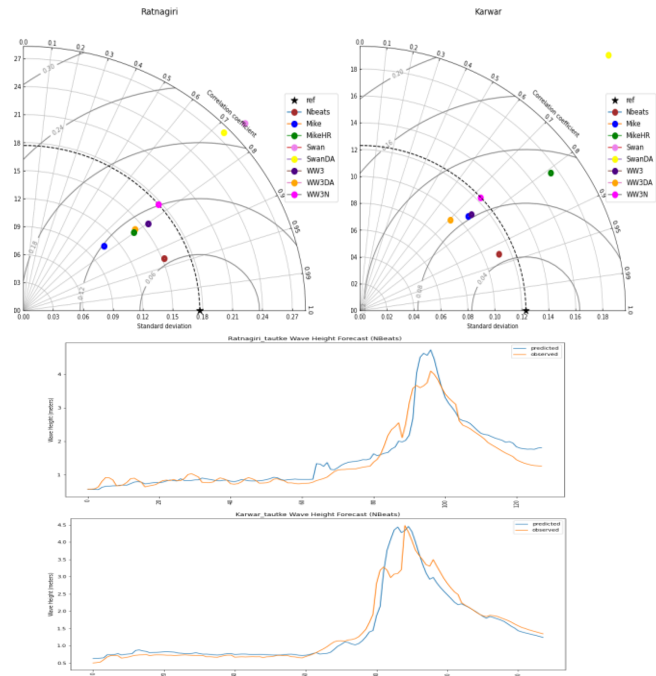
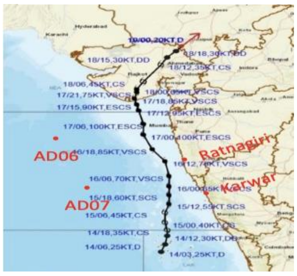


Fig. 8: (a) Comparison of NBeats at Karwar against other ocean forecasting models and time series comparison against observation. (b) Comparison of NBeats at Ratnagiri against other ocean forecasting models and time series comparison against observations



The wave characteristics differ drastically from the Bay of Bengal to the Arabian Sea. Statistical measures of the NBeats forecast are examined even in the Arabian Sea region. During May 2021, the Arabian Sea experienced the Tauktae cyclone, which originated southwest of Kerala and travelled along the shoreline. The observed track of the cyclone from the IMD can be seen in figure. There were many observation stations located along the coast. For this study, we have considered the data from buoys off Ratnagiri and Karwar since the locations are close to the cyclone travelled path. Wind-wave characteristics during the cyclone were studied by Shanas, P. R et al.(2021)[10] specifying the impact and intensity.

All the ocean forecasting models have performed well at the Karwar location, along with NBeats. Almost all the models recorded more than 0.95 correlation and minimal RMSE. In such cases, any model output can be considered for issuing alerts accordingly. The forecast generated by NBeats compared with the observation can be seen in Figure 9 (b) below the Taylor plot. But on observing the forecast at Ratnagiri, Beats has improved the ocean forecasting model outputs with a correlation of 0.95, while the maximum achieved correlation with ocean forecasting models is 0.91. The model has also been tested at other locations, namely AD07 (correlation: 0.909 and RMSE: 0.24) and AD09 (correlation: 0.905 and RMSE: 0.11). At AD07, interestingly, temporal convolutional networks demonstrated an increased correlation factor of 0.926 compared to NBeats, which is 0.909. The data availability problem persisted even for the buoys on the west coast, which was resolved by considering the chip data. Since real time data availability is a major concern for the system and there were many data gaps because of communication failure, this study considered the chip data for training the model. The chip data will be stored persistently in the buoys, irrespective of the communication channel. This ensures data availability over large time intervals.

5. Conclusion

Using the statistical measures of correlation coefficient and root mean square error, it can be concluded that the NBeats ensemble demonstrated better results compared to any individual ocean forecasting model, even during extreme conditions like cyclones. Even though the temporal convolution networks also generated good results and outperformed NBeats in a few locations, there was marginal improvement. To begin, while the N-BEATS ensemble has demonstrated its impressive superiority over individual forecasting models, there is a captivating prospect to delve deeper into the realm of hybrid methodologies. This involves synergizing the strengths of both NBEATS and TCN, potentially yielding predictions of even greater robustness. Secondly, the targeted focus on specific locations, including Visakhapatnam, Pondicherry, Tuticorin, BD08, BD11, and BD14, hints at the possibility of localized models for these regions. Such models could leverage location-specific data augmentation techniques for heightened accuracy. Moreover, the substantial improvements noted during cyclonic events underscore the need to broaden the scope of this study to encompass a wider spectrum of extreme weather conditions. This expanded investigation aims to unveil the behaviour and reliability of the models across various challenging scenarios. Additionally, a crucial consideration involves addressing sensor failures and data quality concerns. Future endeavours could revolve around the development of methodologies for real-time data quality control and imputation, guaranteeing a continuous flow of dependable inputs for the models. Pursuing these avenues, our research sets the stage for more resilient and precise ocean forecasting systems, with potential applications spanning from disaster preparedness to sustainable coastal management.

6. Acknowledgements

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7. Author contributions

RP: Methodology, Data curation, Software Design and Implementation, **BN:** Initial draft preparation, Validation. **LD:** Visualization, Investigation, Reviewing and Editing.

8. Conflicts of interest

The authors declare no conflicts of interest.

9. References

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