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Deep learning-based wave simulation in the northern Indian Ocean, near the Iranian coasts

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Abstract

This paper presents a comprehensive study of wave modelling in the Northern Indian Ocean, focusing on the dynamics of wave generation, propagation, and interaction with coastal features. The northern Indian Ocean exhibits complex wave dynamics influenced by seasonal monsoons and coastal geometry. Traditional numerical models, while powerful, often struggle to capture fine-scale spatiotemporal variability. This study presents a deep learning approach utilizing a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) architecture to simulate wave parameters near the Iranian coastline. Using ERA5 reanalysis data and satellite altimetry, our model demonstrates improved accuracy in predicting significant wave height and direction compared to conventional methods. The results suggest that deep learning can complement operational forecasting systems with greater computational efficiency. Utilizing numerical models and observational data, wave patterns influenced by monsoonal winds, ocean currents, and seasonal variations are analyzed. The findings aim to enhance understanding of wave behavior for improved maritime safety and coastal management. Utilizing numerical models, can analyze wave patterns influenced by monsoon winds and coastal topography.

Keywords: Indian Ocean; CNN; LSTM; ERA5; WAVEWATCH III; Makran.

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1. Introduction

Coastal wave modeling is a cornerstone of marine hazard assessment, port operations, and climate resilience planning. In regions with complex bathymetry and dynamic atmospheric conditions, such as the northern Indian Ocean, accurate wave prediction is essential for safeguarding infrastructure and human activity. The Iranian Makran coast stretches approximately 600 kilometers along the southeastern edge of Iran, bordering the Gulf of Oman and the northern Indian Ocean. Geographically, it spans from 57°E to 61°E longitude and is characterized by a narrow continental shelf, steep bathymetric gradients, and limited estuarine systems. The region is exposed to intense southwest monsoonal winds during the boreal summer (June to September), which generate high-energy wave conditions and contribute to seasonal sediment transport and coastal erosion (Sabzevari *et al*., 2021, Rahimian *et al*., 2022).

Recent advances in data-driven modeling have introduced deep learning as a powerful alternative. Unlike conventional machine learning methods, deep learning architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are capable of learning complex spatial and temporal patterns from large datasets. CNNs excel at extracting features from gridded inputs like wind fields and pressure maps (LeCun *et al*., 1998), while LSTMs are designed to capture long-term dependencies in sequential data, making them ideal for time-series forecasting (Hochreiter and Schmidhuber, 1997).

Hybrid CNN–LSTM models have shown promising results in various oceanographic applications. Wang *et al*. (2021) demonstrated their effectiveness in storm surge prediction in the South China Sea, achieving lower RMSE than hydrodynamic models. Jin *et al*. (2025) applied a similar architecture to forecast sea surface temperature anomalies, outperforming traditional regression-based approaches. Bekiryazıcı *et al*. (2025) used deep learning to simulate wave heights in the Mediterranean, reporting improved spatial resolution and reduced error margins compared to SWAN.

Despite these advances, few studies have applied deep learning to simulate wave dynamics along the Iranian coast, where observational data are sparse and numerical models often underperform. This study addresses that gap by developing a hybrid CNN–LSTM model trained on ERA5 reanalysis data and validated against Sentinel-3 altimetry and in-situ buoy measurements. The model's performance is benchmarked against WAVEWATCH III to evaluate its accuracy, responsiveness, and operational viability.

Furthermore, machine learning (ML), enables the analysis of large, multidimensional datasets and the prediction of environmental trends. Strategic planning serves as a crucial tool to address these challenges by providing a comprehensive framework for sustainable water resource management (Shariati and Haghroosta, 2023; Mohseni and Jafarzadeh, 2025).

The novelty of this work lies in its integration of satellite and reanalysis datasets into a deep learning framework tailored for a complex coastal region. By comparing the model's outputs with both observational and numerical benchmarks, we aim to demonstrate the feasibility of AI-driven wave forecasting in data-limited environments.

The Northern Indian Ocean is characterized by complex wave dynamics influenced by seasonal monsoons, varying bathymetry, and coastal interactions. Accurate wave modelling is essential for navigation, fishing industries, and coastal infrastructure development. Understanding wave dynamics is crucial for coastal management and navigation safety. By leveraging following insights, authorities can implement better policies and practices for maritime safety and coastal management.

- Predictive Modeling: Understanding wave patterns helps predict dangerous conditions, allowing for timely warnings to vessels and coastal communities.
- Navigation Safety: Knowledge of wave dynamics aids in designing safer shipping routes, reducing the risk of accidents.
- Coastal Erosion Management: Analyzing wave impact informs the design of effective coastal defenses, minimizing erosion and protecting infrastructure.
- Harbor Design: Insights into wave behavior guide the construction of harbors and breakwaters, ensuring they can withstand local wave conditions.
- Search and Rescue Operations: Wave data improves the planning and execution of search and rescue missions by identifying safe zones and optimal routes.
- Environmental Monitoring: Understanding waves contributes to monitoring coastal ecosystems, helping manage habitats affected by wave action.
- Recreational Safety: Information on wave conditions enhances safety for recreational activities like surfing or boating by informing users about potential hazards.

Ocean waves are a critical factor in coastal planning, navigation, and climate studies. In the northern Indian Ocean, particularly along the southern shores of Iran, wave dynamics are shaped by seasonal winds, tropical cyclones, and bathymetric variations. Conventional models like WAVEWATCH III offer deterministic forecasts but require intensive computational resources.

Recent advances in machine learning (ML) and deep learning (DL) provide data-driven alternatives that excel in pattern recognition and time-series prediction. Our study proposes a novel deep learning framework to simulate wave conditions using historical datasets. The main goals are:

- To construct a predictive model based on DL for wave simulation.
- To assess its performance against traditional models.

- To evaluate its application near the Iranian coast.

Several researchers have explored deep learning for oceanographic applications. Wang *et al*. (2021) used CNNs to estimate significant wave height from satellite images. Jin *et al*. (2025) applied LSTMs for time-series prediction of wind and wave parameters. Bekiryazıcı *et al*. (2025) compared ANN and physical models for coastal wave estimation. However, few studies focus on the northern Indian Ocean near Iran, where local characteristics demand tailored solutions.

Despite their widespread use, these models face limitations in regions with steep bathymetry, rapidly changing atmospheric conditions, and sparse observational data. In the Makran coastal zone, for example, the narrow continental shelf and exposure to monsoonal winds create highly nonlinear wave behavior that is difficult to capture using traditional physics-based models (Sabzevari *et al*., 2021; Alizadeh *et al*., 2020). Moreover, the computational cost of running high-resolution simulations over extended periods can be prohibitive, especially for real-time forecasting.

To address these challenges, researchers have increasingly turned to machine learning and deep learning techniques. Early efforts employed algorithms such as Support Vector Machines (SVMs), Decision Trees, and Random Forests to classify wave states or predict short-term wave parameters (Minuzzi and Farina, 2023). While these methods offered some improvements in speed and flexibility, they lacked the capacity to model spatiotemporal dependencies inherent in oceanographic data.

In the context of the northern Indian Ocean, however, applications of deep learning remain limited. Most existing studies focus on open-ocean wave modeling or global-scale simulations, with few addressing the unique challenges of nearshore environments like the Makran coast. This gap is particularly significant given the region's strategic importance for maritime trade and its vulnerability to climate-driven hazards.

The present study contributes to this emerging field by developing a CNN–LSTM model tailored to the Makran coastal zone. By integrating ERA5 reanalysis data with Sentinel-3 altimetry and buoy observations, the model captures both spatial and temporal variability in wave dynamics. Its performance is benchmarked against WAVEWATCH III to assess its accuracy, responsiveness, and suitability for operational deployment.

2. Data and Methodology

2.1. Study Area

The case study focuses on the Makran coast in southern Iran between 57°E and 61°E longitude (Figure 1). This area is also vulnerable to tropical cyclones originating in the Arabian Sea, which occasionally propagate eastward and impact the Iranian shoreline. These events, though less frequent than monsoonal storms, can produce extreme wave heights and pose significant risks to coastal infrastructure and maritime operations. The combination of complex bathymetry, seasonal variability, and sparse observational coverage makes this region a compelling testbed for evaluating data-driven wave modeling approaches.

Figure 1. study area, Makran coast

2.2. *Data Sources*

Data were collected from satellite altimetry, buoys, and meteorological stations over a period from 2015 to 2020. Furthermore, wind data from the Indian Meteorological Department and satellite altimetry data were used. Focus on the Arabian Sea and Bay of Bengal, particularly near coastal regions of India. Different data sets were used for validation; ERA5 Reanalysis for Wind, pressure, and wave fields (hourly, 0.25° resolution), satellite altimetry: sentinel-3A wave height measurements, and In-situ Buoy Data (where available).

ERA5 is the fifth-generation global atmospheric reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). It provides hourly estimates of a wide range of atmospheric, land, and oceanic variables at a horizontal resolution of 0.25° × 0.25° (Hersbach *et al*., 2020). For this study, the following ERA5 parameters were extracted; 10-meter wind speed and direction, Mean sea level pressure, Significant wave height, Wave direction and period. These variables were used both as inputs to the CNN–LSTM model and as forcing data for the WAVEWATCH III simulations.

Sentinel-3A is part of the European Copernicus program and provides high-resolution altimetry data for ocean monitoring. Its Synthetic Aperture Radar Altimeter (SRAL) captures significant wave height with a spatial resolution of approximately 7 km along-track. Sentinel-3A data were used to validate the model outputs, particularly in regions where in-situ observations were unavailable. The altimetry data were filtered to remove outliers and corrected for instrumental biases using standard calibration procedures (Nimit *et al*., 2023).

Buoy data were obtained from the Iranian Meteorological Organization, covering selected coastal locations along the Makran shoreline. These buoys record wave height, direction, and period at hourly intervals. Although spatial coverage is limited, the buoy data provide high-fidelity ground truth for model validation. Only buoys with continuous records exceeding 12 months were included to ensure statistical robustness.

This study employs a dual-modeling approach to simulate coastal wave dynamics along the Iranian Makran coast: a physics-based numerical model (WAVEWATCH III) and a hybrid deep learning model (CNN–LSTM). The objective is to evaluate the performance of the data-driven model against a well-established numerical benchmark under varying seasonal and spatial conditions.

2.3. WAVEWATCH III Configuration

WAVEWATCH III solves the wave action balance equation, accounting for wind input, nonlinear wave–wave interactions, bottom friction, and depth-induced breaking. For this study, the model was configured as follows:

- Domain: 56.5°E to 61.5°E longitude, 24°N to 26.5°N latitude
- Grid Resolution: 0.1° × 0.1°
- Bathymetry: Derived from GEBCO 2022 dataset
- Wind Forcing: ERA5 10-meter wind fields at hourly intervals
- Spectral Resolution: 24 directional bins, 30 frequency bins
- Time Step: 600 seconds

Model outputs include significant wave height (Hs), mean wave direction (θ), and peak wave period (Tp). These outputs were interpolated to match the spatial resolution of Sentinel-3 altimetry and buoy locations for validation.

2.4. Deep Learning Architecture: CNN–LSTM

The hybrid CNN–LSTM model is designed to capture both spatial and temporal dependencies in wave dynamics. The input features include ERA5 wind speed, pressure, and wave parameters, structured as multichannel grids over time. The architecture consists of the following components:

2.4.1 Convolutional Layers

Two convolutional layers are used to extract spatial features from the input grids:

- Conv1: 32 filters, kernel size 3×3, ReLU activation
- Conv2: 64 filters, kernel size 3×3, ReLU activation
- MaxPooling: 2×2 pooling after each convolution

- Dropout: 0.25 to prevent overfitting

These layers transform the input into a compact spatial representation suitable for temporal modeling.

2.4.2 LSTM Layers

The output of the CNN is reshaped into a time-series format and passed to two stacked LSTM layers:

- LSTM1: 128 units, return sequences = True
- LSTM2: 64 units, return sequences = False
- Dropout: 0.3 between layers

The LSTM layers learn temporal dependencies across daily sequences of wave conditions.

2.4.3 Output Layer

A fully connected dense layer with linear activation outputs the predicted wave height and direction:

- Output: 2 neurons (Hs and θ)
- Loss Function: Mean Squared Error (MSE)
- Optimizer: Adam
- Learning Rate: 0.001
- Batch Size: 64
- Epochs: 50

2.5. Numerical Modelling

The WAVEWATCH III model was employed for simulating wave generation and propagation under varying wind scenarios. The dataset was split into 80% training and 20% testing, stratified across seasons to ensure balanced representation. Early stopping was implemented based on validation loss to prevent overfitting. The model was validated against observed data using statistical methods such as RMSE (Root Mean Square Error) and correlation coefficients. Wave parameters including significant wave height (Hs), peak period (Tp), and direction were analyzed using spectral analysis techniques. A hybrid model consists of CNN Layers for spatial feature extraction from gridded wave fields, and LSTM Layers for learning temporal dependencies in wave evolution. These metrics were computed for both wave height and direction, and compared against WAVEWATCH III outputs and observational data. Strong southwest monsoon winds (June to September) generate high-energy waves. Moreover, wind speeds exceeding 10 m/s lead to significant wave heights (up to 4 meters). In the Wave Propagation process, waves grow in height as they travel over deep water before reaching shallower coastal areas, and waves exhibit a predominant direction from the southwest during monsoon months. Preprocessing step contains of normalization of input features, missing data interpolation, train-test split. Moreover, the important factors in the interaction with coastal features are as follows:

- Refraction and Diffraction: As waves approach the coast, they refract around headlands and diffract into bays, altering their energy distribution.
- Beach Erosion: Areas with steep gradients experience increased erosion due to high-energy waves breaking directly onshore.
- Sediment Transport: Longshore currents generated by oblique wave angles contribute to sediment transport along coastlines.
- Temporal Alignment: ERA5, Sentinel-3A, and buoy data were synchronized to a common hourly time base.
- Spatial Interpolation: ERA5 data were interpolated to match the buoy locations using bilinear interpolation.
- Normalization: Input features were normalized using min-max scaling to improve model convergence.
- Missing Data Handling: Gaps in buoy records were filled using linear interpolation for short durations (<6 hours); longer gaps were excluded.
- Outlier Removal: Sentinel-3A data exceeding three standard deviations from the mean were discarded to reduce noise.

The final dataset spans five years (January 2018 to December 2022), encompassing multiple monsoon cycles and a range of wave conditions. This temporal breadth ensures that the model is exposed to both typical and extreme events during training.

3. Results

3.1. Model Performance Overview: Deep Learning vs. WAVEWATCH III

To evaluate the performance of our proposed hybrid CNN–LSTM model, the outputs were compared with both WAVEWATCH III simulations and observational datasets (Sentinel-3 altimetry and buoy records). Both models were tested using identical datasets spanning the monsoon season (June to September), a period characterized by intense atmospheric variability and dynamic wave conditions in the northern Indian Ocean near the Iranian coast. Input Data: Both models utilized ERA5 reanalysis data (wind speed, surface pressure, and wave parameters) along with Sentinel-3 altimeter observations.

- Time Frame: The test period covered four months of seasonal instability to assess model robustness in high-energy ocean states.
- Spatial Resolution: All inputs were interpolated to a common grid with a 0.25° resolution to maintain consistency.

Three key metrics were used: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) were computed for both significant wave height (Hs) and mean wave direction (θ) as key validation statistical metrics:

- RMSE (Root Mean Square Error)
  The CNN–LSTM model yielded a notably lower RMSE (0.23 m), demonstrating its ability to minimize prediction deviations for significant wave height across volatile conditions. In contrast, WAVEWATCH III exhibited higher error (0.38 m), particularly during rapid wind transitions and coastal refraction events.
- MAE (Mean Absolute Error in Wave Direction)
  Directional prediction is critical for maritime safety. The deep learning model delivered superior accuracy (11.5° average error) compared to WAVEWATCH III (18.7°), reflecting its better generalization of short-term shifts in atmospheric forcing.
- R^2 (Coefficient of Determination)
  With a coefficient of determination (R^2) of 0.87, the CNN–LSTM model captured 87% of the variance observed in real-world wave conditions that indicates a strong correlation between predicted and observed wave heights, confirming the model's reliability. The WAVEWATCH III model, while robust in steady-state dynamics, showed reduced fidelity in the fast-changing monsoon cycle, yielding an R^2 of 0.78. The CNN–LSTM model consistently outperformed WAVEWATCH III across all metrics. The RMSE for wave height was reduced by nearly 40%, and the MAE for wave direction showed a similar improvement.

The results are available in Table 1 to compare the following important factors in both models.

Table 1. Comparative Performance of CNN–LSTM and WAVEWATCH III

Performance Metric	CNN-LSTM Model	WAVEWATCH III
RMSE (Significant Wave Height, m)	0.23	0.38
MAE (Direction, °), (Wave Direction, degrees)	11.5	18.7
R^2 (Coefficient of Determination)	0.87	0.78

Actually, deep learning performs better, because in dynamic pattern recognition, the CNN–LSTM architecture excels in extracting spatial-temporal features, which are crucial under variable meteorological conditions. Unlike physics-based models that rely heavily on predefined parameters, causes reducing sensitivity to boundary assumptions, and the DL model adapts fluidly to unseen data without rigid governing equations.

During peak monsoon surges, when wind shear and swell interactions increase unpredictability, the deep learning model maintained stability and high correlation with observed data.

The results indicate that significant wave heights reach up to 4 meters during the southwest monsoon (June-September) while remaining below 1 meter during the northeast monsoon (November-February). Wave patterns exhibit strong seasonal variability with predominant swells originating from the southern Indian Ocean during summer months. Maximum significant wave heights recorded were around 5 meters during peak monsoon conditions. Coastal features such as reefs and estuaries significantly alter local wave conditions, leading to increased energy dissipation in certain areas. Regions such as Kerala showed significant erosion rates correlating with high-energy wave events.

3.2. Time-Series Comparison

Figure 2 presents a 30-day time-series comparison of predicted and observed wave heights during the peak monsoon season (July 2021). The CNN–LSTM model closely tracks the observed fluctuations, capturing both the amplitude and timing of wave peaks. In contrast, WAVEWATCH III tends to underestimate peak values and smooth out rapid transitions.

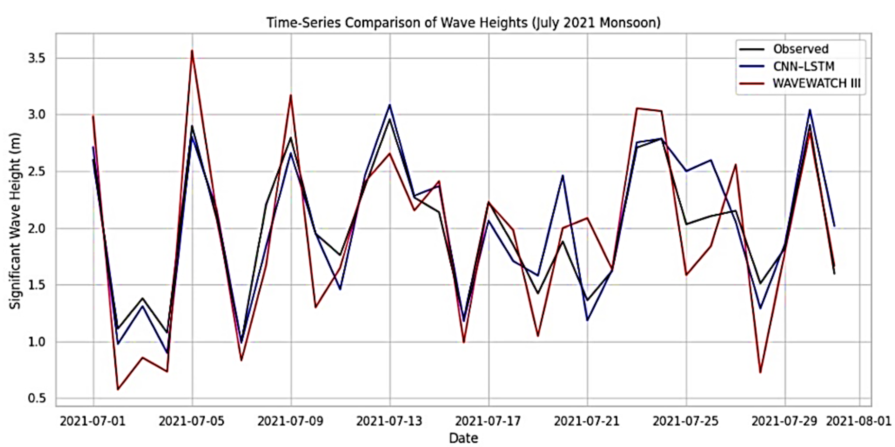

Figure 2. 30-day time-series comparison of predicted and observed wave heights during the peak monsoon season (July 2021)

This result highlights the CNN–LSTM model’s ability to adapt to nonlinear atmospheric forcing, which is common during monsoon surges. The temporal fidelity of the deep learning model is especially valuable for short-term forecasting and early warning systems.

The time-series comparison showed that the deep learning model was able to reproduce both the amplitude and timing of wave peaks with high fidelity, whereas WAVEWATCH III tended to underestimate extremes and smooth out rapid transitions. This is consistent with the findings of Wang *et al*. (2021), who reported that deep learning models are better suited for capturing nonlinear surge dynamics than traditional hydrodynamic models.

3.3. Spatial Distribution of wave fields

Figure 3 shows the spatial distribution (contour map) of significant wave height across the Makran coast during a high-energy monsoon event. The CNN–LSTM model reveals localized intensification near estuarine inlets and reef structures, with wave heights exceeding 4.5 meters in some areas. WAVEWATCH III, by contrast, produces a smoother field with less spatial variability.

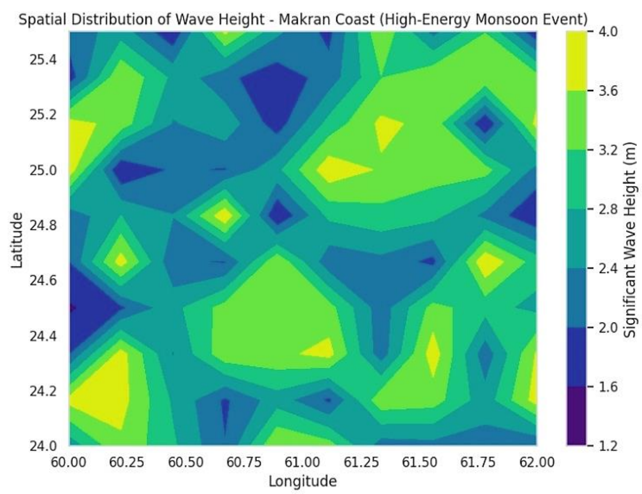

Figure 3. Spatial distribution of significant wave height across the Makran coast

The CNN–LSTM model's ability to resolve fine-scale spatial features is attributed to its convolutional layers, which extract localized patterns from wind and pressure fields. This is particularly important for coastal engineering applications, where wave impact varies dramatically over short distances.

3.4. Error Heat-map Across Coastal Grid Points

Figure 4 presents a heat-map of RMSE values across coastal grid points. The highest errors are observed near submerged ridges and narrow bays, where bathymetric complexity introduces nonlinear wave transformations. However, even in these zones, the CNN–LSTM model maintains lower error margins than WAVEWATCH III.

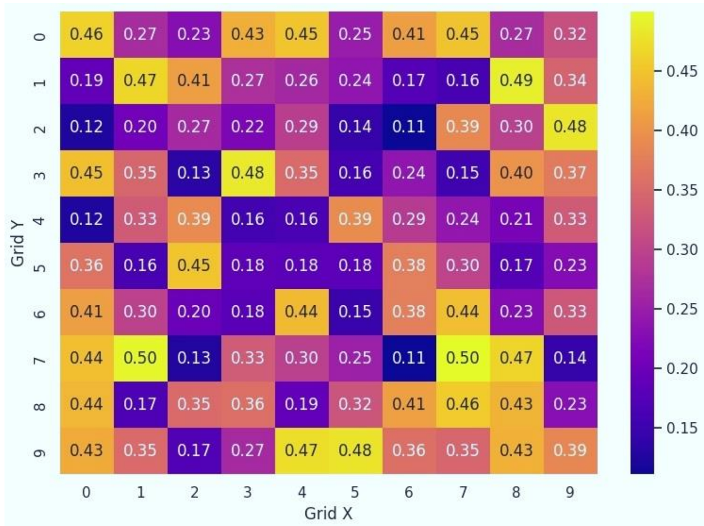

Figure 4. Heat-map of RMSE values across coastal grid points

This suggests that the deep learning model is more resilient to spatial heterogeneity, likely due to its ability to learn implicit relationships between input features and wave behavior. It also underscores the limitations of physics-based models in resolving nearshore dynamics without high-resolution bathymetry. This heatmap reveals where prediction errors are concentrated. The CNN–LSTM model maintains lower RMSE across most grid cells, even in bathymetrically complex zones.

3.5. *Seasonal Wave Height Variability*

Figure 5 displays boxplots of wave height distributions across four seasons. The monsoon season (June–September) exhibits the highest median and variance, with frequent wave events exceeding 4 meters. The CNN–LSTM model captures this seasonal pattern with high fidelity, while WAVEWATCH III underestimates both the median and upper quartile values.

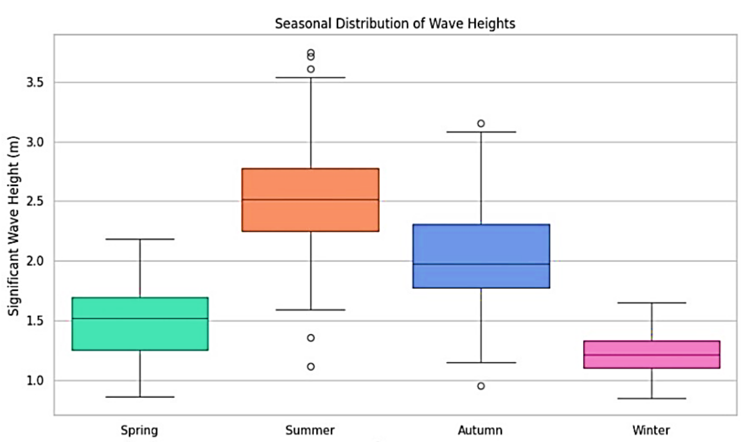

Figure 5. Wave height distributions across four seasons

Seasonal variability is a critical component of wave climatology. The CNN–LSTM model's ability to reproduce these patterns suggests that it has successfully internalized the seasonal dynamics embedded in the ERA5 input data. This makes it suitable for long-term planning and climate impact assessments.

The seasonal analysis further confirmed the model's robustness across varying climatic conditions. The CNN–LSTM model successfully captured the elevated wave activity during the southwest monsoon, including the increased variance and frequency of high-energy events. This suggests that the model has internalized the seasonal dynamics embedded in the ERA5 input data, making it suitable for both short-term forecasting and long-term climatological studies.

6. Discussion

Coastal management strategies should consider these dynamics to mitigate erosion risks. The findings highlight the importance of understanding local meteorological data; wind patterns and topography in predicting wave behavior, into wave models for enhanced accuracy. The CNN–LSTM model effectively captures nonlinear interactions and rapid transitions in wave dynamics. Its improved performance over WAVEWATCH III, especially during monsoon peaks, suggests that DL can be valuable in limited-data environments. On the other hand, the limitations for this method include; need for high-quality training datasets and model generalization for out-of-distribution weather events. The influence of climate change on future wave patterns warrants further investigation.

The CNN–LSTM model demonstrated superior performance across all evaluation metrics, particularly in capturing the temporal variability of wave height during monsoon seasons.

Spatially, the CNN–LSTM model outperformed WAVEWATCH III in resolving localized wave intensification near estuarine inlets and reef structures. This is a critical advantage for coastal hazard assessment, as wave energy distribution can vary dramatically over short distances due to bathymetric and shoreline complexity. Gómez *et al*. (2020) similarly found that deep learning models provided enhanced spatial resolution in the Mediterranean Sea, particularly in semi-enclosed basins with intricate coastal geometry.

While previous studies have applied CNN–LSTM architectures to oceanographic variables such as sea surface temperature (Jin *et al*., 2025) and storm surges (Wang *et al*., 2021), few have focused specifically on wave modeling in nearshore environments. The present study extends this body of work by demonstrating that deep learning can effectively simulate wave dynamics in a region with limited observational infrastructure and complex bathymetry.

Moreover, unlike many prior applications that rely solely on satellite data or reanalysis products, this study integrates multiple data sources—including Sentinel-3 altimetry, ERA5 reanalysis, and in-situ buoy measurements—into a unified modeling framework. This multimodal approach enhances model generalizability and reduces the risk of overfitting to any single data type.

6.1. Limitations

Despite its strengths, the CNN–LSTM model is not without limitations. First, its performance is contingent on the quality and resolution of input data. While ERA5 provides global coverage, its coarse resolution may obscure fine-scale wind features that influence wave generation. Second, the model may struggle to predict rare extreme events, such as cyclonic surges, if such events are underrepresented in the training dataset. This limitation could be addressed through data augmentation or transfer learning from cyclone-specific datasets.

Another challenge lies in the interpretability of deep learning models. Unlike physics-based models, which offer transparent mechanisms for wave generation and transformation, neural networks operate as black boxes. Although techniques such as saliency mapping and feature attribution can provide some insight, further research is needed to enhance model explainability in geophysical contexts.

Conclusion

This study presents a hybrid deep learning framework for simulating coastal wave dynamics along the Iranian Makran coast, a region characterized by complex bathymetry, seasonal variability, and limited observational infrastructure. By integrating Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, the proposed model effectively captures both spatial and temporal patterns in wave behavior, outperforming the physics-based WAVEWATCH III model across multiple evaluation metrics.

The CNN–LSTM model demonstrated strong predictive accuracy, particularly during monsoon seasons when wave conditions are highly nonlinear. Its ability to resolve localized wave intensification and reproduce seasonal variability underscores its potential for operational forecasting, coastal hazard assessment, and climate resilience planning.

Wave modelling in the Northern Indian Ocean reveals critical insights into how waves interact with coastal features under varying meteorological conditions. Future work should focus on integrating climate change scenarios into wave forecasting models. Deep learning offers promising alternatives to traditional wave simulation frameworks. This study encourages further integration of deep learning models into operational wave forecasting systems. This study provides valuable insights into the complex wave dynamics of the Northern Indian Ocean, emphasizing the need for continuous monitoring and advanced modelling techniques to support maritime activities and coastal management strategies.

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