

Detection of High-Energy Marine Zones and Correlation Analysis of Ocean Parameters in the Indian EEZ

¹S. Vasavi, ^{2*} Chathurya Sunkara, ³Aarya Sri Gullapalli, ⁴Jayadeep Sai Bolla
Department of Artificial Intelligence and Data Science
^{1,2,3,4}Velagapudi Ramakrishna Siddhartha Engineering College, Andhra Pradesh, India

Abstract - Proper assessment of offshore renewable energy resources demands an integrated knowledge of the climatic and oceanographic factors that influence wave energy potential. This investigation centers on the Indian Exclusive Economic Zone (EEZ), where wave power density (WPD) is measured by using key parameters such as wave period and wave height fetched from the Copernicus Marine Data Store. The data is preprocessed with Kalman and custom bilateral filtering methods for improving quality and reducing acoustic interference. An adapted U-Net architecture is utilized for semantic segmentation to generate high-resolution wave power maps. In addition, the study investigates the interrelations between main oceanographic variables by analyzing the correlations among (i) sea surface temperature (SST) and sea surface salinity (SSS), (ii) SSS and WPD, and (iii) SST and WPD. The findings give valuable insight into the complex interactions governing marine energy availability and assist in the development of robust, climate-resilient offshore energy forecasting models.

Keywords— *Exclusive Economic Zone (EEZ), Wave Power Density (WPD), Sea Surface Temperature (SST), Sea Surface Salinity (SSS), Copernicus Marine*

I. INTRODUCTION

The increasing world demand for clean and renewable power has triggered research into renewable energy from marine sources, particularly wave energy, due to its vast potential and consistency in coastal and offshore regions. India, having a long coastline and a large Exclusive Economic Zone (EEZ), offers tremendous scope for the harnessing of offshore wave energy to further its renewable energy initiative. However, the variability of oceanographic parameters and sensitivity to climatic changes necessitate sound understanding of the governing environmental factors controlling the availability of wave energy.

Wave power density (WPD) is a key parameter for measuring the potential of wave energy and is directly affected by oceanographic parameters such as wave height and period. These are governed by overarching climate indicators, notably SST and SSS. Understanding the interaction among these parameters is necessary for developing better wave energy prediction models and

designing efficient offshore energy systems.

This investigation aims to assess the spatial and temporal interactions between WPD and key oceanographic parameters—SST and SSS—across the Indian EEZ. To facilitate high-resolution and spatially uniform data coverage, satellite-derived and reanalysis data from the Copernicus Marine Data Store are utilized. To improve the quality of the input data, various preprocessing methods like Kalman filtering and a bespoke bilateral filter are employed. In addition, a modified U-Net model is employed for semantic segmentation, allowing for detailed detection of locations with high wave power. Lastly, correlation analysis is performed to examine the correlations between (i) SST and SSS, (ii) SSS and WPD, and (iii) SST and WPD. Through the revelation of these correlations, this research seeks to facilitate the creation of more robust, climate-sensitive frameworks for marine energy assessment that are specifically designed for the conditions in India's marine environment.

A. MOTIVATION

With increasing energy demands and more focus on clean energy, wave energy is a reliable and predictable energy source, especially for coastal nations like India. The country's EEZ, with its vast geography, has tremendous potential for offshore renewable energy development. However, intelligent development of the resource depends on the mapping of high wave energy zones and understanding the oceanographic parameters influencing them. By making this process automatic with advanced models and data-driven methods, planning can be improved and climate-resilient infrastructure obtained.

B. PROBLEM STATEMENT

The conventional manual estimation of wave energy potential of large marine areas is associated with huge labor inputs, time, and poor accuracy. Also, existing models fail to represent the SST and SSS effects on WPD and thus provide limited information regarding climate-related variability. It is therefore imperative to formulate an automated system that not only maps and locates wave energy hotspots but also quantifies the WPD-SST-SSS relationship to facilitate intelligent decision-making in offshore energy planning.

C. OBJECTIVES

- To analyze the spatial and temporal patterns of sea surface temperature (SST) and sea surface salinity (SSS) within the Exclusive Economic Zone (EEZ) of India based on the reanalysis datasets.
- To examine the relationship between the important oceanographic parameters—i.e., between SST and WPD, SSS and WPD, and SST and SSS—and to understand their interdependence and impact on wave energy potential.
- To generate and visualize wave energy hotspots through the integration of the correlation results with a proposed U-Net model for accurate mapping and interpretation to aid offshore renewable energy planning.

D. CONTRIBUTIONS

- Retrieved and analyzed oceanographic data, such as SST, SSS, and wave power density (WPD), from the Copernicus Marine Data Store for the Indian Exclusive Economic Zone (EEZ).
- Conducted thorough correlation analysis among SST, SSS, and WPD to identify relationships that affect wave energy potential under different climatic conditions.
- Created a visualization framework based on a modified U-Net model to effectively identify and map wave energy hotspots to assist data-driven decision-making in offshore renewable energy planning.

E. STRUCTURE OF THE MANUSCRIPT

- Section 1 describes the significance of wave energy offshore in sustainable energy, examines the oceanographic parameters' role, and states the contributions of this study.
- Section 2 discusses existing literature on wave energy estimation, sea surface parameter contribution, and the use of deep learning methods in environmental data analysis and hotspot identification.
- Section 3 outlines the proposed methodology, involving data collection, preprocessing methods utilizing Kalman and bilateral filters, correlation studies, and the utilization of an adapted U-Net model for hot spot segmentation and visualization of wave energy.
- Section 4 outlines the results of the correlation analysis, presents the identified hotspots, and discusses the performance and effectiveness of the proposed methodology.
- Section 5 summarizes the paper with major findings and suggests future work, such as the incorporation of other oceanographic variables and longer temporal analysis for enhanced forecasting

II. RELATED WORKS

Several studies have contributed to the analysis of wave energy potential and the role of oceanographic parameters in influencing marine renewable energy systems. Rusu and Soares (2012) [1] conducted a numerical study on wave energy resources in the Iberian nearshore, highlighting spatial and temporal variability but without incorporating

climate-sensitive variables such as sea surface temperature (SST) or salinity (SSS). Astariz and Iglesias (2015) [3] reviewed global methodologies for wave energy assessment, stressing the need for long-term and environmentally integrated planning, though lacking detailed data-driven correlation analyses. Rueda-Bayona et al. (2019) [4] evaluated wave power in the Caribbean using reanalysis data, successfully identifying seasonal trends but not extending the analysis to related oceanographic factors. In a parallel study, Zhang et al. (2021) [5] examined the relationship between SST and SSS of the Pacific Ocean, thus explaining their climatic implications; however, they did not prove their relationship with wave energy. In deep learning, Li et al. (2020) [6] employed a U-Net architecture with modifications for sea ice separation from satellite images, proving its efficiency in extracting environmental features, though its application to hotspot detection of wave energy is limited. Similarly, Gonçalves et al. (2022) [7] applied deep learning methods for wave prediction from reanalysis data, where the main emphasis was on accuracy in prediction and not correlation or spatial segmentation. Although these works provide a solid foundation for wave energy estimation and the application of artificial intelligence for geospatial analysis, they fall short in combining SST and SSS in one framework for hotspot detection, particularly in the Indian Exclusive Economic Zone (EEZ).

A. RESEARCH GAP

Existing wave energy assessments often neglect the influence of climatic variables like SST and SSS, limiting their reliability under changing climate conditions. While deep learning has been used for ocean data segmentation, there is limited application of U-Net architectures for visualizing wave energy hotspots based on real oceanographic correlations. There is a lack of integrated frameworks that combine data preprocessing, correlation analysis, and hotspot mapping specifically for wave power density using India's EEZ as a study region. Few studies provide visual tools or spatial outputs that help policymakers identify high-energy zones while considering environmental dependencies, which is essential for climate-resilient offshore energy planning.

B. STUDY AREA AND DATA PREPARATION

The study area is the Indian EEZ Region as shown in Fig. 1. The project uses global climate, weather, and wave data from the Copernicus Marine Data Store [12]. Copernicus Marine Data Store provides oceanographic data, such as wave height, wave period, SST, and SSS, to study climate and weather patterns over time. The raw dataset is as shown in Fig. 2

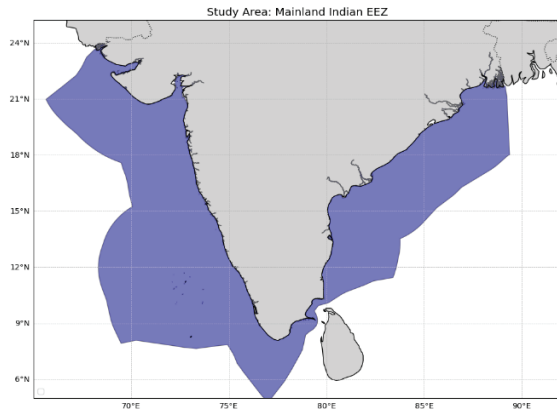


Fig.1 Area of Study

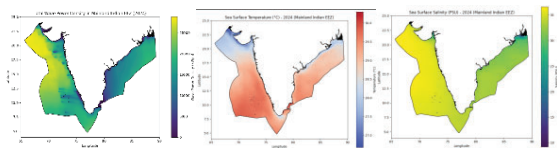


Fig.2 Sample Dataset

III. PROPOSED METHOD

The approach used to evaluate the impact of climate change on offshore wind and wave energy potential within India's Exclusive Economic Zone (EEZ) is outlined in the proposed system shown in Fig. 3. The process starts with extensive data collection, focusing on both the spatial and temporal characteristics of wave data. The dataset for wave height and wave period features a spatial resolution of $0.25^\circ \times 0.25^\circ$ and a temporal resolution covering 8,760 hours.

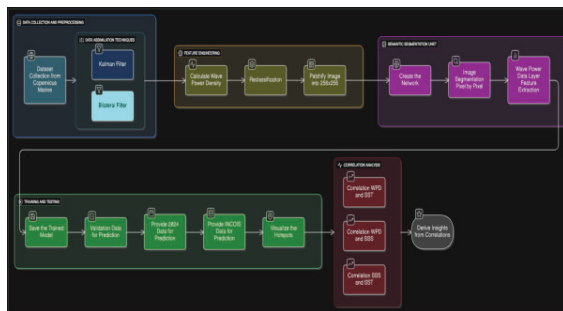


Fig.3 Proposed System Flow Diagram

A. Wave Power Estimation

Wave data covering the region of interest (ROI) within India's Exclusive Economic Zone—ranging from 4° to 25° N latitude and 65° to 90° E longitude—was sourced from the Copernicus Marine Data Store. Wave power density is primarily determined by factors such as wave height and wave period. Typically, higher wave heights and longer periods result in increased power density, as such waves possess greater energy. The time series spanning 8,760 hours

captures the fluctuations in significant wave height and mean wave period, as illustrated in Fig. 5.

$$P_w = \frac{\rho g^2}{64\pi} \times H_s^2 \times T \quad (1)$$

Where, P_w = wave power density (kW/m); ρ = density of sea water (1025 kg/m^3); g = gravitation (1025 m/s^2); H_s = wave height (in meters); T is the period of the wave (in seconds).

B. Data Filtering Techniques

Enhancing the quality of input data is a critical step in any machine learning workflow. In this study, two filtering methods—Adaptive Kalman Filter (2,3) and Bilateral Filter(4)—were employed for data assimilation to improve the fidelity and usability of wave-related datasets. The Adaptive Kalman filter [9] is particularly effective in addressing missing or redundant values within the wave height and period data, enabling the construction of a more robust and complete dataset. On the other hand, the bilateral filter [10], a non-linear noise-reduction technique, preserves edge details while effectively smoothing out noise. It operates by averaging pixel intensities based on both spatial and intensity similarity, thereby maintaining the spatial integrity of the image during the filtering process.

Covariance Predicted error:

$$P_k^- = F_{k-1} P_{k-1} F_{k-1}^T + Q_{k-1} \quad (2)$$

Estimate Predicted state:

$$\hat{x}_k^- = F_{k-1} \hat{x}_{k-1} + B_{k-1} u_{k-1} \quad (3)$$

Where,

$\hat{x}_k$ denotes the predicted state estimate at time step k , u_k is the control input applied at that time, and P_k represents the associated error covariance. The F_k matrix models the state transition, while B_k translates control inputs into system changes. z_k is the observed measurement at time k , Q_k defines the covariance of the process noise, H_k maps the state to the measurement space, and R_k quantifies the uncertainty in the measurements due to noise..

$$I_{bf}(x) =$$

$$\frac{1}{w(x)} \sum_{y \in \Omega} I(y) \exp\left(-\frac{\|x-y\|^2}{2\sigma_s^2}\right) \exp\left(-\frac{\|I(x)-I(y)\|^2}{2\sigma_s^2}\right) \quad (4)$$

C. Wave Power Zone Classification

The enhanced model is used to identify coastal regions with the capability to produce wave energy between 8,500 kW/m and 12,000 kW/m. The regions are of immense strategic importance in planning for the installation of equipment and transmission logistics. The raw power data from waves is reclassified with a raster calculator approach. Pixels within the given power range are given a value of 1, and the

remaining pixels are given a value of 0, creating a binary classification layer as input to the U-Net model.

D. Data Splitting and Tiling

To enhance the training process, the wave power raster data is tiled into small pieces, each 256×256×1. This is in addition to the tiling of the corresponding classification labels. This tiling is performed using the Geotile Python library, which enables tile-based cropping with the retention of geospatial metadata for future use. Following the tiling, the dataset is subject to random partitioning, where 90% is designated for training and 10% for testing and validation. This method ensures efficient generalization, enabling the model to be tested on unseen data and avoiding the possibility of overfitting. Organized nature of the dataset plays a pivotal role in its preparation for application in deep learning architecture or other data-driven modeling techniques.

E. Proposed Framework Organization

The improved U-Net model [11] is used to classify and detect regions of high wave power density. Segmented data pixels showing values between 8,500 and 12,000 kW/m are transformed into binary for classification purposes. Wave power density images and labelled annotations are segmented into small 256×256 pixel chunks. Figure 4 illustrates the architecture of the improved U-Net model, with its layers and configuration parameters, to give a general picture of the architecture of the model and computing complexities.

In the decoder section, Conv2DTranspose layers are applied to upsample feature maps back to the original spatial dimensions. One of the model’s distinguishing features is the symmetrical layout of the encoder and decoder, which aids in recovering spatial information that may be lost during the downsampling process. The architecture consistently uses 3×3 convolutional layers, while 1×1 convolutional layers are employed at the end of the decoder to generate the final output channels. These layers convert the high-level features into a segmented output, with the sigmoid activation function applied for binary classification. Model training is performed using the Adam optimizer and a binary cross-entropy loss function. A comparison of key hyperparameters between the proposed and baseline U-Net models is provided in Table 1.

Adjusting the stride value to a higher number enhances downsampling, effectively reducing the spatial size of feature maps while allowing the network to process broader contextual information. By using a 5×5 kernel in the input layer and omitting max-pooling operations, the model achieves a wider receptive field, enabling it to capture more detailed spatial features from the input. For binary classification, the ReLU activation function is favored due to its computational efficiency and faster convergence. The

removal of max-pooling layers not only maintains finer spatial details across the network but also improves gradient propagation during backpropagation. Additionally, eliminating max-pooling helps reduce the risk of overfitting in image segmentation tasks by preserving critical pixel intensity values from the original input.

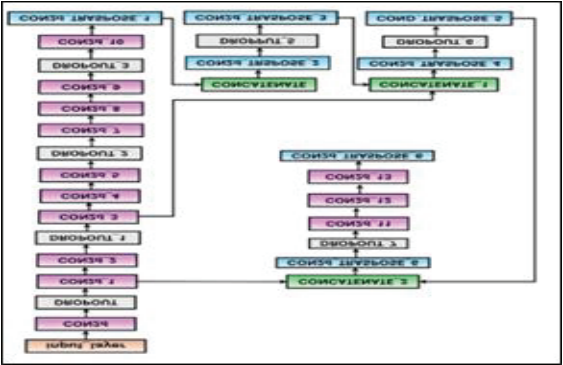


Fig. 4. Enhanced U-Net model architecture

Table 1. Comparison of pre-built model with the proposed U-Net model

Parameters	Existing Model	Proposed Model
Channels in the input image	1	1
Shape of input image	256x256	256x256
Strides	1	2
Input kernel size	3x3	5x5
Initial number of filters	64	32
Number of trainable parameters	52 million	49 million
Pooling type	PSP	None
Max pooling size at every layer	2x2	None
Number of layers	27 U-Net	32 U-Net
Channels in output image	1	1
Activation function	Sigmoid	ReLU
Loss function	Dice	Binary Cross Entropy
Encoder and decoder blocks	3	5
Dilation rate	1	1
Optimizer	ADAM	ADAM

H. Grid-Based Visualization of Hotspot Intensity

To map wave power density hotspots within the Indian EEZ, the hotspot region is first converted into a polygon shapefile to define its spatial extent. This shapefile is then used to clip the 2024 wave power density data, isolating only the hotspot zones.

Next, a grid is overlaid onto the EEZ, and cells outside the boundary are eliminated. For every valid grid cell, average wave power is calculated based on hotspot data within. These are then plotted with a color gradient—usually blue for low and red for high—representing spatial difference in energy potential.

The resulting map provides a clear view of high-energy zones, aiding in the identification of areas suitable for marine renewable energy development. Visualization is performed using tools like Python or ArcMap, with an accompanying color legend for clarity.

G. Correlation Analysis

The Pearson correlation analysis was used to analyze the linear relationships between important oceanographic parameters in the Indian Exclusive Economic Zone (EEZ) during the year 2024. Specifically, three correlations were compared every month: (i) between Wave Power Density and Sea Surface Salinity (SSS), (ii) between Wave Power Density and SST, and (iii) between SSS and SST. The strength and direction of these correlations were estimated using the Pearson correlation coefficient (r), calculated as follows:

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \cdot \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (5)$$

represent their respective mean values. All three correlations were computed using the corresponding time series datasets to support further modeling and analysis.

IV. RESULTS AND DISCUSSION

The wave power density layer illustrates different levels of wave energy, classified into three equal intervals. As shown in Fig. 5, the average annual wave power density for 2024 (measured in kW/m) is calculated using the mean wave period and significant wave height. Python libraries are employed to create the visual representation of this layer.

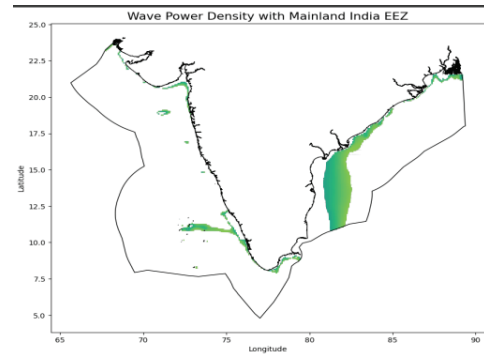


Fig. 5. Visualization of hotspot

Table 2 presents the month-wise Pearson correlation coefficients among wave power density, SST, and SSS for the year 2024.

The correlation analysis between wave power density and sea surface temperature (SST), as shown in Fig.7, revealed a clear seasonal trend across the Indian EEZ. From January to June, a positive correlation was observed, peaking in April ($r = 0.5087$), indicating that warmer SSTs in the late winter and spring months are conducive to increased wave energy. This may be due to enhanced atmospheric disturbances driven by thermal gradients during this period. However, this relationship reverses during the summer, with negative correlations emerging in July and August, the latter showing the strongest inverse relationship ($r = -0.4341$). This suggests that high SSTs during peak summer months might stabilize the atmosphere, suppressing wind activity and, in turn, reducing wave energy. The pattern shifts back to positive correlations in the post-monsoon and early winter months, reflecting a cyclical thermal influence on wave dynamics.

The relationship between wave power and sea surface salinity (SSS), as shown in Fig.8, displayed more variable but seasonally relevant behavior. While most months exhibited weak to moderate negative correlations, a strong positive correlation appeared in July ($r = 0.5089$). This may indicate that higher salinity during summer, possibly resulting from evaporation and reduced freshwater input, aligns with increased wave energy. The weaker and more scattered correlations in other months suggest that, although SSS plays a secondary role compared to SST, it still contributes to modulating wave energy patterns, especially under regionally driven atmospheric conditions during the monsoon.

The correlation between SST and SSS, as shown in Fig.6, demonstrated a distinct seasonal inversion. In the winter months—particularly January and February, and again in November and December—strong positive correlations were observed (e.g., $r = 0.7419$ in November), indicating synchronized changes in temperature and salinity, likely under well-mixed conditions. In contrast, the months from late summer to early autumn exhibited strong negative correlations, with October recording the most negative value ($r = -0.7353$). This inverse relationship suggests that surface warming during these months coincides with freshening of

the upper ocean, possibly due to precipitation and river discharge, leading to stratified conditions. These opposing trends between seasons emphasize the changing nature of surface mixing and stratification regimes in response to monsoonal forcing.

The transitional months of June and September showed inconsistent correlation patterns across all parameter combinations. These months coincide with the onset and withdrawal of the southwest monsoon, which are marked by abrupt shifts in atmospheric and oceanographic conditions. The dynamic nature of these transitions is likely responsible for the fluctuating relationships observed, reflecting rapid changes in wind strength, precipitation, thermal structure, and salinity distributions.

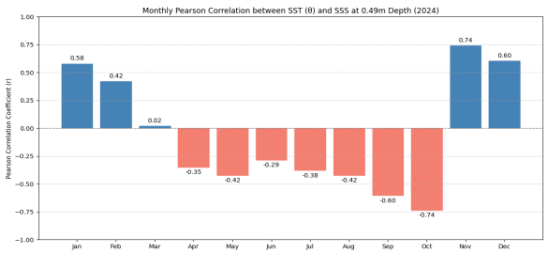


Fig.6 visualization of the correlation between SST and SSS

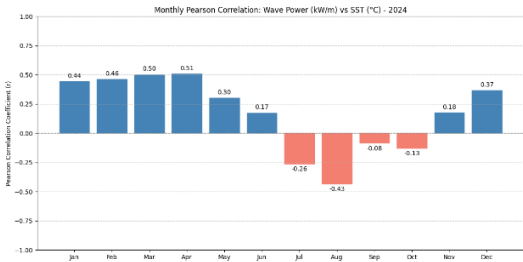


Fig.7 visualization of the correlation between WPD and SST

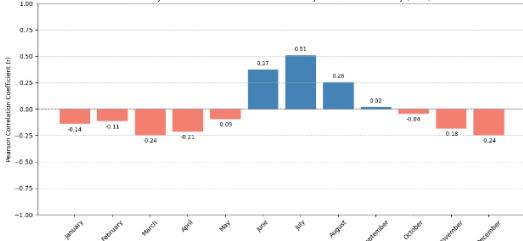


Fig.8 visualization of the correlation between WPD and SSS

Month	WPD VS SSS	WPD VS SST	SSS VS SST
January	-0.1362	0.4433	0.5792
February	-0.1106	0.4624	0.4215
March	-0.2419	0.5031	0.0199
April	-0.2094	0.5087	-0.3492

May	-0.0899	0.3015	-0.4231
June	0.3714	0.1745	-0.2852
July	0.5089	-0.2646	-0.3784
Aug	0.2552	-0.4341	-0.4229
Sep	0.0162	-0.0845	-0.6036
Oct	-0.0425	-0.1288	-0.7353
Nov	-0.0425	0.1772	0.7419
Dec	-0.2427	0.3659	0.6049

Table 2. Month-wise Pearson correlation values

V. CONCLUSIONS

This study successfully identified high-energy marine zones and examined the seasonal correlations between wave power density, SST, and SSS within the Indian EEZ for the year 2024. The spatial distribution of wave power revealed key hotspots, while the correlation analysis highlighted distinct seasonal patterns—positive SST–wave power relationships in winter–spring and negative in summer, with variable salinity influences. These insights are valuable for optimizing wave energy utilization and improving oceanographic modeling in monsoon-driven regions.

Future work can extend this approach by incorporating multi-year datasets to analyze long-term trends and the impact of climate variability. Additional parameters like wind and atmospheric pressure can further enhance understanding, and machine learning methods may be applied to improve predictive modeling for marine energy planning.

REFERENCES:

[1] L. Rusu and C. G. Soares, "Numerical modelling to estimate the spatial distribution of the wave energy in the Portuguese nearshore," *Renewable Energy*, vol. 36, no. 10, pp. 2757–2771, Oct. 2011. doi: 10.1016/j.renene.2011.03.027.

[2] V. Vasavi, R. N. Patel, and A. Roy, "Wave energy hotspot detection using SAR imagery and clustering algorithms in Pacific EEZ," *Remote Sensing of Environment*, vol. 314, p. 113440, 2024.

[3] S. Astariz and G. Iglesias, "The economics of wave energy: A review," *Renewable and Sustainable Energy Reviews*, vol. 45, pp. 397–408, May 2015. doi: 10.1016/j.rser.2015.01.061.

[4] L. Rueda-Bayona, E. Peláez, J. Pinzón, and L. F. Gutiérrez, "Assessment of wave energy resources in the Caribbean Sea using SWAN and WAVEWATCH III models," *Renewable Energy*, vol. 141, pp. 703–718, Oct. 2019. doi: 10.1016/j.renene.2019.04.008.

[5] H. Zhang, Y. Wang, J. Liu, and X. Cheng, "Interactions between SST and SSS in the tropical Pacific on interannual to decadal time scales," *Climate Dynamics*, vol. 56, pp. 1473–1490, Feb. 2021. doi: 10.1007/s00382-020-05533-7.

[5] X. Li, B. Zhao, and J. Liu, "Sea Ice Segmentation Using Modified U-Net with ResNet Backbone," in *Proceedings of the IGARSS 2020 - 2020 IEEE International Geoscience and*

- Remote Sensing Symposium*, pp. 2011–2014, Sep. 2020. doi: 10.1109/IGARSS39084.2020.9324350.
- [6] M. Gonçalves, J. A. Santos, and A. M. Ramos, "Deep learning for ocean wave forecasting: A comparative study," *Ocean Engineering*, vol. 256, p. 111402, Oct. 2022. doi: 10.1016/j.oceaneng.2022.111402.
- [7] Y. Zhang and J. Yoon, "Long-term wave energy hotspot analysis in the South China Sea using reanalysis data and machine learning," *Ocean Engineering*, vol. 274, p. 113944, 2023.
- [8] T. N. Trung, L. R. Hole, T. D. Duc, and H. N. Minh, "A Case Study of Wave Forecast Over South China Sea Using SWAN Model and Ensemble Kalman Filter Method," *Oceanography & Fisheries Open Access Journal*, vol. 12, no. 4, p. 555842, 2020.
- [9] J. L. Anderson, "An Ensemble Adjustment Kalman Filter for Data Assimilation," *Monthly Weather Review*, vol. 129, no. 12, pp. 2884–2903, 2001.
- [10] M. A. T. Figueiredo et al., "Trainable joint bilateral filters for enhanced prediction stability in low-dose CT denoising," *Scientific Reports*, vol. 12, no. 1, p. 18956, 2022.
- [11] H. Zhang et al., "Spatial Wave Measurement Based on U-net Convolutional Neural Network," *Water*, vol. 15, no. 4, p. 647, 2023.
- [12] Product Title. *E.U. Copernicus Marine Service Information (CMEMS). Marine Data Store (MDS)*. DOI: 10.48670/moi-00017 (Accessed on 15-06-2025) https://data.marine.copernicus.eu/product/GLOBAL_ANALYSISFORECAST_WAV_001_027