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Seasonal wave dynamics and model validation at Galesong Beach, south Sulawesi: Evaluating the accuracy of wave prediction

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ABSTRACT

Understanding wave dynamics is vital for effective coastal management, maritime navigation, and disaster risk planning. This study evaluates the performance of four widely used wave prediction models the shore protection manual (SPM), coastal engineering manual (CEM), Sverdrup-Munk-Bretschneider (SMB), and Pierson-Moskowitz (PM) in forecasting wave height and period at Galesong Beach, south Sulawesi. The results reveal strong seasonal dependencies, with the highest wave energy occurring during the December – February monsoon period. Statistical validation using root mean square error (RMSE), mean absolute error (MAE), bias, and coefficient of determination (R^2) shows that the SPM and CEM models offer the most accurate wave height predictions, with RMSE values of 1.44 m and 1.61 m, respectively. In contrast, the SMB and PM models display larger errors, particularly in wave period estimation, limiting their suitability for this coastal setting. These findings emphasize the importance of selecting wave prediction models based on regional climatic conditions. The study highlights the need for seasonal calibration and the use of high-resolution datasets to enhance forecasting performance, providing a scientific basis for improved coastal planning and hazard mitigation.

Keywords: wave prediction models, seasonal wave dynamics, Galesong Beach, model validation, coastal forecasting.

INTRODUCTION

Analyzing the wave characteristics at Galesong Beach, South Sulawesi, is essential not only for effective coastal management but also for understanding and mitigating land degradation along the shoreline. Galesong Beach is highly vulnerable to seasonal monsoon winds and considerable wave activity, which can accelerate erosion, sediment transport, and shoreline retreat contributing to coastal land degradation and loss of productive land. The dynamics of wave-induced sediment transport and erosion are intricate, as evidenced by research in analogous environments like the Venice Lagoon. Here, wave-induced bottom shear stress is pivotal in sediment resuspension and erosion dynamics, which can be represented as a Poisson process (Green and Coco, 2014; Carniello et al., 2016; Tognin et al., 2024). The migration of sandbars, which are spontaneous coastal barriers against erosion, is influenced by wave height, period, and sea level. Increased height of waves and the decrease in wave periods will cause the migration process of sandbars to speed up (Radermacher et al., 2018; Rutten et al., 2018; Wang et al., 2023). The aforementioned wave-type transformations (Shtremel et al., 2022) occurring in a nonlinear manner can evoke periodic sandbar and sedimentary rock movements (Shtremel et al., 2022). These sediment dynamics play a critical role in shaping coastal landforms and affect soil structure, biogeochemical properties, and ultimately, the land-use potential along the beach.

Climate change is modifying global wave climates, resulting in an increased frequency of specific wave patterns that may heighten coastal risks in regions experiencing transitional wave climates, including land subsidence, saltwater intrusion, and the degradation of coastal ecosystems (Odériz et al., 2022; Casas-Prat et al., 2024).

The interaction between the storm surges and wind waves has significantly raised the heights of the coastal water levels, thereby necessitating their inclusion in coastal risk assessments (Lin and Shullman, 2017; Marcos et al., 2019a). Confusion of wave effects by a storm seen as tsunamis interfere with precise hydrodynamic modeling and results in erroneous hazard evaluations (Cox et al., 2020). The numerical modeling of the flow of a wave and the movement of the sea bottom are one of the main components needed for the proper design of the coastal infrastructure and for the proper understanding of the wave dynamics in the near-shore region (Lynett et al., 2017). The difficulty of the interconnection of the mean sea level, tides, storm surges, and waves leads to the necessity of comprehensive modeling approaches (Anderson et al., 2021; Idier et al., 2019; Moftakhari et al., 2024). Such models are also essential for assessing the environmental and socio-economic impacts of erosion-induced land loss.

In this context, integrating wave modeling into broader environmental assessments can inform coastal protection strategies, support land-use planning, and mitigate degradation in coastal regions dependent on marine and agricultural resources (Clarke et al., 2013).

Many models have been developed to predict wave characteristics under different oceanographic and meteorological situations. The shore protection manual (SPM) and coastal engineering manual (CEM) are the most commonly used semi-empirical methods for the estimation of wave height and period in coastal engineering (Salah, 2015). Unlike other models, these models can only be used in short-fetch and moderate wind conditions and, thus, are only applicable to an area like Galesong Beach (Abbasi, 2019). In the meantime, the Sverdrup-Munk-Bretschneider (SMB) model is usually used in the case of fewer fetches but might not predict accurately in the case of monsoon-dominated regions (Aisjah et al., 2016). The Pierson-Moskowitz (PM) model, which is based on sea states in their fully developed stage, is more fitting for offshore wave predictions (Salah, 2015).

The limitations of these models in properly describing the seasonal wave variations, especially in regions with strong monsoonal influences, have been the main topics of the most recent studies. For instance, research conducted in the Strait of Hormuz proved that the CEM model was very effective in predicting wind-induced wave characteristics, while the in-situ buoy measurements showed a high correlation and minimal bias errors (Abbasi, 2019). Besides, research carried out in Asalouyeh Port, Iran, demonstrated that SPM and CEM were more effective than SMB in determining the significant wave height variations with JONSWAP spectral method more compatible with long-duration wave predictions (Ahmadvand et al., 2024).

These factors outlined above play a crucial role not only in coastal engineering but also in better understanding shoreline retreat, sediment instability, and the degradation of beach lands. Since monsoon-induced winds control the wave's height, period, and directional patterns, it necessitates the reassessment of the performance of the existing wave prediction models in representing the seasonal and even longer variations of the waves. This seasonal variability is illustrated in Figure 1, which presents wind rose plots for each season, showing dominant wind directions and intensities that influence wave generation throughout the year. Improved wave prediction can aid in early warning systems and community-based mitigation for erosion-prone areas. This research assumes that SPM and CEM will, in all probability, provide comparative data with more benefits than the rest of the models that are used for forecasting the similarity of ocean waves in the monsoon period. In this regard, it is likewise thought that the main energy of the wave will be achieved in December-January-February (DJF) periods, thereby emphasizing the necessity to conduct season-specific model calibration in addition to enhancing predictive accuracy.

This research aimed to analyze the main wave features at Galesong Beach and to evaluate the effectiveness of four established wave prediction models SPM, CEM, SMB, and PM in capturing seasonal variations in wave characteristics influenced by monsoonal wind patterns. Given the local conditions and previous applications of these models in comparable coastal settings, particular attention is given to the performance

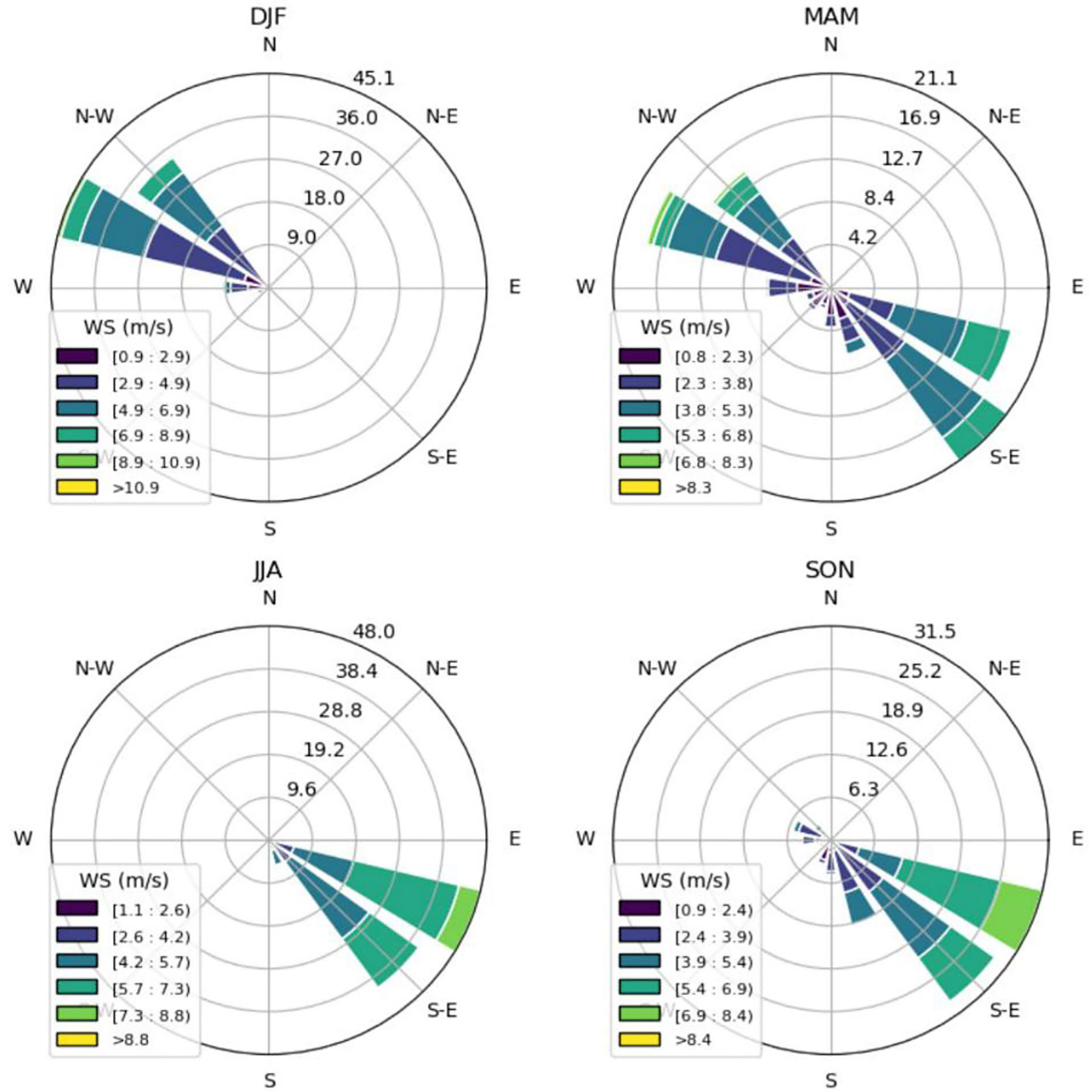

Figure 1. Seasonal wind rose plots depicts wind speed and direction distribution per season: DJF – December-January-February, MAM – March-April-May, JJA – June-July-August, SON – September- October-November

of SPM and CEM, which are expected to align more closely with the wave dynamics observed during the monsoon-dominated periods. The seasonal variability in wind forcing, especially during the December–February peak, is anticipated to significantly influence wave height and period, making this period critical for model evaluation. Using performance indicators such as RMSE, MAE, bias, and R^2, this study aims to identify which model most reliably reflects the observed data and thus holds the greatest potential for application in coastal planning and risk assessment in monsoon-affected regions.

METHODS AND MATERIALS

Galesong Beach, the coast of Takalar Regency in south Sulawesi, Indonesia, is a dynamic coastal area affected by monsoonal wind patterns. Its strategic location within the Indonesian maritime zone subjects it to seasonal wave variations influenced by both local and large-scale atmospheric circulation. Understanding these changes is crucial for maritime transportation, fisheries, and catastrophe risk reduction, as seasonal wave energy fluctuations affect navigation safety, coastal erosion, and fishing activities. The study area and specific data collection points along the coastline are illustrated in Figure 2, providing spatial context for the observed wave dynamics.

The research was conducted 3.42 km offshore from Dermaga Boddia at coordinates 5.323282° S, 119.323219° E. The area has significant seasonal fluctuation, marked by heightened wave activity during the Northwest Monsoon (December–February) and more tranquil conditions during the Southeast Monsoon (June–August). These developments affect coastal erosion, therefore changing the resilience and stability of the beach. Reducing risk and supporting environmentally friendly coastal development depends on accurate wave forecasting models.

Understanding coastal wave dynamics and raising the model accuracy depends on the inclusion of wave elements, including wind. With great respect for spatial wave distributions, satellite altimetry has been widely used to describe wind speed and major wave height. Nevertheless, data limitations and land contamination still plague near-shore regions (Mitsopoulos and Peña, 2023). High-resolution hindcast models like SCHISM combined with WindWingModel enhance near-shore wave predictions and coastal hazard assessments in the setting of climatic variability (Mentaschi et al., 2023). Using models like SWAN, global datasets including the Copernicus ERA5 downscaled yield improved wave data for coastal uses (Bellotti et al., 2021). Furthermore produced by the Coordinated Ocean Wave Climate Project (COWCLIP) are standardized wave climate datasets, thereby facilitating coastal risk assessment and broad-scale wave climatology study (Morim et al., 2022).

Wave prediction models

This study evaluated four widely used wave prediction models. Each is intended to estimate wave height and period based on wind forces and other oceanographic variables. The significant wave height (Hs) and wave period (Ts) were calculated using four-wave prediction models, each of which offers unique advantages for wave forecasting. The shore protection manual (SPM) is primarily used for fetch-limited wave growth, where the wave height and period are determined as follows (1):

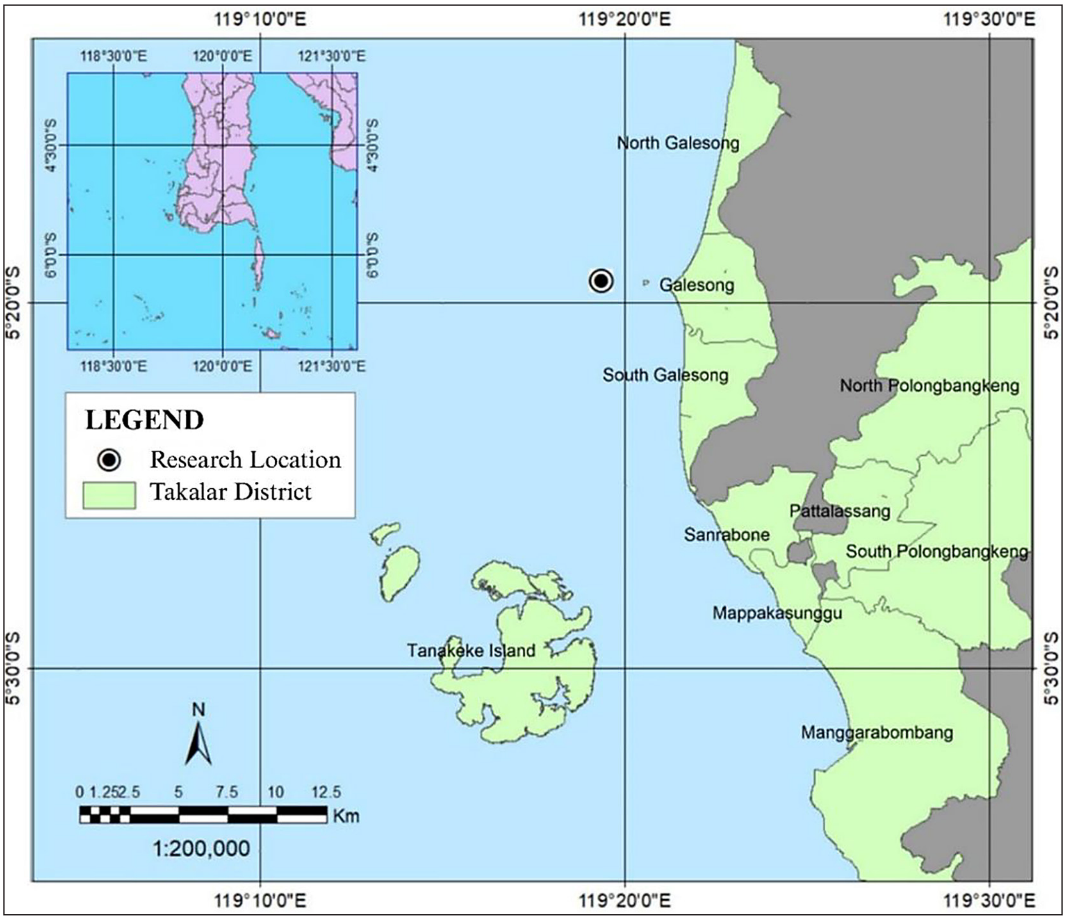

Figure 2. The study area and data collection locations

$$H_s = 0.0016 \times \frac{U^2}{g} \times \left(\frac{gF}{U^2}\right)^{\frac{1}{2}},$$
$$T_s = 0.2857 \times \frac{U}{g} \times \left(\frac{gF}{U^2}\right)^{\frac{1}{3}} \tag{1}$$

where: g is acceleration due to gravity (m/s^2), F is fetch (m), U is wind speed (m/s), the SPM model is widely used in coastal engineering applications to provide practical predictions of wave behavior near shorelines (Karimpour and Chen, 2016).

1. CEM incorporates the frictional velocity (u_*) and drag coefficient (Cd), which refine the wave-prediction process (2):

$$u_* = \sqrt{C_d \times U^2},$$
$$H_s = 0.0413 \times \frac{u_*^2}{g} \times \left(\frac{gF}{u_*^2}\right)^{\frac{1}{2}} \tag{2}$$

This model accounts for more complex coastal interactions, making it effective in locations with irregular bathymetry (Kazeminezhad et al., 2005; Yeganeh-Bakhtiary et al., 2023).

2. SMB is an empirical model designed for fetch-limited waves, assuming that the wave height and period grow in response to wind forcing:

$$H_s = \frac{0.26}{g} \times U^2,$$
$$T_s = 2.4 \times \frac{U}{g} \times \tanh\left(0.077 \times \left(\frac{gF}{U^2}\right)^{0.25}\right) \tag{3}$$

The SMB model provides a simplified approach for estimating the wave parameters in enclosed basins and coastal regions (Aisjah et al., 2016; Alhodairy and Sadeghi, 2019).

3. Pierson-Moskowitz (PM) applies to fully developed sea conditions, assuming that waves reach equilibrium with wind forcing (4).

$$H_s = 0.21 \times \frac{U^2}{g}, \quad T_s = 0.83 \times \sqrt{\frac{U}{g}} \tag{4}$$

This spectral model is commonly used for deep-water wave prediction (Alves et al., 2003; Higgins and Siderius, 2019).

Each wave prediction model was applied to simulate wave conditions at Galesong Beach using historical wind and ocean data for seasonal assessments. The models were tested across four distinct seasons (December-February, March-May, June-August, and September-November) to evaluate their accuracy in capturing seasonal variations in the wave height and period. The performance will be analyzed per season to determine whether specific models perform better under different monsoonal conditions. A comparison between the observed and modeled seasonal trends will effectively assess each model's ability to replicate real-world wave dynamics.

Data processing and statistical model validation

Preprocessing techniques were applied before model evaluation to ensure the accuracy of the observed wave data. This includes data cleaning to remove errors and extreme outliers in the wave height and wind datasets, ensuring consistency and reliability. Time-series analysis was conducted to identify seasonal trends and interannual variations, providing insights into wave behavior across different monsoonal periods. Additionally, normalization techniques were used to standardize the datasets, allowing for fair comparisons between different wave prediction models.

To assess the accuracy and robustness of each wave prediction model, four specific statistical metrics were employed: RMSE, MAE, bias, and the coefficient of determination (R^2). Each of these indicators provides a distinct perspective on model performance in capturing seasonal wave characteristics. Whereas MAE gauges the absolute variations in forecasts, RMSE evaluates the average variance between the actual and expected values. Analyses of bias help to ascertain whether models tend to overestimate or underestimate wave height and period. Finally, the overall fit of the model was assessed by the correlation between observed and predicted values using the coefficient of determination (R^2). These metrics were calculated using the following standard formulas (Chicco et al., 2021):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_i - O_i)^2} \tag{5}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|M_i - O_i| \tag{6}$$

$$bias = \frac{1}{n}\sum_{i=1}^{n}(M_i - O_i) \tag{7}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(M_i - O_i)^2}{\sum_{i=1}^{n}(\bar{O} - O_i)^2} \tag{8}$$

where: M_i and O_i represent the modeled and observed wave parameters respectively, and

$\bar{O}$

$\bar{O}$ is the mean of observed data. These metrics were computed seasonally and then averaged to provide a performance score per model.

RESULTS AND DISCUSSION

Results

The main objective of this research is to evaluate seasonal wave characteristics at Galesong Beach and assess the performance of various wave prediction models in capturing these dynamics. The results provided a comprehensive analysis of seasonal wave height variations, directional trends, model validation, and statistical performance, offering insights into the reliability of different prediction methods for coastal management.

Wave variability

Based on the geographical location of the study area facing west, the waves that occur in the area are generated by winds blowing from the Makassar Strait, especially during winds from the southwest, west, and northwest (Table 1). Wave height is strongly influenced by seasonal winds, namely DJF (December-February), MAM (March-May), JJA (June-August), and SON (September-November). The wave rose plot (Figure 3a) shows that the dominant wave direction shifts with the direction of the monsoon winds, DJF showing waves from the west and northwest due to the strong monsoon wind.

Temporal trends in wave height and period

The time-series analysis in Figure 4 highlights the seasonal fluctuation of wave heights, with pronounced peaks occurring in DJF and JJA, which correspond to the most energetic monsoon seasons. These peaks are driven by strong monsoonal winds that generate higher wave energies, significantly affecting coastal dynamics. The observed variations indicate that wave energy follows a predictable seasonal pattern, which is crucial for understanding wave-induced coastal processes, such as erosion and sediment transport.

The observed and modeled wave heights shows that some models, particularly SPM and CEM, align more closely with the observed

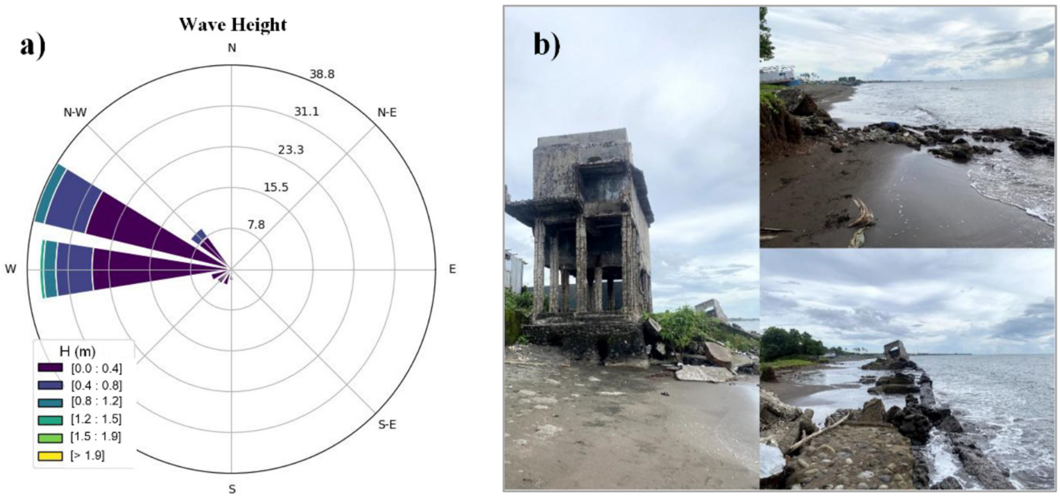

Figure 3. (a) Wave rose plots, represents the distribution of wave height and direction; (b) visible signs of coastal abrasion along the shoreline at Galesong Beach, indicating the physical impact of intensified wave activity

Table 1. Percentage of wave height and direction during 2010–2023

Wave direction (deg)	Wave height (m)						
	0.0–0.4	0.4–0.8	0.8–1.2	1.2–1.5	1.5–1.9	>1.9	Total
Northwest	29.02	9.89	2.26	0.14	0.09	0.04	41.47
West	38.07	6.88	1.74	0.56	0.18	0.04	47.50
Southwest	11.02	0.00	0.00	0.00	0.00	0.00	11.02
Total	78.13	16.77	4.00	0.70	0.28	0.09	100

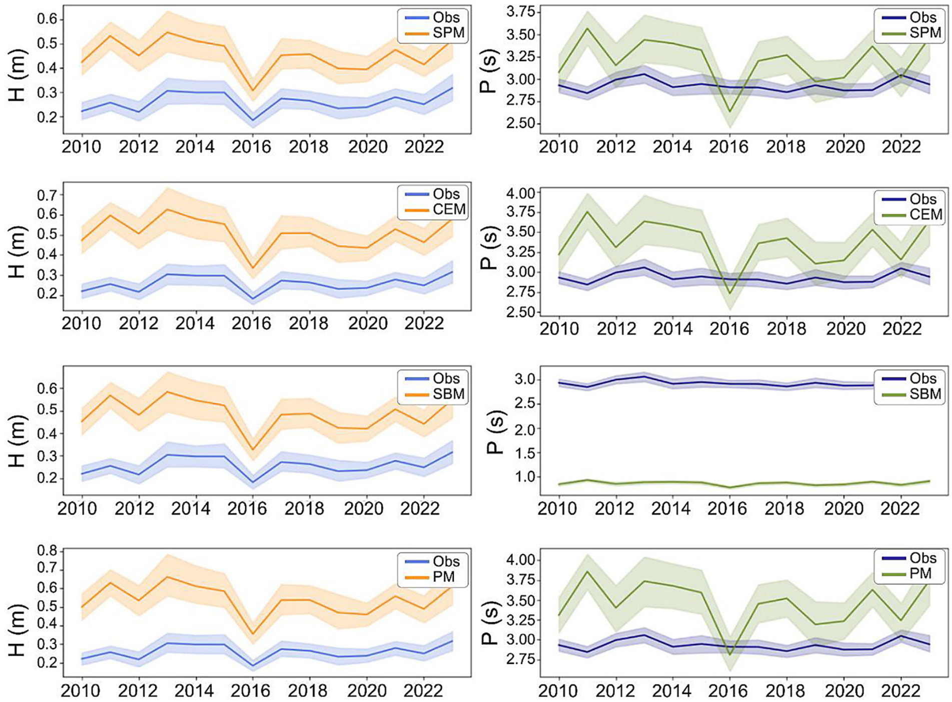

Figure 4. Time-series comparisons of observed vs. modeled wave height and period – demonstrates seasonal trends and long-term accuracy of the models

trends. These models effectively capture seasonal wave behavior, making them more reliable for wave forecasting on the Galesong Beach. The deterministic and not dependent on time (SMB) model struggles to accurately represent the changes in wave periods, which reveals the ability to simulate the full spectrum of wave dynamics with limitations. The contradiction underscores the necessity of better model calibration for a more accurate prediction of the periods of waves.

Figure 5 further concentrates on the monthly wave fluctuations as December, January, and February had the greatest wave heights and June to September had lower wave energies. This trend affirms the fact that the waves are seasonal dependent and makes the season-specific wave modeling approaches all the more necessary. It should be noted that to predict fog, we must modify the model to take into account the monsoonal conditions. Coastal facilities benefit from the implementation of these models in that they provide better planning for maritime activities, shoreline protection, and disaster risk reduction strategies.

Wave model validation and performance assessment

Figure 6 represents a comparative analysis of the modeled and observed wave heights and periods, where model accuracy is measured by the distance from the identity line. The results show

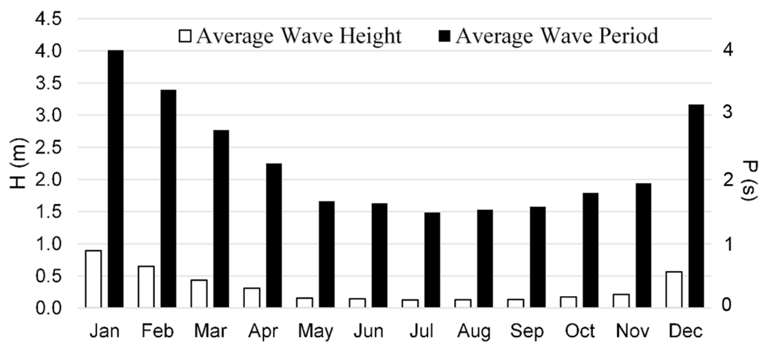

Figure 5. Monthly variations of average wave height and period – highlights seasonal wave fluctuations

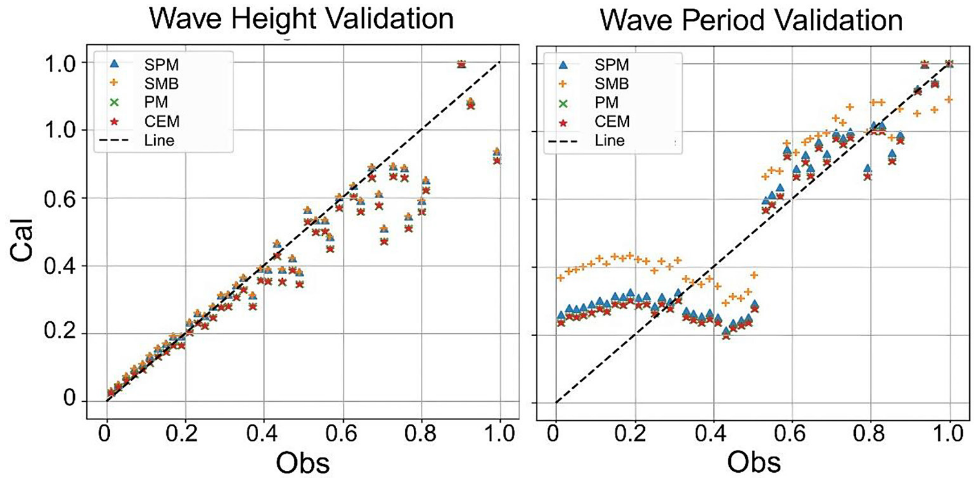

Figure 6. Validation plots comparing modeled vs. observed wave height and wave period (collected from https://cds.climate.copernicus.eu/datasets), providing a quantitative assessment of model accuracy. The black dashed line represents the trendline, indicating the general agreement between modeled outputs and observed data

that SPM and CEM models have the highest correlation with the observed data, and, therefore, they are the most reliable in capturing seasonal wave variations. Conversely, SMB model has substantial differences, especially in the wave period estimation; therefore, it is unsuitable for coastal conditions at Galesong Beach. In Figure 7, these results are further supported by some statistical performance metrics such as RMSE, MAE, bias, and the coefficient of determination (R^2). The SPM model turned out to be the best-performing model, with an RMSE of 1.44 m and the highest R^2 (0.63) for wave height forecasts. The CEM model was very close to it, while the SMB and Pierson-Moskowitz (PM) models showed the highest errors and biases, which rendered them not very suitable for precise wave forecasting.

To extend the analysis of model performance, Figure 8 presents scatter plots comparing observed wave height and period data from Copernicus with simulated outputs from the SPM and CEM models over several years. The visual comparison reveals a strong alignment between the observed and modeled values, particularly for average conditions, although some discrepancies appear under high-energy wave scenarios.

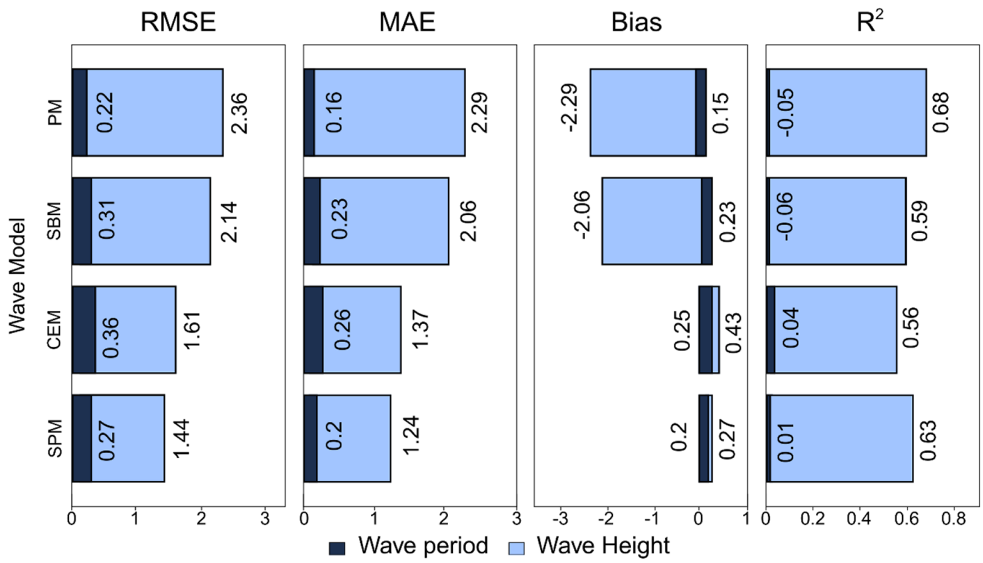

Figure 7. Performance metrics (RMSE, MAE, Bias, R^2) – evaluate and rank the models based on statistical validation criteria

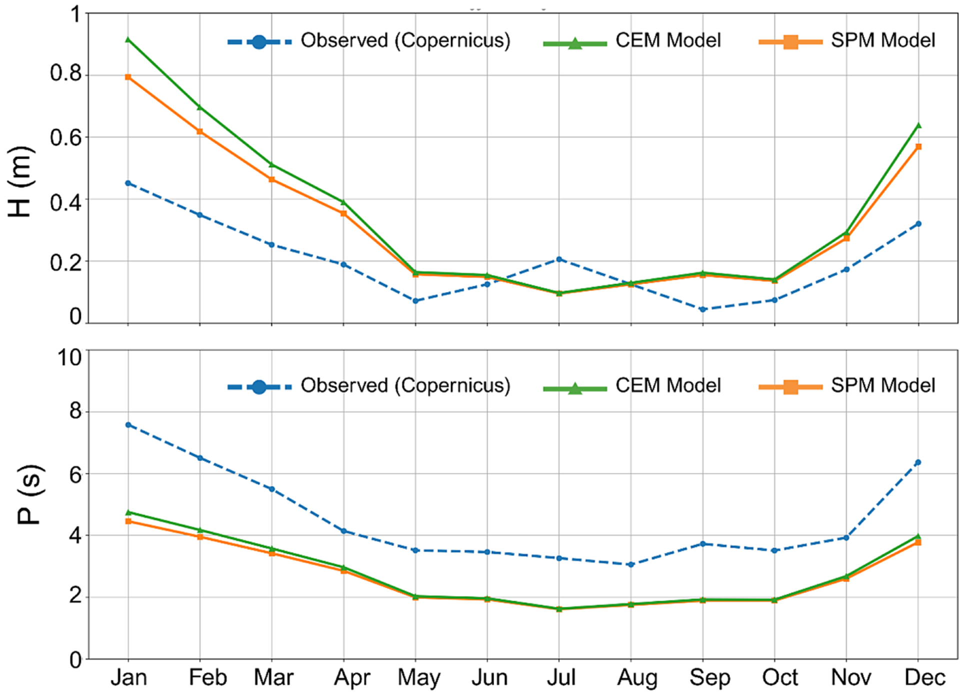

Figure 8. Scatter plots comparing observed wave data from Copernicus with simulated results from the SPM and CEM models. The figure illustrates the agreement between observed and modeled wave height and period

These differences highlight the models' overall robustness in capturing general trends, yet also suggest limitations in simulating extreme wave events with high accuracy. The spread of the data in the scatter plots reflects variability in both the observed and modeled outputs, underscoring the importance of continued refinement in model calibration. These variations are a reminder of the inherent uncertainties in wave forecasting, especially during extreme events. Incorporating higher-resolution datasets and improving parameterization techniques could reduce these uncertainties and enhance the predictive capabilities of wave models. Given their relatively strong performance, the SPM and CEM models are recommended as primary tools for coastal management and disaster preparedness in the Galesong Beach area.

DISCUSSION

The results of this study underscore the significance of seasonality in shaping wave characteristics at Galesong Beach and emphasize the need for predictive models that are well-calibrated to local oceanographic conditions. The observed dominance of waves during DJF and JJA aligns with the prevailing monsoonal wind patterns, corroborating previous findings that highlight the impact of seasonal monsoons on wave energy (Salah, 2015; Abbasi, 2019). Among the evaluated models, SPM and CEM consistently demonstrated superior accuracy in simulating seasonal wave heights and periods, validating their applicability to Indonesian coastal environments. This is consistent with Elbessa and Salah (2024), who reported that parametric models, including SPM and CEM, yielded more accurate long-term predictions compared to spectral-based models in monsoon-dominated regions.

However, the limitations observed in models such as Sverdrup-Munk-Bretschneider (SMB) and PM, particularly in estimating wave periods and extreme events, suggest that further refinement is necessary to improve their predictive performance under high-energy scenarios. These findings are consistent with Ahmadvand et al. (2024), who emphasized that traditional spectral models tend to underestimate extreme wave conditions. While the SPM and CEM models showed robust correlation with Copernicus-derived observations, the discrepancies under high-wave conditions indicate potential for enhancing model performance through integration with high-resolution datasets and climate forecast assimilation. The importance of empirical adjustments and hybrid techniques is also supported by Aisjah et al. (2016), who showed improved wave height prediction in the Java Sea using a modified SMB model.

CONCLUSIONS

This study effectively analyzed the seasonal wave dynamics at Galesong Beach and evaluated the performance of four widely used wave prediction models. The research confirmed that the highest wave energies occur during the DJF months, corresponding to the dry season, which plays a significant role in sediment transport, erosion, and maritime activities in coastal regions. The findings demonstrate the importance of understanding seasonal wave patterns for better coastal management, as they directly influence shoreline dynamics and contribute to coastal land degradation.

The evaluation of model performance revealed that the SPM and CEM models outperformed the others in terms of accuracy in predicting wave heights. The study found that the RMSE, MAE, bias, and R^2 values for these models showed reliable alignment with observed wave data. In contrast, the SMB and PM models exhibited higher error margins, particularly in wave period estimations, which limits their effectiveness in capturing the seasonal wave variations present at Galesong Beach. Through this analysis, the study fills a significant gap in understanding the role of seasonal variability in wave dynamics and its implications for coastal risk assessment and infrastructure development. The results contribute new insights into how the SPM and CEM models, when calibrated for monsoon-affected regions, can offer reliable tools for wave prediction and coastal protection planning. By enhancing the accuracy of these models, this research provides a solid foundation for future coastal hazard mitigation strategies in regions experiencing similar climatic conditions. The current study successfully achieved its goal of evaluating wave prediction models and providing insights into seasonal wave dynamics at Galesong Beach. The findings highlight the critical importance of selecting appropriate models that account for regional conditions, ensuring more accurate predictions for coastal management and the protection of vulnerable coastal areas.

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