

A Three-Component Spliced Lognormal-Weibull-K Distribution Framework for Seasonal Modeling of Significant Wave Height in the Abadi-1 Masela Offshore Area

Gysberth Maurits Wattimena

mauritswattimena@gmail.com

Politeknik Negeri Ambon

Sefnath Johanes Wattimena

Politeknik Negeri Ambon

Roy Robert Lekatompessy

Politeknik Negeri Ambon

Research Article

Keywords: significant wave height, spliced probabilistic model, Lognormal, Weibull, K-distribution, Masela Block

Posted Date: October 23rd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11098303/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

A Three-Component Spliced Lognormal-Weibull-K Distribution Framework for Seasonal Modeling of Significant Wave Height in the Abadi-1 Masela Offshore Area

Gysberth Maurits Wattimena*, Sefnath Johaness Wattimena, Roy Robert Lekatompessy

Ambon State Polytechnic, Ambon, Indonesia

*Corresponding author: Gysberth Maurits Wattimena

Email: mauritswattimena@gmail.com

Abstract

Significant wave height (H_s) is an important oceanographical parameter for the purposes of offshore operation, safety, drilling, subsea pipeline related risk assessment, and weather window definition applications. However, single-distribution based models fail to account for the high variability in wave-height statistical distributions across three wave regimes, namely low wave, moderate wave, and upper tail. This study proposes a Three-Component Spliced Lognormal–Weibull–K Distribution framework for seasonal H_s modeling in the Abadi-1 Masela offshore area. In this model, the Lognormal distribution is assigned to the low-wave regime ($H_s \leq 1.5$ m), the Weibull distribution to the moderate-wave regime ($1.5 < H_s \leq 2.5$ m), and the K-distribution to the upper-tail regime ($H_s > 2.5$ m). The analysis used 3-hourly H_s data for the 2022–2026 period, classified into four seasonal periods: West Monsoon, Transition I, East Monsoon, and Transition II. The results reveal clear seasonal variability, with the East Monsoon exhibiting the highest mean H_s of 1.539 m, while Transition II represents the calmest conditions, with a mean H_s of 0.929 m and no observed upper-tail events. For the West Monsoon, the estimated tail portion is the highest, contributing 4.12% of the total data. Goodness-of-fit measures for single distributions, including AIC, BIC, RMSE, and Kolmogorov–Smirnov statistic, show better performance when one regime dominates. The proposed spliced framework

is useful for characterizing seasonal offshore wave risk and supporting operational decisions at the Masela Block under low-wave, moderate-wave, and upper-tail scenarios.

Keywords: significant wave height; spliced probabilistic model; Lognormal; Weibull; K-distribution; Masela Block.

1. Introduction

1.1 Background

Significant wave height (H_s) is a key parameter for the design and basis of structures offshore as well as for later use regarding the various sea-state conditions or to evaluate the energy of an ocean wave. It plays an important role in mariner safety and the design and operations of marine structures, as well as operations and comfort in sea-state conditions that will be safe for offshore activities. Significant wave height and wind speed are the main criterion for operational performance and safety in relation to the accessibility of offshore sites. They can have the greatest influence on the regulation of operational activities and maintenance procedures in the marine environment [1].

Information on the important wave height (H_s) is useful for many marine logistics and offshore operations. Marine mobilization activities are considerably affected by wave conditions, and operational restrictions are imposed on mobilization activities depending on whether H_s is beyond some threshold value. Thus, the analysis of wave conditions is important, both in terms of pre-operational marine planning and in terms of the safety of offshore operations [2].

Studies on weather windows indicate that significant wave height H_s is more commonly used to identify periods during which sea conditions remain within acceptable operational limits. This process was conducted using H_s thresholds of 0.5 m, 1.0 m, 1.5 m, and 2.0 m, whereby the accessibility of offshore areas varied according to location, season, and the prescribed significant

wave-height limits. The findings indicate that H_s based analysis is essential for optimizing operational schedules, risk management, and cost efficiency in offshore activities [3].

Also, H_s is important for performing risk assessment of subsea pipelines. The hydrodynamic loading in the seabed region, near the pipeline, is induced by the wave and ocean currents. The wave parameters have a direct effect on wave induced pressure on subsea pipelines. Hence, estimation of H_s is important, not only for surface offshore activities, but also for subsea applications, such as pipeline assessment and design [4].

Recent developments of data-driven methods for sea states' wave height estimation and prediction have shown the importance of accurate H_s characterization. These developments, analogous to the modeling of deep hybrid networks for wave height estimation, also show the importance of H_s in the modeling of sea states and its applications in condition based decision making processes [5].

The need for H_s data is especially serious for the offshore Abadi-1 Masela location, where wave data are required for the design and operation of marine structures, drilling, the operation of marine pipelines, safety and weather window analysis. Because of the monsoon in the area, the H_s seasonal model is necessary in order to better differentiate the waves. The seasonal probabilistic modeling in this study, which could be used for offshore wave risk characterization for the Masela Block, was established based on the H_s seasonal model.

1.2 Research Gap

A simple approach for modeling the H_s is still the usage of a single distribution (e.g. Lognormal, Weibull, Rayleigh, Gamma distribution or the distributions of extreme value theory). In many cases, these distributions are suitable for a part of the data. The distribution may have limited capacity for characterizing the entire range of H_s for data that includes low and moderate values as well as upper tail events, although there is evidence that other wave height distributions such as the Lognormal and Weibull can have different estimates for the low, moderate, and extreme parts of the data [6].

To address these limitations, many modified and alternative models for H_s have been proposed. One example is the truncated translated Weibull distribution, which was developed to improve H_s modeling in shallow water environments. This indicates that the standard Weibull distribution is not sufficient for all data conditions [7]. On the other hand, mixture models and bulk tail approaches are commonly employed to overcome the limitations of single distribution models in simultaneously representing the main body of the data and extreme events [8].

When the data have a high proportion of low- or moderate-magnitude values and a low proportion of large-magnitude values, the statistical literature has recommended the use of spliced distributions (concatenations of two or three distributions defined over different ranges of values) to allow greater flexibility on the bulk region and tail regions [9]. However, the three-component spliced-distribution framework over low-wave, moderate-wave and upper-tail states has yet to be considered on a seasonal basis in the Abadi-1 Masela offshore area. This gap in the literature appears to be the reason for this study.

1.3 Novelty and Contribution

The main novelty of the work is the development of a regime-based spliced probabilistic model of the seasonal extreme meaningful wave height H_s in the surrounding waters of the Abadi-1 Masela offshore region although some single distribution models have been developed for the H_s data. This model is a three-regime exploration approach that comprises the low-wave regime, the moderate-wave regime and the upper-tail regime.

Thus, the distributional model is given by the Lognormal distribution for low-wave, the Weibull distribution for moderate-wave, and the K-distribution for high-wave regime upper-tail behavior. The distributional model is not a newly derived distribution. Instead, the model is a three-component spliced model which uses three different probabilistic distributions for the statistical characteristics of the respective wave regimes.

The main contribution of this work thus is the development of the framework H_s , which is much more flexible and interpretable than customary single-distribution based models. From the statistical point of view, the distribution of every wave height domain can be chosen such that it reflects the contribution of that wave height domain to the overall distribution. The operational states in question are the normal, restricted operation and high-risk offshore operational states respectively, for low, moderate and upper-tail conditions. Thus, this research has major contributions to the development of probabilistic wave modeling in this study area and increasing the accuracy of operational risk analysis in the offshore waters of the Abadi-1 Masela block.

1.4 Research Objectives

The aim of this study is to develop and analyze a regime-based probabilistic modeling of H_s in the offshore area of Abadi-1 Masela. More specifically, this study will focus on the seasonal variation of H_s and how the data from each wave regime can be represented with the most appropriate probability distribution.

More specifically, the seasonal features of H_s are examined here for the four seasons, namely West Monsoon, Transition I, East Monsoon and Transition II in order to understand how the low-, moderate- and high-wave conditions are distributed in each of the four sea seasons and the differences among them. Next, the Lognormal, Weibull and K-distribution parameters that are relevant to the sea state are determined: these are μ and σ in the case of the Lognormal distribution, k and λ in the case of the Weibull distribution and v and c in the case of the K-distribution.

The Three-Component Spliced Lognormal-Weibull-K Distribution can then be defined using the distribution parameters from the previous step. The range of H_s from the sea state to the extreme upper tail is spanned. The ability to fit the Three-Component Spliced Lognormal-Weibull-K Distribution to the data set can be determined by the AIC, BIC, RMSE and the Kolmogorov-Smirnov test statistic in addition to the goodness-of-fit achieved with each of the single distributions. The final model can then be used to assess the operational risk offshore (marine operations, drilling support, pipeline and subsea facilities planning, safety assessment and

weather window) for exploration and production activities in the Abadi-1 Masela offshore region.

2. Study Area and Data

2.1 Study Area: Abadi-1 Masela Offshore Area

The study site and research object are located in the Abadi-1 Masela offshore area, which forms part of the Masela Block in the Arafura Sea, Maluku Province, eastern Indonesia. This area is also the calculated area for the Abadi LNG Project. It is one of the largest offshore gas projects in Indonesia. Based on the INPEX report, the Abadi LNG Project is still in the development preparation stage with a need for an LNG production capacity of 9.5 million tonnes per year, pipeline gas supply for domestic needs of 150 million standard cubic feet per day and a maximum condensate production capacity of about 35,000 barrels per day [10].

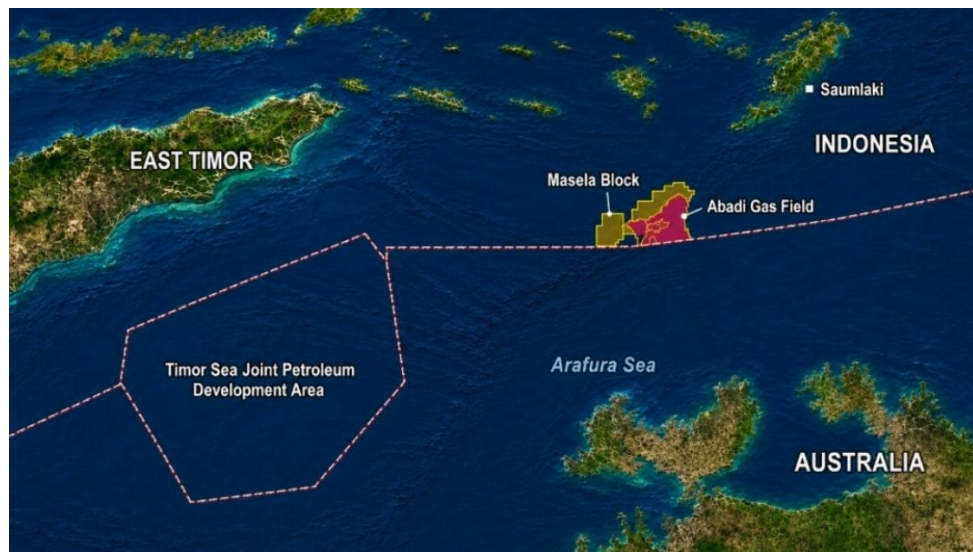


Figure 1. Location of the Abadi-1 Masela Block in the Arafura Sea region, eastern Indonesia.

As an offshore development, knowledge of the oceanographic regime on the Abadi-1 Masela is required, especially H_s wave height due to its influence on marine operations, vessel arrival and

work platform, pipeline alignment, Safety Assessment and weather window. As part of the Masela Block, the Abadi-1 Masela is located in the Arafura Sea, which is considered to be affected by the marine regime of eastern Indonesia and monsoon variability.

The site of Abadi-1 Masela has been chosen as the study region because of its offshore operational importance, oceanographic characteristics, and seasonality. Wave characteristics are important to have information about in seasonal periods with minimum wave conditions, maximum wave conditions, or those with a chance of an upper-tail event that may affect the risk of operations offshore.

2.2 Significant Wave Height Dataset

The wave dataset used in this study is the wave height time series data at the offshore well site of Abadi-1 Masela. The wave height in this study is represented by the variable with the name of VHM0, which, according to the Copernicus Marine documentation, is sea surface wave meaningful height or spectral important wave height (H_{m0}) in meters [11]. The spatiotemporal dataset was 3-hourly from 2022 to 2026 and allows for a better understanding of shorter time scales of wave variability, as well as seasonal wave variability.

H_s data are therefore used to deduce sea state for offshore use, because the three hour temporal resolution of the H_s data set is better suited to describing wave height variation. The statistical analysis of waves, fitting its probability distribution functions and analyzing low, moderate and high waves is possible with these data. Before the analysis, the data were screened so that all H_s were valid and positive which is a requirement to fit such distributions. Table 1 shows the descriptive statistics of the data set used in this study.

Component	Description
Variable	Significant wave height (H_s)/VHM0
Period	2022 - 2026
Temporal resolution	3-hourly

Location	Abadi-1 Masela offshore well
Data format	Time series
Unit	meter

Table 1. Summary of the significant wave height(H_s) dataset for the Abadi-1 Masela offshore well

Similar methodological applications have been carried out based on the same data set for the calculations of the seasonal descriptive statistics, the Three-Component Spliced Lognormal-Weibull-K Distribution fitting, the wave regime classification and the model verification for the Three-Component Spliced Lognormal-Weibull-K Distribution, as well as the seasonal explanatory analysis for the offshore operational risk assessment of the Abadi-1 Masela area.

2.3 Seasonal Classification

Using the H_s data, each measurement was classified into one of four categories, namely West Monsoon, Transition I, East Monsoon and Transition II, to understand the effects of the monsoon on the wave climate of the waters surrounding the Indonesian archipelago. This monthly classification divides the year into four seasons: the West Monsoon (December through February), Transition I (March through May), the East Monsoon (June through August), and Transition II (September through November). The H_s dataset was then grouped according to these seasonal periods prior to descriptive statistical analysis, wave-regime classification, distribution-parameter estimation, and goodness-of-fit evaluation.

Season	Months
West Monsoon	December - February
Transition I	March - May
East Monsoon	June - August
Transition II	September - November

Table 2. Seasonal classification of the significant wave height (H_s) dataset for the Abadi-1 Masela offshore well.

This seasonal classification provided a basis for the analysis of weather patterns. With each season having different characteristics in their H_s distributions, this method of classification provides a more accurate way of measuring seasonal trends in the frequency of low/medium/upper-tail conditions. This classification would later form the basis for the Three-Component Spliced Lognormal-Weibull-K Distribution model, allowing each separate season to be analyzed statistically and wave-related hazards to be assessed more appropriately.

3. Methodology

This study was conducted as one of the stages in the preparation of the regime-based probabilistic model of important wave height parameters of the Abadi-1 Masela offshore site, which consisted of several stages, namely data preparation, descriptive statistical analysis, wave regime classification, modeling by Lognormal, Weibull, and K distribution, modeling with 3-component spliced Lognormal-Weibull-K Distribution, parameter estimation and goodness of fit tests. Standard Lognormal and Weibull distributions may also be used to describe wave heights, but a spliced distribution is appropriate if different ranges of the data have different characteristics.

3.1 Data Preprocessing

In the first part of the processing, the H_s data were validated, homogenized and made suitable for probabilistic modeling. The initial dataset was a time series of data with a temporal resolution of 3 hours. Any incomplete data, data with non-numeric values, and data exceeding physical limits for wave height were identified. As wave height must be strictly positive, only data with $H_i > 0$ were included in the analysis.

$$H_s = H_1, H_2, \dots, H_n, \quad H_i > 0$$

After performing data cleaning, the observations were grouped into four seasonal periods: the West Monsoon, Transition I, the East Monsoon and Transition II. This was done in order to apply distributional analysis to homogenous groups of observations defined by seasonality.

3.2 Descriptive Statistical Analysis

Descriptive statistical analysis was performed to outline the seasonal statistics of H_s , including number of observations, mean, median, standard deviation, minimum, maximum, skewness, and kurtosis. These statistical metrics measured differences of wave characteristics between seasons, the detection of right-skewed distributional behavior, and extreme values in the distribution tail.

This is important when the distribution of wave height is not constant in time and perhaps non-homogeneous throughout the year. The fact that the average value, dispersion, skewness and kurtosis are different each season indicates that each season has a different probabilistic structure: therefore the data should be analyzed seasonally.

3.3 Wave-Regime Classification

The H_s data used in the development of the regime-based probabilistic model were first placed into three different wave regimes. This was done because a single distribution would not be able to capture the H_s data for all wave conditions, specifically if the data set contained low-wave, moderate-wave and upper-tail conditions.

The regime thresholds were defined in this paper as $H_s \leq 1.5$ m, $1.5 < H_s \leq 2.5$ m, and $H_s > 2.5$ m and it was assumed that the distribution of wave heights under the low-wave regime $H_s \leq 1.5$ is the Lognormal distribution. The regime $1.5 < H_s \leq 2.5$ m was defined as the moderate-wave regime and modeled using the Weibull distribution. Meanwhile, the regime $H_s > 2.5$ m was defined as the upper-tail regime and modeled using the K-distribution.

This framework is also consistent with the methodological concept that assigns the Lognormal distribution to low-wave conditions, the Weibull distribution to moderate-wave conditions, and the K-distribution to high-wave conditions, while employing a spliced distribution to integrate the three components based on wave-height intervals.

3.4 Lognormal Distribution

The Lognormal distribution was employed for the low-wave regime because H_s is a positive-valued variable and, in its lower range, generally exhibits a right-skewed distributional pattern. Mathematically, H_s can be modeled using the Lognormal distribution when its natural logarithmic transformation follows a Normal distribution.

$$H_s \sim LN(\mu, \sigma^2)$$

The probability density function of the Lognormal distribution is expressed as follows:

$$f_{LN}(H_s) = \frac{1}{H_s \sigma \sqrt{2\pi}} \exp\left[-\frac{1}{2} \left(\frac{\ln(H_s) - \mu}{\sigma}\right)^2\right], H_s > 0$$

where μ and σ denote the mean and standard deviation of $\ln(H_s)$, respectively. In this model, the Lognormal parameters are estimated using data within the regime $H_s \leq 1.5$ m, so that this component specifically represents low-wave behavior.

3.5 Weibull Distribution

The Weibull distribution was employed for the moderate-wave regime, corresponding to the range $1.5 < H_s \leq 2.5$ m. This distribution was selected because of its flexibility in controlling the shape of the curve through its shape and scale parameters.

$$H_s \sim W(k, \lambda)$$

The probability density function of the Weibull distribution is expressed as follows:

$$f_W(H_s) = \frac{k}{\lambda} \left(\frac{H_s}{\lambda}\right)^{k-1} \exp\left[-\left(\frac{H_s}{\lambda}\right)^k\right], H_s > 0$$

where k denotes the shape parameter and λ denotes the scale parameter. In this study, the Weibull distribution is applied only to the moderate-wave regime, as this range represents the transition zone between low-wave and high-wave conditions.

3.6 K-distribution

The K-distribution was employed for the upper-tail regime, corresponding to the range $H_s > 2.5$ m. This regime represents relatively rare high-wave conditions, which are nevertheless important in the context of offshore risk. In this study, the K-distribution is positioned as a tail model because the distributional tail needs to be modeled separately from the bulk of the data.

$$H_s \sim K(\nu, c)$$

The probability density function of the K-distribution is expressed as follows:

$$f_K(H_s) = \frac{2c}{\Gamma(\nu)} \left(\frac{cH_s}{2}\right)^\nu K_{\nu-1}(cH_s), H_s > 0$$

where ν denotes the shape parameter, c denotes the effective scale parameter, $\Gamma(\nu)$ is the Gamma function, and $K_{\nu-1}(\cdot)$ represents the modified Bessel function of the second kind. This component is estimated only when tail data are available; therefore, the model does not impose an extreme-value distribution on seasons without observations satisfying $H_s > 2.5$ m.

3.7 Proposed Three-Component Spliced Distribution

The Three-Component Spliced Lognormal-Weibull-Distribution (3C-SWL) model fits a combination of three distributions to the H_s data in three ranges of H_s . This model is convenient if the data set is heavily clustered around the low range with rare high-value observations. This is

because a single classic distribution is not able to represent the heterogeneous distributional behavior.

The proposed model is as follows:

$$f_s(H_s) = \begin{cases} w_1 \frac{f_{LN}(H_s)}{F_{LN}(h_1)}, & 0 < H_s \leq h_1 \\ w_2 \frac{f_W(H_s)}{F_W(h_2) - F_W(h_1)}, & h_1 < H_s \leq h_2 \\ w_3 \frac{f_K(H_s)}{1 - F_K(h_2)}, & H_s > h_2 \end{cases}$$

where:

$$h_1 = 1.5, \quad h_2 = 2.5$$

$$w_1 + w_2 + w_3 = 1$$

The weight of each component is calculated from the proportion of the data in each wave regime:

$$w_j = \frac{n_j}{n}, \quad j = 1, 2, 3$$

where n_j is the number of observations through the j -th regime, and n is the total number of observations in the season under consideration. The normalization factor ensures that the model provides a valid probability distribution in the range modeled by each of the two segments.

3.8 Parameter Estimation

Model parameters were estimated using maximum likelihood estimation (MLE). MLE is a common approach to fitting a distribution and estimates the parameters that provide the highest probability of obtaining the observed data under the statistical model. MLE is often applied to fit statistical models to meaningful wave height data and used to estimate the parameters of distributions, such as the Weibull distribution and its variants [12].

For the H_s data, denoted as $H_s = H_1, H_2, \dots, H_n$, the log-likelihood function is defined as follows:

$$H_s = H_1, H_2, \dots, H_n$$

$$l(\theta) = \sum_{i=1}^n \ln f(H_i)$$

where $f(H_i)$ denotes the value of the probability density function at the i -th observation, while θ represents the set of model parameters:

$$\theta = \mu, \sigma, k, \lambda, \nu, c, w_1, w_2, w_3$$

The parameters μ and σ were estimated from the low-wave regime, k and λ from the moderate-wave regime, and ν and c from the upper-tail regime. The estimation was conducted separately for each season to enable the model to capture the seasonal characteristics of H_s

3.9 Goodness-of-Fit Evaluation

The goodness-of-fit tests compared the performance of the single Lognormal distribution, single Weibull distribution, single K-distribution and the 3-component spliced Lognormal-Weibull-K Distribution. The goodness of fit statistics applied were the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean Square Error (RMSE) and Kolmogorov-Smirnov (KS) statistic. AIC and BIC are widely used criteria for model comparison, as they account for both the likelihood and the penalty associated with parameter complexity, whereas the KS statistic is used to measure the maximum distance between the empirical distribution and the fitted model distribution [13].

$$AIC = 2p - 2l$$

$$BIC = p \ln(n) - 2$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n [F_{\text{emp}}(H_i) - F_{\text{model}}(H_i)]^2}$$

$$KS = \max_i |F_{emp}(H_i) - F_{model}(H_i)|$$

where p is the number of parameters, l is the log-likelihood of the model, n is the number of observations, F_{emp} is the empirical distribution function, and F_{model} is the cumulative distribution function of the fitted distribution. Lower values of AIC, BIC, RMSE and KS indicate better model fits. Considering the physical and operational characteristics of the spliced model, we can conclude that the spliced model only explicitly distinguishes between low-wave, moderate-wave, and upper-tail regimes.

4. Results

In this section, the characterization of the probability distribution function (PDF) of H_s in the Abadi-1 Masela offshore area using a seasonal analysis method is presented. The results are described below. Descriptive statistics are reported first, followed by distribution parameter estimation, distribution fitting, and goodness-of-fit tests. The paper's main objectives are to determine if H_s properties differ by season and whether the Three-Component Spliced Lognormal-Weibull-K Distribution provides a statistically interpretable probabilistic representation of the data, as opposed to single distribution models.

Prior to the statistical and distribution analysis, an investigation of the temporal variation of H_s over the 2022-2026 time period was conducted to provide further information on the seasonality of the offshore waves in the Abadi-1 Masela offshore field and as context for the observed seasonal difference in the wave pattern characteristics.

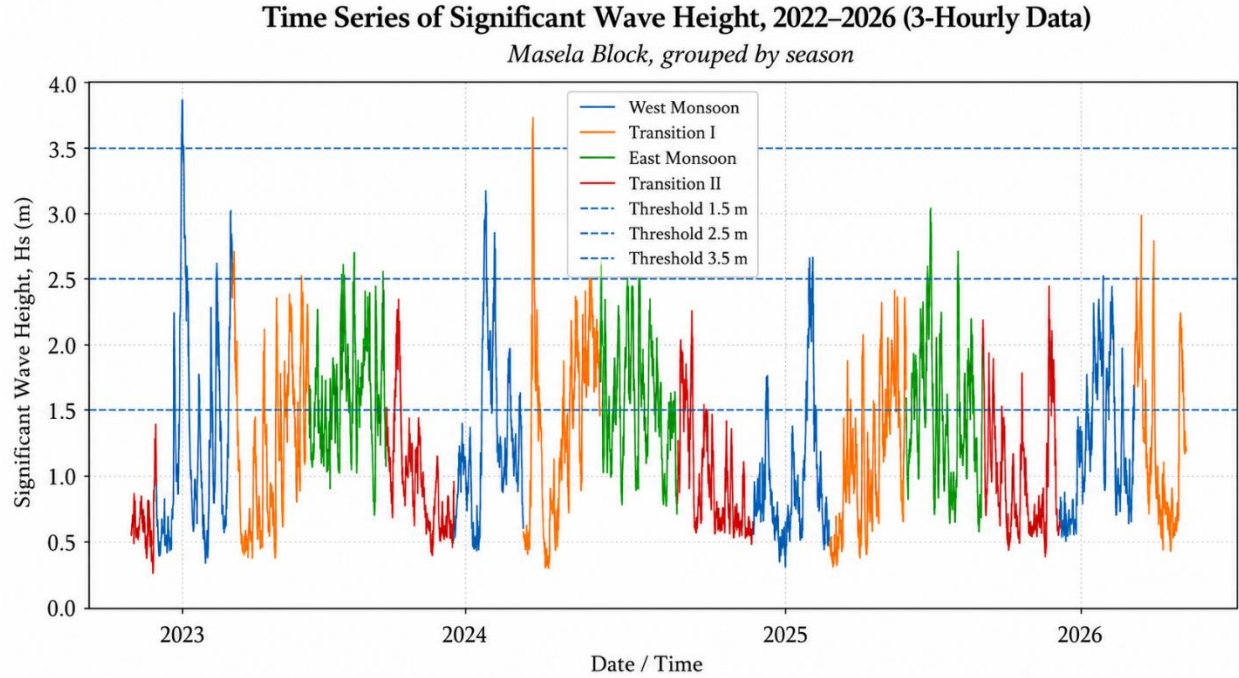


Figure 2. Time series of significant wave height (H_s) at the Abadi-1 Masela offshore location from 2022 to 2026, grouped by monsoonal season.

Despite the time series of H_s shown in figure 2 being highly variable, the relatively few occurrences of H_s being greater than the 2.5 m and 3.5 m thresholds imply that the times of more dangerous high-wave conditions are less frequent than the times of low- and moderate-wave conditions. This pattern reinforces the need for a seasonal analysis and regime-based approach to modeling the distribution of H_s .

4.1 Seasonal Descriptive Statistics

In order to obtain an initial overview about the characteristics of H_s in each season, descriptive statistics for each season were carried out. The result of this study proves that in the offshore Abadi-1 Masela area, H_s has seasonal variations in terms of statistical data (mean, standard deviation, maximum, skewness, kurtosis).

Season	N	Mean	Median	Std. dev.	Min	Max	Skewness	Kurtosis
--------	---	------	--------	-----------	-----	-----	----------	----------

		(m)	(m)	(m)	(m)	(m)		
West Monsoon	2888	1.164	0.980	0.633	0.320	3.870	1.214	1.173
Transition I	2913	1.266	1.210	0.607	0.310	3.740	0.415	-0.517
East Monsoon	2208	1.539	1.525	0.456	0.590	3.030	0.318	-0.370
Transition II	2423	0.929	0.790	0.400	0.280	2.440	1.149	0.713

Table 3. Seasonal descriptive statistics of significant wave height H_s at the Abadi-1 Masela offshore location.

The results presented in the table show that the East Monsoon exhibits the highest mean H_s , at 1.539 m, with a median value of 1.525 m. This indicates that the East Monsoon generally represents the most energetic wave season. In contrast, Transition II has the lowest mean H_s , at 0.929 m, and a maximum value of only 2.440 m, thereby identifying it as the calmest season.

The peak of the West Monsoon is at 3.870 m. Apart from the local maximum, the West Monsoon has positive skewness and positive kurtosis, which indicates that most of the samples in the distribution are low waves, although there exists a distributional tail for extreme high-wave events. Note also that all seasons have skewness (positive) such that the H_s distribution is right-skewed. This provides at least some reason to suggest that single-distribution modeling may not be able to account for the behavior at the far end of the data.

4.2 Wave-Regime Proportions

The H_s data used to develop the spliced model was classified into three regimes, in which low-wave conditions were defined as $H_s \leq 1.5$ m. Moderate-wave conditions are defined as $1.5 < H_s \leq 2.5$ m. High-wave or upper-tail conditions were defined as $H_s > 2.5$ m. The proportions of moderate and high-wave conditions are as follows.

Season	N	Low-wave regime		Moderate-wave regime		Upper-tail regime	
		$H_s \leq 1.5$ m	(%)	$1.5 < H_s \leq 2.5$ m	(%)	$H_s > 2.5$ m	(%)
West Monsoon	2888	2175	75.31	594	20.57	119	4.12
Transition I	2913	1858	63.78	1003	34.43	52	1.79
East Monsoon	2208	1068	48.37	1089	49.32	51	2.31
Transition II	2423	2168	89.48	255	10.52	0	0.00

Table 4. Seasonal distribution of important wave height regimes at the Abadi-1 Masela offshore location.

Table 4 shows differences in the wave-regime structure across seasons. Transition II is strongly dominated by low-wave conditions, with a proportion of 89.48%, and contains no observations in the upper-tail regime. In contrast, the East Monsoon exhibits nearly balanced proportions of low- and moderate-wave conditions, at 48.37% and 49.32%, respectively; therefore, this season can be interpreted as a period dominated by moderate-wave conditions. The West Monsoon, however, has the largest upper-tail proportion at 4.12%, making it the most relevant monsoon for the high-wave risk.

This shows that the regime-based model is valid. The variance in the properties of low-wave, moderate-wave, and tail cases is lost when modeling data with a single distribution. Regime classification thus provides the basis for the Spliced Lognormal - Weibull - K Distribution model, which associates each H_s interval with the distribution function that best represents it.

4.3 Estimated Distribution Parameters

The distribution parameters were estimated seasonally, according to wave regime. In this model, μ and σ represent the parameters of the Lognormal component in the low-wave regime, while k and λ represent the parameters of the Weibull component in the moderate-wave regime, whereas v and c represent the parameters of the K-distribution component in the upper-tail regime. The weights w_1 , w_2 , and w_3 indicate the proportion of each component in the spliced model.

Season	μ	σ	k	λ	v	c	w_1	w_2	w_3
West Monsoon	-0.2098	0.3431	7.5297	2.0581	200.0000	9.6364	0.7531	0.2057	0.0412
Transition I	-0.2044	0.4046	8.2058	2.0103	200.0000	9.9725	0.6378	0.3443	0.0179
East Monsoon	0.1250	0.2072	7.3639	1.9784	200.0000	10.6333	0.4837	0.4932	0.0231

Transition II	-0.2422	0.3181	8.8791	1.8963	-	-	0.8948	0.1052	0.0000
---------------	---------	--------	--------	--------	---	---	--------	--------	--------

Table 5. Estimated distribution parameters and regime weights for the seasonal spliced probabilistic wave model.

Since the weights are not equal for the different seasons, Transition II has $w_1 = 0.8948$, which is evidence that the low-wave regime dominates. However, for the East Monsoon in our case, $w_1 = 0.4837$ and $w_2 = 0.4932$, which indicates that there is a similar impact of both low and moderate seas. The West Monsoon has $w_3 = 0.0412$, the highest of any season, and is the season with the greatest tail contribution.

In Transition II, the parameters ν and c were not estimated because no observations satisfied $H_s > 2.5$ m. This indicates that the spliced model is adaptive, as it does not impose the K-distribution component when the tail regime is not empirically present.

4.4 Distribution Fitting Results

The distribution-fitting results reveal clear visual differences between the single-distribution models and the spliced model. For each season, the H_s histogram was compared with the single Lognormal distribution, single Weibull distribution, single K-distribution, and the Spliced Lognormal–Weibull–K model.

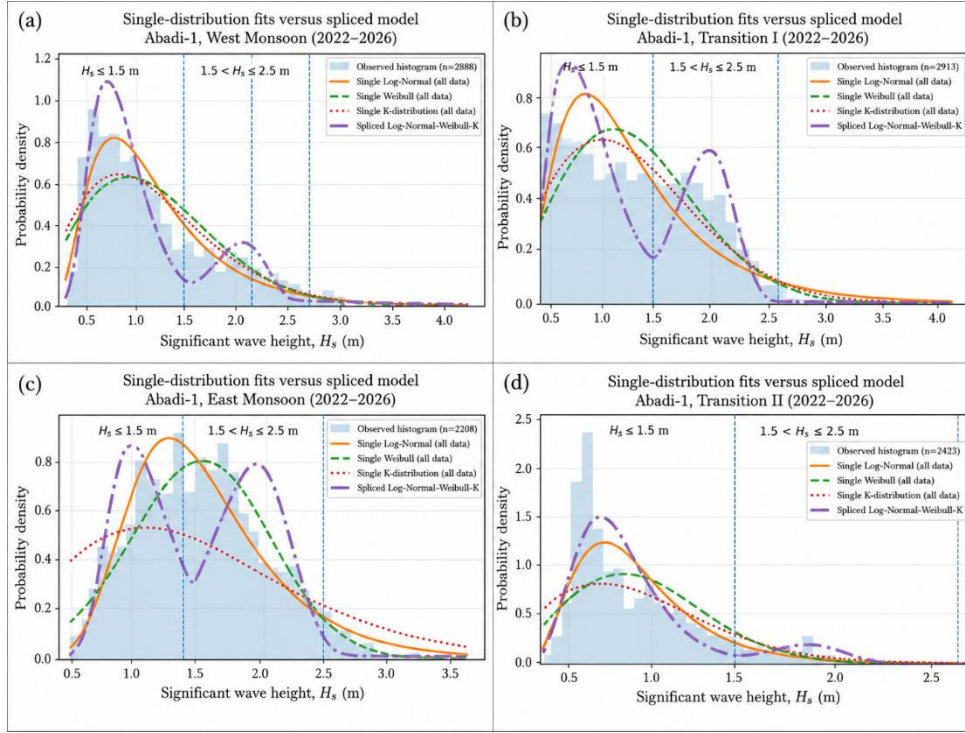


Figure 3. Seasonal probability density fitting of significant wave height H_s at Abadi-1 Masela using single-distribution models and the proposed spliced Lognormal-Weibull-K-distribution model: (a) West Monsoon, (b) Transition I, (c) East Monsoon, and (d) Transition II.

The H_s histogram for the West Monsoon season looks like it has more low values with a prominent right tail. The single Lognormal distribution has the right shape but the tail is better influenced by a K-distribution which is more realistic for modeling large waves. The spliced model, on the other hand, can be interpreted as a single distribution that separates low-wave, moderate-wave and tail data.

If instead the contribution from moderate-wave conditions is increased in Transition I, the Weibull distribution fits the central region well, but fails to capture the tail. Again, a simple Weibull distribution is not adequate and so the spliced model is required, to characterize the low-, moderate- and high-wave portions.

The histogram shows moderate-wave conditions are the most common during the East Monsoon. This condition explains why the Weibull distribution plays an important role during this season.

The spliced model is more informative, as it provides the possibility to distinguish components associated with the low-wave regime, the moderate-wave regime, and upper-tail events.

For Transition II, since the histogram is concentrated towards the low wave regime with no data above 2.5 m, then the spliced model for this case can be taken to be the Lognormal and Weibull distributions only. In other words, there is no K-distribution term during this season and hence, the model does not require the extreme-value distribution to be valid when there is no data.

The visual fitting between the cumulative density function (CDF) of the data and of the model suggests that single distributions can fit only at the extremes of the H_s range. The spliced model is more physically meaningful as each part of the distribution represents a different wave regime.

4.5 Goodness-of-Fit Comparison

Four criteria were used to evaluate the model fit, namely AIC, BIC, RMSE and KS, which were all positively correlated with goodness of fit (the lower the better). The results are shown below.

Season	Model	AIC	BIC	RMSE	KS
West Monsoon	Single Lognormal	4414.9905	4426.9271	0.0271	0.0497
	Single Weibull	4916.6562	4928.5928	0.0517	0.0852
	Single K-distribution	4857.5389	4869.4756	0.0416	0.0992
	Spliced Lognormal-Weibull-K	4568.8186	4616.5652	0.0307	0.0643
Transition I	Single Lognormal	5208.4740	5220.4279	0.0457	0.0794
	Single Weibull	5070.2379	5082.1918	0.0321	0.0581
	Single K-distribution	5131.7014	5143.6553	0.0273	0.0536
	Spliced Lognormal-Weibull-K	5135.5047	5183.3202	0.0404	0.0858
East Monsoon	Single Lognormal	2796.1526	2807.5523	0.0242	0.0528
	Single Weibull	2802.4482	2813.8479	0.0179	0.0320
	Single K-distribution	3845.5619	3856.9616	0.1217	0.2041
	Spliced Lognormal-Weibull-K	3260.0038	3305.6026	0.0520	0.0948
Transition II	Single Lognormal	1624.5957	1636.1812	0.0476	0.1008
	Single Weibull	2174.7648	2186.3503	0.0676	0.1117
	Single K-distribution	2353.2430	2364.8285	0.0739	0.1804
	Spliced Lognormal-Weibull-K	1572.5349	1601.4987	0.0404	0.0739

Table 6. Seasonal goodness-of-fit comparison of single-distribution models against the proposed spliced probabilistic model.

For goodness of fit results, model performance varies by season. For the West Monsoon season, the single Lognormal model has the lowest AIC, BIC, RMSE, and KS value when compared to all other models. This is in agreement with the prevalence of the low-wave regime at this time of year, although the spliced model provides the advantage of isolating the tail contribution of 4.12%.

During Transition I, the single Weibull distribution yields the lowest AIC and BIC values, whereas the single K-distribution produces the lowest RMSE and KS values. This indicates that Transition I has a more complex distributional structure, characterized by a substantial contribution of moderate-wave conditions and the presence of a tail that still requires careful consideration.

During the East Monsoon, the single Weibull distribution yields the lowest RMSE and KS values, which is consistent with the dominance of moderate-wave conditions during this season. The spliced model is analytically convenient because the components of the Lognormal and the Weibull are balanced (as indicated by the near equality of w_1 and w_2).

The best model using each fit statistic was the Spliced Lognormal-Weibull-K Model when tested using Transition II. Since this season was highly skewed to low waves, and tail events were not present, the result confirms that the spliced model is the most appropriate. The absence of the K-distribution component in this season was not seen as a limitation, rather it shows the flexibility of the model and that it was able to capture the empirical characteristics of the data.

The bottom line can be considered as saying that when the data are dominated by a single regime, the one-distribution model is reasonable, but the spliced model is better because it is more explicit about the multi-regime form of the H_s distribution. Model selection should not take place solely on the basis of AIC and BIC, but should take into account how well the model represents the low-wave, moderate-wave and upper-tail regimes that are critical to offshore risk assessment..

5. Discussion

This section analyzes the potential application of these results for the scientific understanding of wave height variations by season, the performance of single distributions against the spliced model, the results of the statistical performance, and the importance of these results in terms of offshore activities in the Abadi-1 Masela block. This is not only a matter of statistical performance but also a question of the ability of a model to reproduce the physical and operating structure of the low-wave, moderate-wave and upper-tail regimes.

5.1 Seasonal Wave Characteristics

Based on descriptive statistics and the fractions of the dominant wave regimes, H_s values in the Abadi-1 Masela offshore area differ in their distribution by season and cannot be described by a single annual average value that would be representative. Therefore, classifying the data into the West Monsoon, Transition I, East Monsoon, and Transition II constitutes an important step in this study.

The East Monsoon exhibits the highest mean H_s , at 1.539 m, with a median value of 1.525 m. In addition, the proportion of moderate-wave conditions during this season reaches 49.32%, which is nearly equal to the low-wave proportion of 48.37%. This condition indicates that the East Monsoon represents the period with relatively the highest wave energy. The dominance of moderate-wave conditions indicates that sea states during this season more frequently occur at levels that may restrict offshore activities, particularly operations sensitive to vessel motion, logistics transfer, and drilling-support activities.

In contrast, Transition II exhibits the characteristics of the calmest wave season. This is indicated by the lowest mean H_s value of 0.929 m, a median of 0.790 m, and the dominance of low-wave conditions, which reaches 89.48%. The absence of observations with $H_s > 2.5$ m during this

season indicates that upper-tail events did not occur throughout the observation period. This condition suggests that Transition II has the potential to provide a more favorable weather window compared with the other seasons.

The West Monsoon exhibits distinct characteristics compared with the other seasons. Although this season is still dominated by low-wave conditions, accounting for 75.31%, its maximum H_s value reaches 3.870 m, which is the highest among all seasons. In addition, the proportion of upper-tail events during the West Monsoon is 4.12%. The value is higher than the average during other seasons, suggesting that the West Monsoon is not the time of the year with the highest mean wave height, but is the period with the most potential for occurrence of high waves. This concept is particularly relevant in offshore risk assessment, where operational risk is driven by tail or extreme events rather than mean or average values.

Transition I, with 34.43% moderate-wave systems and 1.79% extreme upper-tail systems, was again not as active as the East Monsoon season but more active than Transition II, and was considered more active than Transition II. So Transition I can be thought of as a transition from the low-wave conditions to a more energetic sea state.

Overall, the results confirm the finding that the seasonal wave climate in the Abadi-1 Masela offshore area is not homogenous, and the seasonal differences between the various regimes give confidence that implementation of a regime-based approach for modeling the area is more appropriate than a single-distribution approach.

5.2 Comparison with the Single and Spliced Distribution

These fitting results indicate that single distributions could provide a satisfactory description of the data if a single wave regime dominates the data, as is the case for the West Monsoon where the single Lognormal model gives the relative best AIC, BIC, RMSE and KS. This is likely because the bulk of the West Monsoon observations are in a region of low wave number, and the Lognormal distribution fits well there.

Nevertheless, unimodal distributions may be misleading in cases where there are multiple peaks in the dominance distribution (e.g. low vs moderate conditions during East Monsoon), where only a single distribution would be optimal for some subset of the input data. The single Weibull distribution yields the best RMSE and KS values because moderate-wave conditions are highly dominant; however, this model is still unable to explicitly distinguish the low-wave, moderate-wave, and upper-tail regimes.

Another alternate model, the Three-Component Spliced Lognormal-Weibull-Distribution model, does not fit all data to the same distribution. Instead, the H_s domain is split into three regimes where the Lognormal distribution is used to fit the low-wave regime, the Weibull distribution is used to fit the moderate-wave regime, and the K-distribution is used to fit the upper-tail regime. The spliced model gives a better representation of offshore waves than the conventional model does.

The main distinction between the single distribution and spliced model is thus not only the shape of the fitted curve, but also the interpretation of the model. The single distribution tries to find the distribution that best fits all the data, while the spliced model tries to answer the question of which distribution fits which wave-height regime best.

This distinction is important in offshore applications as low-wave, moderate-wave and upper-tail events have different consequences to operations. However, low-wave events are associated with normal operations, moderate-wave events are associated with operational limitations, and upper-tail events are associated with safety issues and possible cessation of operations.

5.3 Model Performance and Statistical Interpretation

The goodness of fit shows that the model with the best fit is not the same for each season or performance criterion, which is expected since AIC, BIC, RMSE and KS measure different aspects of the models' performance. While AIC and BIC are more critical of a model that simply sacrifices a degree of freedom to increase the likelihood, RMSE and KS are more concerned with minimizing the distance of the empirical from the fitted distributions.

During the West Monsoon the single Lognormal distribution has the least AIC and BIC values. This indicates that for the West Monsoon period the Lognormal distribution statistically is a valid way to fit most of the data points in the world. The West Monsoon has the largest upper-tail proportion. Therefore, although the Lognormal distribution performs better numerically, the spliced model retains interpretative value because it is able to separate the tail as a distinct risk-related component.

During Transition I, the goodness-of-fit results indicate a more complex condition. The single Weibull distribution yields the best AIC and BIC values, whereas the single K-distribution produces lower RMSE and KS values. This suggests that the distributional pattern during Transition I cannot be fully explained by a single model. In other words, a model that performs better in terms of likelihood does not necessarily provide the closest representation of the empirical distribution across the entire data range. This condition further strengthens the argument that the H_s data structure is multi-regime in nature.

During the East Monsoon, the single Weibull distribution demonstrates strong performance based on RMSE and KS. This result is consistent with the dominance of moderate-wave conditions during this season. However, since parts of the East Monsoon are also low-wave or upper-tail derived, a definite model is needed to separate the Lognormal, Weibull, and K-distribution contributions. This is another important reason for the spliced model, since a Weibull-only model is insufficient when the other contributions are also present.

In Transition II, the spliced model has been determined to be the best model of those considered, according to all four metrics: AIC, BIC, RMSE and KS. This suggests that, where the data structure is predominantly low-wave conditions without any tail events, the spliced model is effectively a model without the K-distribution. Thus, the absence of the parameters ν and c in Transition II is not a weakness of the model, but rather evidence that the model does not impose a tail component when it is not supported by the empirical data.

Goodness-of-fit tests reject overfitting of single distributions, and provide evidence that the single distributions may outperform alternatives in certain scenarios (e.g. if the data are mostly from a single regime), but since the spliced model can explain H_s in terms of wave regimes it brings an interpretative and conceptual advantage. Therefore, in this study model performance is

judged not only in terms of a single metric, but also in terms of the physics and behavior of offshore waves.

5.4 Offshore Operational Implications

These results have direct applications for operation of offshore structures in the Abadi-1 Masela area, which may have a different risk for each H_s regime. In the design conditions, the low-wave regime ($H_s \leq 1.5$ m) defines normal operation conditions, the moderate-wave regime ($1.5 < H_s \leq 2.5$ m) defines restricted operation conditions, and the upper-tail regime ($H_s > 2.5$ m) corresponds to extreme operation conditions.

Transition II has the most favorable transition. Since almost all of the regime observations fall within the low-wave regime and no observations fall within the upper-tail regime, this season has the most potential for mobilization, inspection, logistics, and execution of marine operations that require more favorable sea state conditions.

This is particularly relevant for the East Monsoon, because almost half of the data are in the moderate-wave regime. Operations requiring a certain level of stability and safety, such as lifting operations, material transfer, subsea inspection and drilling support, may be limited or restricted in this regime. Although the upper-tail proportion is not as large as that observed during the West Monsoon, the dominance of moderate-wave conditions may still reduce the efficiency of offshore operations.

The West Monsoon is particularly important in the context of tail-related risk. Although its mean H_s is not as high as that of the East Monsoon, this season exhibits the highest maximum value and the largest upper-tail proportion. This implies that the West Monsoon requires careful consideration in extreme-risk planning, safety-margin evaluation, and the determination of operational limits. In offshore engineering, infrequent but large magnitude events can be very costly in safety and operations.

Such results are also valid for pipeline design. Both the wave motion and the current can affect the stability of subsea pipelines, during installation and when placed at the seabed. This is why wave data from moderate wave seasons or upper-tail dominated seasons can be used in the planning of operations, installations and metocean risk assessments.

Thus, in addition to the statistics, the spliced model may be interpreted as operational information which can be further utilized in risk-based decision support for marine logistics, for drill support, pipeline design, safety analysis, and for weather window and other applications.

5.5 Methodological Contribution and Limitations

The present work contributes with the modeling of the Three-Component Spliced Lognormal-Weibull-K Distribution as the seasonal model in the Abadi-1 Masela offshore area. The modeling of a Three-Component Spliced Lognormal-Weibull-K Distribution differs from single distribution modeling by dividing the wave height domain into three zones with different statistical and operational significances.

As for the methodology, this model has three main advantages: it is able to separately describe both bulk and tail regions. Second, since each distribution corresponds to a certain wave regime, the model has intuitive physical meanings. Third, the model is reasonably adaptable as the tail component is not required to be applied when data for the upper tail are not sufficient, such as Transition II.

Nevertheless, a few limitations need to be noted. Since this analysis is based on the 2022-2026 data period, the reconstruction of long-term extreme events and return levels needs to be interpreted with caution. Second, although the values $h_1 = 1.5$ m and $h_2 = 2.5$ m are used for regime thresholds here, the sensitivity of this choice on the determination of a regime should be tested further. Third, the number of observations in the upper tail is often small in many seasons, which makes the parameters of the K-distribution more uncertain than those for Lognormal and Weibull distributions. Fourth, this study is still focused on H_s as the influential variable, the

other metocean variables, such as the wave period, wave direction, ocean currents, and wind, have not been included in the model.

Nonetheless, these shortcomings do not affect the contributions of this study, but elucidate some of the needs for future studies. Future work should include threshold sensitivity analysis, bootstrap estimation of the model parameters' confidence intervals, return-level analysis, and inclusion of additional metocean variables in similar studies. Furthermore, these H_s modeling data can be used for GIS-based offshore-onshore pipeline routing optimization and least-cost path analysis as well.

Overall, this study showed that the multi-regime spliced model could be an improvement in probabilistic modeling of H_s seasonal variation and offshore risk assessment over existing models. Its contribution was not only statistical fitting, but also the possibility of linking probability distributions to physical meanings and operational requirements in the specific case of the Abadi-1 Masela offshore region.

6. Conclusions

In this paper, we propose the splicing of three component distributions to yield a new distribution called the Three-Component Spliced Lognormal-Weibull-K Distribution to model the seasonal mean wave height data in the Abadi-1 Masela offshore area. The Three-Component Spliced Lognormal-Weibull-K Distribution is formed by splicing the Lognormal distribution for the low wave regime, the Weibull distribution for the moderate wave regime, and the K distribution for the upper wave regime, where ($H_s \leq 1.5$ m) for low wave regime, ($1.5 < H_s \leq 2.5$ m) for moderate wave regime, and ($H_s > 2.5$ m) for upper wave regime.

In addition, the study found that the H_s conditions were considerably season-dependent. The East Monsoon has the highest mean wave height, at 1.539 m, indicating the most energetic sea conditions in general. Transition II has the lowest mean wave height ($H_s = 0.929$ m), the highest percentage of waves within its lower part (89.48%), and no waves within the upper tail. In

contrast, the West Monsoon has the highest maximum H_s (3.870 m) and upper-tail percentage (4.12%). Consequently, the West Monsoon season is most useful for assessing the risk of high waves.

This is confirmed by the analysis of the wave regime, where a single regime cannot describe all the H_s behavior. It can be enough to describe a single regime if it has an extraordinary size, though. The proposed spliced model is more interpretable, as it divides H_s behavior into low-wave, moderate-wave and upper-tail bands. For the spliced model, it improves the model's ability to describe the seasonal characteristics and links the statistical characteristics to an operationally relevant wave regime.

In conclusion, the model provides this research with a physically interpretable probability model of wave height in the offshore Abadi-1 Masela Block (seasonal). This model can be used as a basis for offshore operational planning, weather window analysis, safety analysis, drilling support, or subsea pipeline development risk analysis. This study has employed statistical fitting as well as wave-regime interpretation to provide strong information on wave-induced seasonal hazards in Masela Block.

Declarations

Funding: The authors received no financial support for the research, authorship, and/or publication of this article.

Consent to Publish: Consent to Publish declaration: not applicable.

Ethics Approval and Consent to Participate : Ethics and Consent to Participate declarations: not applicable. This study did not involve human participants, human data, human tissue, or animals.

Author Contributions

G.M.W. contributed to the conceptualization, methodology, data processing, statistical analysis, model development, visualization, and preparation of the original manuscript. S.J.W. contributed to methodology, validation, interpretation of the results, and review of the manuscript. R.R.L. contributed to supervision, interpretation of the offshore engineering implications, and review and editing of the manuscript. All authors read and approved the final manuscript.

Reference

I. Antipov, Analysis of Sea Clutter Data, Defence Science and Technology Organisation, Electronic and Surveillance Research Laboratory, Salisbury, South Australia, Tech. Rep. DSTO-TR-0647, 1998.

Bacă, A., & Vernic, R. (2024). Modeling Data with Extreme Values Using Three-Spliced Distributions. *Axioms*, 13(7), Article 473. <https://doi.org/10.3390/axioms13070473>

de Alfonso, M., Manzano-Muñoz, F., & Gallardo, A. (2025). Product User Manual for Multi-Year WAVE In Situ Product INSITU_GLO_WAV_DISCRETE_MY_013_045 (Issue 2.3, Ref. CMEMS-INS-PUM-013-045). Copernicus Marine In Situ TAC. DOI: 10.13155/54853

Guedes Soares, C., & Scotto, M. G. (2011). Long term and extreme value models of wave data. In C. Guedes Soares, Y. Garbatov, N. Fonseca, & A. P. Teixeira (Eds.), *Marine Technology and Engineering* (Vol. 1, pp. 97–108). Taylor & Francis Group. ISBN 978-0-415-69808-5.

Haselsteiner, A. F., & Thoben, K.-D. (2020). Predicting wave heights for marine design by prioritizing extreme events in a global model. *Renewable Energy*, 156, 1146–1157. DOI: 10.1016/j.renene.2020.04.112.

INPEX Corporation, “Abadi LNG Project.” [Online]. Available: <https://www.inpex.com/english/business/project/abadi.html>. [Accessed: May 23, 2026].

Kubacka, M., Barbuscha, D., Krężel, A., & Gajewski, J. (2025). Spatial and seasonal accessibility of marine research weather windows in the Polish Exclusive Economic Zone. *Scientific Reports*, 15, Article 7094. <https://doi.org/10.1038/s41598-025-91525-8>

Li, W., Zhang, Y., & Zhang, G. (2016). Sea Clutter Simulation Research based on Lognormal Distribution. In *Proceedings of the 2016 4th International Conference on Advanced Materials and Information Technology Processing (AMITP 2016)*, pp. 545–548. Atlantis Press. DOI: 10.2991/amitp-16.2016.109.

MacDonald, A., Scarrott, C. J., Lee, D., Darlow, B., Reale, M., & Russell, G. (2011). A flexible extreme value mixture model. *Computational Statistics & Data Analysis*, 55(6), 2137–2157. <https://doi.org/10.1016/j.csda.2011.01.005>

Moore, D., Eftekhari, A., & Nash, S. (2024). Weather window analysis for the deployment, operation, and maintenance of marine renewable energy devices in Irish coastal waters. *Journal of Ocean Engineering and Marine Energy*, 10(4), 711–729. <https://doi.org/10.1007/s40722-024-00340-2>

Navya, R., Ramakrishna, D., & Sharma, S. (2024). Adaptive Sea-Clutter Model Based Detection for Coastal Surveillance Radar. *Nanotechnology Perceptions*, 20(S6), 237–252. <https://doi.org/10.62441/nano-ntp.vi.1000>.

Patanè, L., Iuppa, C., Faraci, C., & Xibilia, M. G. (2024). A deep hybrid network for significant wave height estimation. *Ocean Modelling*, 189, Article 102363. DOI: 10.1016/j.ocemod.2024.102363

Rossi, R., Murari, A., Gaudio, P., & Gelfusa, M. (2020). Upgrading Model Selection Criteria with Goodness of Fit Tests for Practical Applications. *Entropy*, 22(4), Article 447. DOI: 10.3390/e22040447.

Rusu, E., & Onea, F. (2022). Evaluation of the adverse weather conditions associated to some significant European marine renewable energy projects. *Energy Reports*, 8(Supplement 16), 185–193. <https://doi.org/10.1016/j.egyr.2022.10.205>

Sayama, S., & Sekine, H. (2001). Weibull, log-Weibull and K-distributed ground clutter modeling analyzed by AIC. *IEEE Transactions on Aerospace and Electronic Systems*, 37(3), 1108–1113. DOI: 10.1109/7.953262.

Vanem, E., & Fazeres-Ferradosa, T. (2022). A truncated, translated Weibull distribution for shallow water sea states. *Coastal Engineering*, 172, Article 104077. <https://doi.org/10.1016/j.coastaleng.2021.104077>

Ward, K. D., Tough, R. J. A., & Watts, S. (2013). *Sea Clutter: Scattering, the K Distribution and Radar Performance* (2nd ed.). London, United Kingdom: The Institution of Engineering and Technology. DOI: 10.1049/PBRA025E.

Xu, Y., Cui, L., Jeng, D.-S., Wang, M., Sun, K., & Chen, B. (2025). Hydrodynamic characteristics around offshore pipelines and oscillatory pore pressures in sand beds under combined random wave and current loads. *Theoretical and Applied Mechanics Letters*, 15(3), Article 100575. <https://doi.org/10.1016/j.taml.2025.100575>

Zapevalov, A., Pokazeev, K., & Chaplina, T. (2021). *Simulation of the Sea Surface for Remote Sensing*. Cham, Switzerland: Springer. DOI: 10.1007/978-3-030-58752-9

Zhang, G., Wang, Y., & Wang, W. (2025). Statistical characteristics of Rayleigh and log-normal distribution sea clutter polarization based on Stokes parameters. In *Fifth International Conference on Applied Mathematics, Modelling, and Intelligent Computing (CAMMIC 2025)*, Proceedings of SPIE, 13644, Article 136440F. DOI: 10.1117/12.3070282