Characterization of Long-period Ship Wave Loading and Vessel Speed for Risk Assessment for Rock Groyne Designs via Extreme Value Analysis

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During the last two decades, increasing vessel size in major German estuaries has led to the significant change of the local loading regime i.e. increased importance of ship-induced waves and currents. As a consequence, the intensity of ship-induced loads has increased considerably, resulting in damage to rock structures such as revetments, training walls, and groynes. Research into the causes of rock structure deterioration by the Federal Waterways Engineering and Research Institute (BAW) has shown that for large ships in relatively narrow waterways, the long-period primary ship wave loading has become the most prescient factor for rock structure damage. Looking into the future, it can be expected that the increase in the vessel dimensions will lead to an increase in the ship-wave loading. For this reason, analysing long-term changing trends of long-period ship waves and vessel speed to understand the wave-structure interaction is of significant importance. In this study, the stochastic characterization of long-period primary wave height, drawdown, and speed of the vessel through the water at Juelssand in the Lower Elbe Estuary was analysed via extreme value analysis and copula modeling, and the bivariate return periods were calculated. The one-parameter bivariate copula was utilized to analyse the data. The dependence pattern between the variables was investigated using five parametric copula families: Gaussian, Gumbel, Clayton, Frank, and student's t.

Keywords: Bivariate Copula, Extreme value analysis, Juelssand, Long-period ship wave, Rock groyne, Wave-structure interaction.

1. Introduction

River and coastal infrastructures shall be designed to withstand severe environmental conditions, such as waves, water levels, and large wind speeds. Structural collapses typically take place when two or more of these incidents reach extreme values simultaneously. Therefore, the design of river and coastal infrastructures requires the analysis of extreme circumstances that the structure is expected to encounter during its lifetime, to ensure sufficient structural capacity against critical infrastructure's loads. In relatively narrow navigation channels, the primary waves play a significant role in designing proper coastal defense structures. However, design circumstances for river and coastal structures can be characterized by the joint distribution of several environmental loads. Following certain environmental conditions, there may be correlations between environmental loads, which affect the relative frequency of occurrence for each. Thus, multivariate analysis of the extreme environment is essential in flood risk assessment and coastal design. To determine the return periods for design periods of a structure and consequently the critical design values, the theory of return period has been extensively used in infrastructure design practices. For this purpose, the extreme value analysis is typically performed in the univariate case. However, determining return periods for more than one variable deals with additional issues that require to be considered. In the

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bivariate case, the direct relation between critical design value and return period in the univariate case is no longer valid. For bivariate return periods, different approaches can be applied depending on whether the variables are considered to be dependent or independent. For both independent and dependent circumstances, two hazard scenarios AND-risk and OR-risk can be investigated (Salvadori et al. 2016).

Over the past 15-20 years, continuing damage to rock structures such as revetment, training walls, and rock groynes have been witnessed across major German estuaries (BAW 2010; BAW 2012) Shipping fleet changes, particularly increasing ship dimensions resulted in severe ship-induced waves on estuary infrastructures. Investigations by BAW (2010) and BAW (2012) have shown that the long-period primary ship waves are the most intense hydraulic loadings for structural failure in several regions of German estuaries. Moreover, ship-induced wave loadings are likely to increase in magnitude and frequency, since container vessels keep growing in size. Besides, the proportion of waterway traffic corresponding to ultra-large container vessels (ULCV) of the Triple E and New Panamax classes are likely to rise. Hence, estimation of long-term changing trends of groyne loads and variables affecting the load data such as vessel speed and vessel dimensions and derivation of univariate critical design values associated with different return periods T, are crucial for safety control and design of groyne structure. Besides, determining the joint distributions and bivariate return periods to calculate design periods, is of great importance.

In this regard, prototype implementations and investigations have been conducted by the Federal Waterways Engineering and Research Institute (BAW) to assess the performance of the optimised groyne designs against long-term ship wave loadings at Juelssand in the Lower Elbe Estuary (Melling et al. 2020). The groyne in the tidal Lower Elbe was reconstructed and optimised to increase its structural resistance. Ship-induced wave loads were recorded during the field experiment. In this study the stochastic characterization and long-term variability of the primary wave height (H_p), drawdown (D_r) and speed of a vessel through water (V_i) were analysed via extreme value analysis and copula modeling.

The method of extreme value analysis (EVA) is typically implemented by applying the cumulative distribution functions to estimate the long-term variation as well as the extrapolation of historical data of a variable of interest (Goda 1992). The unknown parameters of the distribution function can be obtained using fitting methods such as maximum likelihood estimate (MLE), method of moments (MOM), least square method (LSM), etc. (Martins and Stedinger 2000; Coles et al. 2001). Niroomandi et al. (2018) performed extreme value analysis based on generalized extreme value distribution and generalized Pareto distribution functions to obtain design wave heights for different wave periods.

Additionally, for risk assessment and design conditions of coastal infrastructures, understanding the joint behavior of stochastic variables is essential. The joint distribution and dependence structure between each pair of stochastic variables can be determined through bivariate copula modeling. By applying copula approaches, the dependence structure is determined separately from the marginal distributions (Genest and Favre 2007). For the bivariate copulas, different copula families have proved their effectiveness: the Elliptical copulas such as the Gaussian or t copulas, and the Archimedean copulas such as the Gumbel or Clayton copulas to characterize the precipitation for risk assessment of infrastructures (Morales-Nápoles et al. 2017), the Hierarchical Archimedean copulas to characterize the wave-storms in the Catalan coast (Lin-Ye et al. 2016) and the vine-copula for characterization of time series significant wave height and the associated mean zero-crossing periods in the North sea (Jäger and Nápoles 2017) have been applied and found valuable.

The main objective of this study is to define the bivariate probabilities of exceedance and consequently the bivariate return periods for design periods for each pair of variables primary wave height, drawdown, and speed of vessel through water. To reach this goal, for hazard scenarios AND-risk and OR-risk, the traditional approach for independent random variables and the copula-based approach for dependent random variables were implemented. In the traditional method, all variables are considered to be extreme and treated separately since they are assumed to be independent. Thus, the possible dependence between variables or processes is not taken into account. In the copula-based method, only the dominant variable is extreme and its concomitants are not necessarily extreme. The correlation between every pair of variables is calculated using copulas.

This paper outlines the necessary steps to be able to calculate bivariate exceedance probabilities and bivariate return periods and provides the results of such an analysis applied to the data recorded at an optimised groyne structure at Juelssand in the Lower Elbe estuary. Initially, the univariate extreme value analysis (EVA) based on the generalized extreme value distribution function (GEV) was performed and the critical design values for extreme data were obtained. Calculating the bivariate return periods (for dependent random variables) requires the determination of joint distribution between each pair of random variables. For this purpose, five copula families comprising Gaussian, student's t, Clayton, Gumbel, and Frank were used.

2. Wave-structure Interaction

The water level alterations generated by a passing ship are divided into the systems of primary and secondary waves (Schiereck and Verhagen 2012). Fig. 1 shows the schematic depiction of primary and secondary ship-induced waves system in confined and shallow water. The primary wave begins with a bow wave, afterward a depression in water level is established along the vessel's hull and a stern wave is produced at the end. This stern wave generally contributes to severe damage to the coastal defence structures. The long-period primary wave travels across the coastline at an identical speed with the vessel speed and is hydraulically bound to the vessel hull. As a result of the stern wave transition, the ambient water level is restored as the water level depression (drawdown) is reimbursed with the slope supply flow (Melling et al. 2020). The primary wave height is obtained as the difference between the highest and lowest water levels. While the drawdown is the difference between the ambient water level and the lowest water level.

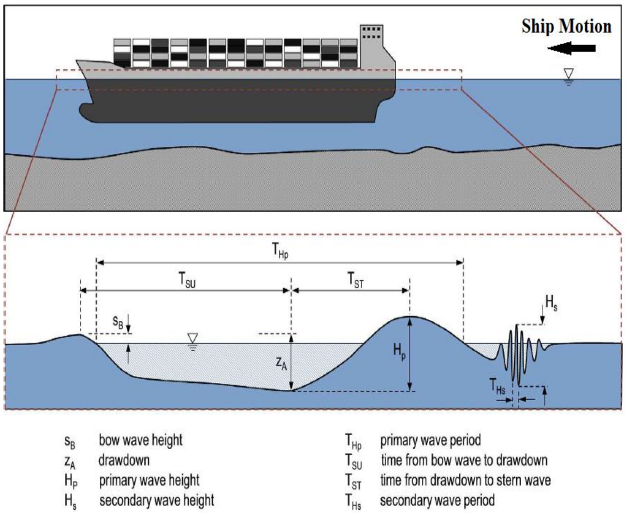


Fig.1. Schematic cross-section of ship wave loading in shallow and confined water with parameters description (Melling et al. 2020).

3. Site Description and Prototype Field Survey

The investigated groyne structure (B29) is situated at the Juelssand on the Lower Elbe Estuary, alongside the main channel to the Hamburg port (Fig. 2). In this region, the groyne structures experience significant structural failure owing to the action of the ship-induced waves on them. Thus, pilot research was done by BAW, and the groyne B29 was reconstructed using optimised design approaches. Sufficient long-time series of loading data were recorded at the groyne prototype with a monitoring program. To measure the water level alterations, pressure sensors (Driesen & Kern and RBR) were installed on the groyne at its different locations in the head, crest, foot, and root areas. The wave recording for the groyne B29 was conducted in the time interval of the field experiment from 07.2015 to 02.2019 (Melling et al. 2020). In this study, the wave measurements at the pressure sensor 1 installed on the tip of the groyne (Fig. 2) were carried out for over 18000 events from which the extreme values were extracted.

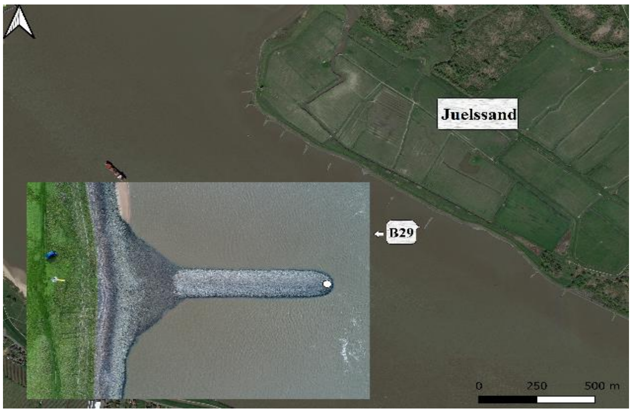


Fig.2. Study site location at Juelssand with investigated groyne B29 (The position of pressure sensor 1 is shown by a white dot).

4. Extreme Value Analysis (EVA)

Extreme value analysis (EVA) is a probabilistic technique that allows for estimating the likelihood of extreme events in a sample (Coles et al. 2001). EVA has wide utilization in various fields of study such as business, finance, public health, climate change, marine coastal engineering, etc. There are two methods for extreme value analysis comprising block maxima and peak-over threshold (POT). In the block maxima approach, the data are divided into the constant non-overlapping intervals named block (e.g., annual, seasonal, monthly, and daily maxima), then the peak value of each block is chosen. The extreme value distribution is then fitted to a sample of maxima. For the POT approach, the high threshold values are initially selected, then the extreme value analysis is performed for the data above the given thresholds. Theoretically, it has been proven that for an adequately long sequence of independent and identically distributed random variables, the maxima of a sample of size n, can be fitted into the generalized extreme value distribution (GEV). The cumulative distribution function of the GEV distribution ($G(z)$) is given as follows (Coles et al. 2001):

$$G(z) = exp\left\{-\left[1+\varepsilon\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\varepsilon}\right\} \quad \varepsilon \neq 0 \qquad (1)$$

$$G(z) = exp\left\{-\exp\left(-\left(\frac{z-\mu}{\sigma}\right)\right)\right\} \quad \varepsilon = 0 \qquad (2)$$

where ε, σ and μ are the shape, scale, and location parameters, respectively. The GEV distribution consists of three types: for $\varepsilon = 0$ (Type I) the GEV is Gumbel distribution, for $\varepsilon > 0$ (Type II) is Fréchet distribution and for $\varepsilon < 0$ (Type III) is Weibull distribution. One main application of EVA is the approximation of the critical design value (X_C), a value that is estimated to exceed in the unit of time T. For example, on average every 50 years, which causes structural destruction. The critical design value X_C associated with a return period $T = 1/P(X > X_C)$ (P is the probability of exceedance) is the inverse of the cumulative distribution function of the generalized extreme value distribution $G(z)$ and can be determined as follows (Coles et al. 2001):

$$X_C = G^{-1}(1-P) = \mu - \frac{\sigma}{\varepsilon}[1 - \{-\log(1-P)\}^{-\varepsilon}] \quad \varepsilon \neq 0 \quad (3)$$

$$X_C = G^{-1}(1-P) = \mu - \varepsilon log\{-\log(1-P)\} \quad \varepsilon = 0 \quad (4)$$

In this paper, primarily the generalized extreme value distribution (GEV) function was fitted to the monthly maxima data (41 data), and the critical design values for different return periods for the primary wave height, drawdown, and speed of vessel through water variables were obtained. It has to be noted that in this case, all the variables were considered extreme. The unknown parameters of the fitted GEV distributions were obtained through the maximum likelihood estimate (MLE) method. The maximum likelihood is a common and flexible approach for the estimation of unknown parameters of a distribution function. Amongst fitting methods, the MLE is unique as it shows high adaptability to the changes in the models. Particularly, by modifying the model through changing the estimating equations, the underlying technique remains unchanged. Additionally, the MLE assigns the greatest probabilities to the observations, by adapting a model with the highest likelihood (Coles et al. 2001). Given return periods and exceedance probabilities, the design values were calculated.

5. Bivariate Copula

A bivariate copula is a joint distribution on a unit hypercube for which the marginal distribution of each random variable is uniform on the interval [0, 1]. Copulas are utilized to characterize the dependence structure between random variables. Assuming X and Y continuous random variables, their joint cumulative distribution function $F_{X,Y}(x,y)$ can be described in terms of copula and univariate marginal distribution functions (Morales-Nápoles et al. 2017):

$$F_{X,Y}(x,y) = C[F_X(x), F_Y(y)] = C(u,v) \quad (5)$$

where C is the copula function, $F_X(x)$ and $F_Y(y)$ are the marginal cumulative distribution functions of the random variables X and Y (or uniform ranks of X and Y), and u and v are marginal uniform variates on the interval [0, 1]. In copula modeling, the rank correlation coefficient is equal to Pearson's product-moment correlation coefficient computed with the ranks of random variables X and Y. The Pearson's product-moment correlation is defined as:

$$\rho\,(X,Y) = \frac{E(X,Y) - E(X)E(Y)}{\sqrt{\mathrm{var}(X)\mathrm{var}(Y)}} \quad (6)$$

In the current study, the joint distribution between every pair of random variables was modeled using copula functions. Two types of copulas comprising Elliptical (Gaussian and student's t) copulas and Archimedean (Clayton, Gumbel, and Frank) copulas were fitted to the data, and the dependence pattern between each pair of variables was determined. For copula modeling, the primary wave height is considered the dominant variable, and hence extreme. The remaining variables (drawdown and speed of vessel through water) are its concomitants and not necessarily extreme. The goodness of fit tests for copulas Cramer-von Mises M statistic and semi-correlations techniques were performed for different copulas. The Cramer-von Mises M statistic is the sum of square variations between the fitted (parametric) and empirical copulas and for a sample of length n is defined as follows (Genest, Rémillard, and Beaudoin 2009).

$$M_n(u) = \sum_{|u|} \left\{C_{\theta_n}(u) - B(u)\right\}^2, \quad u \in [0,1]^2 \quad (7)$$

where $C_{\theta_n}(u)$ is the parametric copula, θ_n is the unknown parameter of parametric copula which can be derived from the observations and $B(u) = \sum 1(U_i \leq u)$ is the empirical copula. The best-fit copula can be defined based on the lowest values of the Cramer-von Mises M statistic test. The method of semi-correlation is another diagnostic technique to obtain the best fit copula (Joe 2015). In the semi-correlation test, Pearson's product-moment correlation coefficients are calculated in the upper and lower quadrants of the observations transformed to standard normal. Positive correlations are corresponding to the upper right (NE) and lower left (SW) which are computed according to the following formulas (Morales-Nápoles et al. 2017):

$$\rho_{ne} = \rho\left(Z_i, Z_j \middle| Z_i > 0, Z_j > 0\right) \quad (8)$$

$$\rho_{sw} = \rho\left(Z_i, Z_j \middle| Z_i \leq 0, Z_j < 0\right) \quad (9)$$

where (Z_i, Z_j) is the standard normal transformation of (X_i, X_j). The negative semi-correlations in the upper left ρ_{nw} (NW) and lower right ρ_{se} (SE) can be computed analogously to Eqs. (8) and (9). In general, the rank correlation coefficient of the whole dataset is compared to the largest absolute value of semi-correlation in a specific quadrant and the opposite quadrant reveals tail dependence.

6. Bivariate Extreme Value Analysis

The process of performing extreme value analysis for two or more variables is more complicated than performing univariate EVA. For the univariate analysis, the most extreme observations of a set of variables are obtained by extracting the maximum or minimum values. For bivariate cases, peak values of one most dominant variable are selected. For the remaining variables, the corresponding concomitant values recorded coinciding with the dominant variable are chosen. For the bivariate extreme value analysis, various methodologies can be applied based on that the variables are taken into account dependent or independent. For instance, the AND bivariate exceedance probability of two independent random variables that occur simultaneously is calculated by multiplying the univariate probabilities of occurrence of variables. For dependent events, the joint distribution and dependence structure between every pair of variables can be determined in terms of bivariate distributions and copulas. By applying a copula function, the dependence structure is obtained independently from the marginal distributions (Sellés Valls 2019).

6.1. *Bivariate return period*

Using the definition of the univariate return period (section 4), for different hazard scenarios of AND-risk and OR-risk (Salvadori et al. 2016), the bivariate return periods for the dependent random variable X and Y are given as follows:

$$T_{AND} = \frac{1}{P(X>x,Y>y)} = \frac{1}{1-F_X(x)-F_Y(y)+C(F_X,F_Y)} \quad (10)$$

$$T_{OR} = \frac{1}{P(X>x \text{ or } Y>y)} = \frac{1}{1-C(F_X,F_Y)} \quad (11)$$

where C is the copula. For the AND-return period (T_{AND}), both variables exceed their critical design values, while for the OR-return period (T_{OR}), at least one of the variables exceeds its critical design value. For independent random variables, all the variables are considered extreme, and extreme value analysis is applied individually to each random variable (traditional approach). To calculate the AND bivariate probabilities of exceedance, we can easily multiply both individual probabilities of exceedance. The OR bivariate exceedance probability is equal to the sum of the individual probabilities mines the AND bivariate probability of exceedance.

7. Results and discussion

To design the river and coastal structures, it is essential to take into consideration the impact of multivariate environmental loads. Accordingly, the joint distribution between variables is commonly determined. Moreover, by calculating the joint probabilities of occurrence, the joint return periods for design periods are obtained. To achieve this objective, in this study, primarily the univariate critical design values for the primary wave height (H_p), drawdown (D_r) and speed of vessel through water (V_i) variables were obtained by fitting the generalized extreme value distribution function (GEV) to the extreme values. Since the observations at groyne B29 were recorded for the duration of 6 years (2015-2019), sufficient data are not available to perform the GEV method for the yearly maxima. Thus, for each random variable, 41 monthly maxima observations were extracted, which is sufficient to obtain reliable results as according to Cook (1985), at least 20 extreme observations are essential to perform the Block maxima method. The monthly maxima were arranged in ascending order and the non-exceedance probabilities (P_i) were calculated through plotting position formula of Weibull as follows (Goda 2011):

$$P_i = \frac{m}{N+1} \quad (12)$$

where m is observations in the ascending order and N is the number of data. In Fig. 3, the fitted GEV distribution to extreme observations for primary wave height is shown in terms of the cumulative exceedance probability plot. The solid line is the calculated values resulting from the fitted GEV distribution. In addition, the 95% and 68% confidence intervals are plotted. Most of the empirical values fall within the 95% confidence intervals, indicating that the GEV is a reliable model for the investigated data. The parameters and type of the GEV distribution for each random variable are presented in Table 1. The type of GEV is typically determined based on the shape parameter. For the primary wave height variable, the shape parameter revealed a Fréchet distribution, however, its value is approximately zero, and thus the best fit distribution is considered Gumbel. For the drawdown variable, the shape parameter is negative, but it's very close to zero, thus a Gumbel distribution was interpreted. The distribution of speed of vessel through water was obtained as Weibull. For different return periods, the univariate design values are derived from Eqs. (3) and (4) (Table 2).

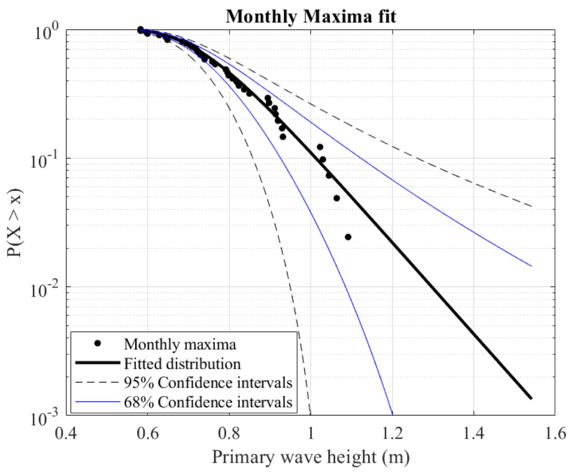
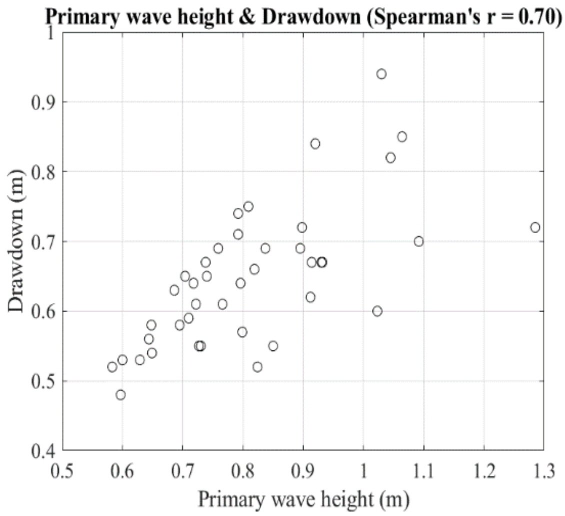


Fig.3. Cumulative exceedance probability plot for the extreme primary wave height variable.

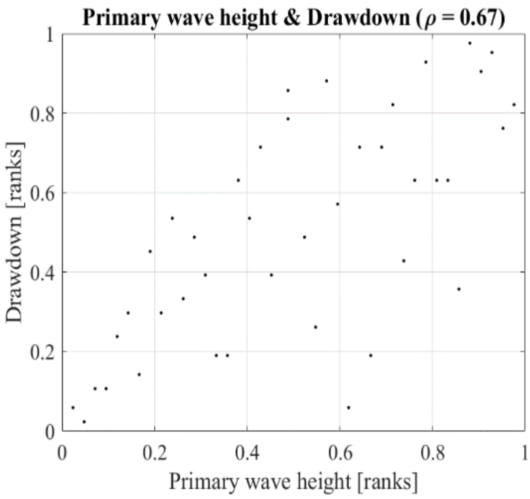
Table 1. Parameters of the GEV distributions and type of GEV fit.

variables	Shape parameter ε	Scale parameter $\sigma\ (m)$	location parameter $\mu\ (m)$	Fitted GEV
H_p	0.0031	0.12	0.72	Gumbel
D_r	-0.04	0.07	0.62	Gumbel
V_i	-0.3	1.9	16.17	Weibull

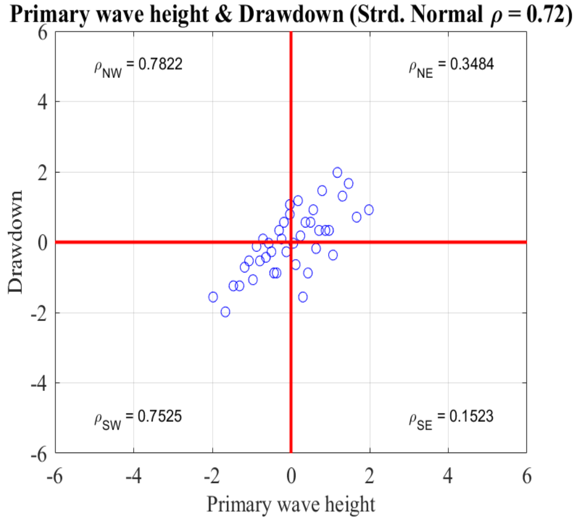
At the next phase, the joint distribution and dependence pattern between each pair of variables were determined through copulas. The correlation between primary wave height and drawdown and the transformation from empirical data (Fig. 4 (a)) to pseudo-observations (Fig. 4 (b)) are illustrated. The Spearman's correlation coefficient for H_p and D_r was obtained 0.7. For the pair H_p and V_i and the pair D_r and V_i, the Spearman's correlation coefficient was obtained 0.44 and 0.17, respectively. The pseudo-observations are the observations transformed into the intervals [0,1] using the empirical margins. The data were fitted to the five copulas. The goodness of fit semi-correlation results for primary wave height and drawdown is shown in Fig. 4 (c). Results of semi-correlations and Cramer-von Mises M statistic indicated that the best-fit copula for the pair H_p and D_r and the pair H_p and V_i is Gumbel. The Gaussian copula is the best model for D_r and V_i in terms of dependence structure. The results of copula modeling (best-fit copula) will be used to calculate the bivariate probabilities of exceedance and consequently the bivariate return periods.



(a)



(b)



(c)

Fig.4. Primary wave height and drawdown: (a) original observations, (b) pseudo-observations, (c), semi-correlations at each quadrant.

Results of bivariate exceedance probabilities and bivariate return periods for both independent and dependent random variables for AND-risk and OR-risk hazard scenarios are shown in Tables 2 and 3. It has to be noted that since the analysis was conducted for monthly maxima data, for a return period equal to 10 years, the corresponding exceedance probability is calculated as 1/(10*12)= 0.00833. The wave measurements were carried out for 12 months.

Table 2. Univariate design values (columns 3-6), probabilities of exceedance, and return periods for AND-risk and OR-Risk scenarios (random variables are considered to be independent and extreme).

Return period (years)	Univariate exceedance probability (yearly)	H_p (m)	D_r (m)	V_i (kn)
10	8.33E-03	1.32	0.96	21
25	3.33E-03	1.43	1.02	21.36
50	1.60E-03	1.52	1.06	21.58
100	8.33E-04	1.6	1.1	21.75

Table 2 (continued)

AND exceedance probability	AND return period	OR exceedance probability	OR return period
6.94E-05	1.44E+04	1.66E-02	6.03E+01

1.11E-05	9.02E+04	6.65E-03	1.50E+02
2.56E-06	3.91E+05	3.20E-03	3.13E+02
6.94E-07	1.44E+06	1.67E-03	6.00E+02

Table 3. Probabilities of exceedance (P) and return periods (R) for AND-risk and OR-risk scenarios (random variables are considered to be dependent, only H_p is extreme).

Return period (years)	AND-P	AND-P	AND-P	AND-R	AND-R	AND-R
	(H_p, D_r)	(H_p, V_i)	(D_r, V_i)	(H_p, D_r)	(H_p, V_i)	(D_r, V_i)
10	4.51E-03	3.57E-03	2.75E-04	18.46	23.34	303
25	1.86E-03	1.91E-03	1.16E-04	44.75	43.44	712.77
50	9.53E-04	1.07E-03	6.56E-05	87.35	77.24	1269.98
100	5.08E-04	6.21E-04	3.69E-05	163.98	134.07	2256.43

Table 3 (continued)

Return periods (year)	OR-P	OR-P	OR-P	OR-R	OR-R	OR-R
	(H_p, D_r)	(H_p, V_i)	(D_r, V_i)	(H_p, D_r)	(H_p, V_i)	(D_r, V_i)
10	1.21E-02	1.56E-02	1.9E-02	6.85	5.32	4.37
25	4.04E-03	1.11E-02	1.31E-02	16.52	7.6	6.34
50	2.62E-03	9.58E-03	1.11E-02	31.75	8.69	7.6
100	1.41E-03	8.79E-03	9.62E-03	58.96	9.47	8.65

Considering the traditional method (independent variables), the return period of a response that is based on the parameters from an AND probability is smaller than the return period for the given parameter combination. Whereas, the return periods derived from an OR probability of exceedance could be more reasonable in this case. However, since there is a correlation between each pair of random variables, it is essential to consider the dependency between them. The return periods resulting from OR probabilities for dependent variables (Table 3) are smaller than the return periods for univariate variables (Table 2, column 1), and are smaller than OR-return periods for independent random variables (Table 2). This is a direct impact of considering the dependence between variables. Thus, the OR-return period resulting from the dependent case could not be used herein.

Taken into consideration both independent and dependent cases, the AND probabilities of exceedance for the traditional method (Table 2) are smaller than the calculated AND probabilities of exceedance for the dependent variables (copula-based method) (Table 3). As a consequence, the obtained return periods from the traditional method are much greater than those derived from the copula-based method, which is not reasonable. Generally, the more reliable return periods were obtained from the OR-return period for independent random variables and AND-return periods for dependent random variables. However, since in the infrastructure design practices, it is essential to consider the interaction between variables, thus, the AND-return periods for dependent random variables may be taken for a reliable design.

8. Conclusion

In the current study, the stochastic characterization of primary wave height (H_p) and drawdown (D_r) and speed of vessel through water (V_i) was investigated for an optimised groyne design at Juelssand in the Lower Elbe Estuary and bivariate return periods for AND-risk and OR-risk hazard scenarios were calculated by considering random variables both dependent and independent. The univariate critical design values were obtained by fitting the GEV distribution function to the extreme observations. The dependence pattern between each pair of variables was determined using copulas. The fitted GEV distribution for H_p and D_r considered as Gumbel, and the Weibull distribution was the best fit for V_i. Results of copula modeling indicated that the Gumbel copula is the best model for the pair H_p and D_r and the pair H_p and V_i. The best-fit copula for D_r and V_i was found to be Gaussian. The results of the bivariate analysis indicated that the AND-return periods for the dependent model may be considered for a design.

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