frontiers | Frontiers in Built Environment

ORIGINAL RESEARCH
published: 08 July 2022
doi: 10.3389/fbuil.2022.816020

A Copula-Based Simulation of Wave-Induced Pore Water Pressure Gradient and Local Acceleration Within Surf Zone for Natural and Laboratory Barred Beach Profiles

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Specialty section:
This article was submitted to Coastal and Offshore Engineering, a section of the journal Frontiers in Built Environment

Received: 16 November 2021
Accepted: 13 June 2022
Published: 08 July 2022

Citation:
Tabasi M, Suzuki T and Cox DT (2022) A Copula-Based Simulation of Wave-Induced Pore Water Pressure Gradient and Local Acceleration Within Surf Zone for Natural and Laboratory Barred Beach Profiles. Front. Built Environ. 8:816020. doi: 10.3389/fbuil.2022.816020

Wave-induced pressure gradients and local accelerations are important interconnected physical mechanisms involving several hydrodynamic and morphodynamic coastal phenomena. Therefore, to provide a reliable and realistic hydrodynamic and morphodynamic simulation, the dependencies among different parameters, such as water level, pressure gradient, local acceleration, and sediment concentration, should be considered. Herein, a copula-based simulation is presented for modeling multivariate parameters and maintaining their statistical characteristics within the surf zone. Archimedean and elliptical copula families are applied to investigate the dependency construction between the parameters in two case studies: one from a field site on the east coast of Japan, and another from a large-scale laboratory barred beach profile. The dependency between variables is evaluated using Kendall's τ correlation coefficient. The water level, pressure gradient, and local acceleration are shown to be significantly correlated. The correlation coefficients between the variables for the natural beach are lower than the laboratory data. The marginal probabilistic distribution functions and their joint probabilities are estimated to simulate the variables using a copula approach. The performance of the simulations is evaluated via the goodness-of-fit test. The analysis shows that the laboratory data are comparable to the field measurements, implying that the laboratory simulation results can be applied universally to model multivariable joint distributions with similar hydrodynamic conditions.

Keywords: wave-induced pressure gradient 1, local acceleration, surf zone, copula, multivariate analysis, barred beach

1 INTRODUCTION

Surf zone sandbars are ephemeral nearshore bathymetric features that play a fundamental role in beach profile morphology (Ribas et al., 2012; Tabasi et al., 2017; Tabasi et al., 2018; Suzuki et al., 2018; Bryan et al., 2019). Surf zone sandbars enhance depth-induced wave breaking and subsequently initiate complex fluid motions generated by breaking waves in the surf zone. As a result of these fluid motions and the resulting sediment suspension and transport, the morphology of the nearshore can change rapidly. Because the morphological response of surf zone sandbars is governed by nearshore hydrodynamics, the prediction of surf zone sandbar morphological evolution is associated with the understanding of nearshore waves and current characteristics.

Field sites have been established along many coastlines to measure coastal hydrodynamic and morphodynamic characteristics, depending on the available budget and data necessity. Therefore, instruments for recording data may be deployed for a short or long duration. In some critical locations, for gathering data over seasons or years, instruments are installed permanently with the requirement for regular maintenance. However, owing to time and financial limitations, long-term data recording is not practical. Moreover, the gathered datasets may include missing data either due to the maintenance procedure of instruments, intentional pausing of recording to maintain the safety of instruments during coastal disasters or extreme events, and failure of instruments. Because of the abovementioned issues and coastal regions where no captured data are available, it is reasonable to generate data using different methods. The generated data should be modified and validated using the data recorded from a nearby location.

Generating data using different methods is important in turbulent environments, such as the surf zone, where not only do hydrodynamic parameters change abruptly, but also morphological components such as the sandbar shape change rapidly. Therefore, an improved prediction of hydrodynamic and morphodynamic parameters is closely associated with the understanding of several interconnected mechanisms, such as acceleration, velocity skewness, and pressure gradient, to obtain accurate surf zone sand bar shapes. Although several morphodynamic models have been proposed (e.g., Roelvink et al., 2010; Kuriyama, 2012; Tabasi et al., 2020), a comprehensive model that includes all interconnected mechanisms applicable to various coastal areas has not yet been developed. Researchers are attempting to include and evaluate several interconnected parameters in morphodynamic models. Suzuki et al. (2009) and Anderson et al. (2017) have shown that pressure gradients within sediment layers driven by waves and currents resulted in surf zone sandbar migrations. Subsequently, they investigated the pore water pressure gradient and current acceleration based on the wave height.

Various methods can be used to simulate water level, pressure gradients and accelerations. Fundamentally, the flow properties can be determined by solving the Navier-Stokes equations. However, due to turbulence terms in these equations, the exact solution of these equations is still incomplete except for very small control volumes. Nevertheless, these equations can be simplified by neglecting the term describing viscous motions of the flow to yield the Euler equations. Using intensive numerical models, pressure gradients and accelerations can be obtained using Euler's inviscid momentum equations for a short duration. For solving these equations, the volume of fluid should be discretized or divided into several cells which is known as mesh. Open-source software (e.g., OpenFOAM, DualSPHysics) is readily available to obtain water level, pressure gradients, and accelerations via momentum equations (Brown et al., 2016; Lowe et al., 2019). However, depending on the required accuracy and the complexity of the flow, a more sophisticated discretization method with a high mesh resolution is required. Thus, the implementation of the numerical model will be more complicated. Because of the complicated model setup and code-compiling processes, the model computation time is often extremely long. Nevertheless, numerical simulations can be very useful approaches to predict and realize a wide variety of water environment processes.

Linear wave theory describes the propagation of waves or fluid surface changes assuming that the fluid is inviscid, incompressible, irrotational, and the surface of the fluid has a sinusoidal shape. However, the linear wave theory is valid for uniform small-amplitude waves and the linear wave model should be modified by including the effects of second-order nonlinearities such as Stokes drift, wave crest conservation, and mean mass conservation. Among the second-order wave approaches for solving the nonlinear waves, Stokes's approach is very well-known. This approach proposes a solution for applying the boundary condition at the free surface position expanding the potential flow quantities in a Taylor series. Depending on the required accuracy, higher-order nonlinear wave approaches can be estimated accordingly. Valuable reviews about different wave theories and proposed models for the simulation of the water surface can be found in (Forristall, 2000; Tayfun and Fedele, 2007; Myrhaug et al., 2015).

Statistical methods are useful for simulating wave and wave-induced parameters such as wave heights, pressure gradients, and accelerations. For example, wave heights can be simulated using statistical-based wave spectra such as Neuman, JONSWAP, ITTC, and P-M spectrums. These spectra have been performed and evaluated in several coastal engineering studies such as Dawson et al. (1993); Ryabkova et al. (2019); Edwards et al. (2021). Similarly, Monte Carlo is a reliable simulation method (Bang Huseby et al., 2013; Clarindo et al., 2021) and can be used to account for the joint probability of correlated coastal parameters. Statistical multivariate regression models have been used to represent the relationships between dependent different parameters (Condon and Sheng, 2012). Although regression modeling is a very common method and almost all statistical packages are equipped with regression tools, the reliability of regression models generally decreases as the number of parameters increases.

Because of the complexities of coastal phenomena, the interdependency of coastal parameters should be considered in the calculations. In statistics, if the magnitude of one variable affects the magnitude of other variables, then the particular variable can be considered dependent. The dependency between two variables can be described using correlation coefficients. As mentioned above, owing to the importance of the dependency between variables, several methods have been proposed to model the bivariate joint probability of two variables. Plackett (1965) proposed a method for constructing a one-parameter bivariate distribution based on marginal functions. Vrijling and Bruinsma (1980) applied marginal distributions to model the significant wave height (H_s) and wave steepness (S_p). In this model, the peak period (T_p) is described as a function of

(H_s, S_p). Bitner–Gregersen and Haver (1989) developed a conditional modeling approach to model the joint distribution of H_s and T_p using regression curves. Zachary et al. (1998) presented a non-parametric approach to model meta-ocean parameters. Repko et al. (2004) described and compared five approaches to model the dependency between H_s and T_p. Sellés Valls (2019) summarized that five bivariate models presented limitations when variables other than H_s and T_p were used.

The copula approach, originally proposed by Sklar (1959), allows for the marginal distribution of dependent variables to be estimated separately based on a dependent structure, and numerous studies have been conducted to investigate the applicability to a range of problems. Nelsen (2006) described the construction of different copulas and their properties, whereas Schmidt (2006) provided a more concise guide into the theory of the copula approach. In coastal science and engineering, by De Waal and Van Gelder (2005) proposed the Burr–Pareto–logistic copula to model extreme significant wave heights and wave periods during severe storm events. De Michele et al. (2007) established a four-dimensional model for the analysis of significant wave height, storm duration, inter-arrival time, and wave direction. Salvadori et al. (2011) proposed multi-parameter multivariate extreme value (MEV) copulas to assess return periods and design qualities. Wahl et al. (2011) applied the Gumbel–Hougaard copula to analyze storm surge parameters. Subsequently, Wahl et al. (2012) extended the proposed bivariate statistical model to investigate the extreme significant wave height and peak sea level. Corbella and Stretch (2013) applied Archimedean and MEV copulas to simulate storm parameters such as peak wave period, storm duration, and inter-arrival time.

More recently, Li et al. (2014a) estimated coastal dune erosion along the Dutch coast via a statistical simulation of storm events developed by Li et al. (2014b), who employed a Gaussian copula to simulate the dependency relation of ($H_{s,max}$, h, D, T_p), where $H_{s,max}$ is the maximum significant wave height during storms; h is the water dept, D is the storm duration; T_p is the peak wave period. Salvadori et al. (2016) presented a multivariate copula-based framework for performing multivariate design during disasters and providing failure probabilities. Jane et al. (2016) developed a copula-based approach focusing on the Gaussian and Student's t copulas to predict H_s and the wave direction (θ) at different locations along the southern coast of England. Lin et al. (2020) proposed a copula mixture model to provide a long-term joint distribution for H_s and a mean zero-crossing wave period (T_z).

The aim of this study is to provide a computationally efficient approach to model the joint probability and distribution for the height of the wave crest above the still-water level (η_{max}), the maximum horizontal pressure gradient ($\partial(P/\rho)/\partial x_{max}$) induced by η_{max}, and the maximum local horizontal acceleration ($\partial u/\partial t_{max}$) induced by η_{max} within the surf zone of a natural coastal zone and a large-scale wave flume using a fully statistical approach. Initially, several theoretical marginal distribution functions were employed to fit the empirical cumulative probability of (η_{max}, $\partial(P/\rho)/\partial x_{max}$, $\partial u/\partial t_{max}$). Subsequently, copula approaches were used to provide the dependence structures between variables. The importance of the pressure gradient and current acceleration for surf zone sandbars has been investigated extensively. Although numerous studies have been conducted to investigate the interdependency of coastal parameters using copula-based statistical modeling, the performance of copula approaches for simulating pressure gradients and acceleration is yet to be investigated.

The remainder of this paper is organized as follows: **Section 2** describes the marginal distribution functions, the copula concept, and the description of the methodology for dependency construction using the copula approach. The methodology used in this study can be broadly categorized into two subsections, which are described in **Sections 2** and **3**. In **Section 3**, a summary of the experimental tests is presented prior to the results obtained from the laboratory tests, and the simulated and observed data are compared. Finally, the discussion and conclusions are presented in **Sections 4** and **5**, respectively.

2 STATISTICAL MODELS AND COPULA THEORY

2.1 Empirical and Theoretical Cumulative Distribution Functions

The empirical cumulative distribution function (ECDF) in statistics represents the cumulative distribution probability of the measured data and is defined as follows:

$$P(n) = \frac{1}{n+1}\sum_{i=1}^{n}\alpha_i \tag{1}$$

where n is the total amount of measured data, and $\sum_{i=1}^{n}\alpha_i$ represents the ith rank of the measured data.

Theoretical cumulative distribution functions (TCDFs, also known as marginal functions) have been proposed to fit the cumulative distribution probability based on their statistical characteristics. Extreme value (EV), normal, generalized extreme value (GEV), logistic, Nakagami, Rician, Weibull, inverse Gaussian, and gamma distributions were tested for fitting. **Supplementary Table S1** shows the equations of the TCDFs and their parameters selected for this study. The parameters of the TCDFs can be varied over a wide range to fit the curve of TCDFs with the ECDF. To achieve a good estimation of the parameters, the maximum likelihood estimation (MLE) method was used. The goodness of fit (GOF) between the TCDFs and ECDFs was assessed using the two-sample Kolmogorov–Smirnov (KS) test. The KS test, expressed as $F_n(x)$, is a nonparametric hypothesis test that evaluates the difference between the TCDF and ECDF values. In other words, the KS test can be used to reach a decision regarding the GOF of selected TCDFs using the following equation:

$$F_n(x) = \frac{1}{n}\sum_{i=1}^{n} I_{[-\infty,x]}(X_i) \tag{2}$$

where $I_{[-\infty,x]}(X_i)$ are indicator functions. The KS test is based on the null hypothesis. If $X_i < x$, then the indicator function equals 1, which indicates the rejection of the null hypothesis; otherwise, the indicator factor equals 0, and the GOF of the cumulative distribution functions (CDFs) can be evaluated and ranked using asymptotic p-values ranging from 0 to 1.

2.2 Copula Theory

The theoretical foundation for the application of copulas is derived from Sklar's theorem (Sklar, 1959). According to Sklar's theorem, a copula function C describes the dependence structure between TCDFs, as follows:

$$F(x_1, x_2, \ldots, x_n) = C[F_1(x_1), F_2(x_2), \ldots, F_n(x_n)] \quad (3)$$

where $F_1(x_1), F_2(x_2), \ldots, F_n(x_n)$ are TCDFs, and $x_1, x_2, \ldots, x_n$ are random variables. By considering (X, Y) as two dependent variables, a joint distribution by specifying marginal univariate distributions, $u = F_X(x)$ and $v = F_Y(y)$, can be constructed as $F_{XY}(x, y)$. Let

$$F_{XY}(x, y) = C(u, v) \quad (4)$$

where C is a copula function for any x and y. The unique values for $C(u, v)$ can be obtained when $F_X(x)$ and $F_Y(y)$ are both continuous. Conversely, by considering $C(u, v)$ as a copula and $F_X(x)$ and $F_Y(y)$ as distribution functions, $C(u, v)$ can be a joint distribution function with margins of $F_X(x)$ and $F_Y(y)$. Based on the assumption that the marginal functions are continuous, the random variables u and v are uniformly distributed within the range of 0–1. Copula models are multivariate models with cumulative marginal distribution functions. Hence, the range values and domain for a copula model are distributed in the interval [0, 1].

Based on Sklar's theorem, the joint density for marginal distributions with densities of $f_X(x)$ and $f_Y(y)$ can be defined as

$$f_{XY}(x, y) = f_X(x) f_Y(y) c(u, v) \quad (5)$$

where $c(u, v)$ is the copula density, which is expressed as

$$c(u, v) = \frac{\partial^2 C(u, v)}{\partial u \partial v} \quad (6)$$

In addition, the conditional distribution function can be derived via the partial differentiation of the joint distribution functions, as follows:

$$P(V \le v | U = u) = \frac{\partial C(u, v)}{\partial u} \ and \ P(U \le u | V = v) = \frac{\partial C(u, v)}{\partial v}$$

Let $F_{X|Y}(x|y) = P(V \le v|U = u)$ and $F_{Y|X}(y|x) = P(U \le u|V = v)$. Therefore, the conditional density can be expressed as follows: $f_{X|Y}(x|y) = f_X(x)c(u, v)$ and $f_{Y|X}(y|x) = f_Y(y)c(u, v)$.

One of the advantages of the copula compared with the other joint distribution models is the freedom to select any TCDFs for the variables; this is because the copula approach creates a dependency structure between correlated variables by selecting the TCDFs independently. Various types of bivariate parametric copula families and classes have been proposed. Each of these families or classes exhibits various characteristics. Among them, Archimedean and elliptical families, which are frequently applied in coastal engineering, were selected for this study.

2.3 Dependency Construction Using Copula Approach

To construct a dependence structure among the water level, local acceleration, and pressure gradient, Archimedean copulas (including the Clayton, Frank, and Gumbel–Hougaard copulas) and elliptical copulas (including the Gaussian and Student's t copulas) were considered in this study. In general, these copulas encompass a wide range of dependency and correlation patterns. However, the compatibility of these copulas with the dependence variables must be ensured via GOF tests. The theoretical proofs and mathematical justifications for the construction of these copulas are presented below.

2.3.1 Archimedean Copulas

In practice, Archimedean copulas are frequently applied in several fields of study (Kwon and Lall, 2016; Bacigál et al., 2019; Garcia-Jorcano and Benito, 2020). Because the family of Archimedean copulas comprises a wide range of possible dependency patterns and properties, they can be easily constructed (Nelsen, 2006). Generally, an Archimedean copula based on an algebraic method can be written as follows:

$$C(u, v) = \varphi^{-1}(\varphi(u) + \varphi(v)) \quad (7)$$

where $u = F_X(x)$ and $v = F_Y(y)$ are marginal functions; φ is the generator function with domain $\theta = [0, \infty)$; φ^{-1} is the inverse function of φ and can be generally expressed as

$$\varphi^{-1}(t, \theta) = \begin{cases} \varphi^{-1}(t, \theta) & if\ 0 \le t \le \varphi(0, \theta) \\ 0 & if\ \varphi(0, \theta) \le t \le \infty \end{cases} \quad (8)$$

where t is a random number between zero and one. Clayton, Gumbel, and Frank copulas, which are the most well-known one-parameter families of Archimedean copulas, were used in this study. These copula functions, their generator functions, and the domain of the generator functions are shown in **Supplementary Table S2**.

Archimedean copulas present different and special tail dependencies based on their generator functions. For example, the Gumbel copula presents upper tail dependence and is more appropriate for data with significant dependencies at higher values than at low values. By contrast, the Clayton copula presents a lower tail dependence and is suitable for data with significant low-value dependencies, whereas the Frank copula presents no tail dependence and is an appropriate model for data with weak dependencies.

2.3.2 Elliptical Copulas

The Gaussian and Student's t copulas, as the most typically recommended members of the elliptical copulas, were applied to simulate the variables in this study. The main advantage of elliptical copulas is that they can easily generalize to a high number of dimensions. The elliptical copulas mentioned above are presented below.

2.3.2.1 Gaussian Copula

The Gaussian or normal copula is a member of the elliptical copula family. This copula can easily simulate a high number of dimensions as it is an n-variate distribution over the unit cube $[0, 1]^n$. By assuming $x_1, \ldots, x_n$ as a set of correlated variables with a correlation matrix $R \in [-1, 1]^{n\times n}$, the Gaussian copula can be defined as

$$C_R(u) = \varphi_R\left(\varphi^{-1}(u_1), \ldots, \varphi^{-1}(u_n)\right) \tag{9}$$

where φ_R denotes the n-dimensional normal distribution function, and φ^{-1} the inverse cumulative distribution function of the standard normal. Therefore, the multivariate CDF is expressed as

$$\begin{aligned} F(x_1, \ldots, x_n) &= C(F_1(x_1), \ldots, F_n(x_n)) \\ &= \varphi_R\left(\varphi^{-1}(F_1(x_1)), \ldots, \varphi^{-1}(F_n(x_n))\right) \end{aligned} \tag{10}$$

Finally, the mathematical formulation of the Gaussian copula can be written as follows:

$$C(u,v) = \int_{-\infty}^{\varphi^{-1}(u)} \int_{-\infty}^{\varphi^{-1}(v)} \frac{1}{2\pi(1-\theta^2)^{1/2}} \exp\left\{ -\frac{x^2 - 2\theta xy + y^2}{2(1-\theta^2)} \right\} dxdy \quad -1 \le \theta \le 1 \tag{11}$$

2.3.2.2 Student's t Copula

The Student's t copula represents the dependence structure of a multivariate Student's t distribution. In fact, the Student's t distribution is a generalization of the Gaussian distribution, and the Gaussian copula is a limited version of the Student's t copula with a limited degree of freedom. Compared with the Gaussian copula, the Student's t copula performs better in capturing the dependence between variables in a dataset.

If $x_1, \ldots, x_n$ is a set of correlated variables with a correlation matrix $R \in [-1, 1]^{n\times n}$, then the Student's t copula can be defined as

$$C_{vR}(u) = t_{vR}\left(t^{-1}(u_1), \ldots, t^{-1}(u_n)\right) \tag{12}$$

where t_{vR} denotes the one-dimensional Student's t distribution function with v degrees of freedom, and t^{-1} the inverse Student's t cumulative distribution function with v degrees of freedom. The Student's t copula can be expressed as follows:

$$C(u,v) = \int_{-\infty}^{t^{-1}(u)} \int_{-\infty}^{t^{-1}(v)} \frac{1}{2\pi(1-\theta^2)^{1/2}} \left\{ 1 + \frac{x^2 - 2\theta xy + y^2}{v(1-\theta^2)} \right\}^{-(\delta+2)/2} dxdy \quad -1 \le \theta \le 1,\ \delta \ge 2 \tag{13}$$

2.4 Simulation Based on Constructed Copulas

To simulate dependent multivariate data using a copula, the following procedures were implemented. First, the linear correlation coefficient was calculated to specify the linear correlation between variables. In this regard, Kendall's τ or Spearman's ρ are appropriate. Kendall's τ, which ranges from −1 to 1, is a non-parametric approach for measuring the association between two variables. The correlation between two variables is perfect when the coefficient value is 1. Similarly, a value of −1 indicates a perfect negative correlation between two variables. Moreover, the coefficient is expected to be approximately zero when the two variables are independent. Kendall's τ depends only on the copula C, and for a pair of dependent variables (u, v), it is defined as

$$\tau = 4\int_0^1\int_0^1 C(u,v)dC(u,v) - 1 \tag{14}$$

For Archimedean and elliptical copulas, Kendall's τ can be expressed as a function of the generator. For example, Kendall's τ for Archimedean copulas can be estimated as follows:

$$\tau = 1 + 4\int_0^1 \frac{\varphi(t)}{\varphi'(t)} dt. \tag{15}$$

Similar to Kendall's τ, Spearman's ρ assesses the correlation level between two variables. In addition, the values of Spearman's ρ are between -1 and 1. Spearman's ρ is expressed as follows:

$$\rho = 12\int_0^1\int_0^1 C(u,v)dudv - 3 \tag{16}$$

Here, ρ can be expressed as a function of the generator. For Archimedean copulas, ρ is defined as

$$\tau = 3 + 12\int_0^1 \frac{\varphi(t)}{\varphi'(t)} dt \tag{17}$$

Second, the TCDF of each variable was estimated and fitted to their calculated ECDFs. Subsequently, the data were fitted to different copulas using the MLE method. Next, random values between 0 and 1 were generated from the fitted copulas. Finally, the generated values were inverted to achieve the original scale data using inverse functions.

3 DATA ACQUISITION

3.1 Field Setup and Data

The field data employed in this study were based on a field experiment conducted by Suzuki et al. (2009) during a 5-day experiment on February 16–20, 2007, at the Hasaki Oceanographical Research Station (HORS), a research facility operated by the Port and Airport Research Institute in Japan. The HORS is located in Ibaraki Prefecture, approximately 100 km east of Tokyo, and faces the Pacific Ocean (**Supplementary Figure S1**). The shoreline orientation was 31° anticlockwise from the north. A 427-m-long pier equipped with different instruments for various field measurements was located perpendicular to the Hasaki shoreline. The HORS is situated on a sandy coast composed of fine sand with a median sediment grain of approximately 0.18 mm, as reported by Katoh and Yanagishima (1995). The mean water level during the experiment was 0.651 m, based on the datum level at the HORS (Tokyo Peil: 0.687 m). Additionally, the low and high water levels were -0.196 and 1.252 m, respectively. Hence, the HORS had a mean tide range of 1.5 m during the experiment. The offshore wave data was recorded at a depth of 23.4 m off the Kashima port.

Supplementary Figure S2 shows the cross-shore beach profile on the first day of the measurements as well as the instrumentation setup. Three instrument sets were used in the experiment to measure the water level, velocity, water pressure, and sediment concentration. The water levels were recorded using a capacitance-type wave gauge (CHT5-200, KENEK). The velocities were recorded using three Nortek acoustic Doppler velocimeters (ADVs) positioned 10 cm above the bed. Pressure gradients were estimated using data recorded by an array of pressure transducers composed of five sensors (BPR-A-50KPS, KYOWA). Sediment concentrations were recorded using three optical backscatter sensors (OBS-3, D&A Instrument Comp.) Additional details regarding the field measurements and instrumentation can be obtained from the paper by Suzuki et al. (2009). It is noteworthy that seabed erosion occurred after installation; consequently, the seabed level around the array of instruments decreased. Therefore, to avoid the effect of erosion, only data measured on the first day were used in this study.

3.2 Laboratory Instrumentation and Data

In this study, experimental tests were conducted by Mieras et al. (2017) and Anderson et al. (2017) in a large-scale wave flume at the O. H. Hinsdale Wave Research Laboratory at the Oregon State University (**Supplementary Figure S3**). The flume had a length of 104 m, a width of 3.7 m, and a depth of 4.6 m, with a fixed barred beach profile constructed based on the average observed beach profile on 11 October 1994 from Duck, NC, during the Duck94 field experiment (Faria et al., 1997; Scott et al., 2005) conducted at the U.S. Army Corps of Engineering Field Research Facility.

The fixed barred profile comprised impermeable slopes of concrete slabs to ensure repeatability, and morphological changes did not cause the position of wave breaking to vary during the experiment. A sand pit composed of two sections was installed on the sandbar crest. The main section had a width of 3.66 m with a depth of 0.18 m. To install the experimental instruments, a subsection with a length and width of 1.2 m and a total depth of 0.61 m was installed beneath the main sand pit. The sand pit was filled with sediments of two different sizes. Because most of the trials were conducted using sediments with D_{50} = 0.17 mm, D_{16} = 0.10 mm, and D_{84} = 0.28 mm, only data obtained from trials using D_{50} = 0.17 mm were used in this study.

A series of approximately 10 monochromatic waves with three different wave periods, i.e., T = 5, 7, and 9 s, was conducted for each trial. The wave heights for each wave within a trial were measured at the toe of the beach profile (H_i) and at the seaward boundary of the sandbar crest (H_{bar}). The trials were conducted with wave heights H_i ranging from 0.09 to 0.65 m and H_{bar} ranging between 0.1 and 0.96 m. The waves were categorized based on the wave period and D_{50}, as summarized in **Supplementary Table S3**.

The tests involved measurements of water surface elevation, pore water pressure, instantaneous bed bathymetry, and velocity. To measure the water surface elevations from offshore to onshore, 11 resistance-type wave gauges were deployed. The wave gauges starting from the toe of the beach profile, i.e., 17.7 m from the wave maker, were mounted along the flume wall at intervals of 3.65 m. A wave gauge positioned at the seaward boundary of the sandbar crest was deployed to record the wave transformation over the sandbar. In addition, a pressure gauge was installed immediately above the sediment bed to measure the water depth over the sandbar crest.

An array of 7 GE Druck PDCR 81 pressure transducers composed of a horizontal row of five pressure transducers and a vertical row of two pressure transducers was embedded beneath the sediment to observe the pore pressure and pressure gradient (**Supplementary Figure S3**). The pore pressure transducers were spaced equally at 20 mm intervals. A conductivity concentration profiler with a width of 5.6 mm and a thickness of 5.6 mm was installed in the sediment pit to measure the instantaneous bed bathymetry at 8 Hz with 1 mm resolution. Moreover, near-bed velocities were measured using a vertical array of Vectrino I ADVs mounted approximately 0.1 m above the initial bed level. Additional details regarding the experimental setup, instrumentation, and test conditions can available in Anderson et al. (2017), Mieras et al. (2017), and Mieras et al. (2019).

3.3 Data Analysis

This research focuses on the dependency structure among the η_{max}, maximum horizontal pore pressure gradient ($\partial(P/\rho)/\partial x_{max}$), maximum vertical pressure gradient ($\partial(P/\rho)/\partial z_{max}$), maximum horizontal acceleration ($\partial u/\partial t_{max}$), maximum vertical acceleration ($\partial w/\partial t_{max}$), and maximum near-bed sediment concentration ($C_{b,max}$) induced by η_{max} based on field and laboratory measured data. First, the results for each dataset were analyzed separately. Subsequently, the relationship between the two datasets was established.

3.3.1 Dependent Field Data

As described in **Section 3.1**, the water level, velocity, water pressure, and sediment concentration were measured as field data. The pressure gradients for each water level based on the central difference scheme were estimated as follows:

$$\frac{\partial p}{\partial x} = -\frac{p_1 - 8p_2 + 8p_4 - p_5}{12\Delta x} \tag{18}$$

where p is the pressure, the subscripts represent the position of each transducer, and Δx is the distance between the transducers, i.e., 8.4 cm. Furthermore, the accelerations were estimated using the measured wave induced velocities based on a centered difference approximation in time, as follows:

$$\frac{\partial u}{\partial t} = \frac{u(i) - u(i-1)}{\Delta t} \tag{19}$$

where u is the wave induced velocity, and i the different time steps.

Wave-by-wave analysis was conducted to assess the measured parameter behaviors. **Supplementary Figure S4A,C,E** show the wave-induced pressure gradients, local accelerations, and bottom sediment concentration for different water levels, starting from the still water to maximum water levels for each wave. By considering the maximum water level as η_{max}, **Supplementary Figure S4B,D,F,G** show the multivariate (η_{max}, $\partial(P/\rho)/\partial x_{max}$, $\partial u/\partial t_{max}$, $C_{b,max}$) assessed for the copula simulation of the field observations. Red dots in **Supplementary Figure S4** show the pressure gradients, local accelerations and sediment concentrations which are corresponding to η_{max}.

3.3.2 Dependent Laboratory Data

Anderson et al. (2017) used a method similar to that of Suzuki et al. (2010) to calculate the pressure gradient in both the horizontal and vertical directions. The horizontal gradients can be estimated as follows:

$$\frac{\partial p}{\partial x} = \frac{-2p_2 - 3p_3 + 6p_4 - p_5}{6\Delta x} \tag{20}$$

where Δx was 2 cm. Positive and negative values for $\partial p/\partial x$ indicate the offshore and onshore directions, respectively. Similarly, the vertical pore pressure gradient is calculated as follows:

$$\frac{\partial p}{\partial z} = \frac{-3p_3 + 4p_6 - p_7}{2\Delta z} \tag{21}$$

where Δz was 2 cm in this study, and positive values indicate the downward direction. **Supplementary Figure S5** shows wave induced maximum pore pressure gradients and their corresponding maximum accelerations.

4 DISCUSSION

4.1 Multivariate Analysis for Copula Simulation

To assess the correlation between variables, Kendall's τ and the corresponding p-values were calculated, and the summary for each pair is presented in **Supplementary Table S4**. As expected, η_{max} was significantly correlated with the pressure gradients and accelerations. This implies that the larger the η_{max}, the higher is the pressure gradients and accelerations. Meanwhile, the ($\partial u/\partial t_{max}$, η_{max}) and ($\partial u/\partial t_{max}$, $\partial(P/\rho)/\partial x_{max}$) pair indicated a significant positive dependence on the laboratory data, whereas a lower correlation was indicated in the field dataset. This can be attributed to the effect of several aggregated phenomena. Although the main significant difference between the laboratory and field experiment is the existence of longshore currents inside the natural surf zones, the influence of other parameters such as undertow and beach reflection on the reduction of correlation coefficient values under sophisticated hydrodynamic conditions in the natural coastal areas might be more considerable than laboratory conditions. On the other hand, the calculated correlation factors between the wave periods and (η_{max}, $\partial(P/\rho)/\partial x_{max}$, $\partial u/\partial t_{max}$) were not high enough to select for the copula simulation. It is noteworthy that $\partial(P/\rho)/\partial z_{max}$ and $\partial w/\partial t_{max}$ are independent. Similarly, $C_{b,max}$ was not selected for the copula simulation owing to its low correlation with η_{max}. Finally, based on Kendall's τ, it was observed that the dependencies among ($\partial(P/\rho)/\partial x_{max}$, η_{max}), ($\partial u/\partial t_{max}$, η_{max}), and ($\partial u/\partial t_{max}$, $\partial(P/\rho)/\partial x_{max}$) were perfectly linear for the laboratory dataset and reasonable for the field data. Therefore, the interdependency structure and simulation using the copula approach were provided for a three-dimensional multivariate analysis of (η_{max}, $\partial(P/\rho)/\partial x_{max}$, $\partial u/\partial t_{max}$). To render the laboratory data applicable to the field data and to generalize both laboratory and field data for different coastal locations, the datasets were normalized by their root mean square (RMS) values. **Supplementary Figure S6** shows the normalized multivariate (η_{max}, $\partial(P/\rho)/\partial x_{max}$, $\partial u/\partial t_{max}$) for both the laboratory and field datasets.

4.2 Distributions and Estimations of CDFs

The marginal distributions or TCDFs, as a first step for simulating the correlated variables using the copula approach, should be determined. Therefore, the empirical probabilities for (η_{max}, $\partial(P/\rho)/\partial x_{max}$, $\partial u/\partial t_{max}$) were calculated using **Eq. 1**. The TCDFs summarized in **Supplementary Table S1** were selected from among the available TCDFs to fit the distribution of cumulative probabilities. The parameters of the TCDFs were approximated using the MLE method.

Supplementary Figures S7, S8 show the ECDFs of the experimental data (blue asterisks) and TCDFs applicable to non-dimensional (η_{max}, $\partial(P/\rho)/\partial x_{max}$, $\partial u/\partial t_{max}$). The estimated parameters for fitting the TCDFs to the ECDFs are provided in **Supplementary Table SA1** in the Appendix. The values of (η_{max}, $\partial(P/\rho)/\partial x_{max}$, $\partial u/\partial t_{max}$) were normalized using their RMS values. Generally, the laboratory results of the CDF calculations show that the values of ECDFs for small waves and the associated low pressure gradients and accelerations were higher than those of the TCDFs, whereas the values of the ECDFs for $<\eta_{max}>$, $<\partial(P/\rho)/\partial x_{max}>$, $<\partial u/\partial t_{max}> = 0.5$ to 1, where $<\,>$ denotes the normalized values, were relatively lower than those of the TCDFs. Additionally, the peak values of the ECDFs were higher than the corresponding TCDF values. It can be concluded that for $<\eta_{max}>$, $<\partial(P/\rho)/\partial x_{max}>$, $<\partial u/\partial t_{max}> = 0$ to 0.5 and for values less than 1, the TCDFs were underestimated, whereas for values between 0.5 and 1, they were overestimated. In addition, the field results of $<\partial(P/\rho)/\partial x_{max}>$ and $<\partial u/\partial t_{max}>$ included negative values, and the TCDFs showed overestimated results. Similarly, for values between 0 and 0.5, it can be concluded that the values of the ECDFs were lower than the estimated values of the TCDFs. The Nakagami function was the only TCDF that fitted well with the field wave height data. Although the Nakagami function yielded favorable results for $<\eta_{max}>$ and $<\partial(P/\rho)/\partial x_{max}>$, its performance was not reliable for $<\partial u/\partial t_{max}>$.

The GEV distribution as a TCDF with three parameters showed excellent agreement with the laboratory experimental data. Meanwhile, the EV and logistic distributions with two parameters indicated excellent trends for the ECDFs involving the laboratory data, unlike the case for the field dataset calculations. The p-values from the KS tests for the field variable statistical investigations indicated no significant superiorities among the GEV, EV, and logistic distributions because their p-values exceeded 90%. However, the GEV distribution required two empirical parameters, and compared with the EV and logistic distributions, the computational procedure was more complicated. Meanwhile, the low p-values for the Nakagami and Gamma distributions indicated that they did not fit well with the laboratory data compared with the GEV, EV, and logistic distributions. Based on the p-values, the normal, Rician, and Weibull distributions demonstrated relatively good agreement with the laboratory data. However, it was difficult to select the appropriate distribution among them based on the KS test because they demonstrated similar characteristics.

Supplementary Figure S9A shows a comparison between the marginal functions for field and laboratory data based on p-values. The results indicate that the range of p-values was wide. Therefore, the marginal functions yielded different performances based on the dataset. By contrast, similar fitting parameters were achieved for each coastal parameter regardless of the study location (**Supplementary Figure S9B**).

4.3 Fitting Data to Different Copulas and Comparison of GOFs

The Archimedean and elliptical copulas discussed in **Sections 2.3.1** and **2.3.2**, respectively, were employed to model the dependency between the variables. The joint probabilities for (η_{max}, $\partial(P/\rho)/\partial x_{max}$) and their corresponding simulated data are shown in **Supplementary Figures S10–S13**. For the GOF analysis, the corrected Akaike Information Criteria (AICc) was used. AICc can be calculated by

$$AICc = -2LL + 2P + \frac{2(P+1)(P+2)}{n-P-2} \quad (22)$$

where LL is the maximized value of the log-likelihood function for the model, P is the number of parameters, and n is the sample size. Smaller AICc values indicate better simulation results (**Supplementary Table S5**). The estimated correlation coefficients, such as Kendall's τ, indicate a high linear dependency between the variables. Hence, symmetric copulas such as Archimedean and elliptical copulas can be expected to yield reasonable results. The AICc test was used to compare the performances of the copulas adopted.

The calculated p-values imply that the field data can be analyzed using Archimedean and elliptical copulas. Among the Archimedean copulas, the Clayton and Frank copula generally performed better than the other member of the Archimedean family. Based on the results, it can be concluded that the Gumbel copula is not a good candidate for simulating the field data of (η_{max}, $\partial(P/\rho)/\partial x_{max}$) and ($\partial(P/\rho)/\partial x_{max}$, $\partial u/\partial t_{max}$) then could not accurately characterize the dependency between data points. Nevertheless, the performance of the simulations for (η_{max}, $\partial(P/\rho)/\partial x_{max}$, $\partial u/\partial t_{max}$) can be ranked as follows:

Field Dataset

- (η_{max}, $\partial(P/\rho)/\partial x_{max}$): Clayton > Gaussian > Student's t > Frank > Gumbel.
- (η_{max}, $\partial u/\partial t_{max}$): Gumbel > Student's t > Gaussian > Clayton > Frank.
- ($\partial(P/\rho)/\partial x_{max}$, $\partial u/\partial t_{max}$): Clayton > Frank > Gumbel > Student's t > Gaussian

Laboratory Dataset

- (η_{max}, $\partial(P/\rho)/\partial x_{max}$): Frank > Gaussian > Students' t > Clayton > Gumbel.
- (η_{max}, $\partial u/\partial t_{max}$): Student's t > Gumbel > Gaussian > Frank > Clayton.
- ($\partial(P/\rho)/\partial x_{max}$, $\partial u/\partial t_{max}$): Frank > Student's t > Gaussian > Clayton > Gumbel.

4.4 Model Application

Researchers who investigated pore water pressure gradients such as Suzuki et al. (2010) indicated that the correlation among the water surface, pore pressure gradient, and horizontal velocity should be investigated in future studies. The results of this study show that the pressure gradient and current acceleration can be estimated using the wave height. Some morphodynamic models such as those developed by Madsen (1974) and Sleath (1999) demonstrated that the pressure gradient over the bar can be considered an important parameter for suspending sediments and can cause a momentary failure of the bed. The pressure gradients estimated in this study can be used for the calculation of the Sleath number which can be defined as

$$S = \frac{dP/dx}{(\rho_s - \rho)g} \quad (23)$$

where ρ_s is the dry density of sediment, ρ is the density of fluid, and g is the gravitational acceleration. Commonly, the incipient motion of the sediment and momentary bed failure is parameterized with the Shields number (Shields, 1936), which represents the non-dimensional bed shear stress of a single sand grain layer as

$$\theta = \frac{f_w U_m}{2(s-1)gd_{50}} \quad (24)$$

where f_w is the wave friction factor, U_m is the fluid velocity amplitude, and s is the sediment specific gravity. The friction factor can be calculated by a modified empirical equation proposed by Swart (1974) as follows

$$f_w = \exp\left(5.5\left(\frac{k_s}{A}\right)^{0.2} - 6.3\right) \quad (25)$$

where k_s is the grain roughness height and $A = U_m T/2\pi$. Wilson (1989) showed a linear relationship between the sheet flow layer thickness and the maximum Shields parameter which can be written as follows

$$\frac{(\delta_s)_{max}}{d_{50}} = \Lambda\theta_{max} \quad (26)$$

where Λ is a proportionality constant. Mieras et al. (2017) found a wide range of values for Λ using very high accurate measured instantaneous sheet flow layer thicknesses. Since the momentary bed failure in the sheet flow is not the only related to the Shields number, as an attempt to reduce the range of Λ, Sleath number was added to the Shields number in this study. Therefore, **Eq. 26** can be rearranged as

$$\frac{(\delta_s)_{max}}{d_{50}} = \Lambda(\theta_{max} + S) \quad (27)$$

Supplementary Table S6 shows the hydrodynamic conditions and sheet flow thicknesses measured by Mieras et al. (2017). It was found that the range of values for Λ is smaller for the modified equation, i.e., the range of Λ based on values presented in **Supplementary Table S6** for the cases with the involvement of the Sleath parameter is from 8 to 12 while the Λ values are between 19 and 31 based on **Eq. 26**. Thus, using the pressure gradient values estimated by the copula method and calculating the Sleath parameter, it seems more accurate sheet flow layer thicknesses can be obtained.

On the other hand, since there are several empirical equations proposed for the estimation of the Shields parameter, the results achieved by each equation should be different. Mieras et al. (2017) found a wide range for Shields parameter magnitudes using different proposed equations. That is due to the sensitivity of the Shields parameter equation to the estimation of the wave friction factor, fluid velocity amplitude and grain roughness. However, the correlation between the Sleath parameter and sheet flow thicknesses was assessed, in this study. A reasonable correlation between the Sleath parameter and the sheet flow thickness for the laboratory dataset was found. **Supplementary Figure S14** show the result of simulated sheet flow thicknesses using the Sleath parameter by the copula method. Using wave heights and pressure gradients obtained in this study, it is possible to achieve a reasonable estimation for the wave-induced sheet flow thickness.

The effect of the pressure gradient on momentary bed failure was investigated by Anderson et al. (2017), who analyzed the initiation of erosion as well as the magnitude of erosion depth. The importance of the pressure gradient on momentary bed failure was revealed in numerical simulations (Cheng et al., 2017). Cheng et al. (2017) emphasized the importance of the horizontal pressure gradient for bed instability. Almost all of the beach profile morphodynamic models are including the Shields parameter without the involvement of the Sleath parameter (and therefore the pressure gradient) in the sediment transport modules. The accurate estimation of sediment erosion and sandbar formation is a sort of challenging issue for these models. Since the bed failure is a function of both Sleath and Shields parameters (Cheng et al., 2017). A more accurate simulated beach profile can be expected by using the Sleath parameter. Thus, the results generated by the copula method should be useful for the statistical-process based morphodynamic models.

Wave induced local acceleration has been employed in various sediment transport equations. The simulated data using the copula approach can be useful for all of the abovementioned purposes. In future studies, this approach can be extended to other coastal parameters. In addition, the effect of sediment size on copula-based simulations can be considered for the future studies.

5 CONCLUSION

In this study, a fully statistical model was used to investigate and simulate the interdependency of coastal parameters. Because the water level is one of the most important and well-known parameters for most coastal applications, this parameter and its effect on other coastal parameters should be considered. In addition, the effects of pressure gradient and acceleration on sediment transport mechanisms have been investigated extensively (e.g., Sleath, 1970; Madsen, 1978; Tabasi et al., 2021). To investigate the effects of different parameters on the sediment transport mechanism, Suzuki et al. (2009) and Mieras et al. (2017) conducted field measurements and large-scale experiments, respectively. The results highlighted the importance of the dependencies of $\partial(P/\rho)/\partial x_{max}$, and $\partial u/\partial t_{max}$. In this study, it was discovered that η_{max} can be used to correlate $\partial(P/\rho)/\partial x_{max}$ and $\partial u/\partial t_{max}$. Moreover, among the variables, the dependence among (η_{max}, $\partial u/\partial t_{max}$), ($\eta_{max}$, $(P/\rho)/\partial x_{max}$), and ($\partial(P/\rho)/\partial x_{max}$, $\partial u/\partial t_{max}$) was significant.

The copula approach was used to simulate the abovementioned parameters. To obtain a reliable simulation, a group of TCDFs was utilized to fit the variables. Multivariate dependency structures were constructed and fitted with Archimedean and elliptical copulas for (η_{max}, $\partial u/\partial t_{max}$), ($\eta_{max}$, $(P/\rho)/\partial x_{max}$), and ($\partial(P/\rho)/\partial x_{max}$, $\partial u/\partial t_{max}$) pairs. The KS test allowed us to assess the GOF and hence the performance of the models. The AICc test results revealed that both Archimedean and elliptical copulas can generate and extrapolate correlated parameters using limited observational data. Because acquiring data from different coastal zones for a long period is an expensive process, the observational data were limited. Hence, laboratory experiments and statistical models suitable for calibration using limited measured data should be employed. It was discovered in this study that the laboratory dataset of multivariate (η_{max}, $\partial(P/\rho)/\partial x_{max}$, $\partial u/\partial t_{max}$) can be applied to simulate the same natural conditions using normalized data. Hence, the results achieved by the statistical models were not site dependent. The copula models selected for a specific site have the potential to be generalized for other case studies with the normal (non-storm) hydrodynamic condition. However, in addition to providing sufficiently accurate simulations, the models were based on a fully statistical approach, and physical constraints could not be considered for very different hydrodynamic and morphodynamic applications. Both the laboratory and field datasets were under normal wave conditions (non-storms) within the surf zone. Therefore, the results might not be valid for other zones, such as the swash zone under storms or other extreme conditions.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

MT: Simulation, data analysis and writing the manuscript. TS: Discussions of the data analysis and conduct the field experiments DC: Discussions of the data analysis and conduct the laboratory experiments.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fbuil.2022.816020/full#supplementary-material

REFERENCES

Anderson, D., Cox, D., Mieras, R., Puleo, J. A., and Hsu, T. J. (2017). Observations of Wave-induced Pore Pressure Gradients and Bed Level Response on a Surf Zone Sandbar. *J. Geophys. Res. Oceans* 122, 5169–5193. doi:10.1002/2016JC012557

Bacigál, T., Komorníková, M., and Komorník, J. (2019). State-of-the-art in Modeling Nonlinear Dependence Among Many Random Variables with Copulas and Application to Financial Indexes. *Jamris* 13, 84–91. doi:10.14313/JAMRIS/3-2019/31

Bang Huseby, A., Vanem, E., and Natvig, B. (2013). A New Approach to Environmental Contours for Ocean Engineering Applications Based on Direct Monte Carlo Simulations. *Ocean. Eng.* 60, 124–135. doi:10.1016/j.oceaneng.2012.12.034

Bitner-Gregersen, E. M., and Haver, S. (1989). "Joint Long Term Description of Environmental Parameters for Structural Response Calculation," in 2nd International Workshop on Wave Hindcasting and Forecasting (Vancouver), August 11–16, 1991 (Edinburgh, The United Kingdom: ISOPE-I-91-031).

Brown, S. A., Greaves, D. M., Magar, V., and Conley, D. C. (2016). Evaluation of Turbulence Closure Models under Spilling and Plunging Breakers in the Surf Zone. *Coast. Eng.* 114, 177–193. doi:10.1016/j.coastaleng.2016.04.002

Bryan, K. R., Davies-Campbell, J., Hume, T. M., and Gallop, S. L. (2019). The Influence of Sand Bar Morphology on Surfing Amenity at New Zealand Beach Breaks. *J. Coast. Res.* 87, 44. doi:10.2112/SI87-005.1

Cheng, Z., Hsu, T.-J., and Calantoni, J. (2017). SedFoam: A Multi-Dimensional Eulerian Two-phase Model for Sediment Transport and its Application to Momentary Bed Failure. *Coast. Eng.* 119, 32–50. doi:10.1016/j.coastaleng.2016.08.007

Clarindo, G., Teixeira, A. P., and Guedes Soares, C. (2021). Environmental Wave Contours by Inverse FORM and Monte Carlo Simulation with Variance Reduction Techniques. *Ocean. Eng.* 228, 108916. doi:10.1016/j.oceaneng.2021.108916

Condon, A. J., and Sheng, Y. P. (2012). Optimal Storm Generation for Evaluation of the Storm Surge Inundation Threat. *Ocean. Eng.* 43, 13–22. doi:10.1016/j.oceaneng.2012.01.021

Corbella, S., and Stretch, D. D. (2013). Simulating a Multivariate Sea Storm Using Archimedean Copulas. *Coast. Eng.* 76, 68–78. doi:10.1016/j.coastaleng.2013.01.011

Dawson, T. H., Kriebel, D. L., and Wallendorf, L. A. (1993). Breaking Waves in Laboratory-Generated JONSWAP Seas. *Appl. Ocean Res.* 15, 85–93. doi:10.1016/0141-1187(93)90023-Q

De Michele, C., Salvadori, G., Passoni, G., and Vezzoli, R. (2007). A Multivariate Model of Sea Storms Using Copulas. *Coast. Eng.* 54, 734–751. doi:10.1016/j.coastaleng.2007.05.007

De Waal, D. J., and Van Gelder, P. H. A. J. M. (2005). Modelling of Extreme Wave Heights and Periods through Copulas. *Extremes* 8, 345–356. doi:10.1007/s10687-006-0006-y

Edwards, S. J., Troesch, A. W., and Collette, M. (2021). Estimating Extreme Characteristics of Stochastic Non-linear Systems. *Ocean. Eng.* 233, 109042. doi:10.1016/j.oceaneng.2021.109042

Faria, A. F. G., Thornton, E. B., and Stanton, T. P. (1997). Small-scale Morphology Related to Wave and Current Parameters over a Barred Beach. *Proc. Coast. Eng. Conf.* 1, 3391–3404. doi:10.1061/9780784402429.262

Forristall, G. Z. (2000). Wave Crest Distributions: Observations and Second-Order Theory. *J. Phys. Oceanogr.* 30, 1931–1943. doi:10.1175/1520-0485(2000)030<1931:wcdoas>2.0.co;2

Garcia-Jorcano, L., and Benito, S. (2020). Studying the Properties of the Bitcoin as a Diversifying and Hedging Asset through a Copula Analysis: Constant and Time-Varying. *Res. Int. Bus. Finance* 54, 101300. doi:10.1016/j.ribaf.2020.101300

Jane, R., Dalla Valle, L., Simmonds, D., and Raby, A. (2016). A Copula-Based Approach for the Estimation of Wave Height Records through Spatial Correlation. *Coast. Eng.* 117, 1–18. doi:10.1016/j.coastaleng.2016.06.008

Katoh, K., and Yanagishima, S. (1995). "Changes of Sand Grain Distribution in the Surf Zone," in Coastal Dynamics - Proceedings of the International Conference, 12-16 June, 2017 (Helsingør, Denmark: Ocean Dynamics).

Kuriyama, Y. (2012). Process-based One-Dimensional Model for Cyclic Longshore Bar Evolution. *Coast. Eng.* 62, 48–61. doi:10.1016/j.coastaleng.2011.12.001

Kwon, H.-H., and Lall, U. (2016). A Copula-Based Nonstationary Frequency Analysis for the 2012-2015 Drought in California. *Water Resour. Res.* 52, 5662–5675. doi:10.1002/2016WR018959

Li, F., Gelder, P. H. A. J. M. V., Vrijling, J. K., Callaghan, D. P., Jongejan, R. B., and Ranasinghe, R. (2014a). Probabilistic Estimation of Coastal Dune Erosion and Recession by Statistical Simulation of Storm Events. *Appl. Ocean Res.* 47, 53–62. doi:10.1016/j.apor.2014.01.002

Li, F., van Gelder, P. H. A. J. M., Ranasinghe, R., Callaghan, D. P., and Jongejan, R. B. (2014b). Probabilistic Modelling of Extreme Storms along the Dutch Coast. *Coast. Eng.* 86, 1–13. doi:10.1016/j.coastaleng.2013.12.009

Lin, Y., Dong, S., and Tao, S. (2020). Modelling Long-Term Joint Distribution of Significant Wave Height and Mean Zero-Crossing Wave Period Using a Copula Mixture. *Ocean. Eng.* 197, 106856. doi:10.1016/j.oceaneng.2019.106856

Lowe, R. J., Buckley, M. L., Altomare, C., Rijnsdorp, D. P., Yao, Y., Suzuki, T., et al. (2019). Numerical Simulations of Surf Zone Wave Dynamics Using Smoothed Particle Hydrodynamics. *Ocean. Model.* 144, 101481. doi:10.1016/j.ocemod.2019.101481

Madsen, O. S. (1974). Stability of a Sand Bed under Breaking Waves. *Coast. engng. Proc.* 2, 776–794. doi:10.1061/9780872621138.048

Madsen, O. S. (1978). Wave-Induced Pore Pressures and Effective Stresses in a Porous Bed. *Géotechnique* 28, 377–393. doi:10.1680/geot.1978.28.4.377

Mieras, R. S., Puleo, J. A., Anderson, D., Cox, D. T., and Hsu, T. J. (2017). Large-scale Experimental Observations of Sheet Flow on a Sandbar under Skewed-asymmetric Waves. *J. Geophys. Res. Oceans* 122, 5022–5045. doi:10.1002/2016JC012438

Mieras, R. S., Puleo, J. A., Anderson, D., Hsu, T. J., Cox, D. T., and Calantoni, J. (2019). Relative Contributions of Bed Load and Suspended Load to Sediment Transport under Skewed-Asymmetric Waves on a Sandbar Crest. *J. Geophys. Res. Oceans* 124, 1294–1321. doi:10.1029/2018JC014564

Myrhaug, D., Ong, M. C., and Holmedal, L. E. (2015). Suspended Sediments Due to Random Waves Including Effects of Second Order Wave Asymmetry and Boundary Layer Streaming. *Ocean. Eng.* 104, 414–421. doi:10.1016/j.oceaneng.2015.05.022

Nelsen, R. B. (2006). *An Introduction to Copulas*. New York, NY: Springer. doi:10.1007/0-387-28678-0

Plackett, R. L. (1965). A Class of Bivariate Distributions. *J. Am. Stat. Assoc.* 60, 516–522. doi:10.1080/01621459.1965.10480807

Repko, A., Van Gelder, P. H. A. J. M., Voortman, H. G., and Vrijling, J. K. (2004). Bivariate Description of Offshore Wave Conditions with Physics-Based Extreme Value Statistics. *Appl. Ocean Res.* 26, 162–170. doi:10.1016/j.apor.2004.10.001

Ribas, F., Swart, H. E., Calvete, D., and Falqués, A. (2012). Modeling and Analyzing Observed Transverse Sand Bars in the Surf Zone. *J. Geophys. Res.* 117. doi:10.1029/2011JF002158

Roelvink, J. A., Reniers, A. J. H. M., Van Dongeren, A. R., van Thiel de Vries, J. S. M., Lescinski, J., and McCall, R. T. (2010). XBeach Model Description and Manual. Available at: http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:XBeach+Model+Description+and+Manual#0.

Ryabkova, M., Karaev, V., Guo, J., and Titchenko, Y. (2019). A Review of Wave Spectrum Models as Applied to the Problem of Radar Probing of the Sea Surface. *J. Geophys. Res. Oceans* 124, 7104–7134. doi:10.1029/2018JC014804

Salvadori, G., De Michele, C., and Durante, F. (2011). On the Return Period and Design in a Multivariate Framework. *Hydrol. Earth Syst. Sci.* 15, 3293–3305. doi:10.5194/hess-15-3293-2011

Salvadori, G., Durante, F., De Michele, C., Bernardi, M., and Petrella, L. (2016). A Multivariate Copula-Based Framework for Dealing with Hazard Scenarios and Failure Probabilities. *Water Resour. Res.* 52, 3701–3721. doi:10.1002/2015WR017225

Schmidt, T. (2006). "Coping with Copulas," in *Copulas - from Theory to Applications in Finance* (London: Bloomberg Press).

Scott, C. P., Cox, D. T., Maddux, T. B., and Long, J. W. (2005). Large-scale Laboratory Observations of Turbulence on a Fixed Barred Beach. *Meas. Sci. Technol.* 16, 1903–1912. doi:10.1088/0957-0233/16/10/004

Sellés Valls, S. (2019). A Vine-Based Approach for Defining Critical Infrastructure Loads. Available at: https://repository.tudelft.nl/islandora/object/uuid%3A9a133d6d-00ca-4fcc-a244-b88215dfd578.

Shields, A. (1936). Anwendung der Aehnlichkeitsmechanik und der Turbulenzforschung auf die Geschiebebewegung. *Technology* 26, 26.

Sklar, A. (1959). *Fonctions de Reparition a n Dimensions et Leurs Marges*. Paris: Publ. l'Institute Stat. l'Universite Paris.

Sleath, J. F. A. (1999). Conditions for Plug Formation in Oscillatory Flow. *Cont. Shelf Res.* 19, 1643–1664. doi:10.1016/S0278-4343(98)00096-X

Sleath, J. F. A. (1970). Wave-Induced Pressures in Beds of Sand. *J. Hydr. Div.* 96, 367–378. doi:10.1061/jyceaj.0002325

Suzuki, T., Inami, Y., Yanagishima, S., Sakihama, S., and Cox, D. (2018). OBSERVATIONS OF SEDIMENT PARTICLE MOVEMENTS UNDER ACCRETIVE WAVE CONDITIONS. *Int. Conf. Coast. Eng.* 36, 68. doi:10.9753/icce.v36.sediment.68

Suzuki, T., Mori, N., and Cox, D. T. (2009). Statistical Modeling of Near-Bed Pressure Gradients Measured on a Natural Beach. *Coast. Eng. J.* 51, 101–121. doi:10.1142/S0578563409001965

Suzuki, T., Shin, S., Cox, D. T., and Mori, N. (2010). Spatiotemporal Characteristics of Near-Bed Pressure Gradients on a Barred Beach. *J. Waterw. Port. Coast. Ocean. Eng.* 136, 327–336. doi:10.1061/(asce)ww.1943-5460.0000055

Swart, D. H. (1974). Offshore Sediment Transport and Equilibrium Beach Profiles. Delft: Institutional Repository. doctoral thesis.

Tabasi, M., Soltanpour, M., Jayaratne, R., Shibayama, T., and Okayasu, A. (2018). A NUMERICAL MODEL OF CROSS-SHORE BEACH PROFILE EVOLUTION: THEORY, MODEL DEVELOPMENT AND APPLICABILITY. *Int. Conf. Coast. Eng.* 36, 69. doi:10.9753/icce.v36.papers.69

Tabasi, M., Soltanpour, M., and Jayaratne, R. (2017). "Study and Modeling of Cross-Shore Sediment Transport at Zarabad Fishery Port," in 37th IAHR World Congress (Kuala Lumpur: Cross-shore Sediment Transport), 3256–3265.

Tabasi, M., Soltanpour, M., Suzuki, T., and Jayaratne, R. (2020). Modeling of Berm Formation and Erosion at the Southern Coast of the Caspian Sea. *Int. Conf. Coast. Eng.* 19, 19. doi:10.9753/icce.v36v.papers.19

Tabasi, M., Yamada, M., and Suzuki, T. (2021). Laboratory Investigation of the Influence of Sediment Compaction on Wave-Induced Pore Pressure Gradient and Sediment Concentration for a Sandbar. *J. Jpn. Soc. Civ. Eng.* 77, 397–402. doi:10.2208/kaigan.77.2_i_397

Tayfun, M. A., and Fedele, F. (2007). Wave-height Distributions and Nonlinear Effects. *Ocean. Eng.* 34, 1631–1649. doi:10.1016/j.oceaneng.2006.11.006

Vrijling, J. K., and Bruinsma, J. (1980). Hydraulic Boundary Conditions. Hydraulic. Aspects Of Coastal Structures. *Developments In Hydraulic*, 2, 109–133.

Wahl, T., Jensen, J., and Mudersbach, C. (2011). A Multivariate Statistical ModeL for Advanced Storm Surge Analyses in the North Sea. *Int. Conf. Coast. Eng.* 1, 19. doi:10.9753/icce.v32.currents.19

Wahl, T., Mudersbach, C., and Jensen, J. (2012). Assessing the Hydrodynamic Boundary Conditions for Risk Analyses in Coastal Areas: A Multivariate Statistical Approach Based on Copula Functions. *Nat. Hazards Earth Syst. Sci.* 12, 495–510. doi:10.5194/nhess-12-495-2012

Wilson, K. C. (1989). Friction of Wave-Induced Sheet Flow. *Coast. Eng.* 12, 371–379. doi:10.1016/0378-3839(89)90013-6

Zachary, S., Feld, G., Ward, G., and Wolfram, J. (1998). Multivariate Extrapolation in the Offshore Environment. *Appl. Ocean Res.* 20, 273–295. doi:10.1016/S0141-1187(98)00027-3

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