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Bayesian network for the analysis of significant storms in the southern Baltic Sea

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Abstract

Coastal emergency managers increasingly require reliable tools to enhance preparedness for extreme coastal storms and their impacts. With the growing availability of methods and frameworks for the development of Early Warning Systems (EWSs) for coastal storm hazards, accurate prediction of dune erosion remains a fundamental challenge. In this context, probabilistic modeling approaches, such as Gaussian Bayesian networks, provide a flexible framework for integrating multiple storm parameters and quantifying erosion forecasts.

In this study, the interdependence of the parameters of significant storms is investigated via an expert Gaussian Bayesian network. The network was trained using data from 1978–2009, during which 32 significant storms were recorded. The model's predictive ability was evaluated for eight additional storm events from 2010–2017, which were not considered during model estimation. In a second validation approach, the leave-one-out (LOO) cross-validation method was applied to the entire dataset of 40 storm events to evaluate the predictive ability and stability of the Bayesian network model parameters.

Based on the proposed expert Gaussian Bayesian network, satisfactory forecasts of dune erosion magnitude, expressed as $\log(D)$, were obtained. Storm energy was modeled as an event-scale descriptor of storm intensity and included in the Gaussian Bayesian network framework for dune erosion prediction. Model estimation for $\log(D)$ yielded satisfactory results, and the coefficient of determination (R^2) indicated a relatively good agreement between the modeled and observed values.

Finally, the Bayesian Gaussian network was used to estimate exceedance probability thresholds for dune erosion magnitude (D) and its logarithm $\log(D)$, corresponding to erosion levels expected to be exceeded once every 10, 100, and 1000 storm events, respectively.

Keywords

Dune erosion; Significant storm parameters; Gaussian Bayesian network model; Exceedance probabilities; Return levels

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1. Introduction

Storm events occurred in the past, occur at present, and will continue to occur in the future as an integral component of coastal system dynamics, despite substantial uncertainty regarding their future frequency, intensity, and overall trends (Mentaschi et al., 2017; Reguero et al., 2019; Meucci et al., 2020). Numerous extreme storm events worldwide have demonstrated the destructive potential of marine hazards. In Europe, the 1953 North Sea flood, Storm Xynthia in 2010, and Storm Xavier in 2013 resulted in extensive coastal flooding and substantial loss of life and property (Wolf and Flather, 2005; Chadenas et al., 2014; Fernández-Montblanc et al., 2019). Similarly, Hurricane Katrina in 2005 highlighted the catastrophic consequences of the combined effects of storm surge and wave action, leading to more than 1,500 fatalities in Louisiana alone (Blake et al., 2011).

Although the southern Baltic Sea is generally less energetic than open-ocean regions, it is not immune to storm-related impacts. The Polish coast has experienced numerous severe storm surges (Majewski et al., 1983; Sztobryn et al., 2005; Wiśniewski and Wolski, 2009), and in recent decades several storm events caused significant damage to coastal infrastructure and extensive dune erosion (Furmańczyk and Dudzińska-Nowak, 2009; Tylkowski, 2017).

Storm-induced coastal erosion has been predicted using a wide range of approaches, including empirical and

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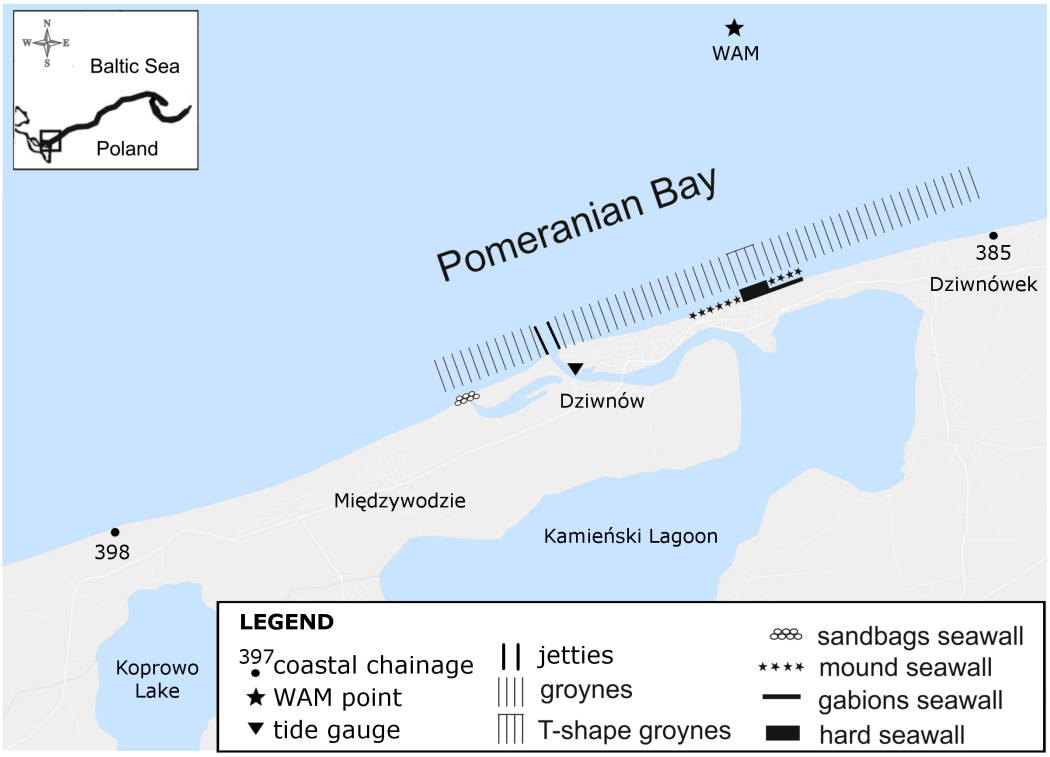

Figure 1. Map of the study area along the Dziwnów Spit (southern Baltic Sea), covering the coastal section from 385 to 398 km according to the kilometre-based shoreline reference system used by the Maritime Offices in Poland. The map shows coastal chainage, locations of hydrodynamic data sources (tide gauge and WAM wave model point), and major coastal protection structures.

statistical models (e.g. Dolan and Davis, 1992; Ruggiero et al., 2001; Morton, 2002), process-based morphodynamic models (e.g. Larson et al., 2004; Roelvink et al., 2009), and probabilistic methods (e.g. Callaghan et al., 2009; Plant and Stockdon, 2012). The choice of method typically depends on data availability, spatial scale, and the intended application.

Bayesian networks, also referred to as probabilistic graphical models, belief networks, or causal networks, have recently gained popularity as a tool for representing knowledge under uncertainty. A Bayesian network is an acyclic-directed graph that contains a qualitative part, which is a set of variables – the nodes of the graph – along with the probabilistic relationships between them, and a quantitative part, which represents the joint probability distribution for these variables (Pearl, 1988).

Recently, Bayesian networks (BNs) have been increasingly applied to the analysis of complex marine and coastal systems. Their main advantages include relatively low computational complexity and the ability to reveal causal relationships among variables, rather than just statistical associations. In addition, they can be used as predictive tools (Beuzen et al., 2018a).

BN methods have been applied in studies of cliffed coasts, for example to predict short-term cliff erosion (Hapke and Plant, 2010), as well as dune coasts, to predict the effects of storm events (Plant and Stockdon, 2012; Palmsten et al., 2014; Wilson et al., 2015), or shoreline changes (Beuzen et al., 2018a). BNs are increasingly being used in conjunction with process-based models such as XBeach and with early warning systems (EWSs) (van Verseveld et al., 2015; Poelhekke et al., 2016; Plomaritis et al., 2018; Sanuy and Jiménez, 2021), enabling their application in hazard and risk management in coastal zones.

Bayesian network models built from continuous-type random variables (Gaussian Bayesian networks), as well as discrete random variables (multinomial Bayesian networks), have been explored (Lauritzen, 1996). To implement discrete BNs, various discretization methods for continuous variables have been investigated, achieving prediction accuracies of approximately 74% in coastal erosion studies (Beuzen et al., 2018b). However, in this study, the analyzed variables encompass a wide range of dune erosion magnitudes, with erosion volumes varying by up to 50–100 m^3, which makes discretization less suitable.

Studies applying Bayesian networks to analyze storm impacts along the southern Baltic Sea coast are scarce. To date, only a nonparametric BN has been used to describe short-term cliff erosion in this region (Terefenko et al., 2019). Learning BN structures directly from data is a chal-

lenging task, as the number of possible candidate graphs increases superexponentially with the number of variables. Consequently, data-driven structure learning requires very large datasets. Alternatively, the network structure can be defined by expert knowledge, which does not require large sample sizes and is therefore well suited to the present study.

In this study, the interdependence of significant storm parameters was investigated using an expert Gaussian BN (GBN), which is described in detail in Section 2.2. The parameters of the GBN were estimated using data from 1978–2009, during which 32 significant storm events were recorded. The predictive ability of the model was evaluated using data from 2010–2017, comprising eight storm events that were not included in the model training process. In the second validation approach, the leave-one-out (LOO) cross-validation method was applied to the complete dataset of 40 storm events to assess both the predictive ability and the parameters stability of the BN model.

The obtained empirical results indicate that the proposed model is capable of approximating the underlying cause-and-effect relationships between significant storm parameters. Based on the expert GBN model, quantiles of order of 0.9, 0.99, and 0.999 were determined for dune erosion magnitude (D) and its logarithm $\log(D)$, corresponding to values expected to be exceeded once every 10, 100, and 1000 events, respectively. This research extends previous one- and two-dimensional statistical analyses of the impact of significant storms conducted for a 14-kmfflong coastal section, the Dziwnów Spit (Figure 1), located in the western part of the southern Baltic Sea (Bugajny et al., 2024). The coastal protection structures shown in Figure 1 represent the configuration relevant to the study period.

The Dziwnów Spit is a Holocene coastal landform whose development has been governed by longshore sediment transport and cross-shore processes related to sea-level variability (Furmańczyk and Musielak, 2015). The seaward part of the spit consists mainly of marine and aeolian sands, while the landward side includes low-lying back-barrier areas composed of sandy and organic deposits (Dobracki and Zachowicz, 2005). The coastline is characterized by sandy beaches backed by dune systems that act as a natural barrier against storm-induced flooding and erosion (Furmańczyk and Dudzińska-Nowak, 2009). Hydrodynamic forcing in the study area is dominated by storm surges and wave action generated primarily by westerly and northwesterly winds. The most energetic conditions typically occur during the autumn-winter season (Zeidler, 1995). Although the Baltic Sea is a microtidal environment, storm surges represent the main source of extreme water levels along this coast and play a key role in shaping dune erosion during severe storm events (Sztobryn et al., 2005; Musielak et al., 2017).

The Dziwnów Spit exhibits pronounced spatial variability related to both natural processes and human interventions. Since the construction of an artificial inlet at the turn of the 20th century, the spit has been divided into a narrower, more urbanized eastern section and a wider, more natural western section (Dudzińska-Nowak, 2006, 2015). The eastern part, where the town of Dziwnów is located, is characterized by relatively low and narrow dunes and has therefore been extensively protected using a combination of hard engineering structures and soft, nature-based measures (Racinowski and Seul, 1999; Dudzińska-Nowak, 2006, 2015). In contrast, the western part of the spit is wider and contains well-developed dune systems that provide more effective natural protection.

2. Material and methods

2.1 Data

Following Furmańczyk and Dudzińska-Nowak (2009), storm events were not defined based on hydrometeorological characteristics but rather on the negative effects of these phenomena on coastal areas, expressed as dune erosion volume. This approach has been successfully applied in subsequent studies (Furmańczyk et al., 2011, 2012a,b; Bugajny et al., 2024). The dune erosion volume constitutes unique data and represents the amount of dune material lost (m^3) during individual storms along the analyzed coastline section. After each storm, inspections of post-storm damage related to dune erosion and coastal infrastructure are conducted by employees of the Maritime Office. Based on these inspections, post-storm reports containing an estimated volume of eroded dune material are prepared. In addition to dune erosion volume, data describing the negative effects of storms and their relationships with other storm parameters, such as significant wave height, wave azimuth, sea level, storm duration, and energy, were used in the present study.

Sea level during each storm was measured using a tide gauge operated by the Institute of Meteorology and the Water Management – National Research Institute. The gauge is referenced to the Amsterdam zero datum (500 cm for the Polish coast) and is located near the Harbormaster's Office in Dziwnów.

Wave parameters, including maximum significant wave height and wave azimuth during storms, were derived from simulations performed with the WAM wave model (WAMDI Group, 1988) for the Baltic Sea. Wave reconstruction for the period 1958–2001 was based on wind fields from the REMO atmospheric model and was carried out within the framework of the EU HIPOCAS project led by the Institute of Oceanography at the University of Gdańsk (Cieślikiewicz and Paplińska-Swerpel, 2008). For subsequent years, wind data from the UMPL model (2002–2008) and the COAMPS model (2009–2017), provided by the Interdisciplinary Centre for Mathematical and Computational Modeling at the University of Warsaw, were used.

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Comparison between the modeled and observed time series of wave field parameters against Directional Waverider buoy (DWR) and satellite altimetry observations demonstrated sufficiently good agreement (Paplińska, 1999; Cieślikiewicz and Paplińska-Swerpel, 2008). Wave data were extracted from the computational grid point located closest to the study area.

Storm duration was defined as the time period during which the significant wave height consistently exceeded 1 m (Robakiewicz, 1991). Storm energy was calculated as the sum of the square of the significant wave height in each unit of time (e.g. hour) during the duration of the storm $\Sigma(\Delta t \times H_s^2)$. This formulation represents a simplified expression for wave energy (Holthuijsen, 2007) and allows the total storm energy to be estimated by accounting for both the wave intensity and storm duration (Mendoza and Jiménez, 2006). In contrast to the storm power index proposed by Dolan and Davis (1992), this approach reduces potential over- or underestimation of storm energy associated with the choice of a single statistical wave-height measure. In the regression equations, H denotes the maximum significant wave height of the storm event, whereas storm energy L was derived from the full wave-height time series.

All collected data concerning both erosion magnitude and wave and storm surge parameters were statistically analyzed using the R environment (open-source software; http://www.r-project.org). Individual storm events were treated as statistically independent observations. The assumption of independence follows from the physical nature of storm events and was additionally verified by analyzing the autocorrelation function (ACF) of individual variables (see Supplementary Information, Figure S1).

Between 1978 and 2017, a total of 40 significant storm events were recorded (see Supplementary Information, Table S1). The following storm parameters were included in the analysis: dune erosion volume (D), sea level (F), storm duration (T), maximum significant wave height during the storm (H), storm energy (L) and wave azimuth (A).

2.2 Description of the Gaussian Bayesian model

An expert GBN was used to analyze the interdependence of significant storm parameters along the western shore of the southern Baltic Sea for the period 1978–2009. The BN is represented by a directed acyclic graph, in which the vertices represent the storm parameters and the edges represent the causal relationships between them. Storm parameters are treated as random variables. Descriptive statistics for these variables for the 32 storm events used for model estimation are provided in Table S2 in the Supplementary Information. On the basis of a preliminary analysis of the data and multivariate normality tests, the analyzed parameters were assumed to follow a multivariate normal distribution. More precisely, the random vector ($\log(D)$, T, A, F, $\log(L)$, H) was assumed to have a six-dimensional normal distribution. This assumption is confirmed by the results of the Mardia skewness (p-value = 0.10) and Mardia kurtosis (p-value = 0.59) normality tests (see Supplementary Information, Tables S3–S4 and Figure S2). An expert GBN was established, and the corresponding dependency graph is presented in Figure 2.

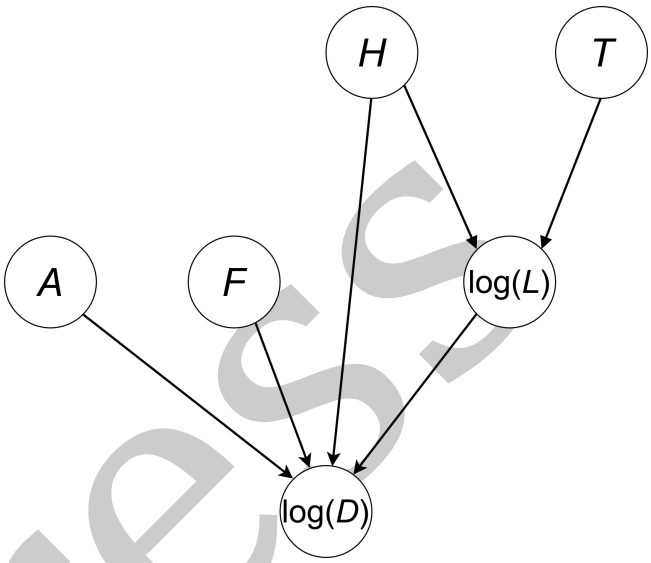

Figure 2. Dependency graph of the expert Gaussian Bayesian network (GBN). A – wave azimuth, F – sea level, H – maximum significant wave height, T – storm duration, $\log(L)$ – logarithm of storm energy, $\log(D)$ – logarithm of dune erosion volume.

In the model, five variables describing significant storm conditions are used to assess their effects on coastal areas, specifically the volume of dune erosion. The Bayesian network represents general dependencies between storm characteristics and coastal response rather than a full process-based description. Dune erosion ($\log D$) is directly conditioned on sea level (F), wave direction (A), and maximum significant wave height (H), and storm energy ($\log L$), which jointly describe the accessibility of wave action to the dune, the exposure of the coastline, peak storm forcing, and the cumulative storm intensity. Storm energy ($\log L$) is computed as an integrated measure of storm intensity based on wave height and storm duration. While H represents the peak hydrodynamic forcing during the storm, $\log L$ reflects the cumulative effect of storm energy over time, allowing the model to distinguish between short-duration high-intensity storms and longer-lasting events with comparable peak wave heights.

The inclusion of the mean period corresponding to the maximum significant wave height (H), in the expert network model was considered. This variable was found to be strongly correlated with maximum significant wave height H (cor = 0.83; see Supplementary Information, Figure S3). However, including this variable caused the joint distribution of the analyzed parameters to deviate markedly from

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multivariate normality, as confirmed by Mardia's multivariate normality tests (p-value < 0.05). Consequently, the Bayesian Gaussian network model could not be applied when the mean period of maximum significant wave height was included. On the other hand, the strong correlation of this variable with the wave height H means that the influence of this variable is largely included in the expert network model via the variable H. A similar but simplified model was developed for the Australian coast, and it also incorporates morphodynamic parameters related to the beach volume before storm events occur along the coast (Beuzen et al., 2018b).

A GBN is equivalent to a system of linear regressions, where each vertex of a graph is associated with an explanatory variable (response variable), and the explanatory variables are associated with the vertices intersecting these vertices (Lauritzen, 1996). The above model (Figure 2) can be written as a system of linear regression equations:

$$\log(D) = a_0 + a_1 A + a_2 F + a_3 H + a_4 \log(L) + e_1 \quad (1)$$

$$\log(L) = b_0 + b_1 H + b_2 T + e_2 \quad (2)$$

where a_0–a_4, b_0–b_2 are the model parameters, and e_1, e_2 are independent random errors that are normally distributed with a mean of zero and standard deviation σ. Assuming multivariate normality of the distribution of variables (storm parameters), the only possible relationships between variables are linear. Linear relationships between storm parameters can also be a preliminary approximation of more complex relationships. Recently, Ibaceta and Harley (2024) consider linear relationships between post-storm coastal changes and various storm parameters. Equation (1), which represents the dependence of the log of the erosion magnitude on the variables A, F, H and $\log(L)$, is a generalization of the log-linear model in Bugajny et al. (2024). Equation (2) reflects the relationship between the storm energy L and H and T, which is physically well justified. Equation (2) represents a regression approximation of storm energy based on maximum significant wave height and storm duration, whereas storm energy itself was calculated from the full wave-height time series. Storm energy (L) was retained in the model as an event-scale measure of storm intensity and included as a direct explanatory variable of dune erosion in the final GBN structure.

2.3 Quantiles of the magnitude of dune erosion

On the basis of the expert GBN model, quantiles of order of 0.9, 0.99, and 0.999 were determined for the dune erosion magnitude (D) and its logarithm $\log(D)$, which correspond to values expected to be exceeded once every 10, 100, and 1000 events, respectively. Since, on average, one significant storm occurs per year (Bugajny et al., 2024), these levels can be interpreted as return periods of approximately 10, 100, and 1000 years.

In the GBN model, the magnitude of the logarithm of erosion is expressed by the linear regression equation (Eq. (1)). The quantile w_α is defined such that

$$P(\log(D) > w_\alpha) = \alpha \quad (3)$$

where $\alpha = 0.1, 0.01, 0.001$.

On the basis of the assumed normality of the random variables on the right-hand side of equation (1) and the dependency structure described by the relationships between $A, F, H, \log(L)$ the random variable $a_0 + a_1 A + a_2 F + a_3 H + a_4 \log(L) + e_1$ follows a normal distribution with mean

$$\mu = a_0 + a_1 E(A) + a_2 E(F) + a_3 E(H) + a_4 E(\log(L)) \quad (4)$$

and standard deviation

$$\sigma = \left(a_1^2 Var(A) + a_2^2 Var(F) + a_3^2 Var(H) + a_4^2 Var(\log(L)) + 2V + Var(e_1)\right)^{1/2} \quad (5)$$

where

$$V = a_1 a_2 Cov(A,F) + a_1 a_3 Cov(A,H) + a_2 a_3 Cov(F,H) + a_1 a_4 Cov(A,\log(L)) + a_2 a_4 Cov(F,\log(L)) + a_3 a_4 Cov(H,\log(L)) \quad (6)$$

$E(X)$ represents the expected value of the random variable (r.v.) X, $Var(X)$ represents the variation in r.v. X and $Cov(X,Y) = E(XY) - E(X)E(Y)$.

Therefore, the quantile for $\log(D)$ equals

$$w_\alpha = \mu + qnorm(1-\alpha) \times \sigma \quad (7)$$

and the corresponding quantile for D is

$$v_\alpha = \exp(\mu + qnorm(1-\alpha) \times \sigma) \quad (8)$$

where $qnorm(1-\alpha)$ is the quantile of order $1-\alpha$ of the standard normal distribution. To obtain these values, the parameters appearing in the expressions for μ and σ must be estimated. The coefficients $a_0 - a_4$ from regression Equation (1) are estimated using the least squares method. $Var(e_1)$ is estimated from a regression equation as an estimator of the variance of the model residuals. The population moments $E(X)$, $Var(X)$, $Cov(X,Y)$ are replaced by their corresponding empirical estimates derived from the sample.

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3. Results

3.1 Model estimation

The regression coefficients in Equations (1)–(2) were estimated using the least squares method. The resulting estimated regression functions are presented below. As these equations represent the estimated conditional relationships, the unobservable random error terms e_1 and e_2 are not included.

$$\log(D) = -23.01325 + 0.01672A + 0.05148F + 0.79707H - 0.57907\log(L) \quad (9)$$

$$\log(L) = 3.33886 + 0.33636H + 0.01412T \quad (10)$$

Equation (10) provides a very good fit to the data ($R^2 = 0.84$), indicating that storm energy is well explained by maximum wave height and storm duration. Equation (9) yields a moderate fit ($R^2 = 0.36$), indicating that the model captures a substantial but incomplete portion of the variability in dune erosion magnitude.

Volume of dune erosion (D) represents the impact of the storm on the coastal area. The model incorporates key hydrodynamic controls on dune erosion, including maximum wave height, wave direction, sea level, and storm energy, which together represent extreme wave forcing, exposure, cumulative storm intensity, and water-level control. The influence of wave direction on dune erosion also depends on the orientation of wave approach relative to the shoreline, which affects the interaction of wave forcing with the coastal system.

3.2 Selection and justification of the GBN expert network

The proposed network model (see Figure 2) represents the interdependencies between storm parameters: A, H, T, F, $\log(L)$, and $\log(D)$. The assumption of multivariate normality implies linear relationships between the variables at each graph node and the variables entering that node. The relationships described by Equation (1) are therefore natural within this framework. During the model selection stage, the possibility of nonlinear relationships was examined by adding interaction terms $A \times F$ and $F \times H$. Adding such variables causes a departure from the Gaussian model, however, these interactions did not improve the model fit and significantly increased the AIC and BIC information criteria. Similarly, adding iteration terms to Equation (2) significantly worsened the AIC/BIC, which may be a result of overfitting the model to the data with a relatively small sample size. Another issue was whether to select additional relationships H on T and H on F, which have been considered in the literature (Sanuy et al., 2020). However, in the present dataset, these relationships yielded very low coefficients of determination ($R^2 = 0.04$ and $R^2 = 0.01$, respectively) and resulted in increased prediction errors. Consequently, they were not included in the final network structure. The assumption of multivariate normality of the considered variables was not rejected by normality tests and based on the graphical quantile qq-plot method (Supplementary Information, Figure S2). Nevertheless, the limited sample size requires a cautious approach to the final verification of this assumption. Departing from this assumption and allowing nonlinear relationships would be essentially unverifiable with such a small sample, and would entail ahigh risk of overfitting nonparametric Bayesian network models to such a small dataset. Initial processing excluded variable interaction terms, confirming the validity of using linear relationships. The proposed expert assessment is somewhat subjective, reflecting possible causal relationships between storm parameters. The final structure network was validated using cross-validation and standard leave-one-out cross-validation. Acceptable relative forecast errors were obtained. Additionally, to reduce forecast uncertainty, 95% confidence intervals for the variable predictions from the proposed model were provided.

3.3 Model validation

To test the predictive ability of the proposed model, the obtained Bayesian networks were used to forecast storm parameters for data from 2010–2017, which were not used in model estimation. The forecast from the GBN model consists of taking the value of maximum significant wave height (H), wave direction (A) and sea level (F) from the test sample, as these variables are not conditioned on other nodes in the dependency graph (Figure 2). Based on the final network structure, storm energy ($\log L$) was first estimated from maximum significant wave height (H) and storm duration (T) using Eq. (2). Subsequently, dune erosion ($\log D$) was predicted using the conditional regression relationship defined by Eq. (1). The comparison between observed and modeled values of $\log D$ was used to evaluate the predictive performance of the Bayesian network.

Figure 3 and Table 1 show the forecasts along with the relative forecasting errors calculated using the following formula:

$$Error = \left(Y - \widehat{Y}\right)/Y \times 100\% \quad (11)$$

where Y is the real value and $\widehat{Y}$ is the prediction of Y from the model.

The relative forecasting error for the logarithm of the magnitude of dune erosion $\log(D)$ varies from -40.00% to $+6.55\%$ (Figure 3a). The forecasting error is skewed toward overestimation, indicating that the model occasionally predicts significantly higher erosion volumes than those observed. This behavior reflects the difficulty of capturing extreme, threshold-driven erosion events using a limited set of storm-scale predictors. For the forecasts of

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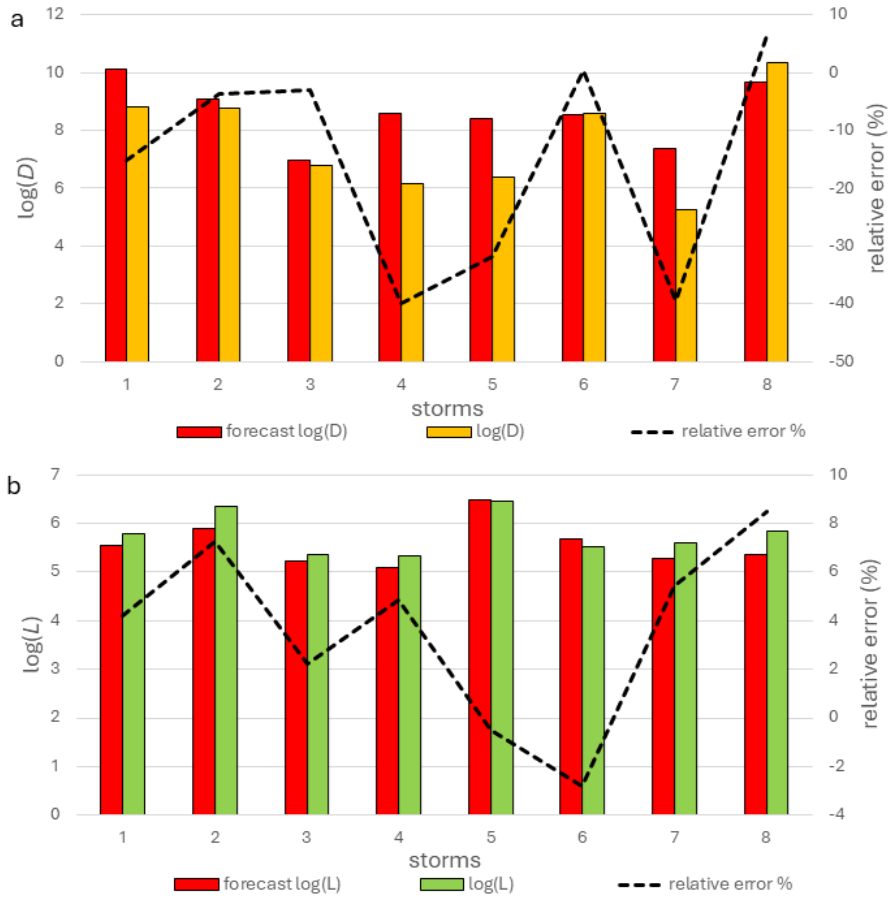

Figure 3. Forecasts and relative errors of forecasts.

Table 1. Relative errors for forecasts from the GBN based on data from 1978–2009 (forecasts calculated on the test sample 2010–2017).

Forecast	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
$\log(D)$	−40.00	−33.82	−9.44	−15.79	−2.16	6.55
$\log(L)$	−2.83	1.54	4.50	3.63	5.88	8.50

Table 2. Predicted $\log(L)$ and $\log(D)$ with 95% confidence intervals.

	$\log(L)$			$\log(D)$		
No	fit	lwr	upr	fit	lwr	upr
33	5.59	5.50	5.69	10.13	8.36	11.89
34	5.96	5.79	6.13	9.08	6.98	11.18
35	5.23	5.12	5.35	6.97	5.71	8.24
36	5.12	5.03	5.22	8.58	7.90	9.26
37	6.52	6.31	6.72	8.41	6.45	10.37
38	5.69	5.56	5.82	8.55	7.56	9.55
39	5.36	5.21	5.51	7.35	5.75	8.95
40	5.39	5.30	5.48	9.65	8.58	10.72

lwr – left end of the confidence interval, upr – right end of the confidence interval, fit is the predicted value

Table 3. Relative errors of forecasts from the GBN via LOO cross-validation.

Forecast	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
$\log(D)$	−84.37	−20.22	2.49	−4.55	11.79	38.94
$\log(L)$	−17.32	−3.44	0.75	−0.45	3.13	7.84

Explanations: log: natural logarithm; D: dune erosion; L: storm energy

the logarithm of storm energy $\log(L)$ (Figure 3b), the error ranges from −2.83% to +8.50%. In contrast to $\log(D)$, the prediction errors for $\log(L)$ are more symmetrically distributed and notably smaller, indicating that storm energy is more consistently and accurately predicted by the model. Overall, these results demonstrate that although storm energy can be robustly estimated within the Gaussian Bayesian network framework, the prediction of dune erosion remains inherently more uncertain, reflecting the complex and nonlinear nature of erosion processes.

In order to assess the uncertainty of the forecasts, 95% confidence intervals for the obtained forecast values are given in Table 2.

Table 4. Estimators of parameters for Equations (1)–(2) with median of estimators from LOO cross-validation.

Estimators and median of estimators	Intercept	A	F	H	T	$\log(L)$
Eq. (1) estim. param. median from LOO	−24.49	0.01899	0.05561	0.7362		−0.8303
Eq. (2) estim. param median from LOO	3.257			0.3861	0.01388	

Table 5. The values of the high-order quantiles are 0.9, 0.99, and 0.999 for dune erosion (D).

Quantiles	Log-linear models Bugajny et al. (2024)				Model GBN	
	log-$norm(D)$ [m^3]	$\log(D)$	log-$lin(F)$ [m^3]	log-$lin(F,H)$ [m^3]	log-$norm(D)$ [m^3]	$\log(D)$
0.9	95,051	11	97,437	91,749	92,405	11
0.99	544,012	13	570,273	509,852	876,626	14
0.999	1,947,840	14	2,075,505	1,786,580	4,541,711	15

Explanations: log: natural logarithm; log-lin: logarithmic-linear distribution; D: dune erosion; F: sea level; H: maximum significant wave height

Forecasts for $\log(L)$ and $\log(D)$ values were made using a standard predictive confidence interval based on Gaussian linear regression Equations (1)–(2). The obtained confidence intervals for individual storms from the test sample characterize the prediction uncertainty from the proposed model. As expected, more precise forecast results (shorter confidence intervals) were obtained for $\log(L)$ than for $\log(D)$.

3.4 LOO model validation

Here, the GBN model is considered using all 40 observations and apply leave-one-out (LOO) validation. In this approach, one observation is removed at a time and the model is fitted using remaining observations. The removed observation is then used to evaluate the forecast error. Repeating this procedure yields 40 estimates of the relative errors of individual forecasts. The LOO approach (Geroldinger et al., 2023) is a special case of cross-validation, a widely used method for testing machine learning models in which data are partitioned into separate training and testing sets to provide an unbiased evaluation of model predictive ability (Elsner and Schmertmann, 1994; Beuzen et al., 2018b). The relative forecasts errors obtained using the LOO method for the individual linear regression equations are presented in Table 3.

The forecast for $\log(D)$ is fairly accurate, with a low median relative error of 2.49%, indicating only a slight tendency to underestimate the observed values. However, the spread of the typical error (ranging from −20.22% to 11.79%) reflects variability in predictions, with the model occasionally overestimating erosion values by relatively large margins. The forecast for storm energy $\log(L)$ is more accurate than that for $\log(D)$. With a median relative error of 0.75% and an interquartile range of errors from −3.44% to +3.13%, the model produces more consistent predictions, characterized by low bias and relatively narrow error bounds around the observed values.

Finally, the stability of the GBN model was assessed using leave-one-out (LOO) cross-validation. The results are presented in Table 4. The estimated parameter values obtained from Equations (1)–(2) are very close to the corresponding median values derived from LOO cross-validations. This indicates a high level of stability of the model parameters.

3.5 Quantiles of the magnitude of dune erosion

Table 5 presents dune erosion values corresponding to events with exceedance probabilities of 0.9, 0.99, and 0.999 (i.e. events expected once every 10, 100, and 1000 years). The estimates were obtained using univariate log-normal distributions of D and $\log(D)$, log-linear models of dune erosion developed for this section of the Polish coast (Bugajny et al., 2024), and the GBN model proposed in this study.

The log-linear models of dune erosion considering sea level (F) and sea level together with maximum significant wave height (F, H) are defined as $\log(D) = a0 + a1 \times F + e$ and $\log(D) = a0 + a1 \times F + a2 \times H + e$, respectively (Bugajny et al., 2024). In the GBN model, the quantiles were computed based on Equations (7)–(8), and the resulting values are listed in Table 5.

For the 0.9 quantile, the predicted dune erosion values are comparable across all considered models. The univariate and log-linear approaches yield D values close to 95,051 m^3 with $\log(D) = 11$, while the GBN model produces a slightly lower estimate ($D = 92,405$ m^3) with the same value of $\log(D)$. Predictions obtained from the log-linear models incorporating F and (F, H) are marginally higher but remain within a similar range.

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For the 0.99 quantile, the predicted erosion values increase substantially. The univariate log-linear model yields $D = 544,012\ \mathrm{m}^3$, whereas the GBN model predicts a higher value of $D = 876,626\ \mathrm{m}^3$. The corresponding $\log(D)$ values are 13 for the log-linear model and 14 for the GBN model. Predictions from the log-linear models incorporating (F) and (F, H) remain below $600{,}000\ \mathrm{m}^3$.

For the 0.999 quantile, the predicted erosion volumes increase markedly. The univariate log-linear model yields $D = 1,947,840\ \mathrm{m}^3$, while the GBN model predicts a substantially higher value of $D = 4,541,711\ \mathrm{m}^3$. The corresponding $\log(D)$ values are 14 and 15, respectively. The log-linear models incorporating (F) and (F, H) produce values approaching 2 million but do not reach the extremes obtained with the GBN model.

Overall, the comparison indicates that differences between the models increase with increasing storm return period. While erosion estimates are similar for the 0.9 quantile, the GBN model predicts more than twice the erosion of the univariate and log-linear models for the 0.999 quantile. This suggests that the GBN model assigns a higher probability to extreme erosion events. The results therefore highlight clear differences between the previously developed log-linear models (Bugajny et al., 2024) and the GBN model proposed in this study, particularly for high-order quantiles. The estimated quantiles should be interpreted as statistical extrapolations derived from the fitted models, as direct observations of dune erosion corresponding to such high return-period storm events are not available.

4. Discussion

The use of Bayesian networks for analyzing descriptive relationships among variables, as well as their predictive abilities, represents an important approach for assessing processes occurring in coastal zones, particularly the impact of storms on coasts. In this research, an expert Gaussian Bayesian Network (GBN) model was developed to analyze the interdependence of significant storm parameters in coastal areas and assessed its predictive performance. Bayesian networks are commonly used to investigate causal relationships; in this study, the influence of hydrodynamic parameters on dune erosion was examined. This approach enables the representation of complex interconnections among storm parameters and their effects on coastal systems.

This research extends previous studies in which the effects of significant storm parameters (dune erosion, sea level, significant wave height and storm duration) on natural and protected coastal sections were analyzed using one- and two-dimensional statistical methods (Bugajny et al., 2024). In the present research, additional parameters related to storm energy and wave directions were considered, while the coast was treated as a single system and not subdivided into natural and protected sections.

The predictive ability of the expert GBN model, defined as its capacity to predict events not used in model calibration, was evaluated for eight storm events. The average relative absolute error for $\log(D)$ was 17.53%, indicating satisfactory predictive performance. It should be noted that the obtained forecast errors are satisfactory given the nature of the data, especially the approximate and imprecise values of dune erosion in the Maritime Office reports. Comparable results were reported for an optimal Bayesian network model by Beuzen et al. (2018a), where the average relative absolute error for changes in beach width was 22.22% for five storm events. A key difference between the two approaches is that the present model is based on expert knowledge and a predefined network structure, whereas the model of Beuzen et al. (2018a) is data-driven. Moreover, the present model is Gaussian and does not rely on variable discretization.

On the basis of the expert GBN model, high-order quantile of 0.9, 0.99, and 0.999 were estimated for dune erosion magnitude (D) and its logarithm $\log(D)$, corresponding to events expected to be exceeded once every 10, 100, and 1000 events, respectively. These results were compared with results obtained using previously developed log-linear models for the same coastal section (Bugajny et al., 2024).

The proposed methodology has several limitations. One important limitation is the relatively small sample size, with only 40 storm events. Other studies (Beuzen et al., 2018a; Ibaceta and Harley, 2024) commonly rely on morphological parameters regarding storm effect such as shoreline changes (waterline), which can be obtained very easily from publicly available data (i.e. satellite images), hence their attempts are more numerous. In contrast, data on dune volume changes can only be obtained from field studies, and their quantity depends not only on measurement frequency but also on specific hydrodynamic and meteorological conditions, as well as on the geological and geomorphological conditions of the studied area.

Furthermore, the expert GBN model does not include pre-storm morphological characteristics of the coastal zone. Previous studies have shown that pre-storm beach volume is a key predictor of dune erosion (Athanasiou et al., 2022), and that additional characteristics, such as beach width, beach slope, nearshore slope (Athanasiou et al., 2022; Bugajny and Furmańczyk, 2022), and underwater longshore bar morphology (Castelle et al., 2015), play important roles in controlling post-storm dune erosion. Unfortunately, such information was not available for the oldest events analyzed in this study. For more recent periods, these parameters are typically measured only once per year, which limits their applicability when multiple storm events occur within a single year and prevents explicit representation of storm sequencing effects. As a result, cumulative erosion caused by closely spaced storms may be underestimated or misrepresented, particularly

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when the final storm in a sequence produces disproportionately large dune erosion, as observed during the storm of 3 November 1995.

Previous studies have confirmed the importance of storm sequencing along the Dziwnów Spit (Furmańczyk and Dudzińska-Nowak, 2009), particularly in coastal sections characterized by low dune elevations or modified by coastal protection structures (Furmańczyk et al., 2011, 2012a,b). These characteristics highlight the spatial heterogeneity of the study area and its exposure to varying storm impacts. A sensitivity analysis excluding the storm of 3 November 1995 yielded very similar results, indicating that the model performance and conclusions are not driven by this single extreme event.

Another important limitation is the implicit assumption of unlimited sediment availability. The model does not explicitly account for sediment supply constraints or sediment starvation, which may occur due to natural factors or as a result of coastal protection measures. Such interventions can significantly modify local sediment budgets. Hard and soft coastal protection methods, such as biological methods, can play important roles in the process of dune erosion during storm events. With the development and construction of hydroengineering structures and protective measures in the area of the Dziwnów Spit (Dudzińska-Nowak, 2006, 2015), the study area is currently one of the few sections of the Polish coast characterized by a wide range of coastal protection measures making it a particularly complex coastal system. This spatial heterogeneity is not explicitly represented in the current model formulation. As a consequence, the model may overestimate dune erosion in locations where sediment availability is limited, particularly in heavily protected coastal sections.

Furthermore, processes related to seasonal ice cover are not included in the model. Ice cover can temporarily reduce wave energy reaching the shore and inhibit sediment mobilization, potentially limiting dune erosion during cold-season storms. As these processes are not explicitly represented, the model may overestimate erosion during such events. Consequently, the predictive performance of the model under future climate conditions, including sea-level rise and changes in storm frequency or seasonality, cannot be assumed to remain unchanged and should be interpreted with caution.

Other limitations regarding the spatial uniformity of hydrodynamic data reported in previous research (Bugajny et al., 2024) were mitigated in the present study by treating the study area as a single coastal system rather than subdividing it into protected and natural sections. However, this approach also precludes explicit consideration of local coastal protection measures. In future work, dune erosion will be calculated per 1 km of coastline for predefined alongshore segments, which will allow incorporation of coastal protection effects and alongshore variability in hydrodynamic forcing.

It should also be emphasized that the parameters of the expert GBN model are site-specific, as they were estimated from observations collected for the investigated coastal sector. Consequently, they reflect the overall response of the investigated coastal system to its local geological and morphological setting, prevailing hydrodynamic conditions, and anthropogenic modifications, including coastal protection measures. Therefore, the estimated parameter values should not be directly transferred to other coastal settings without recalibration using local data. Despite these limitations, the proposed model has potential applications in coastal zone management, particularly for the development of early warning systems and the assessment of storm-related hazards along the Polish coast. To date, such systems have been developed only for selected coastal sections (Ciavola et al., 2011; Haerens et al., 2012; Furmańczyk et al., 2014) using process-based models such as XBeach (Bugajny et al., 2013, 2015; Bugajny and Furmańczyk, 2022). Notwithstanding the above limitations and given its relatively low data and computational requirements, the proposed modeling framework, once further refined and locally recalibrated, could potentially be applied to other sections of the Polish coast as an effective risk management tool and an alternative to a sectional system based on highly detailed, site-specific process-based modeling approaches.

5. Conclusions

The aim of this study was to investigate the interdependencies among significant storm parameters using an expert Bayesian network. For this purpose, an expert Gaussian Bayesian network (GBN) was developed based on 32 storm events recorded between 1978 and 2009. Its predictive performance was evaluated using eight independent storm events from 2010–2017 and further assessed through leave-one-out (LOO) cross-validation. The LOO procedure was also used to examine the stability of the model parameters.

The high stability of the estimated parameters and satisfactory forecast errors indicate that the model provides a reasonable approximation of more complex dependencies between storm parameters. In the case where the assumption of multivariate normality holds, the model offers an accurate description of these dependencies. Moreover, on the basis of the expert GBN model, high-order quantiles of 0.9, 0.99, and 0.999 were determined for the dune erosion magnitude (D) and its logarithm $\log(D)$, corresponding to values expected to be exceeded once every 10, 100, and 1000 events, respectively.

Model estimation for the magnitude of dune erosion $\log(D)$ yielded satisfactory results, with the coefficient of determination (R^2) indicating relatively good agreement between the modeled and observed data. During the validation process using the first approach, the average absolute error for $\log(D)$ was 17.53%, while the corresponding

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value for log(L) was 4.47%.

The forecast of dune erosion based on log(D) is fairly accurate, with a low median relative error of −9.44%, suggesting only a tendency to overestimate the true values. However, the spread of the typical error (between −33.82% and −2.16%) reflects some variability in predictions.

The proposed method of using a GBN is simple to implement, as it relies on a system of ordinary linear regression equations and does not require large datasets, in contrast to nonparametric copula-based approaches. An additional advantage of the GBN framework is that, unlike discretized Bayesian networks, it preserves the full information content of continuous variables and allows prediction uncertainty to be quantified explicitly. Overall, the prediction errors obtained for dune erosion are acceptable, supporting the applicability of the proposed model.

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Data availability

The datasets analyzed during the current study are available in the Supplementary Information.

Conflict of interest

None declared.

Author contributions

- Konrad Furmańczyk: Conceptualization, methodology, software, formal analysis, investigation, validation, writing – original draft, writing – review & editing, visualization, project administration, funding acquisition.
- Natalia Bugajny: Conceptualization, methodology, data curation, formal analysis, investigation, validation, writing – original draft, writing – review & editing, visualization, project administration, funding acquisition.
- Kazimierz Furmańczyk: Conceptualization, formal analysis, writing – review & editing, supervision.

Supplementary material

Supplementary material associated with this article can be found here.

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