



# Classification of soft cliff dynamics using remote sensing and data mining techniques

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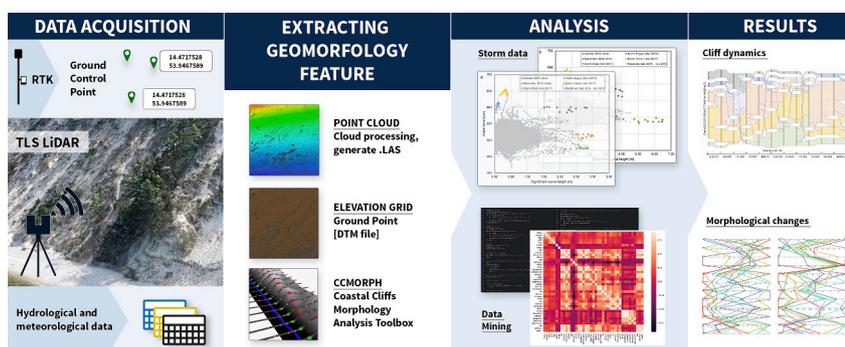
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## HIGHLIGHTS

- Utilizing high-resolution hydrometeorological data and advanced data mining tools to assess soft cliff dynamics.
- Evaluating the conditional dependence between cliff erosion and hydrometeorological data.
- Highlighting the significance of interactions between precipitation and cliffs in the study of seasonal erosion patterns.
- Describing the susceptibility of cliff coastlines to extreme water levels and precipitation events.
- Precipitation emerged as the most significant variable for explaining seasonal cliff dynamics.

## GRAPHICAL ABSTRACT



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## ABSTRACT

Coastal soft cliffs are subject to changes related to both marine and subaerial processes. It is imperative to comprehend the processes governing cliff erosion and develop predictive models for effective coastal protection. The primary objective of this study was to bridge the existing knowledge gap by elucidating the intricate relationship between changes in cliff system morphology and the driving forces behind these changes, all within the context of ongoing climate change. Therefore in this study, we employed various quantitative numerical methods to investigate the factors influencing coastal cliffs and the adjacent beaches. Our analysis involved the extraction of several morphological indicators, derived from terrestrial laser scanning data, which were then used to assess how cliffs respond to extreme weather events. The data span two winter storm seasons (2016–2018) and encompass three soft-cliff systems situated along the southern Baltic Sea, each characterized by distinct beach and cliff morphology. We conducted a detailed analysis of short-term cliff responses using various data mining techniques, revealing intricate mechanisms that govern beach and cliff changes. This comprehensive analysis has enabled the development of a classification system for soft cliff dynamics. Our statistical analysis highlights that each study area exhibits a unique conditional dependency between erosion processes and hydrometeorological

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conditions, both during and between storm events. Furthermore, our findings underscore the vulnerability of cliff coastlines to extreme water levels and episodes of intense precipitation.

## 1. Introduction

Coastal regions worldwide face mounting challenges arising from the dual impact of climate change and increasing human activities (Defeo et al., 2009; Fanini et al., 2020). Those are analyzed by employing diverse approaches, ranging from change models based on global shoreline movement patterns (Musielak et al., 2017; Paprotny et al., 2021; Vousdoukas et al., 2020) to land cover dynamic analysis (Giza et al., 2021). The European Commission Joint Research Centre has issued a dire warning, suggesting that nearly half of the world's beaches could vanish by the century's end due to coastal erosion driven by sea level rise (SLR) (Vousdoukas et al., 2020). However, SLR is not the sole threat to sandy coastal development (Cooper et al., 2020) as those are shaped also by coasts is shaped not only by numerous single and cascading storm events as well as precipitation and insolation (Kostrzewski et al., 2015; Terefenko et al., 2018a, 2018b). Sandy shores may undergo various responses to SLR, including (1) landward migration through onshore sediment transport via overwash without losing beach width (e.g., barrier beaches on gentle substrates), (2) recession due to offshore sediment transport (e.g., beaches backed by non-erodible cliffs or seawalls), or (3) submergence as intact sand bodies on the seabed (overstepped), a scenario requiring rapid SLR or specific combinations of morphology and sediment supply (Green et al., 2014). Remarkably, sandy coasts may even expand under SLR when there is a significant positive sediment budget (Brooke et al., 2019).

Concurrently, coastal cliffs encompass a substantial 52 % of the global shoreline (Young and Carilli, 2019). These cliffs face structural degradation resulting from the combined actions of marine and sub-aerial processes, manifesting as gradual erosion and episodic mass movements (Earlie et al., 2018). Predicting beach-fronted soft cliffs erosion is more challenging than forecasting sandy beach evolution due to the involvement of a multitude of factors (Bray and Hooke, 1997; Terefenko et al., 2018a), beyond those influencing beach erosion as previously mentioned. In essence, comprehending the processes governing cliff erosion and predicting their trajectory is of paramount importance, as cliff erosion can contribute to flood risk mitigation (Dawson et al., 2009) and serve as a vital sediment source for beaches (Dean and Dalrymple, 2001).

Numerous studies on the erosion of soft cliffs backing beaches have identified various factors as significant in shaping cliff morphology. Notably, beach geometry (width, slope, and height) plays a crucial role in modulating wave energy dissipation (Dornbusch et al., 2008; Trenhaile, 2016). In-situ observations confirm correlations between coastal changes, wave energy, and the interaction between wave run-up and beach levels (Paprotny et al., 2014; Sallenger et al., 2002; Swirad and Young, 2022a; Young et al., 2021). Extreme water levels, particularly in conjunction with wave heights and storm surge frequencies, directly impact volumetric cliff changes (Lee, 2008; Terefenko et al., 2018b; Walkden and Dickson, 2008; Walkden and Hall, 2005; Winowski et al., 2022).

While subaerial and marine processes drive cliff erosion, geological conditions exert a substantial influence on erosion rates, depending on lithological compositions (Benumof et al., 2000) and rock resistance (Sunamura, 2005). Erosion occurs when wave forces surpass rock resistance (Sunamura, 2005) and further geological structure determines the spatial intensity of erosion processes (Winowski et al., 2022).

Beyond the lithosphere and hydrosphere impacts on erosion rates, cliff development is influenced by atmospheric factors. Meteorological variables, such as rainfall, have demonstrated correlations with upper cliff erosion (Young et al., 2021). Furthermore, wind speed, in certain

cases, exhibits a stronger correlation with cliff morphology changes than wave height indicators, often proving a superior predictor of the wind-driven waves responsible for shoreline retreat (Terefenko et al., 2019). Moreover, in the absence of substantial wave forces directly triggering cliff failures, cliffs are affected by moisture and the presence of water within the cliff (Dietze et al., 2020).

The factors influencing the dynamics of coastal cliffs and their adjacent beaches have been investigated using diverse quantitative numerical methods, ranging from basic correlation matrices (Prémaillon et al., 2018) to stochastic simulations (Hall et al., 2002) and numerical modeling (Earlie et al., 2018). These analyses have assessed the relationship between beaches and cliffs in the context of climate change and sea level fluctuations, considering both long-term (Walkden and Hall, 2011; Young and Ashford, 2006) and short-term timeframes (Earlie et al., 2018; Young et al., 2016, 2021). Given the potential for future increases in SLR and storm activity (Giza et al., 2021; Haigh et al., 2016; Paprotny et al., 2019; Śledziowski et al., 2022; Vousdoukas et al., 2020), it is crucial to continue investigating spatiotemporal patterns of cliff erosion (Swirad and Young, 2022b) to address existing uncertainties related to the processes leading to cliff erosion.

This study sought to address this knowledge gap by analyzing soft cliff dynamics using innovative techniques. We utilized high-resolution in-situ monitoring datasets and applied various data mining methods tailored to the study's objectives, including classification, grouping, and correlation analysis. To this end, we employed six distinct methods, namely: (1) multivariate regression trees (MRTs), (2) component analysis, (3) correspondence analysis (CA), (4) canonical CA (CCA), as well as (5) multivariate analysis (MVA) and (6) multivariate random forests (MRFs). Employing this array of data mining tools not only enabled us to explore the roles of specific factors, such as wave characteristics, beach morphology, rainfall, and storm energy, in shaping cliff morphology but also facilitated the development of a novel classification system for soft cliff coast dynamics.

## 2. Study site description

Our analysis was conducted within the non-tidal basin of the Baltic Sea. Along the entire German-Polish coastline, cohesive Clastic Pleistocene and Holocene deposits are prevalent. The study area encompasses three selected cliff sites characterized by the presence of till, intermorainic clay, sand, and gravel (Terefenko et al., 2018a; Winowski et al., 2022). Each test site exhibits distinct geomorphological features (Fig. 1). The region under analysis has witnessed an increased frequency of storms and elevated storm surge levels (Tönisson et al., 2013; Vousdoukas et al., 2016), resulting in intensified erosion processes along the coastal cliff areas. Depending on the measurement methodology and the location of the test sites, cliff retreat values range from 20 to 80 cm per year (Kostrzewski et al., 2015; Terefenko et al., 2019).

Firstly, the western portion of the study area is represented by the Langer Berg cliffs, situated adjacent to the coastal resort of Bansin in Germany. This area constitutes the most dynamic section of Usedom Island, characterized by a north-eastern exposure and cliffs reaching a height of 54 m. In front of these soft cliffs lies an unusually wide beach, spanning 30 m. The Bansin resort represent an area with numerous protective measures implemented to protect the city since the late 19th Century (Schumacher, 2002). These protective measures include a cliff rampart reinforced by a triple wall, groins, three wave-breakers, and modern sand nourishment practices. However, for our analysis, we selected the most dynamic 500 m-long stretch of coastline less than one kilometer from the resort and the coastal defence systems which is not directly protected by human-made structures. Coastal changes in this

section of the Baltic Sea has been conducted by Schwarzer et al. (2003) who estimate that Langer Berg cliffs retreated ca. 100 m in the last 300 years.

The following two research areas are located in Poland and, in contrast to Langer Berg, feature a north-western exposure. While both cliff formations primarily comprise glacial and glaciofluvial deposits, till, and eolian deposits, their landscape relief varies significantly. The Biała Góra coastline, situated near the popular seaside resort of Międzyzdroje on Wolin Island, is composed of high cliffs reaching approximately 57 m in height. Along the 500 m-long investigation area, the beach is relatively narrow, with an average width of 8 m and a maximum of 14 m. During the summer, it is mainly covered with a mixture of sand and gravel. Winter storms typically erode the sandy portion, leaving behind the heavier gravel component and occasionally exposing flat concrete blocks buried in the beach to protect the cliff face from extreme events (Terefenko et al., 2019). Research studies on the Wolin Island cliff-coast dynamics have concentrated mainly on issues of geology and geomorphology (Kostrzewski et al., 2015; Terefenko et al., 2018a; Terefenko, 2020; Winowski et al., 2022).

The geomorphological context of the easternmost analyzed test site, located near the village of Wicie, differs significantly. The cliff face here is notably lower, reaching only 11 m in analyzed sections. Furthermore, the beach width exhibits fluctuations, ranging from <1 to 20 m along the test site, representing the highest diversity among all the test sites. Due to the high erosion risk, the coastline is safeguarded by a system of groins. This particular section constitutes the least researched test area, with some geomorphological investigations conducted by Terefenko et al. (2019). The analysis focused on creating a statistical model of the beach and cliff system's geomorphological response using a non-parametric, continuous Bayesian network.

### 3. Materials and methods

#### 3.1. Light detection and ranging measurements

The geometry of the cliffs was captured through a series of 13 laser scanning campaigns conducted at each of the three test sites within corresponding time intervals from November 2016 to June 2018. Our

calculations were carried out over 12 analytical periods (Table 1). Additionally, an extra analytical period labeled “0,” commencing on 01.09.2016, was employed to facilitate the correlation of beach width and cliff slope with hydrometeorological variables. Topographic surveys were conducted using terrestrial laser scanner technology, commonly known as LiDAR (Light Detection And Ranging). LiDAR is a widely adopted technique for measuring areas, generating digital terrain models and maps, and quantifying coastal changes through multi-temporal comparisons (Johnson et al., 2020; Kolander et al., 2013; Loiotine et al., 2021; Nunes et al., 2011). Post-storm surveys were conducted using a Riegl VZ-400 scanner. These campaigns were executed from 10 scanner stations, situated on average approximately 50 m from the coastline, resulting in the acquisition of 90 to 100 points per m<sup>2</sup> of the measured surface. Based on the laser return data, vegetation and other obstacles were removed, and datasets from all 13 campaigns were processed to create “bare earth” point clouds. The data were then overlapped and clipped to identify the area common to all campaigns at each of the three test sites. Finally, the original point cloud representing the coastal surface was filtered to produce profile lines with 50 m-wide spacing. The data can be found in the Mendelay Data repository (<https://data.mendeley.com/datasets/g448xnxp2j/1>). More detailed information about data has been described further by Terefenko (2020).

Finally dealing with uncertainties is important issue when establishing confidence in the results of volumetric changes as they inherit the uncertainty in the data used to its computation. The calculation of volumetric changes both for beach and the cliff face has been realized directly on the point cloud (Fig. 2) separately for each 50 m section of the coast with the use of dedicated PYTHON script. The vertical absolute accuracy of LiDAR surveys has been proved to represent the values between 4 and 7 mm as determined by comparison of control points (geodesic benchmarks) between following LiDAR surveys and real-time kinematic positioning.

#### 3.2. Hydrodynamic data collection

To ensure the completeness and resolution of meteorological and hydrological data in this study, information was gathered from multiple

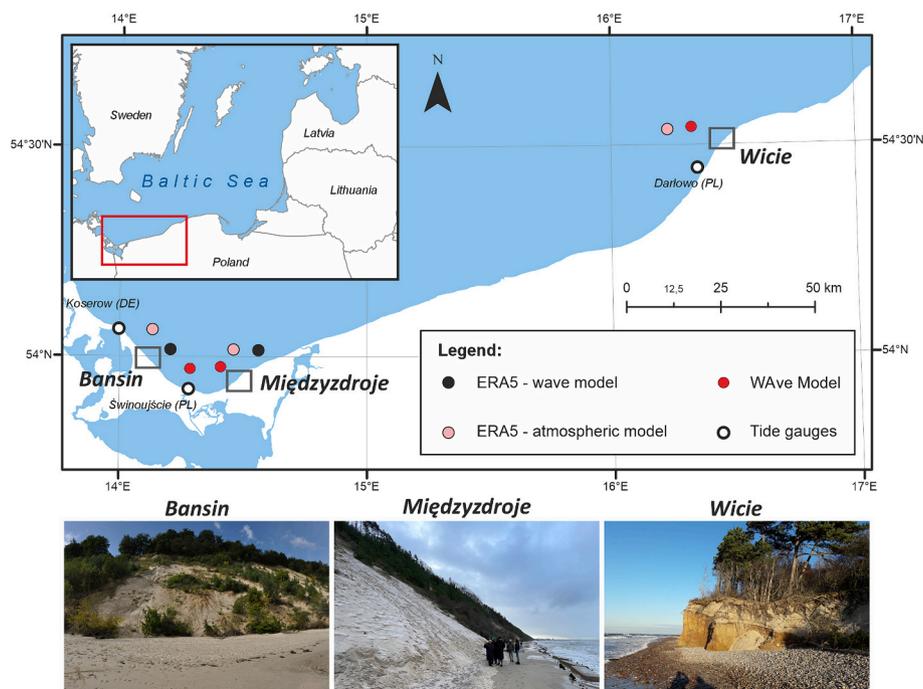


Fig. 1. Location map showing the study sites, tide gauges, and grid data points.

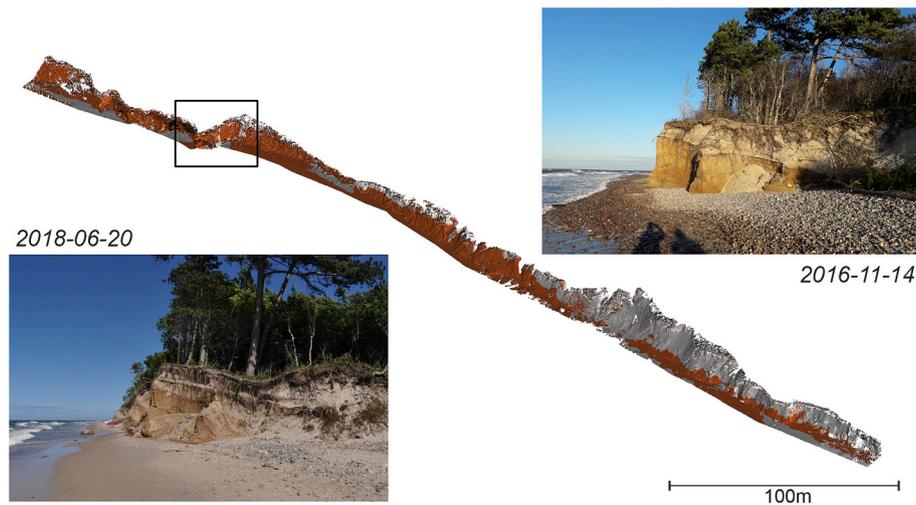
**Table 1**  
Analytical periods used in the study according to survey dates by test site.

Analytical period	Langer Berg cliff	Biała Góra cliff	Wicie cliff
1	09.11.2016–19.12.2016	03.11.2016–14.12.2016	14.11.2016–12.12.2016
2	19.12.2016–29.12.2016	14.12.2016–30.12.2016	– <sup>a</sup>
3	29.12.2016–16.02.2017	30.12.2016–14.02.2017	12.12.2016–15.02.2017
4	16.02.2017–06.04.2017	14.02.2017–03.04.2017	15.02.2017–10.04.2017
5	06.04.2017–07.06.2017	03.04.2017–06.06.2017	10.04.2017–09.06.2017
6	07.06.2017–04.09.2017	06.06.2017–11.09.2017	09.06.2017–01.09.2017
7	04.09.2017–17.10.2017	11.09.2017–16.10.2017	01.09.2017–18.10.2017
8	17.10.2017–06.11.2017	16.10.2017–07.11.2017	18.10.2017–29.11.2017 <sup>b</sup>
9	06.11.2017–12.01.2018	07.11.2017–09.01.2018	29.11.2017–15.01.2018 <sup>c</sup>
10	12.01.2018–01.02.2018	09.01.2018–19.02.2018	15.01.2018–02.02.2018
11	01.02.2018–21.03.2018	19.02.2018–04.04.2018	02.02.2018–23.03.2018
12	21.03.2018–26.06.2018	04.04.2018–14.06.2018	23.03.2018–20.06.2018

<sup>a</sup> Survey on 28.12.2016 was unsuccessful due to high water levels.

<sup>b</sup> Survey was unsuccessful at two profiles.

<sup>c</sup> For two profiles, the analytical period was 15.01.2018–18.10.2017.



**Fig. 2.** Point cloud model for Wicie test site. In red beach and cliff sections eroded during first analytical period. Field photos represent area marked in the black frame taken in November 2016 and June 2018.

sources. Water level data for the Polish coastal sections were obtained from tide gauges maintained by the Institute of Meteorology and Water Management (IMGW). Specifically, measurements from Świnoujście and Ustka tide gauges were utilized for the Międzyzdroje and Wicie test sites, respectively. For the German test site in Bansin, water levels from the nearest tide gauge in Koserow, operated by the German Federal Waterways and Shipping Administration (WSV), were employed. To maintain consistency, all water level data were corrected to the same reference level (Kronstadt zero-level). This data was collected through personal communication with IMGW and the German Federal Institute of Hydrology (BfG).

Relevant wave parameters, including significant height, period, and direction, were obtained for offshore waves that were transformed for coastal areas using the WAM wave model in the Baltic Sea. Data has been obtained by dedicated API and the graphical version is available at ICM website (<https://old.meteo.pl/>). This model relies on wind data from the COAMPS model and is hosted by the Interdisciplinary Centre for Mathematical and Computational Modeling at Warsaw University (ICM). The validation of the WAM model for the Baltic Sea was conducted as part of the HIPOCAS EU project (Cieślakiewicz and Paplińska-Swerpel, 2008) with the use of offshore buoy data and satellite data. The model has a resolution of  $1/12^\circ$  (approximately a 5 by 9 km grid in the study area) with 1 h time steps. For each test site, the nearest grid point was identified for data retrieval. This information was obtained through personal communication with ICM.

It is worth noting that the WAM data contains gaps. To address this, the data underwent verification and supplementation. Minor gaps, spanning a few hours during calm weather, were filled using interpolation. More substantial gaps were identified for three periods in December 2016, June 2017, and February 2018, totaling 36 days across all three locations. Data for these periods were sourced from ERA5 reanalysis (Hersbach et al., 2020), an operational model from the European Center for Medium-Range Weather Forecasts (ECMWF). The ERA5 wave model provides hourly data with a spatial resolution of  $0.36^\circ$ . Due to its lower resolution, which reflects wave conditions in deeper seas compared to WAM, ERA5 values were adjusted using a constant factor specific to each study area, time, and variable. This adjustment factor was determined by comparing the available WAM data for the entire month when the data gap occurred with corresponding ERA5 data. The correction factor was calculated by dividing the average values of the two models for the same time steps. Lastly, the ERA5 reanalysis atmosphere model, with a resolution of  $0.28^\circ$ , supplied temperature and precipitation data for all locations. These reanalysis data can be downloaded from the Copernicus Climate Change Service.

### 3.3. Extraction of geomorphic features and hydrometeorological variables

Our initial task was to establish a methodology for describing cliff morphology using various indicators to facilitate subsequent statistical analysis. Therefore, we opted to extract geomorphic features using line

indicators, as this method is commonly used in monitoring coastal areas (Bugajny et al., 2015; Bugajny and Furmańczyk, 2022; Keijsers et al., 2016; Vos et al., 2022). These indicators include shoreline, cliff base line and cliff top line. Their position is further used to calculate following parameters: shoreline retreat and beach width (Deng et al., 2017; Nunes et al., 2011), beach and cliff volume balance (Kolander et al., 2013; Winowski et al., 2022), cliff foot and top retreat (Le Mauff et al., 2018), and cliff slope (Terefenko et al., 2019).

The shoreline delineation was relatively straightforward and has been realized by extraction the 1 m contour above mean sea level (MSL). Data limitations arose due to high water levels and post-storm survey timing did not allowed to use zero MSL. The delineation of cliff foot and top proved more challenging. Working with 39 different topographic surveys demanded precise and reproducible line detection. Manual digitalization was deemed inadequate in terms of precision and reproducibility (Le Mauff et al., 2018; Palaseanu-Lovejoy et al., 2016). Therefore, we implemented an automatic methodology using the Coastal Cliffs Morphology Analysis Toolbox (CCMORPH). CCMORPH comprises Python scripts and a JavaScript tool designed to generate georectified information tailored for the creation and quantitative analysis of coastal cliff morphology (Lysko et al., 2023; Terefenko et al., 2024).

Having prepared all geomorphological variables, our second task involved generating hydrometeorological predictors to elucidate different cliff classification types. In this study, we analyzed a total of 34 variables, including various parameter calculations related to wave, wind, water level, temperature, and precipitation. We computed values representing minimum, maximum, average, and 95th percentile using a dedicated Python script called Storm Data Analyser (STODA) over the entire period between survey campaigns or during storms that occurred within those periods.

Additionally, the STODA script was utilized to calculate several synthetic variables describing storm energy and wave power, as listed below.

Storm energy was calculated as follows (Eq. (1)) (Dean and Dalrymple, 1991):

$$E = \sum_{i=1}^t \frac{1}{8} \rho g H_i^2 \quad (1)$$

where  $\rho$  is the density of seawater ( $\sim 1020 \text{ kg/m}^3$ ),  $g$  is the gravity ( $9.81 \text{ m/s}^2$ ),  $H_i$  is the significant wave height (m) at time step  $I$ , and  $t$  is the storm duration.

Accumulated excess storm energy was calculated as follows (Eq. (2)) (Hackney et al., 2013):

$$E = \sum_{i=1}^t \frac{1}{8} \rho g \left( (H_i + S_i)^2 - R^2 \right) \quad (2)$$

where  $S_i$  is the water level (m) at time step  $I$ , and  $R$  is the threshold of minimum cliff base line height to be affected by waves. It has been set on the basis of coastal profile characteristics at 2 m value for all three test areas. Wave power was calculated as follows (Eq. (3)) (Earlie et al., 2018):

$$P = EC = \frac{1}{16} \rho g H^2 \frac{g}{4\pi} T_m = \frac{\rho g^2}{64\pi} H^2 T_m \approx 500 H^2 T_m \quad (3)$$

where  $C$  is the wave celerity (m/s), and  $T_m$  is the mean wave period (s). The equation gives wave power in W/m, hence:

$$P \approx 0.5 H^2 T_m \quad (4)$$

gives wave power in kW/m. For maximum wave power the equation is:

$$P \approx 0.5 H^2 T_p \quad (5)$$

where  $T_p$  is the peak wave period (s).

### 3.4. Data mining methodology

Data mining methods are a crucial component in the study of coastal processes (Rogers, 2020) and are extensively employed for the analysis of a growing number of available observational datasets (Guillou and Chapalain, 2021). In this study, we employed various methods to categorize cliff dynamics types and assess the most influential hydrometeorological factors in shaping both geomorphological parameters and changes in cliff profiles.

Initially, we attempted to classify coastal cliff dynamics types based on geomorphological parameters using cluster analyses with gap statistics to determine the optimal number of clusters. However, this method did not reveal any distinct clusters in the data. As a result, we conducted another analysis using ordination methods and a MRT analysis. Two ordination methods, namely principal component analysis (PCA) and CA, were tested. To facilitate CA, we normalized the values of beach geomorphological parameters to fall within the range of zero and one since CA does not accommodate negative numeric values. Both PCA and CA were executed using the “vegan” package in R. We extracted the coordinates of the first two axes from the ordination model, which explained the highest amount of variation. These coordinates were then employed as response variables, while the geomorphological parameters served as explanatory variables in the MRT analysis to determine cliff dynamics types. Tree-based approaches are advantageous as they can handle linear and non-linear relationships, high-order interactions, and multicollinearity, making them generally more accurate than traditional linear methods (De'Ath and Fabricius, 2000). The most parsimonious MRT models were selected through pruning to minimize cross-validation error based on the complexity parameter, and the percentage of variation ( $R^2$ ) explained by the MRT using the explanatory variables was calculated ( $R^2 = 1 - \text{relative error}$ ). The relative error is the sum of the within-group sum of squares divided by the total sum of squares of the response data for all groups at a partition level. The MRT analysis was performed using the “mvpart” package in R (De'ath, 2002).

Further investigation was conducted using MVA as an adopted method to explore the relationships between coastal erosion and hydrometeorological features. MVA methods are often employed to elucidate and discuss the principal components governing coastal zone processes (Baltranaitė et al., 2020). These methods encompass various sub-methods for in-depth and enhanced evaluation of different features. Pearson correlation coefficient, factor analysis, PCA, and clustering using K-means MVA methods were used to analyze the relationship between hydrometeorological and morphological datasets.

To support the MVA analysis, we applied two additional multivariate methods: (a) MRFs and (b) CCA to identify the most influential hydrometeorological factors in shaping geomorphological parameters. MRF is advantageous over CCA as it can handle non-linear relationships, high-order interactions, and multicollinearity (De'Ath and Fabricius, 2000). CCA was used to identify patterns in coastal cliff morphological types and link them to hydrometeorological processes. CCA is considered a multivariate linear statistical analysis and is often employed in various fields when examining associations between numerous independent and dependent variables. Larson et al. (2000) introduced CCA to the field of coastal analysis, and it has since been successfully used to predict beach profiles with wave probability density functions (Horrillo-Caraballo and Reeve, 2008) and to determine wave-shoreline dynamics (Ruiz de Alegría-Arzaburu et al., 2010). In our study, we used CCA to assess coastal cliff profile evolution over time and correlate it with the influencing hydrometeorological climate. The main steps of the methodology are summarized in Fig. 3.

## 4. Results

### 4.1. Hydrodynamic conditions

During the analyzed period, several storms resulted in extreme water

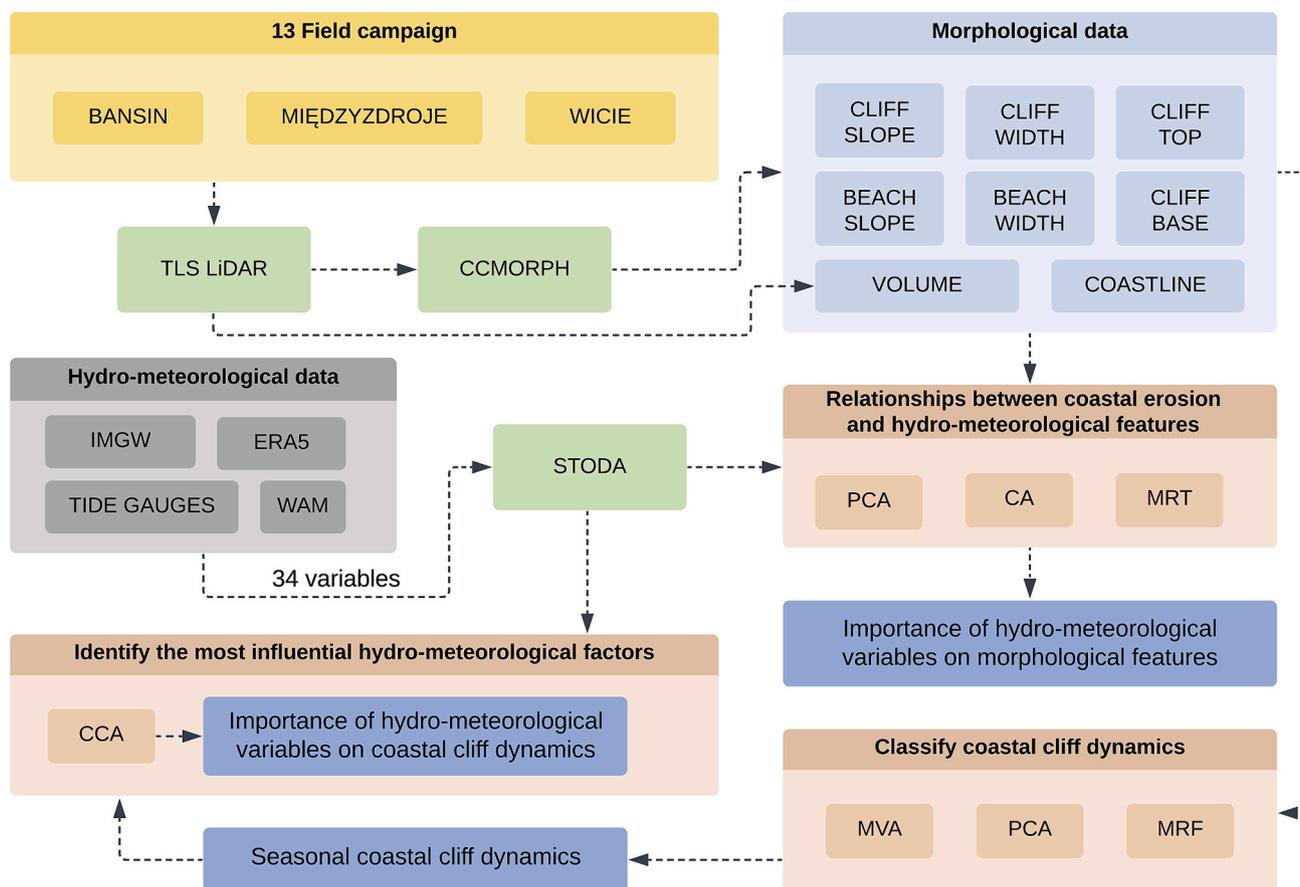


Fig. 3. Flow chart of the main steps and processing of the methodology used in this paper.

levels and wave heights. Following Wiśniewski and Wolski (2009) who realized a comprehensive study of storm surges on the Baltic Sea we define storm surges as sea levels 0.6 m above the mean or higher. The total number of surges varied, with 22, 15, or 14 recorded at different tide gauges as we move eastwards along the coast. However, it is important to note that high sea levels were not always accompanied by strong wave action, and vice versa. This is linked with events where high waves being generated by strong winds associated to high-pressure systems that do not involve barometric surge, or storm approach direction being oblique to the coast and not shore-normal.

Fig. 4 presents sea level and wave height data for all data points, with distinct storms highlighted in different colors (only 12 h windows centered around the peak are marked). The three largest surges, in terms of water level, were all a consequence of extratropical storms that initially affected northwestern Europe. These storms triggered landslides in the British Isles about a week before reaching the study area. For example, Storm Conor (known as Axel in Germany), which resulted in a surge of up to 1.55 m (at the Koserow gauge), swept through the German and Polish coasts on January 4–5, 2017. During this event, waves at all cliff sites did not exceed 1 m.

In contrast, an earlier storm, Angus (November 27–28, 2016), caused both high surges (about 1 m) and significant waves (up to 3–4 m). One year later, Storm Brian (or Herwart, October 29–30, 2017) led to high water levels (up to 1.15 m) but only generated small waves (no >0.6 m).

Two other storms highlighted in Fig. 4 could not be linked to any extratropical storms affecting a broader area of Europe. These were local phenomena characterized by low water levels. During the December 2016 event, sea levels were mostly below average, while wave heights reached their peak during this period at the Polish cliff sites. Conversely, at the Bansin cliff, the largest waves were recorded during the October 2016 event.

Overall, the two winter seasons analyzed exhibited significant differences, with the 2016/2017 season being much more intense compared to the 2017/2018 season. In the first period, 11–13 storms occurred, while in the second period, there were only 4–9 storms, depending on the tide gauge.

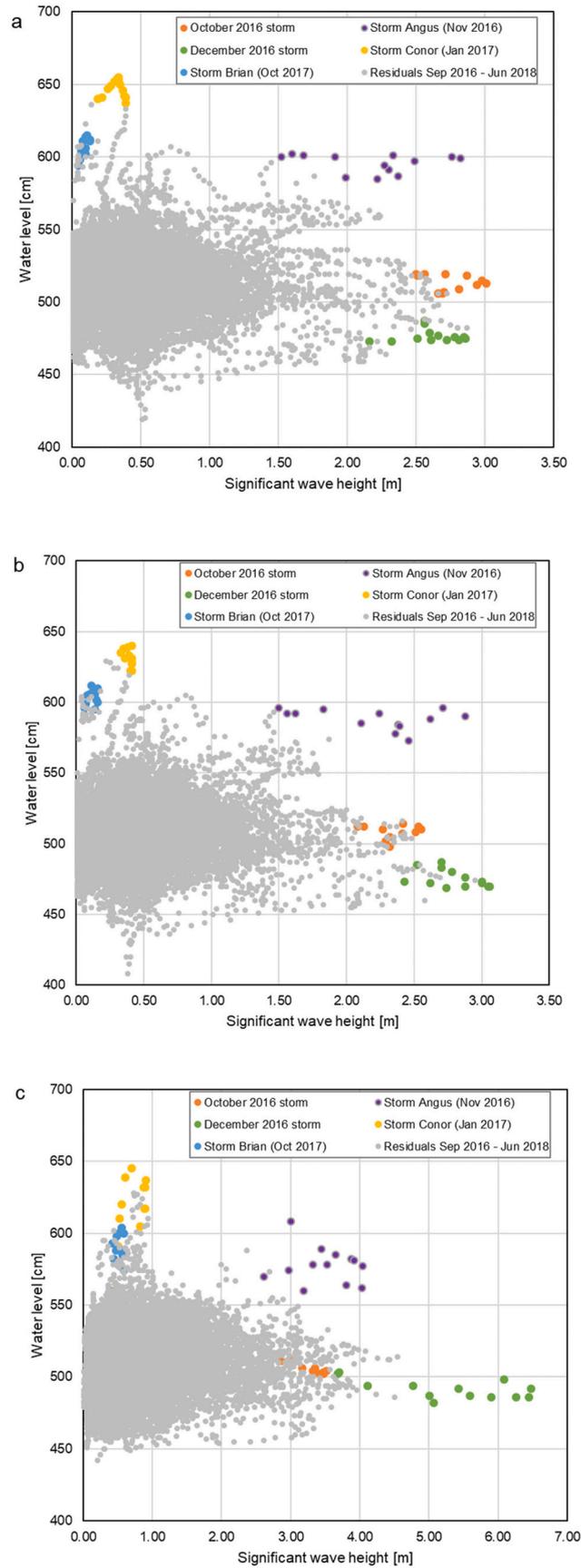
#### 4.2. Features controlling coastal morphology changes

##### 4.2.1. Beach

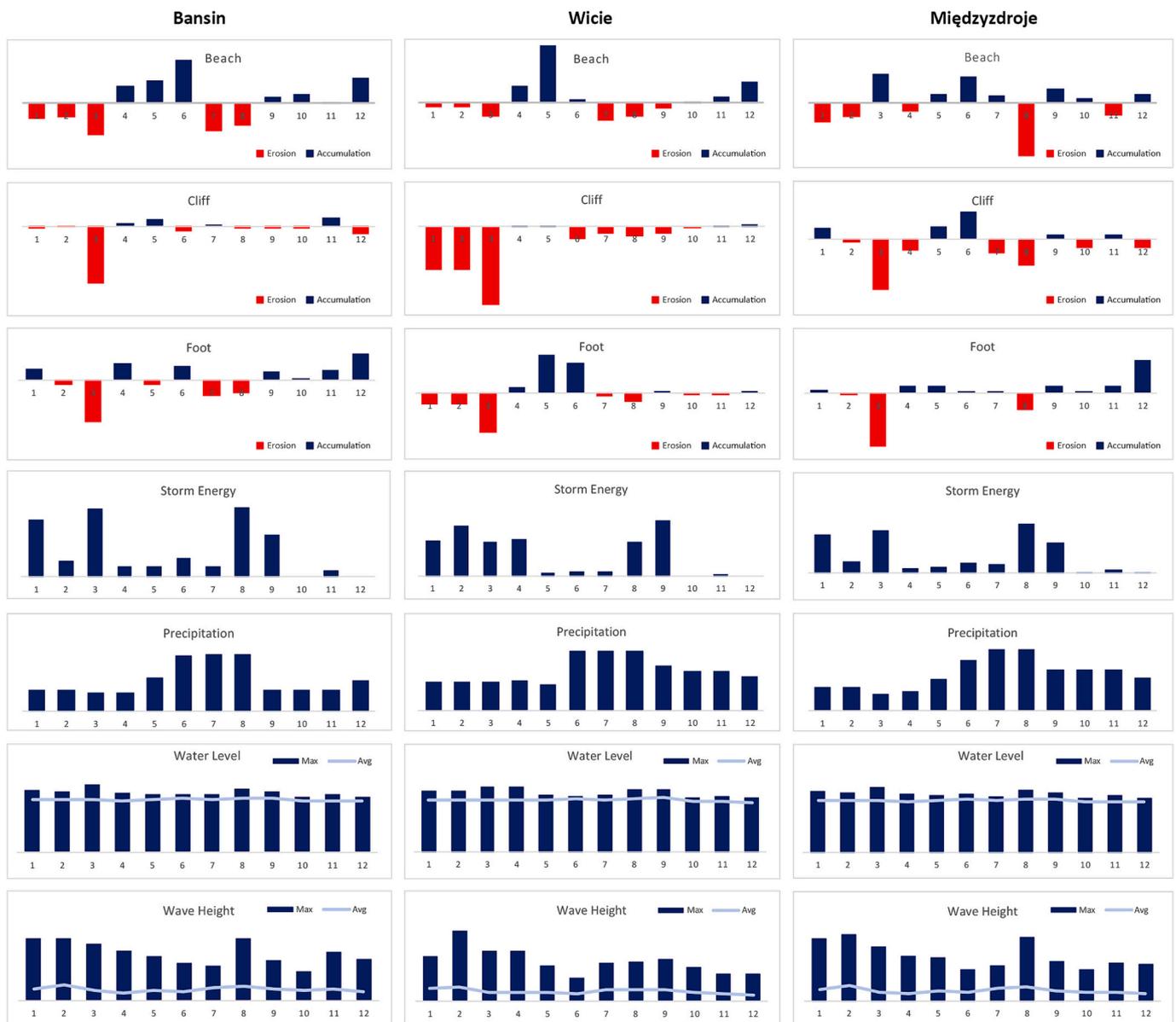
Divergent hydrometeorological conditions observed over 2 years at three distinct test sites allowed for the analysis of morphological changes and the identification of major forces influencing the beach-cliff system. Statistical analysis was conducted using various data mining methods presented in Section 3.

All three investigated test sites underwent significant morphological changes between surveys. Analyzing cross-shore changes along the coast, we observed substantial variability in shoreline movement (1 m contour above MSL – see Section 3.1), beach width and volume, elevation of the cliff foot (referred to as the beach-cliff (b-c) junction), and cliff slope and volume. Erosion and sedimentation were unevenly distributed in both time and space (Figs. 5 and 6).

The beach slope in Bansin, Międzyzdroje, and Wicie generally remained relatively stable. However, significant changes in beach width and volume occurred during both storm seasons. From November to December 2016, successive beach narrowing and lowering occurred at all test sites. In Bansin and Międzyzdroje, beach width changes occurred relatively evenly along the entire beach length, reaching up to a maximum of 19 and 14 m, respectively. In Wicie, the change was slightly smaller, with the highest value of 11 m, occurring only in two measured profiles, while all others did not exceed 7 m. The elevation of the b-c junction varied up to 4 m in Bansin, 3.3 m in Międzyzdroje, and almost 6



**Fig. 4.** Water levels and significant wave height from September 2016 to June 2018 in (a) Koserow, (b) Świnoujście, and (c) Darłowo. Highlighted are selected storm events, with names of windstorms from the UK and Ireland where applicable.



**Fig. 5.** Summary of results for the 12 analytical periods. From top to bottom: Beach volume changes, cliff volume changes, cliff foot elevation changes, storm energy, precipitation, maximum and average water level, maximum and average wave height. The left panel is for Bansin, the middle for Wicie, and the right for Międzyzdroje. Analytical periods, represented by numbers from 1 to 12, correspond to the dates of surveys by the test site, as presented in Table 1.

m in Wicie.

Due to wider beaches and significant b-c junction changes, Bansin experienced more than triple the erosion observed in Międzyzdroje, with a total volumetric loss of 2191 m<sup>3</sup> compared to 627 m<sup>3</sup>. When normalized according to the length of the beach (500 m at both sites), this equates to 4.3 and 1.2 m<sup>3</sup> volume lost per meter of beach length, respectively. The highest beach erosion values reaching 2566 m<sup>3</sup> were reported in Wicie, resulting in over 5 m<sup>3</sup> volume loss per meter of length. This high volume was reached despite relatively narrow beaches, which means there was less material available to be potentially eroded. In some sections during high water levels, even small waves were able to reach the cliff foot for a longer duration, resulting in the highest changes in the b-c junction elevation.

The analyzed changes in shoreline and beach confirmed that these are the most dynamic components of the coast, and their changes have the highest number of high-importance explanatory variables (Tables 2 and 3). According to correlation analysis (Table 2), the highest associations were observed with wave direction during the storm period

(WaveDirect\_Storm) and maximum water levels (WaterLevel\_Max). These parameters highlight the importance of storm surges in the process of beach lowering and narrowing during the initial phase of the storm season. Their influence has been confirmed by the results of MRT analysis (Table 3).

The horizontal scales represent 12 the number of period and selected morphology or hydrometeorological parameters: *beach* – volume changes [m<sup>3</sup>]; *foot* – heights changes [m]; *cliff* – volume changes [m<sup>3</sup>]; *waterlevel\_max* and *waterlevel\_avg* – maximum and average water level [mm]; *waveheight\_max* – maximum wave height [m]; *storm\_energy* – storm energy [kJ/m<sup>2</sup>]; *windspeed\_max* – maximum wind speed [m/s]; *prec\_max* – maximum precipitation [mm]; *temp\_avg* – average temperature [°C].

Surprisingly, neither shoreline nor beach width correlated with wave heights. Those are more related to wave direction, as the highest association was observed with both wave direction during the storm period (WaveDirect\_Storm) and average wave direction (WaveDirect\_Avg). Nevertheless, their average (WaveHeight\_Avg) and maximum values

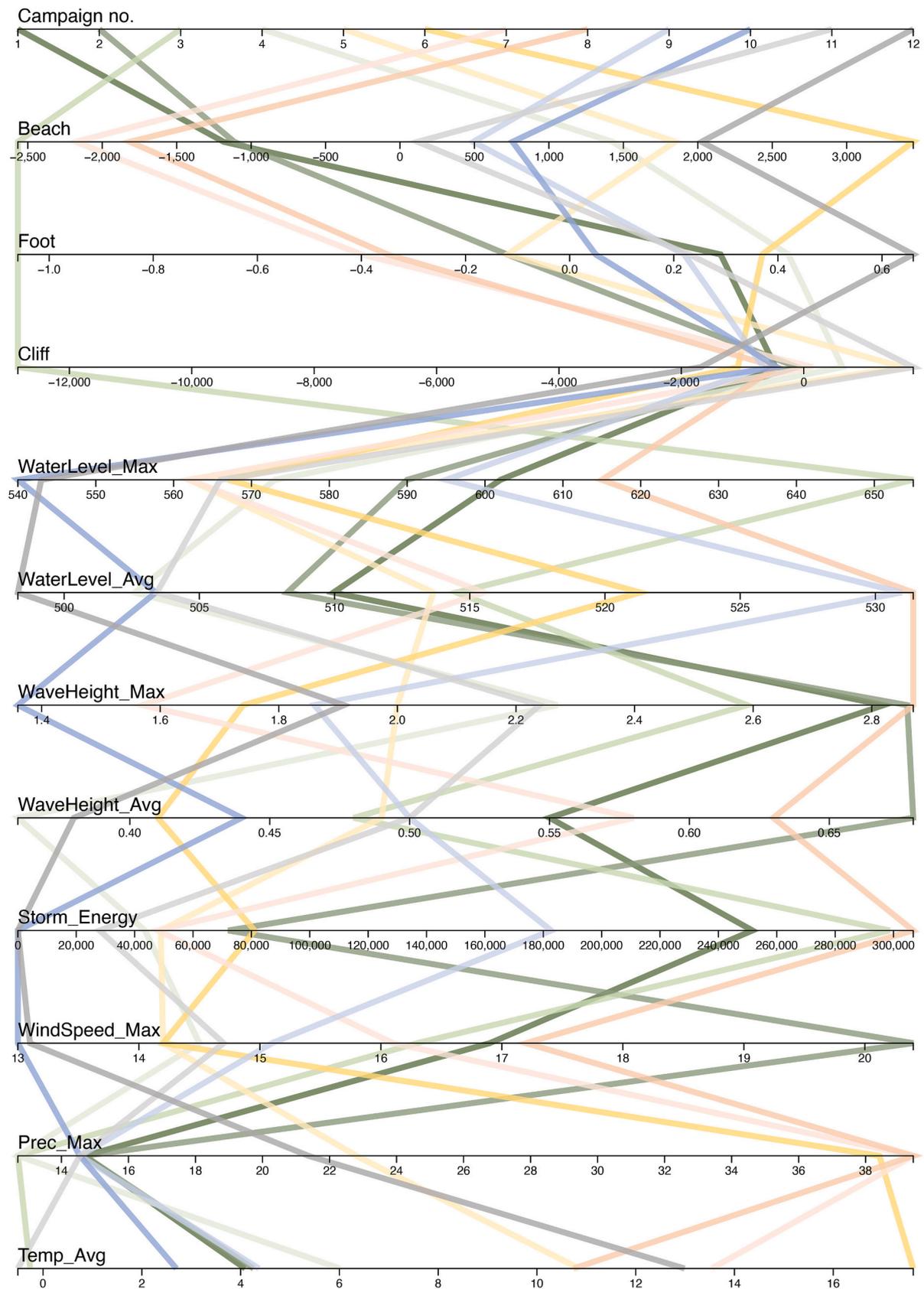


Fig. 6. Summary of results for 12 analytical periods representing direct calculated values in Bansint test site. Each color line represents a single analytical period (e.g., dark green represents values for analytical period no. 1).

**Table 2**  
Importance of selected hydro-meteorological variables on morphological features based on multivariate analysis.

Variable	Shore	Beach width	Beach volume	Cliff foot	Cliff volume	Cliff top	Cliff slope
WaveHeight_Avg			***	**	**		
WaveHeight_Max			**	***	***	*	
WaveHeight_Storm		**					
WaveDirect_Avg	***						
WaveDirect_Storm	***	***			**		
WavePeakPeriod_Max	*	***	**				
Storm_Energy		*			*		**
WaterLevel_Max	***	**	***	**	***		
WindSpeed_Max		***	**			*	
Temp_Avg		*	***				
Prec_Max		**	**		*	***	**
WavePower_Max				***	***	**	

Statistically significant correlations are indicated as follows: \*\*\*0.001; \*\*0.01; \*0.05.

**Table 3**  
Importance of selected hydro-meteorological variables on morphology features based on multivariate regression tree analysis.

Variable	Shore	Beach width	Beach volume	Cliff foot	Cliff volume	Cliff top	Cliff slope
WaveDirect_Avg	0.42	0.43	0.49	0.5	0.41	0.27	0.34
WaveDirect_Storm	0.30	0.37	0.3	0.35	0.15	0.21	0.64
WaveDirect_05	0.29	0.26	0.56	0.54	0.26	0.24	0.78
WavePeakPer_95	0.19	0.33	0.35	0.58	0.39	0.63	0.44
Storm_Energy	0.74	0.84	0.89	1	1	1	0.72
WindSpeed_Avg	1	0.62	1	0.57	0.26	0.22	1
Prec_Max	0.45	1	0.01	0.12	0.15	0.16	0.26
Prec_Storm	0.35	0.54	0.47	0.47	0.58	0.63	0.3
WaterLevel_Max	0.92	0.49	0.55	0.61	0.32	0.11	0.21

Importance values range from 0 (no importance) to 1 (most important).

(WaveHeight\_Max), together with maximum water levels (WaterLevel\_Max), are controlling complex mechanisms regulating beach and cliff volumes. While water levels are considered preparatory factors for erosion processes, waves are responsible for erosion volumes. These variables, along with maximum wave power (WavePower\_Max) and storm energy (Storm\_Energy), showed the highest correlation with cliff foot changes. Movement of the b-c junction directly corresponds to cliff erosion. Material from cliff erosion could be deposited on the beach, which would explain the high correlation of high waves on the beach and cliff volumes.

Both implemented statistical methods also highlight wind speed as one of the most important features explaining beach width and volume changes. While the influence of maximum wind speed (WindSpeed\_Max) naturally associated with maximum wave heights and their impact on beach width does not surprise, the strong correlation with averaged wind speed (WindSpeed\_Avg) shown by the multivariate analysis can be explained by the influence of wind on the coast not only during the storm season when it can be directly linked to particular storms but also throughout the whole year due to eolian processes. Furthermore, wind is more dynamic than offshore waves and, in correlation analysis, is a better predictor of small wind-driven waves.

Other significant variables affecting beach dynamics include precipitation, both maximum values (Prec\_Max) and those during storm periods (Prec\_Storm), and temperature (Temp\_Avg).

#### 4.2.2. Cliff

During the first two winter months, beach erosion accounted for over 80 % of the total erosion volume in Bansin, Międzyzdroje, and Wicie. As the beach continued to lower, the proportions changed, and cliff erosion started to dominate. During the subsequent three months of the storm season (January–April), over 85 % of the total volume loss can be attributed to cliff face and top erosion. In the 2016–2017 storm season, several severe storms affected the cliff face much more than the beach. In Międzyzdroje, the total volumetric loss was 6000 m<sup>3</sup>, while Bansin experienced twice that, and Wicie three times, with erosion values

reaching up to 12,000 and 18,000 m<sup>3</sup>. This equates to 12, 24, and 36 m<sup>3</sup> per m of cliff length in Międzyzdroje, Bansin, and Wicie, respectively.

The period of the strongest erosion impact in the 2016–2017 storm season can be linked to a sequence of two storms. The late December event, characterized by large waves and high energy values, significantly affected all three beaches. With a drop of nearly 2 m in beach elevation, the beach could not regenerate in time to protect the cliff when storm Connor hit the coast in January, resulting in significant cliff erosion despite relatively low storm energy, but due to an extremely high sea level.

Less beach and cliff erosion was recorded during the spring and summer seasons, although the total volumes were lower, they exhibited higher variability in both time and space distributions. Additionally, beach recovery processes began in May 2016 in all three areas. The compilation of spring/summer surveys revealed both accumulation and erosion patterns, with a modest positive overall sediment budget of 800 m<sup>3</sup> in Bansin, 600 m<sup>3</sup> in Międzyzdroje, and 400 m<sup>3</sup> in Wicie. Volume values between surveys fluctuated from –2870 to 9280 m<sup>3</sup> for the beach and –3520 to 3683 m<sup>3</sup> for the cliff. In Wicie, the positive overall value is directly linked to beach recovery, while in Bansin and Międzyzdroje, it differs, and total erosion values for beaches are generally negative. However, these values for the beach and the positive values for the cliffs can be explained as a consequence of methodology used to calculate the volumetric changes. In situation of cliff undercutting calculations always represent negative values. In case of landslide very often the cliff base line moves seaward. In such cases beach is becoming very narrow (high negative volume changes) and at the same time the cliff volume calculations include partially the earlier volume of beach finishing with positive values. Such methodology was used in order to better represent the whole coastal dynamics (both beach and the cliff).

As described in Section 4.2.1, water levels are considered a preparatory factor and are responsible for the process of lowering and narrowing the beach in the first phase of the storm season. Following volumetric change patterns and according to statistical analysis, it is evident that erosion processes in the next stage, especially the cliff

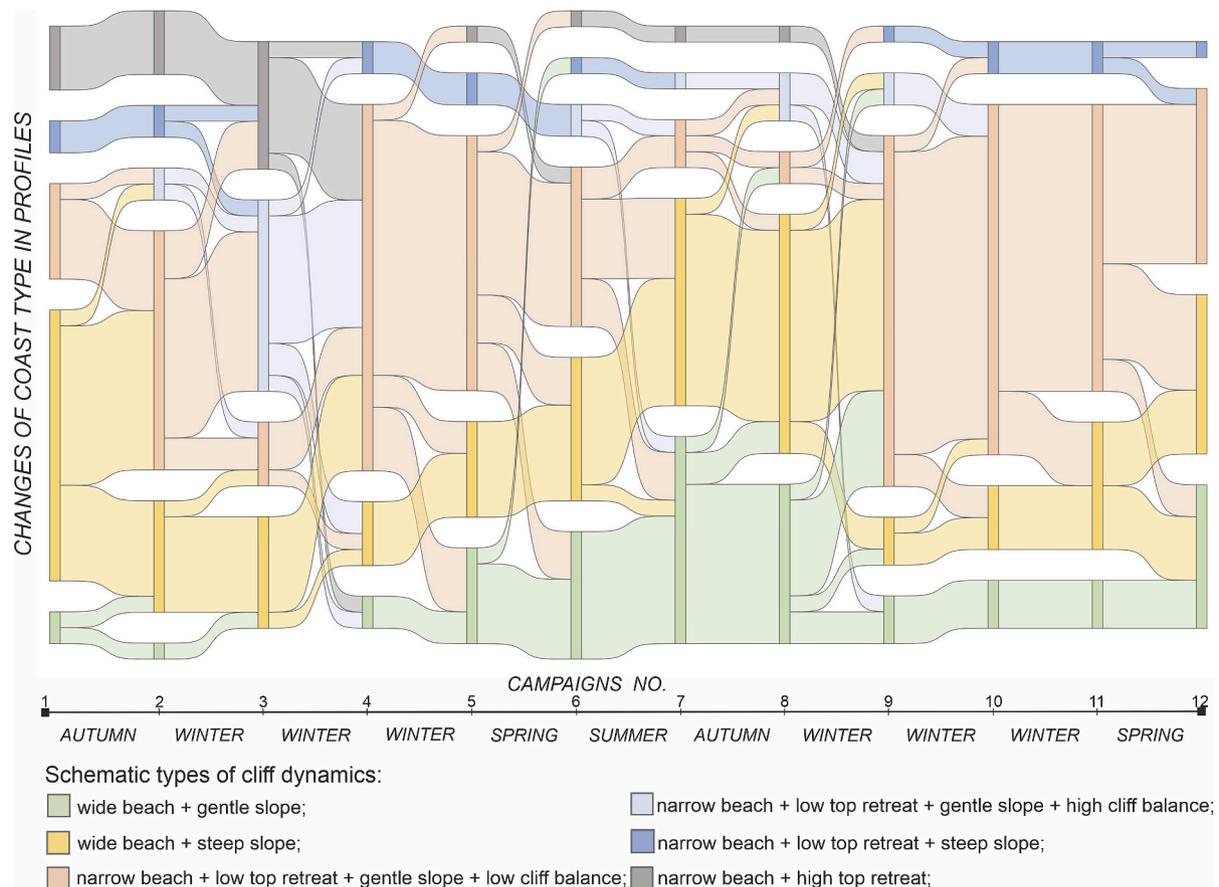


Fig. 7. Seasonal coastal cliff dynamics.

volume balance, depend primarily on waves (WaveHeight\_Avg) undercutting the cliff, resulting in eventual cliff face landslides. The material deposited at the cliff foot during the landslide process is further affected by very high waves, as indicated by wave power and maximum wave heights (WavePower\_Max and WaveHeight\_Avg). These are represented by storm energy (Storm\_Energy), which is the most important variable according to MRT analysis. Another significant feature correlated with the cliff volume balance is water level (WaterLevel\_Max). While we do not expect water level to directly affect cliff erosion, the high baseline sea level could increase the number of waves that reach the cliff, thus appearing as a good variable explaining compound erosion effects on the cliff.

Undercutting the cliff foot by waves, especially during storms with high water levels, ultimately leads to landslide processes. The cliff slope, an indicator that represents these changes in our research, is the least dynamic. According to MVA analysis, this morphology indicator and the cliff top retreat correlate with maximum precipitation values and storm energy. In particular, rainfall (Prec\_Storm and Prec\_Max) influences

**Table 4**  
Marginal importance of selected hydro-meteorological variables on the occurrence of different types of cliff dynamics based on canonical correlation analysis.

Variable	Relative importance (F value)	Statistical significance level (p value)
Prec_Max	22.8381	0.001
Prec_Storm	9.9782	0.001
Storm_Energy	8.6109	0.001
WavePeakPer_95	6.1126	0.008
WaveDirect_05	5.4347	0.012
Temp_Avg	2.9121	0.086
WaveDirect_Storm	2.3409	0.124
WindSpeed_Avg	1.0905	0.387

have been confirmed by MVA and MRT (Tables 2 and 3). As precipitation weakens the structure of the soft cliff, making it more vulnerable to collapse, there are also other factors at play. While the storm energy correlation represents the linkage of cliff face changes with storm conditions, the influence of average windspeed and wave direction (Table 3) is more complex. We assume that the very high correlation between cliff slope and windspeed revealed in the MRT analysis represents a direct connection of meteorological variables with eolian processes occurring on the selected parts of the cliff face that are not protected by vegetation. Wave direction, however, emphasizes the importance and susceptibility of the coast to storm conditions from specific directions.

#### 4.2.3. Seasonal coastal cliff dynamics

Data mining analysis has been further employed to define coastal cliff dynamics types and analyze their seasonal variability. The coordinates of the first two axes of CA explained 72 % of the variation in morphological features, whereas PCA explained 60 %. In MRT, the geomorphological parameters explained >70 % of the variation in the coordinates of the first two axes of CA. Morphological features such as cliff volume, beach width, cliff slope, and cliff top retreat mainly elucidate the variance of the two axes in MRT, splitting the data into different classes of the most frequently occurring types of coastal profiles. This data-driven machine learning erosion model allowed us to determine six schematic types of cliff dynamics. Descriptively, they can be characterized as follows:

- (i) Stable, wide beach, and gentle cliff slope;
- (ii) Stable, wide beach, and steep cliff slope;
- (iii) Narrow beach, gentle cliff slope with low cliff balance and low top retreat;
- (iv) Narrow beach, gentle cliff slope with high cliff balance and low top retreat;
- (v) Narrow beach, steep cliff slope with low top retreat;
- (vi) Narrow beach and high cliff top retreat.

The distribution of different types of cliff dynamics changes between

campaigns. The way in which the types evolve over time during the intensive transformation and stabilization periods is visible in Fig. 7. This figure has been used to analyze the seasonal coastal cliff dynamics. It presents six types of distinguished cliff dynamic types represented with different colors. On the horizontal axis, it is possible to observe one type transitioning into another within the seasonal timeframe. For example, the dynamic type represented by a narrow beach and high top retreat within the seasonal change transitions into two other types: (1) narrow beach, steep cliff slope with low top retreat and (2) narrow beach, gentle cliff slope with low cliff balance and low top retreat.

The seasonality of processes operating in the coastal zone is also apparent. Where erosion processes are insignificant, the equilibrium state is directly connected with wide beaches. This is detectable in spring/summer months when regular wave inundation is limited not only due to smaller waves but mainly to high beach elevation, hence the position of still water relative to cliff foot. During the winter, however, high geomorphological activity is observed. The interaction between storms and cliff erosion is still partially controlled by beach width. High cliff volume balance changes were mainly possible after changes in the morphology of the beach fronting the cliff. This rule is bypassed only during exceptional storm surges with the highest water levels, and the pattern of successive changes is disrupted.

Finally, a statistical analysis using CCA was performed to uncover the relationship between the different identified types of coastal dynamics and measured hydrometeorological conditions. Based on previous results (Terefenko et al., 2019), we expected heavy rainfall to be responsible for weakening the beach structure and increasing erosional material flow. As shown in Table 4, precipitation, including both maximum values and rainfall during the storm season, emerged as the most significant variables for explaining seasonal cliff dynamics. They surpassed the importance of storm energy and wave action (direction and period). Furthermore, average temperature can be considered a valuable seasonal indicator corresponding to the seasonality of coastal dynamics, i.e., the different periods of beach erosion and accumulation.

## 5. Discussion

### 5.1. 5.1 General geomorphic and geological discussion

Marine and subaerial erosion processes are interconnected due to the feedback mechanisms in the coastal cliff erosion cycle (Young et al., 2009). The results of this study provide insights into the short and medium-term episodic processes of coastal cliff erosion within a data-driven context. However, even in coastal systems with well-known forcing functions, the cliff's response can be complex. Previous studies on coastal cliff systems have highlighted the significance of beach volume in influencing cliff foot inundation, wave impact, and subsequent processes (Earlie et al., 2018; Walkden and Hall, 2011). According to our results, beach growth between storm seasons protects the cliff face and is associated with a reduction in the recession rate of the cliff toe. During summer months, when wave inundation is limited due to smaller waves and high beach elevation, the coastal cliff system's ability to remove material along the shore is relatively small. Therefore, beach morphology, including the slope of the upper shoreface and the beach-cliff junction, plays a crucial role in modifying wave energy delivery to the cliffs. This aligns with the findings of Walkden and Hall (2011), who emphasized that during such periods, the supply of sediment from the cliff is restricted, limiting the volume the beach can attain.

Similar to the findings of Ruggiero et al. (2004), our data-driven model suggests that beach volumes are influenced by maximum water levels. Several smaller extreme events, often associated with high water levels, play a pivotal role in lowering and narrowing the beach during the initial phase of the storm season. Furthermore, the effect of high water levels is more pronounced when combined with waves approaching the coastline from NW-NE directions, as this orientation is typically perpendicular to the dominant shoreline exposure. To initiate

cliff erosion, wave action must create unstable slopes. Therefore, the rate of rain-triggered cliff failures depends on both waves and rainfall (Young et al., 2021). Our findings support this general principle. Cliff face erosion, particularly the cliff volume balance, primarily depends on wave height, storm energy, and rainfall amounts. Although erosion volumes were found to be twice as great at the cliff site with a narrower beach in Wicie compared to Bansin and three times greater than Międzyzdroje, this highlights the importance of the preparatory beach conditions established during the pre-storm season.

The changes observed in cliffs are also influenced by their internal structure. Wave energy degrades cliffs with varying intensity, largely determined by the geological composition of the cliff (Castedo et al., 2013; Uścińowicz et al., 2014; Winowski et al., 2022). The lack of detailed geological data describing complex internal structures in the study areas is a significant limitation, and as such, such data has not been integrated into the proposed data-driven statistical models. However, limited geological information enables us to analyze hydro-meteorological drivers in light of different geological structures. In general, the coastal cliffs in Langer Berg (Bansin) and Biała Góra (Międzyzdroje) are composed of sand (Winowski et al., 2022), while the Wicie section consists of till and intermorainic clay cliffs covered with relatively thin layers of eolian sands (Uścińowicz, 2023). According to Winowski et al. (Winowski et al., 2022), the most significant erosion on Baltic Sea cliffs occurs on sandy cliffs, while clay cliffs experience the smallest erosion. This observation is related to the mechanical behavior of these materials. Sand has no cohesion and this means that it is more susceptible to erosion, whereas clay is characterized by a certain degree of cohesion as well as also partial saturation, which can provide a surplus of shear strength, when those conditions exist in the field. Furthermore this is attributed to the presence of colluvial sediments, which act as a buffer against cliff erosion by sea activity and have a substantial impact on the volume changes in the cliffs (Winowski et al., 2022). Such colluvial sediments, forming deposition zones for sediment, can be observed in Bansin and Międzyzdroje, where sandy cliffs supply enough material to create these forms between storm seasons. In contrast, the Wicie test site faces a sediment shortage, resulting in very narrow and steep beaches, sometimes only 1–2 m wide. In this environment, waves break closer to the cliff (Trenhaile, 2016; Walkden and Hall, 2005). With a short distance to dissipate energy after wave breaking, this leads to higher run-up heights and more intensive erosion, regardless of the theoretically erosion-resistant clay sediments of the cliff face.

On the other hand data-driven statistical model implies much higher correlation between cliff erosion volumes and rainfall values during storm in the clay cliffs of Wicie section compared to sandy formations of Międzyzdroje and Bansin. In general, continued wetting and drying processes during the storm season weaken the rock (Hall and Hall, 1996; Souleymane et al., 2008). This recognized direct and indirect effect of wetting and drying weathering on the degradation of rocks must have a significant effect on local strength within coastal cliff environment. Due to precipitation and groundwater level changes, coastal cliffs often cycle between dry and wet states. It is expected that higher correlation of rainfall amounts and erosion volumes on the clay cliffs than on sandy cliffs would be associated with different aspects of rock permeability. Nevertheless to confirm this hypothesis additional measurements of groundwater level and cliff face moisture should be performed.

### 5.2. Data-driven model discussion

Studies on erosional changes of Baltic Sea soft coastal cliffs constructed from postglacial sediments, primarily clay and sand, span various temporal and spatial ranges. Different monitoring and calculation techniques have been employed, resulting in relatively consistent erosion volume estimates (Averes et al., 2021; Frydel et al., 2018; Kostrzewski et al., 2015; Terefenko et al., 2019; Winowski et al., 2022). This research, with erosion rates reaching 12, 24, and 36 m<sup>3</sup> per meter of

cliff length per year in Międzyzdroje, Bansin, and Wicie, respectively, falls on the higher end of this magnitude. Comparatively lower erosion volumes were recorded on the shores in Germany (Schleswig-Holstein), estimated at 1.5 m<sup>3</sup> per m of shoreline (Averes et al., 2021). Similar studies, utilizing LiDAR, on the Baltic Sea shores in Poland indicate erosion rates of 6.6–17.3 m<sup>3</sup> per meter of shoreline on Wolin Island (Winowski et al., 2022) and 11–26 m<sup>3</sup> in the central Polish coast (Frydel et al., 2018).

The results also highlight two additional aspects to consider when analyzing storm seasons' influence on coastal cliffs. Firstly, hydrometeorological parameters control not only cliff erosion but also the development of colluvial sediments transported from the upper parts of the cliff, as well as erosion and deposition processes on the beach in front of the cliff face. The coastal zone is influenced by the complexity and diversity of physical processes, making detailed topography data acquired repeatedly over time essential for understanding erosion processes and revealing patterns of cliff dynamics (Hapke and Plant, 2010; Kostrzewski et al., 2015; Winowski et al., 2022; Young et al., 2021; Young and Ashford, 2006). Fig. 4 summarizes the distribution of morphology changes and various selected forcing and controlling factors over time (between LiDAR campaigns) and space (different test sites). Fig. 5 enables the examination of exact values of morphological changes in Bansin (A) and Międzyzdroje (B), as well as selected hydrometeorological conditions during consecutive campaigns. Each line represents a single campaign, following a color scheme (from dark green as campaign no. 1 to dark grey as campaign no. 12), facilitating the analysis of exact parameter values during measurement periods.

While hydrometeorological conditions remained relatively consistent across all test sites over the two-year analytical period, it is evident that Bansin experienced the most energetic events due to its exposure (Figs. 5 and 6). However, the wide beach in Bansin also provided greater protection to the cliff than in other areas. Moreover, the differences in erosion values, both for the beach and the cliff, as well as their timing, suggest a high diversity of controlling forces influencing coastal morphology.

Recent studies have emphasized the significant impact of extreme waves and water levels on coastal cliff erosion (Brain et al., 2014; Earlie et al., 2018; Terefenko et al., 2019; Vann Jones née Norman et al., 2015; Winowski et al., 2022; Young et al., 2021). This study reaffirms the importance of these two key factors in influencing erosion rates. However, while wave height has a direct correlation with erosion volumes, it does not significantly contribute to changes in beach width. Beach width is primarily controlled by variations in water levels. Consequently, a high baseline sea level can allow even small waves to reach the cliff, contributing to cliff erosion. This explains the strong correlation between this type of erosion and the average wave indicator.

According to Earlie et al. (2018), during the winter season, the interaction between storm waves and the beach becomes a more critical factor than still water levels in determining the delivery of wave energy to the cliffs. This phenomenon is observed in the Wicie study area, confirming that on steeper beaches, waves break closer to the cliffs (Walkden and Hall, 2011). Additionally, the narrower beach in this area results in higher run-up heights compared to other areas, as the reduced distance allows less time for energy dissipation after wave breaking (Stockdon et al., 2006).

Other crucial factors influencing the dynamics of cliff erosion are rainfall and wind. It has been demonstrated that precipitation is typically correlated with upper cliff erosion (Young et al., 2021) and plays a role in transporting sediments from the cliff top down to colluvial sediments (Castedo et al., 2013). In this study, heavy rainfall episodes were identified as one of the explanatory variables through CCA. However it is worth noting that, according to another study, precipitation is a major source of errors in hydrological models, so its influence should be carefully analyzed (Bárdossy et al., 2022). Based on achieved results we can state that on the Baltic soft cliffs heavy rainfalls during storm season not only affect the cliff face but, when combined with other extreme

conditions, also intensifies beach erosion processes. Further during weak storm events and summer period heavy rain episodes are responsible for the redeposition of colluvial sediments. Therefore while influencing morphology changes during both winter and summer periods it becomes best indicator of seasonal cliff dynamic.

Furthermore, wind speed features, which are sometimes overlooked in cliff erosion analyses, exhibit a higher correlation with cliff morphology changes than wave height indicators in some cases. This can be attributed to the characteristics of wind which is more dynamic than offshore waves containing significant inertia and therefore might be used as a better predictor of the small wind-driven waves that influence coastal erosion. Additionally, wind may represent more complex eolian processes occurring between measurement campaigns such as low grain size sand transport which has not been analyzed in presented study (Terefenko et al., 2019).

The direct connection between extreme waves, water levels, and several other controlling factors and their impact on erosion volumetric changes during specific measurement campaigns is illustrated in Fig. 5, with their correlations and importance presented in Tables 2 and 3.

The results highlight another aspect related to morphology changes and their influence on the further development of coastal cliff profiles. Previous studies have emphasized the role of beach morphology, including width and slope, in coastal cliff erosion (Earlie et al., 2018; Walkden and Hall, 2011). Beach morphology affects the position of the water level and influences the wave energy reaching the cliff foot line. Therefore, changes in the beach profile can result in significantly greater erosion on the cliff face.

According to Bayesian Network analysis conducted on the same study areas of the Wolin and Usenam cliffs (Terefenko et al., 2019), the highest correlation between shoreline retreat distance was observed with the 95th percentile of wind speed, which demonstrated slightly higher correlation than indicators of wave height. The width of the beach before the occurrence of erosion is the second factor influencing shoreline retreat. The results presented here regarding coastal type dynamics and their seasonal changes confirm that beach width is itself influenced by maximum wave heights, leading to narrower beaches and, consequently, the shift in dynamic type.

Furthermore, the analysis indicate that average temperature ranging from 2.4 °C in winter season through 12 °C and 8,5 °C, respectively in spring and autumn, up to 17,6 °C during summer months is an excellent indicator of the time of year, as beaches tend to be narrower during the autumn/winter storm season compared to the warmer spring or summer. This was confirmed by the CCA, which identified average temperature as a feature of high importance in explaining changes between coastal dynamics types (Fig. 7 and Table 4).

Interestingly, the results also highlight maximum precipitation episodes as a crucial factor influencing seasonal coastal cliff dynamics (Table 4). While rainfall has previously been considered a significant factor in cliff top retreat, it has not been widely acknowledged as suitable for investigating intra-annual (seasonal) analysis. Maximum observed precipitation events occurred during autumn and summer reaching 44 and 37 mm respectively. Twice lower values has been noted in winter (21 mm) and spring (22 mm). During the storm season precipitation intensifies beach and cliff face erosion when combined with other extreme conditions though during summer it is responsible for a symmetrical crossshore and alongshore sediment redistribution. However, influencing the coastal morphology during the whole year rainfall can also be considered a force governing not only event-based, short-term cliff dynamics but also season-term cliff recession and fronting beach reconstruction processes.

## 6. Conclusions

Repeated laser scanning campaigns conducted on the coast of Germany (Bansin) and Poland (Międzyzdroje and Wicie) during two winter storm seasons (2016–2018) provided valuable insights into the

morphological dynamics of soft cliffs along the Baltic Sea. These areas, characterized by clastic Pleistocene and Holocene deposits, exhibited significant variability in cliff height (ranging from 11 to 57 m) and fronting beach width (varying from 8 to 54 m). All sites experienced extreme hydrometeorological events, with Bansin facing the highest levels of storm energy. Analysis of morphology changes enabled to create of an original coastal dynamic type classification for Baltic soft cliffs.

The study revealed strong spatial and seasonal variability, with over 80 % of volumetric erosion losses occurring during the winter seasons. Cliff erosion rates were found to be three times higher in Bansin and twice as high in Wicie compared to the Międzyzdroje coast. While the larger erosion values could be attributed to more energetic hydrometeorological conditions, the analysis of coastal cliff dynamics types also underscored the significance of changes in fronting beach morphology. Machine learning models provided a classification of soft cliff coast dynamics, highlighting the complexity of mechanisms governing beach and cliff changes, along with the vulnerability of cliff coasts to extreme water levels and precipitation events.

The importance of storm surges in lowering and narrowing beaches during the initial phase of the storm season was evident in all analyzed areas. In subsequent phases of coastal dynamics, waves and maximum water levels played a critical role in regulating beach and cliff volumes.

Modeling the interactions between precipitation and cliffs under various morphological conditions provided compelling evidence that rainfall is a key factor responsible for controlling coastal morphology dynamics. Precipitation, including both maximum values and rainfall during the storm season, emerged as the most significant variables for predicting seasonal cliff dynamics. They have surpassed more than twice the importance of storm energy and wave action (direction, height and period), parameters which are commonly recognized as the most important in shaping cliffs morphology. This influence extended beyond high-magnitude events to include seasonal patterns of cliff type profiles.

The results, achieved through the combination of remote sensing and data mining methods, highlighted the value of site-specific and data-driven investigations in elucidating the relationships between erosion rates and selected factors. Short-term information on the most relevant variables influencing coastal cliffs contributes to understanding how extreme events impact coastal cliffs over the long term. This research also fills a critical gap in our understanding of the relationship between changes in cliff system morphology and the driving forces behind these changes in the context of increasing extreme events associated with climate change.

#### CRedit authorship contribution statement

**Paweł Terefenko:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Andrzej Giza:** Visualization, Validation, Investigation, Funding acquisition. **Jakub Śledziowski:** Methodology, Formal analysis, Data curation. **Dominik Paprotny:** Writing – review & editing, Formal analysis, Data curation. **Martynas Bučas:** Writing – review & editing, Validation, Formal analysis. **Loreta Kelpšaitė-Rimkienė:** Writing – review & editing.

#### Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Terefenko Paweł reports financial support was provided by National Science Centre Poland. Terefenko Paweł reports financial support was provided by Minister of Science in Poland. Giza Andrzej reports financial support was provided by European Commission. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence

the work reported in this paper.

#### Data availability

I have shared the link to the data <https://doi.org/10.1016/j.dib.2020.106291>

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