



### Key Points:

- Clustering of daily maximum storm surge levels finds six distinct northwestern European regions
- Regional extreme surge variability is associated with large-scale climate modes, especially the NAO, AO, and Scandinavian pattern
- The identified surge patterns are consistent with interactions between bathymetry, wind-stress curl, and distinct storm-track configurations

### Supporting Information:

Supporting Information may be found in the online version of this article.

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# Spatiotemporal Variability and Large-Scale Drivers of Storm Surge Extremes on the Northwestern European Shelf

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**Abstract** Extreme Sea Level (ESL) poses a high risk to coastal communities and infrastructure, with its frequency and intensity projected to increase in the future. In this study, we focus on the storm surge component of sea level variability, a key contributor to extreme still water levels during storms. The spatiotemporal variability of regional extreme surge events and their connection to climate teleconnections and large-scale weather processes remains poorly understood. We analyze over 70 years of daily maximum storm surge data from a hydrodynamic model by applying state-of-the-art clustering techniques for the first time. This analysis shows that regional surge variability can be categorized into six regions in the northwestern European continental shelf, with eight sub-regions identified within the North Sea. By inspecting wind-stress curl patterns, sea-level-pressure anomalies, and storm tracks, we show that the cluster variability is consistent with regionally distinct interactions between large-scale atmospheric forcing and bathymetry. We find that the NAO and AO are positively correlated with regional surge variability in most regions, while the Scandinavian pattern (SCAN) exhibits distinct, mainly inverse links in northern clusters. Our results provide a new spatial framework for regional surge variability that could support region-specific surge prediction, surge distribution analysis, and improved assessment of how changes in storm-track behavior and large-scale climate modes translate into regional coastal flooding risk. Our study also provides a foundation for future analyses of how regional extreme surge patterns may respond to changes in oceanographic circulation (such as the Atlantic Meridional Overturning Circulation) and atmospheric forcing.

**Plain Language Summary** Coastal areas around Europe are increasingly at risk from flooding caused by extreme sea-level events. These events happen when storms, strong winds, and rising sea levels combine to push water onto the land. In this study, we analyze more than 70 years of sea-level data from around the northwestern European Shelf and the North Atlantic. We first remove the daily tides and seasonal changes to focus on the part of the sea level that is driven by weather, the surge level. We then group different parts of the coastline into regions that tend to experience extreme surge levels at the same time. We link these regions to large-scale weather and climate patterns over the Atlantic, such as those that change where and how storms travel. We find that many extreme surge level events in each distinct region can be traced back to these climate patterns. For example, the North Sea is especially sensitive to changes in wind and air pressure during certain phases of the North Atlantic Oscillation. Our findings help explain why and when extreme surge levels occur along different European coasts. This knowledge can support better flood warnings, improve climate-risk assessments, and inform long-term planning for coastal protection.

## 1. Introduction

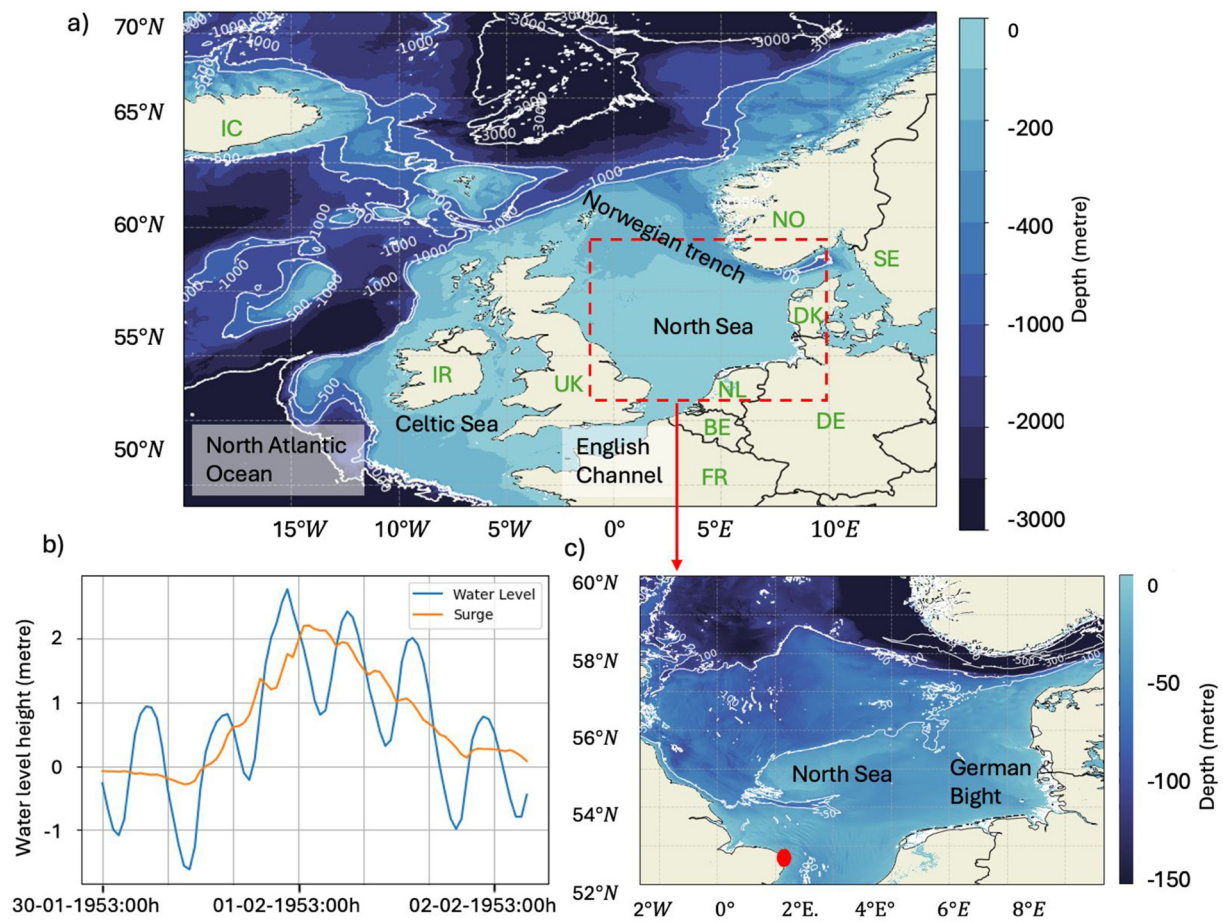
Extreme Sea Level (ESL) events are projected to become more frequent and intense due to climate change (Kossin et al., 2020; Tebaldi et al., 2021), and pose increasing risks to coastal communities and infrastructure. ESLs are usually characterized by combined components of mean sea level rise, tidal height, the storm surge component and wave effects (Kossin et al., 2020; Vousdoukas et al., 2018). Here, we focus on the storm surge contribution to ESLs, as it is a key driver of extreme still water levels during storms, especially in coastal regions, while excluding wave effects.

ESLs are traditionally recorded by tide gauges, such as the Global Extreme Sea Level Analysis data set (GESLA, Haigh et al. (2023)), which offers long-term hourly water level data but with sparse spatial coverage. More recently, global data sets, such as the Coastal Data set for the Evaluation of Climate Impact (CODEC, Muis et al., 2020), provide high-resolution historical and projected water-level and storm surge estimates on a regular spatiotemporal grid. CODEC has previously been evaluated against tide-gauge observations from GESLA and shows good skill in reproducing historical coastal water-level variability and extremes (Muis et al., 2020), performing particularly well in northwestern Europe. Using data sets like CODEC, global-scale analyses have estimated ESL return periods, and spatial variation (Muis et al., 2020; Voudoukas et al., 2017). However, these studies primarily focus on long-term statistics or extreme-value analysis, rather than providing a phenomenological description of the short-term dynamics and spatial coherence of extreme storm surge variability at daily timescales.

The northwestern European Shelf is a region with high ESLs and strong storm surge variability, due to its complex bathymetry (see Figure 1) and interaction with large-scale weather systems, such as extratropical cyclones that can generate strong winds and pressure gradients, contributing to coastal surge setup. These atmospheric-oceanographic processes influence regional ESL variability (Chafik et al., 2017; Cotton & Challenor, 1999; Mailier et al., 2006). Jacob and Stanev (2017) showed that atmospheric variability, which largely accounts for the surge component, is as important as the tidal component in many areas. For example, during the 1953 North Sea flood, which affected the eastern UK (Figure 1c) and the Netherlands, extreme water levels resulted from a rare coincidence of a severe storm surge with spring tides (Wadey et al., 2015). Figure 1b shows the storm surge level and total water level during this event, using the CODEC data set. The surge component of ESL is strongly linked to the track and intensity of extratropical cyclones (Cotton & Challenor, 1999; Mailier et al., 2006; Weisse et al., 2014). These systems also influence the wind-driven Ekman transport and the convergence of water toward the coasts (Apel, 2013). Specifically in the North Sea, wind stress is considered a dominant driver of storm surge extremes (Pineau-Guillou et al., 2023).

Due to the importance of wind stress, previous studies have connected sea level variability with weather patterns and atmospheric jet stream variability (Madonna et al., 2017; Mangini et al., 2021). On a larger scale, the variability of sea level and storm track is influenced by atmospheric modes of variability (Calafat et al., 2012; Dangendorf et al., 2014; Mailier et al., 2006; Tsimplis et al., 2006; Woolf & Wolf, 2013). In northwestern Europe, the North Atlantic Oscillation (NAO), Scandinavian (SCAN) pattern, Arctic Oscillation (AO), and the East Atlantic pattern (EA) have most strongly been linked to regional sea level variability in northwestern Europe, as shown in observational studies based on tide gauges and satellite altimetry (Chafik et al., 2017; Dangendorf et al., 2012). In the North Atlantic, the leading mode of variability is the NAO, which is defined using sea level pressure anomalies in the Atlantic between Iceland and the Azores, characterizing the strength and paths of westerly winds and storm tracks (Hall et al., 2015; Hurrell, 1995). Specifically, the correlation of total sea level to the NAO has been shown to be the strongest in the southern North Sea (Wakelin et al., 2003). Calafat et al. (2012) showed that the wind stress and pressure are the most important effects of NAO on coastal sea level responses, which is reflected in the storm surge component. Tide gauge-based and reanalysis-driven studies have focused more directly on the link between the climate mode drivers, like the NAO and wind- and pressure-driven storm surge (Wakelin et al., 2003; R. Mawdsley et al., 2014; Marcos & Woodworth, 2017), and storm tracks (Mailier et al., 2006; Seierstad et al., 2007).

Several studies have used clustering methods on sea level variability and storm surges to uncover spatial footprints and to understand their spatial variations (Oelsmann et al., 2024; Poropat et al., 2024; PupiĆ Vurilj et al., 2025). Haigh et al. (2016) clustered ESL and the surge component using tide gauge records, and several studies have clustered storm tracks (Camus et al., 2021; Malagon Santos et al., 2017). Poropat et al. (2024) classified regions of variability from satellite observations using Gaussian Mixture Models (GMM), with spatial modes of Empirical Orthogonal Function (EOF) analysis from monthly sea level anomalies as input. EOF analysis is a common tool for extracting dominant spatial and temporal modes of variability in sea level data (Ayinde et al., 2023; Chafik et al., 2017; Leclercq et al., 2025; Wise et al., 2024). Previous clustering studies, such as Poropat et al. (2024), Mangini et al. (2021), and Oelsmann et al. (2024), have shown spatial coherence for sea level variability and strong links to atmospheric processes, yet most have relied on monthly data or have been event-based and spatially sparse. Thus, spatiotemporal regional variability studies using the high-frequency surge component remain limited, particularly on a regular grid and including offshore ocean regions. These high-



**Figure 1.** Northwestern European shelf and northeast Atlantic study areas. (a) The study domain with countries (green), sea regions (black) and bathymetry (blue), (b) the Coastal Data set for the Evaluation of Climate Impact (CODEC) total water level (TWL) and storm surge level (surge) at the Great Yarmouth station, during the 1953 North Sea flood and (c) the North Sea domain with sea region descriptions (black) and bathymetry (blue), and Great Yarmouth tide gauge station (red dot). Country names in green are for Iceland (IC), Norway (NO), Sweden (SE), Denmark (DK), Ireland (IR), the United Kingdom (UK), the Netherlands (NL), Germany (DE), Belgium (BE), and France (FR). Bathymetric contours in panel (a) are shown at 1,000 m intervals, while panel (c) includes contours at depths of 50, 100, 300, and 500 m. The bathymetry was retrieved from the GEBCO Global Bathymetry and Topography data set (GEBCO Compilation Group, 2024), and CODEC can be retrieved from the Copernicus Climate Change Service (C3S) (2022) (created by Muis et al., 2022).

frequency components, like storms and wind gusts, are important for understanding the variability of short-term events.

We have two objectives in this study:

- Identify regions of coherent daily maximum storm surge variability in the northwestern European shelf,
- Determine the atmospheric and oceanographic drivers of these regions, linking regional patterns to large-scale climate modes and storm track variability.

For the first time, we classify regions of spatiotemporal surge variability across the northwestern European shelf by applying spatial clustering to the daily maximum storm surge. We use the CODEC storm surge data set, which provides high temporal resolution data on a regular spatial grid. First, EOF analysis is applied to the daily maximum detided surge residuals to extract the dominant spatial modes and suppress noise. We then apply GMMs to the leading spatial EOF components, following the novel approach of Poropat et al. (2024). In Section 3.2, we show the cluster results for the northwestern European shelf and for the North Sea specifically. In Section 3.3, we discuss the physical characteristics of the identified clusters, while in Section 3.4 we examine links between monthly 95th-percentile surge variability and large-scale climate indices. We then perform composite analysis in Section 3.5, based on extreme surge days, on sea level pressure and wind stress components to understand non-local and synoptic atmospheric patterns within the North Atlantic sector. We conclude by

discussing the importance of understanding local variability of storm surge levels and their connection to large-scale drivers and climate modes.

## 2. Data and Methodology

Storm surge variability is analyzed on a regular spatial grid and at high temporal resolution, starting from hourly resolution, using the CODEC data set. This reanalysis product combines tide and storm surge models, forced by ERA5 atmospheric fields (Hersbach et al., 2023; Muis et al., 2020). Relative to GESLA and satellite altimetry data sets, CODEC provides enhanced spatial coverage and temporally consistent data at high temporal resolution, both of which are critical for understanding high-frequency surge variability, including moderate and extreme events. When validated against GESLA, the CODEC annual maxima have a mean absolute error of 0.21 m (standard deviation: 0.26 m) Muis et al., 2020. However, in the higher ranges of total water level (approximately over 6 m) it tends to overestimate in certain regions, likely as a result of the meteorological forcing by ERA5 and high tidal range (Muis et al., 2020). The data set provides reanalysis-based storm surge estimates from 1950 to 2024 on 10-min resolution, and  $0.1^\circ$  spatial resolution along coastlines and  $0.5^\circ$  globally. As we are particularly interested in the atmospheric-oceanographic processes that impact regional sea levels, this study focuses on the detided total water level height, hereafter the storm surge. The CODEC detided product was directly downloaded from the Climate Data Store (Copernicus Climate Change Service (C3S), 2022; Muis et al., 2022). The storm surge level contains meteorological contributions to the total water level, but also includes (non-linear) tide-surge interaction (Zijl et al., 2013). The data set was then filtered to  $47^\circ$  to  $68^\circ$  latitude and  $-23^\circ$  to  $12^\circ$  longitude, the area shown in Figure 1a. This region includes the northwestern European continental shelf with shallow water (below 150 m depth, like in Wakelin et al., 2003), but also includes the deeper eastern North Atlantic regions. To remove remaining non-linear tidal interaction signals from the detided product, specific tidal frequencies were removed from the hourly time series using Fast Fourier Transforms, following studies by Høyer and Andersen (2003) and Guarneri et al. (2025). Many tidal periods were filtered to isolate the atmospheric signal, as tidal periods cause distortions and non-linear interactions specific to shallow and coastal water like in Howarth (2001), Høyer and Andersen (2003). These tidal constituents include the primary semi-diurnal and diurnal constituents (M2, S2, K1, O1, P1, Q1, N2, and K2), non-linear overtones and compound tides (M4, MS4, M6, S4, and M3) and long-period tides (Mf, Mm, Msf, Ssa, and Sa), similar to Chen et al. (2014). Power spectral analysis showed that the residual time series did not show spectral peaks for these tidal constituents. See the Table S1 in Supporting Information S1 for the removed periods associated with these constituents.

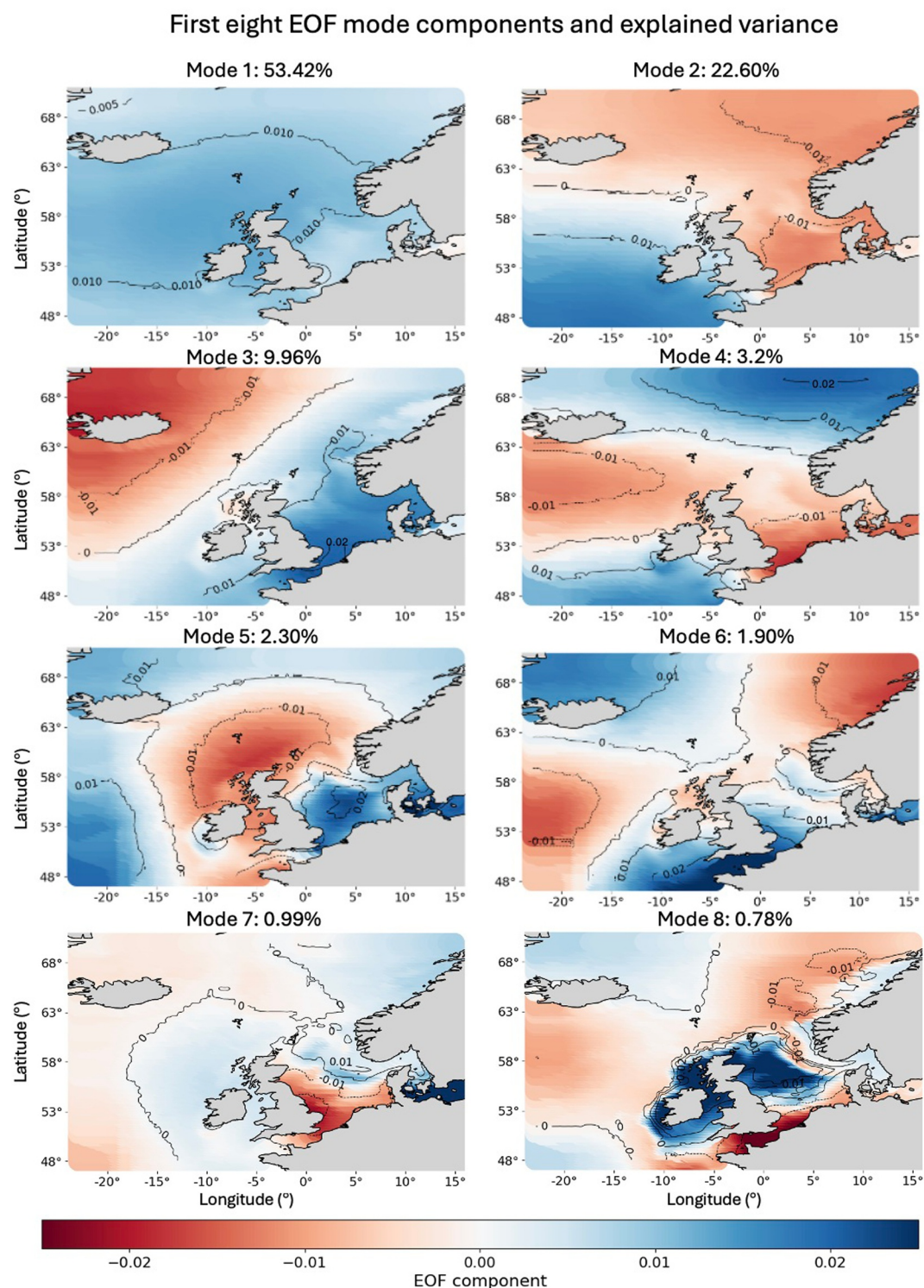
### 2.1. EOF Analysis

To ensure resolution compatibility with other ERA5-derived data sets, the CODEC storm surge data set was regridded to a  $0.25^\circ$  spatial grid using the xESMF Python package (Rieger & Levang, 2024). The hourly storm surge was first detrended and deseasonalized using SciPy's seasonal decomposition (Virtanen et al., 2020). To represent the high and independent occurrences of sea level extremes in this analysis on a regular temporal grid, the daily maximum value was extracted. This reduces noise and computational volume and reduces autocorrelation while ensuring temporal consistency and capturing peak responses.

EOF analysis was then applied to the storm surge daily maximum to extract the dominant spatial modes and further reduce the noise of the data, as in Poropat et al. (2024). We computed up to 20 EOF modes, of which the first eight spatial modes are shown in Figure 2. EOF analysis decomposes a set of spatial and temporal modes to explain as much of the data's variance as possible. EOF spatial patterns and principal component scores are dimensionless because the input fields were standardised prior to decomposition. We used the xEOFS package (Rieger & Levang, 2024), and applied spatial weights using the square root of the cosine of latitude. This EOF dimensionality reduction step also improves computational efficiency and helps reduce overfitting during clustering in the next stage, similar to Poropat et al. (2024).

### 2.2. Gaussian Mixture Modeling

To identify coherent regions of variability, the spatial components of the EOF modes were used as input to Gaussian Mixture Models (GMM, Bilmes et al., 1998; Bishop, 2006), using the Python library Scikit-learn (Virtanen et al., 2020). GMMs provide a probabilistic clustering framework in which the data are represented as a weighted sum of multivariate Gaussian distributions, enabling uncertainty quantification through soft



**Figure 2.** First eight Empirical Orthogonal Function (EOF) modes of detrended and deseasonalized daily maximum storm surge from the Coastal Data set for the Evaluation of Climate Impact (CODEC, Muis et al., 2022). EOF components and scores are dimensionless, due to scaling and weighting. Mode 1 (53%) shows a basin-wide coherent signal with the strongest amplitudes along the northwest of the British Isles. Mode 2 (23%) displays a north-south dipole between the British Isles and the Norwegian Sea. Modes 3 and 4 highlight variability in the southern North Sea, English Channel, and Bay of Biscay. Higher-order modes (<3% each) capture more localized patterns. Together, the first four modes explain ~90% of total variance. Temporal scores of these EOF modes are provided in Figure S2 of Supporting Information S1.

classification, but similar classification results were obtained by using methods like K-means (Anderberg, 2014; Cam & Neyman, 1967; Virtanen et al., 2020). We further describe GMMs in Text S2 of Supporting Information S1. We used scaled EOF spatial components as input to reduce noise and increase computational efficiency. GMMs assign probabilities to each cluster by soft classification (Cao et al., 2015), allowing for gradual boundaries and uncertainty.

Due to the stochastic nature of GMMs and random initialisations of the function parameters, ensembles of 100 runs were used to establish good fits, similar to Poropat et al. (2024). We set the covariance type to full so that each component has its own covariance matrix, and used the expectation maximization algorithm (Dempster et al., 1977). Soft voting of classes among an ensemble (Cao et al., 2015), based on averaged Posterior Probability (PP) and proximity to the GMM mean, was used to select the final clustering across the ensemble. PP represents the GMM-estimated probability that a grid point belongs to its assigned cluster, where a low PP indicates uncertain or transitional classification.

Both the number of clusters and the number of EOF modes as input need to be determined for the best fit. A good fit balances overfitting and model complexity. The optimal fit was determined using the Silhouette Score, the Bayesian Information Criterion (BIC), and the Within-Cluster Sum of Squares (WCSS) score using the elbow method.

The Silhouette Score measures how well each data point fits within its clusters compared to other clusters (Rousseeuw, 1987).

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}, \quad (1)$$

where  $a(i)$  is the average distance between point  $i$  and all other points in the same cluster, and  $b(i)$  is the lowest average distance between point  $i$  and points in any other cluster.

For the BIC, model fit (likelihood) is balanced with model complexity and parameters in the model (Schwarz, 1978). Lower values indicate a better model.

$$\text{BIC} = -2 \cdot \ln(L) + k \cdot \ln(n), \quad (2)$$

where  $L$  is the likelihood of the fitted model,  $k$  is the number of estimated parameters in the model, and  $n$  is the number of data points.

Lastly, the WCSS measures the total variance within each cluster, thus, the optimal number of clusters is identified near the elbow of the WCSS curve, where further increases in cluster number yield diminishing reductions in within-cluster variance (Cui, n.d.).

$$\text{WCSS} = \sum_{j=1}^k \sum_{x_i \in C_j} \|x_i - \mu_j\|^2, \quad (3)$$

where  $k$  is the number of clusters,  $C_j$  is the set of points in cluster  $j$ ,  $x_i$  is a data point in cluster  $C_j$ , and  $\mu_j$  is the centroid of cluster  $j$ .

A combination of these three metrics, with Silhouette Score as the primary evaluation metric, combined with a clear elbow point in the WCSS score and low BIC score, is used to choose the optimal fit for the data, like in Poropat et al. (2024). We used configurations with a high silhouette score to evaluate intra-cluster separation, and overfitting was evaluated using the BIC score and WCSS elbow method. Average posterior membership probability across points belonging to clusters was also used to assess the spread of likelihood values across clusters.

### 2.3. Source Attribution

In order to link the GMM cluster output with typical weather processes and teleconnection indices associated with surge extremes, we evaluated the spatially-averaged time series for each cluster. This was achieved through two methods of data interpretation, using teleconnection indices and composite analysis.

Firstly, we investigated the relationship between climate mode indices and surge extremes. We correlated large-scale teleconnection indices with the monthly 95th-percentile surge time series for each cluster. At each grid cell, the 95th percentile of the hourly detided surge within each calendar month was taken (following a percentile-based approach like in Mawdsley and Haigh, 2016 and Marcos and Woodworth, 2017). The time series were then detrended and deseasoned, and the resulting anomalies were averaged across the cluster, by weighting each location by its PP. All climate indices used in the correlation analysis were linearly detrended and deseasoned prior to analysis. Lead-lag correlations were evaluated from 6 months prior to 6 months after, significance was tested using the p-value (Virtanen et al., 2020), and residual independence was evaluated using the Durbin-Watson test for lag-1 serial autocorrelation (Savin & White, 1977), like in Bushra and Rohli (2021), Field (2024). Climate indices (such as the NAO and AO) were gathered from NOAA (Physical Sciences Laboratory, NOAA/ESRL, 2025). The key indices (for which we obtained the highest correlations) were derived from EOF analysis on monthly pressure anomalies. Specifically, the NAO corresponds to the leading EOF of pressure anomalies at 500 hPa between the Icelandic Low and the Azores High (Hurrell, 1995; Physical Sciences Laboratory, NOAA/ESRL, 2025), whereas the AO is the leading EOF of pressure anomalies at 1,000 hPa from 20° poleward (Physical Sciences Laboratory, NOAA/ESRL, 2025; Thompson & Wallace, 1998).

We then used composite analysis to understand the atmospheric circulation associated with extreme surge days; these are defined as days on which the cluster-averaged daily maximum surge exceeded its cluster-specific 95th percentile. Because composites require an event that occurs simultaneously across the whole cluster, the surge series was averaged across the cluster prior to thresholding, weighted by PP. This series is neither detrended nor deseasonalized, as our aim is to characterize conditions during actual extreme events. Composite anomalies are the difference between the mean atmospheric field on extreme surge days and on all remaining days, comparing extreme surge conditions to background (non-extreme) conditions. Atmospheric fields, in contrast, were deseasonalized, so composites represent each day's departure from climatology. We perform composite analysis on the detrended and deseasonalized ERA5 mean sea level pressure and on wind stress curl, derived from the ERA5 10-m wind components ( $u_{10}$ ,  $v_{10}$ , Hersbach et al., 2020). The curl is used to infer Ekman transport and coastal convergence, which, in addition to sea level pressure, are key drivers of surge elevation (Chelton et al., 2004; Mangini et al., 2021; Pugh et al., 2014). Details of wind stress calculations are provided in (Text S1 of Supporting Information S1, following work by Yelland and Taylor, 1996 and Pugh et al., 2014). Statistical significance was assessed using a student's  $t$ -test (using Scipy Virtanen et al., 2020).

For the positive composite extreme surge days for the sea level pressure variable, we evaluated corresponding extratropical cyclone tracks. The C3S windstorm track data set is used (Copernicus Climate Change Service (C3S), 2025; Sangelantoni et al., 2025), based on Hodges tracking algorithm. On extreme surge days (above the 95th percentile on the raw time series), cyclone positions were composited up to 48 hr prior to their intersection with each cluster during an extreme surge day. Only tracks west of 10°E were considered, to investigate Atlantic origins, as storms of non-Atlantic origin did not show distinct and coherent tracks. Ensemble mean storm tracks and associated spread were then calculated, using great-circle distances.

In summary, EOF analysis and clustering used the detrended, deseasonalized daily maximum surge. We define the monthly 95th-percentile surge time series as the 95th percentile of the hourly detided surge in each calendar month, subsequently detrended and deseasonalized; and extreme surge days as days exceeding the 95th percentile of the cluster-averaged, non-detrended, non-deseasonalized daily maximum series.

GPT-5 was used during Python code development (OpenAI, 2025).

### 3. Results and Discussion

This section presents the dominant spatial modes of surge variability from EOF analysis, followed by clustering results and their links to regional oceanographic and atmospheric processes, and teleconnection indices.

#### 3.1. Dominant Modes of Variability

The EOF analysis of daily maximum storm surge levels reveals that the first three modes explain 86% of the total variance (approximately 53%, 23%, and 10%, Figure 2), a result consistent across different temporal inputs and averaging methods.

The leading mode represents a basin-wide coherent pattern with the largest amplitudes across the northeastern Atlantic, reflecting a common large-scale forcing. The second mode exhibits a north–south dipole between the British Isles and the Norwegian Sea, separated by the Greenland–Scotland Ridge, which acts as a major bathymetric and oceanographic boundary between the North Atlantic and the Nordic Seas (Hansen et al., 2008; Hansen & Østerhus, 2000). The third mode highlights variability in the southern North Sea and English Channel, consistent with localized wind set-up in semi-enclosed basins. Together, the first four modes account for ~90% of the total variance, with higher-order modes capturing only localized or transient structures (Figure 2). Temporal scores and their spectra are provided in (Figure S2 of Supporting Information S1), showing peaks at interseasonal to semi-annual timescales, distinct from tidal frequencies. To provide a spatial analysis of the spatial variability of the EOF components, we now cluster these into distinct regions. Links to large-scale atmosphere–ocean processes of these regions are explored further in Sections 3.3 and 3.4.

### 3.2. Regional Clusters

Following the EOF analysis, we apply GMM clustering to delineate spatially coherent regions with distinct surge characteristics. This section first examines the sensitivity of clustering to the number of EOFs and clusters, before focusing on the Northeast Atlantic and the North Sea as key regions of interest.

We first evaluated the sensitivity of clustering to the number of EOF components and Gaussian functions. For each configuration, ensembles of 100 runs were performed to account for variability in model initialization, balancing model stochasticity and computational efficiency. Model performance was assessed using Silhouette scores, BIC, and WCSS, balancing explanatory skill against the risk of overfitting. Higher-order EOFs contributed only marginally to variance and mainly represented localized or residual variability, making them less physically interpretable and adding noise to the clustering (Poropat et al., 2024).

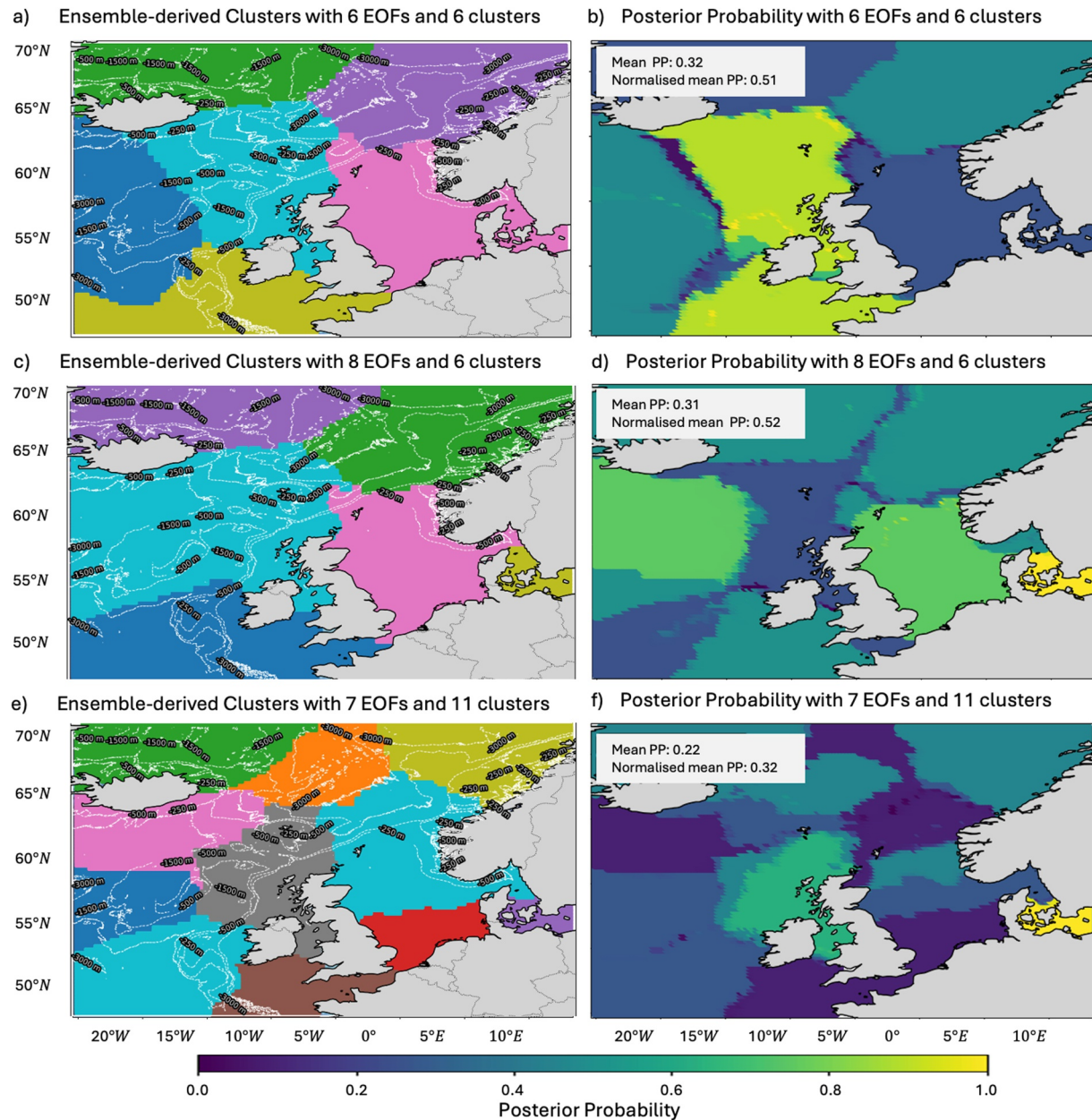
#### 3.2.1. Northeast Atlantic Regions

Figure 3 shows that coastal regions are particularly sensitive to the inclusion of additional EOFs. Incorporating EOF Mode 7, for example, produces a clear separation of the Baltic Sea with high PP assignment (Figures 3d and 3f).

In the north, a distinct coastal-to-offshore transition is observed along the 250 m depth contour, where the Norwegian trench and Continental shelf break dictate cluster boundaries (Figures 3a and 3c). The clustering does not distinguish between a coastal region off northern Norway, following depth contours, but some clusters rather include both coastal and offshore regions. The associated posterior probabilities are relatively low, indicating limited ensemble agreement and suggesting that this boundary reflects a gradual transition rather than a sharply defined bathymetric control. Increasing the number of clusters yields an additional region northwest of the UK with high PP support, and further subdivides the Atlantic, separating the coastal slope toward the English Channel from deeper offshore waters. Across most configurations, the ensemble robustly identifies the northern boundary of the North Sea with the Atlantic, where planetary waves break over the continental shelf (Sündermann & Pohlmann, 2011; see Figure 1c). With higher cluster numbers, the Baltic Sea as well as the northern and southern North Sea become distinct regions (Figure 3e). In contrast, boundaries within the North Sea show low ensemble agreement (Figure 3f), alluding to the complexity and atmospheric forcing of the region.

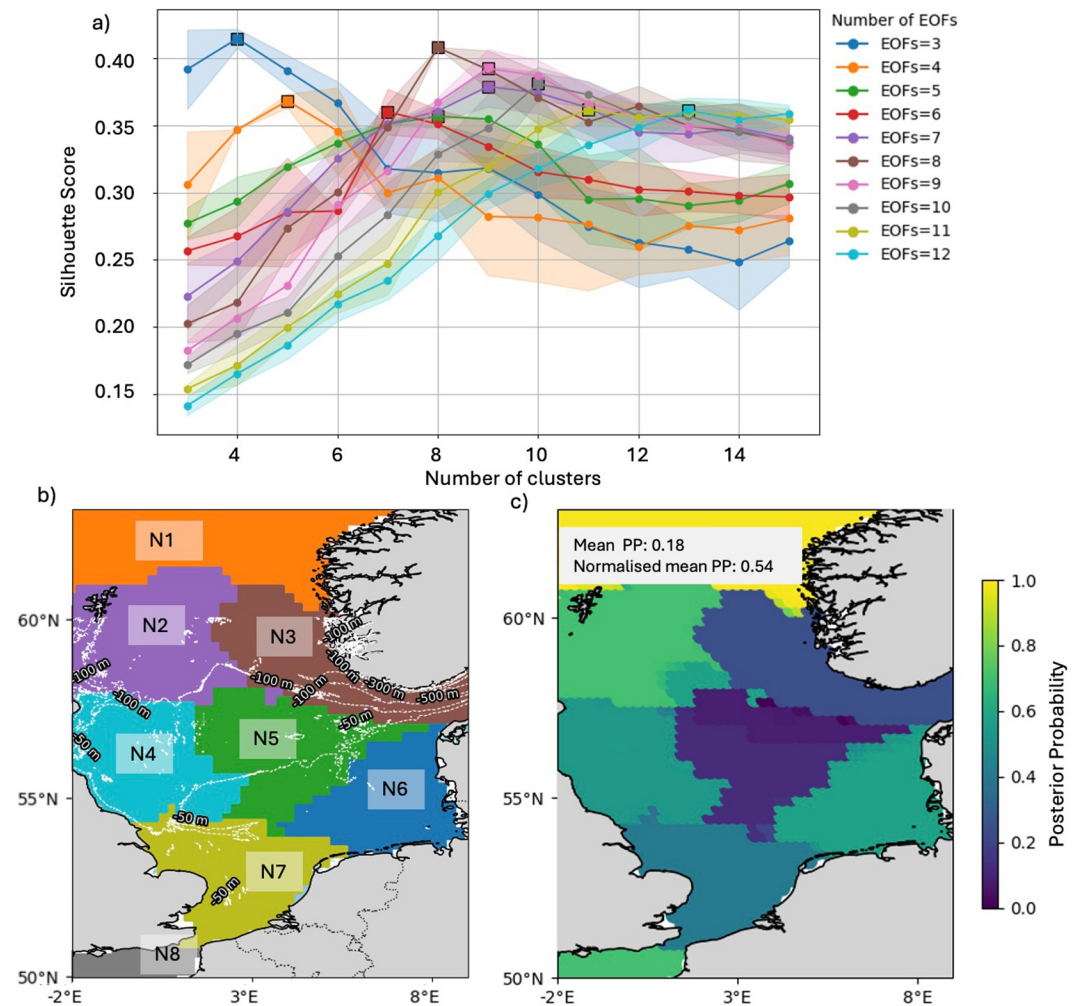
#### 3.2.2. North Sea Regions

A separate EOF analysis and GMM classification were performed in the North Sea region ( $-2^{\circ}$  to  $10^{\circ}$  longitude and  $52^{\circ}$  to  $63^{\circ}$  latitude). These EOF spatial components can be seen in Figure S3 of Supporting Information S1. The North Sea was analyzed separately because it is a shallow semi-enclosed basin with strong bathymetric controls (10–150 m deep, see Figure 1c), high flood exposure, and spatially heterogeneous surge dynamics that were only partially resolved in the clustering analysis in Section 3.2.1. Figure 4a shows that the silhouette score for the North Sea region generally favors more complex models with a high number of EOF components as input. This suggests that the North Sea contains spatially heterogeneous surge dynamics that require additional EOF modes to resolve. A good silhouette score and an agreeing elbow point (see Figure S4 in Supporting Information S1) were found for eight EOFs and eight clusters (Figure 4a), with low variability and high agreement amongst the ensemble.



**Figure 3.** Ensemble-based Gaussian Mixture Model (GMM) clustering under different model configurations, varying the number of Empirical Orthogonal Function (EOF) modes and clusters. Panels (a, c, and e) show the spatial distribution of clusters for GMM fits using six EOFs and six clusters, eight EOFs and six clusters, and seven EOFs with 11 clusters, respectively. These clusters were obtained from repeated GMM fits with random initialisations, and configurations with the highest Silhouette Score are shown. Panels (b, d, and f) show the ensemble-mean posterior membership probability (PP) for the assigned cluster, indicating how consistently each grid point is classified across the ensemble. Summary values display the domain-mean PP and its min–max normalized equivalent. Warm colors indicate strong ensemble agreement and high posterior support, whereas cool colors indicate weak agreement or transitional regions between clusters. The bathymetry in panels (a, c, and e) was retrieved from the GEBCO Global Bathymetry and Topography data set (GEBCO Compilation Group, 2024).

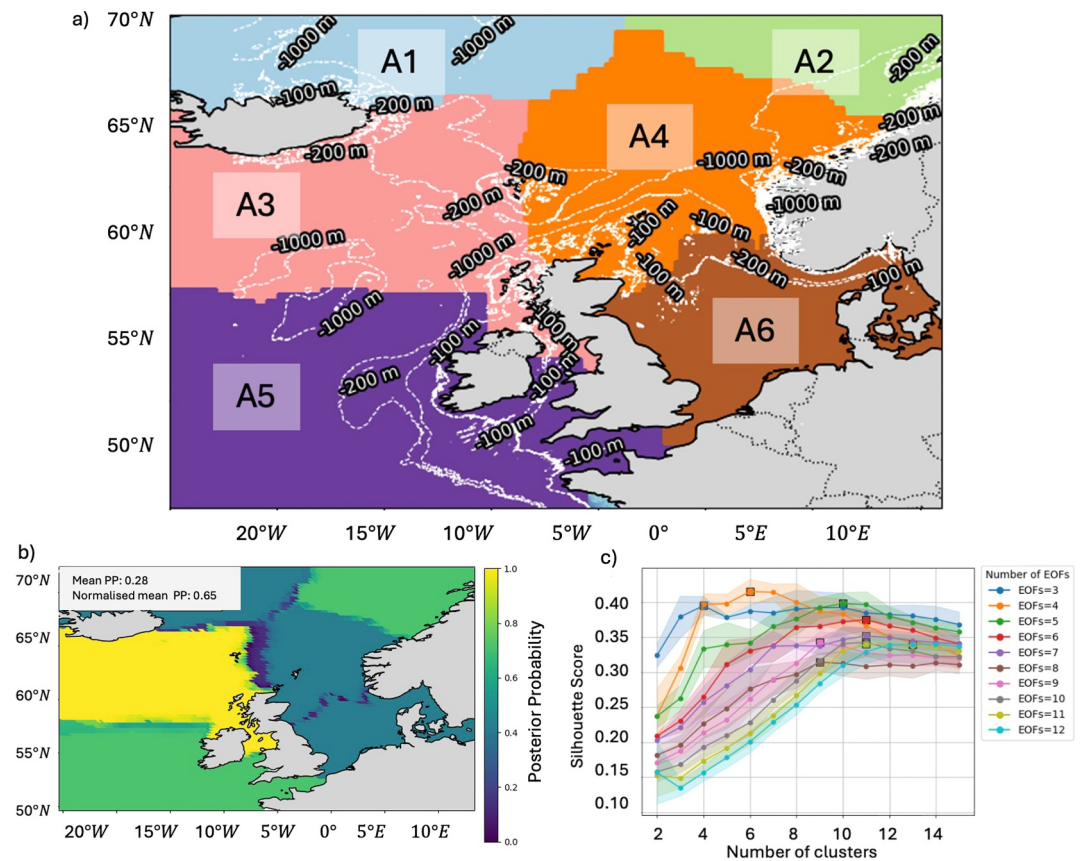
We now analyze the clusters in the North Sea region, where its complex bathymetry is known to shape and direct surges (Sündermann & Pohlmann, 2011). To highlight this, the clusters are overlaid with the bathymetric contours (Figure 4b). Cluster N3 represents the Norwegian trough, characterized as the entry to the Baltic Sea with depths over 500 m and high strengths of geostrophic currents (Howarth, 2001; Sündermann & Pohlmann, 2011). The northern boundary of N7 is defined by the 50 m contours, and the 100 m contour separates N4 and N5 from N2 and N3, which is consistent with studies of Høyer and Andersen (2003) and Poropat et al. (2024). The narrow English Channel separates processes between N7 and N8, acting as a bottleneck.



**Figure 4.** Regional clustering results for the North Sea with an overlay bathymetry over the clusters. (a) Silhouette scores for Gaussian Mixture Model (GMM) clustering across varying numbers of clusters and EOF inputs. Each line corresponds to a different number of EOF modes, with shaded envelopes indicating one standard deviation across an ensemble of 100 GMM runs. The squares correspond to the average score for each ensemble. (b) Ensemble-derived cluster assignments for the North Sea using 8 EOFs and 8 clusters, overlaid with bathymetric contours at 50, 100, 300, and 500 m from GEBCO Compilation Group (2024). (c) Ensemble-mean posterior membership probability (PP) for the assigned cluster at each grid point, representing the consistency of cluster classification across the ensemble. Summary values display the domain-mean PP and its min–max normalized equivalent. Warm colors indicate strong agreement and high posterior support, whereas cool colors identify ambiguous or transitional regions.

A clear east–west contrast emerges where the western North Sea (N4) is consistent with surge propagation from the North Atlantic, while the eastern North Sea (N6) appears strongly influenced by wind-driven surge variability and the interaction with the shallow bathymetry of the German Bight and Danish coasts (Høyer & Andersen, 2003). During strong westerly winds, surges propagate cyclonically through the North Sea (from N2, N4, N7 to N6), a pattern consistent with Kelvin wave propagation from the Atlantic (Howarth, 2001; Sündermann & Pohlmann, 2011). Cluster N6 overlaps with the German Bight, a shallow and steeply sloping coastline with a large tidal range and strong tide–surge interactions (Jacob & Stanev, 2017). This region experiences the most extreme surges when low-pressure systems track from Iceland, whereas other storm tracks tend to affect the broader coastline more uniformly (Sündermann & Pohlmann, 2011).

Cluster N5 shows the lowest posterior assignment probabilities across the 100 runs in the ensemble (Figure 4c), indicating that grid points in this central region are classified into several clusters in the ensemble. This could be due to the central region being dominated by less spatially distinct and varying processes. In contrast, the

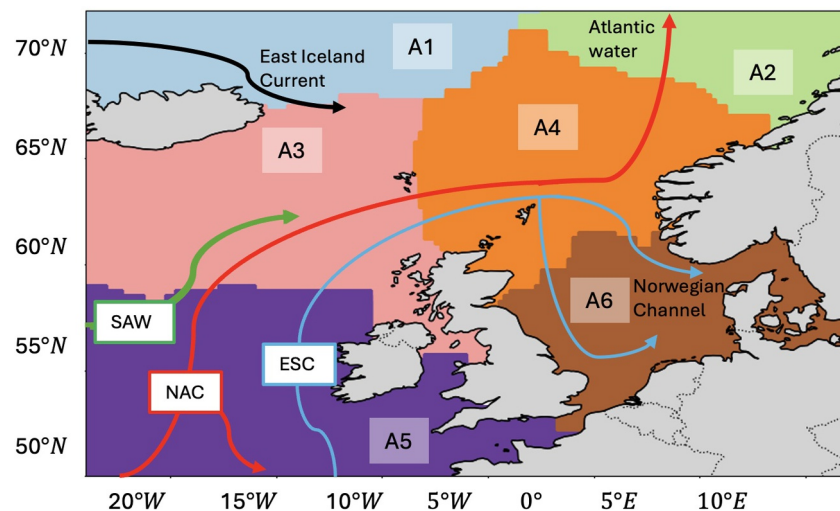


**Figure 5.** Clustering results for the optimal classification, determined by a combination of the silhouette score, BIC and WCSS elbow method. (a) Spatial distribution of clusters from Gaussian Mixture Model (GMM) classification using four Empirical Orthogonal Function (EOF) components, with bathymetry contours in meters overlaid for geographic context. (b) Average posterior membership probability that each grid point belongs to its assigned cluster across the ensemble. High values (yellow) indicate that the model assigns the point clearly to one cluster, while low values (purple) mark boundary or transitional regions. (c) Silhouette scores for different cluster numbers and EOF combinations are used to evaluate clustering performance. The squares correspond to the average score for each ensemble. This setup of four EOFs was identified based on a combination of silhouette scores, Bayesian Information Criterion (BIC), and the Within-Cluster Sum of Squares (WCSS) elbow method. The bathymetry was retrieved from the Global Bathymetry and Topography data set (GEBCO Compilation Group, 2024).

ensemble shows a high PP for Cluster N1, which also corresponds well with the clustering patterns in the full domain. The boundary between N1, N2 and N3 is similar to the upper North Sea limits, as can be seen in Figure 3. Cluster N7 may also reflect residual tidal influence, as it contains the M2 amphidromic point. Although tides were filtered from the storm surge, incomplete removal and non-linear tide–surge interactions can result in leakage of tidal variability into the clustering. The strongly coupled variability of tides and atmospheric variability can constrain the impact of atmospheric variability on the sea level, as suggested by Jacob and Stanev (2017).

### 3.3. Coastal Ocean and Atmospheric Processes

In order to understand the atmospheric processes and teleconnections that impact storm surge levels, consideration is given to a specific configuration of EOFs and cluster numbers (Figure 5). This configuration is chosen using a combination of Silhouette, BIC and WCSS scores, as shown in Figure 5c. Although some alternative configurations yielded similar or slightly higher individual scores, the selected solution of four EOFs and six clusters provided a better balance of robustness, interpretability, and ensemble consistency. This configuration also balances explanatory power against model complexity. While higher-order EOFs capture additional variance, they primarily represent localized or residual variability and would add noise to the clustering rather than improving its interpretability.



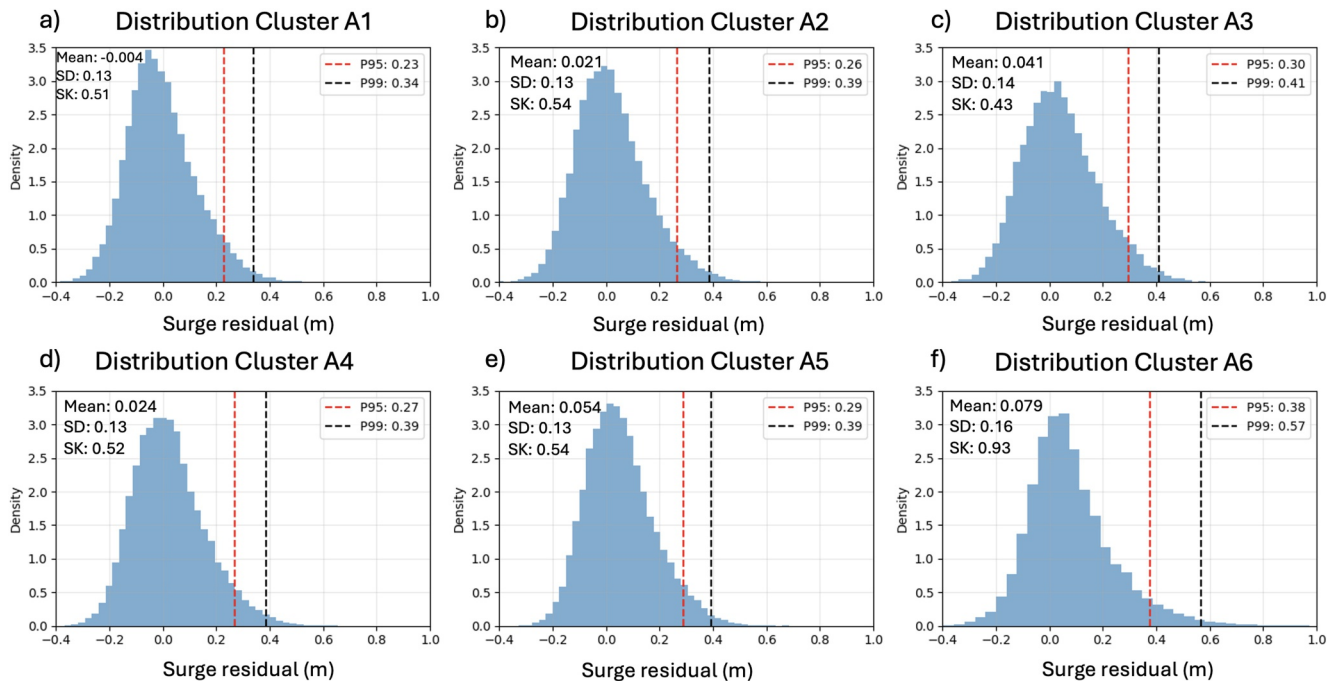
**Figure 6.** Oceanographic and atmospheric phenomenology over the northeast Atlantic overlaid on the clusters (A1–A6), shown in Figure 5a. Shown are the North Atlantic Current (NAC), Subarctic Water (SAW), the European Slope Current (ESC), and the East Iceland Current, together with the Norwegian Channel and the oceanic polar front. Current pathways and frontal positions are schematic and indicate approximate rather than precise mean locations. Ocean currents approximate locations were adapted from Orvik and Niiler (2002), Trap Føroyar (2025), McCarthy et al. (2025), and Hátún et al. (2017).

The spatial configuration derived from the ensemble clustering, specifically for the four-EOF and six-cluster configuration (Figure 5) partitions the study area based on coherent surge dynamics that are linked to major atmospheric and oceanographic features. Many cluster borders align well with bathymetric features, such as the northern boundary of Cluster A6, which includes Clusters N4–N7 from the North Sea clustering. The varying assignment probabilities of the cluster boundaries reflect the complexity of the underlying physical processes.

Clusters A1, A3, and A5 represent the offshore clusters, which are well connected to the Northeast Atlantic Ocean. In Figure 5b, the boundary between Clusters A3 and A5 has relatively low PP, indicating weak cluster membership. This uncertainty band may reflect a transition zone between different large-scale oceanographic regimes, as well as atmospheric variability. At this transition zone, warm North-Atlantic Current (NAC) water masses meet cooler subpolar waters (Figure 6). The NAC then separates into the currents at the Norwegian Trough, entering and breaking into the North Sea, or moves further northwards along the Norwegian coast (into Cluster A2). The large uncertainty and low PP corresponding to the separation of A3 and A5, could also depend on the exact location of the North Atlantic Storm tracks, where extratropical cyclogenesis may occur further southward, overlapping the NAC. The location of the jet stream and frontal zone between cold and warm air masses shifts meridionally with shifts in storm track and eddy-driven jet position (Hurrell, 1995). A more positive NAO phase, typically associated with a northward-shifted North Atlantic storm track, tends to favor storm tracks across A3, whereas during a more southerly or negative NAO phase, storms are displaced toward A5 (Hall et al., 2015; Woollings et al., 2010). The relation between climate modes and extreme surges in each cluster will also be discussed in Section 3.4.

Cluster A1 may be more influenced by the cold sub-Arctic waters of the Norwegian Sea and adjacent currents. Cluster A1 also lies downstream of one of the main North Atlantic cyclogenesis regions at the southern tip of Greenland, where storms form before typically propagating northeast toward Norway and Cluster A2 (Wernli & Schwerz, 2006). The frequent passage of such storms, and the associated upper-level jet maxima above A1, are consistent with strong air–sea coupling and large-scale surge forcing in this region.

The low assignment probabilities along the borders of Cluster A4 (Figure 5b) likely reflect the influence of multiple interacting coastal processes, highlighting the diversity and complexity of this region. This includes the interaction of shelf-edge dynamics (e.g., the European Slope Current variability, Marsh et al., 2017), coastal-trapped waves, and storm-driven setup along the continental margin on longer timescales. In contrast, the well-defined boundary between A6 and A5 (Figure 5b) may reflect the dynamical isolation of the North Sea system, where the English Channel forms a hydraulic bottleneck and surge propagation is constrained to

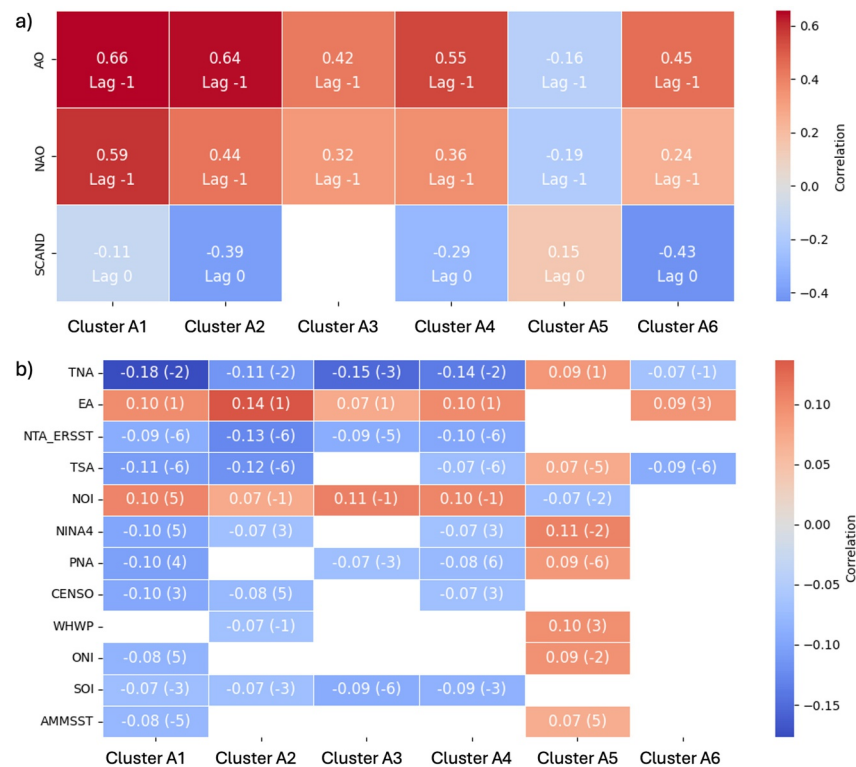


**Figure 7.** Statistical distributions of each cluster for the daily maximum, and cluster-averaged storm surge time series from the Coastal Data set for the Evaluation of Climate Impact (CODEC) data set. The CODEC data set can be retrieved from Copernicus Climate Change Service (C3S) (2022). The value for the 95th and 99th percentiles of the distribution (P95 and P99, respectively) is shown in the legend. The mean, Standard Deviation (SD), and Skewness (SK) are also shown.

coastal-trapped modes along the UK–Dutch coastline. To characterize the statistical properties of the storm surges for each cluster, we analyzed the distribution of the daily maximum surge time series, averaged across all grid points within each cluster and weighted by their PP. For the distributional analysis in Figure 7, we use daily maximum surge residuals rather than the deseasonalized anomalies to describe the absolute magnitude of storm surge within each cluster. These specific distributions and statistical values can be found in Figure 7. Clusters A1 and A2 have narrow, near-symmetric distributions with low means and weak skewness, consistent with relatively quiescent open-ocean conditions (Figures 7a and 7b). Cluster A3 shows slightly higher mean values and a moderate positive skew, while A4 and A5 exhibit broader distributions with higher variability. Cluster A6, corresponding to the North Sea, stands out with the largest mean storm surge, the highest standard deviation, and the highest skewness (0.079, 0.16, and 0.93 m respectively, Figure 7f). This indicates a long right tail and a higher frequency of extreme surge events relative to the other regions. A6 also has the highest values for the 95th and 99th percentile (0.38 and 0.57, respectively) (Figure 7f). The contrast between A6 and the more oceanic clusters (A1–A2) highlights the strong influence of shallow bathymetry and coastal dynamics on surge extremes, in line with earlier findings (Poropat et al., 2024).

Despite the use of band-stop filtering to remove dominant tidal frequencies, residual tidal influence may persist due to non-linear tide–surge interactions. These interactions can shift surge timing and amplitude, particularly in shallow regions, and may therefore contribute to uncertainty at some cluster boundaries. Previous studies have shown that such coupling can localize and intensify extreme sea levels (Jacob & Stanev, 2017), while also being difficult to represent accurately in tide–surge models (Zijl et al., 2013). Observations further indicate that storm surge levels often peak several hours before high tide (Jenkins et al., 2025), reinforcing the need to consider tide–surge dynamics when interpreting regional clustering results.

In this study, we also applied clustering to a wide domain including both deep ocean offshore processes, as well as shallow coastal regions. Because the analysis domain includes deep-ocean regions, some EOF variability likely reflects large-scale offshore dynamics in addition to shelf surge processes. However, the spatial structure of several leading EOFs also exhibits coherent shelf and coastal variability, suggesting that the decomposition retains physically meaningful coastal surge patterns.



**Figure 8.** Significant correlations between teleconnection indices and monthly 95th-percentile surge time series, averaged over each cluster. (a) Correlations ( $r$ ) and corresponding optimal lag values (in months) per cluster, where  $p < 0.05$  and correlations exceed  $|r| > 0.05$  (b) Correlations and optimal lags in brackets for teleconnection indices that are less significant, where  $p < 0.05$  and correlations exceed  $|r| > 0.05$ . Rows represent teleconnection indices: Arctic Oscillation (AO), North Atlantic Oscillation (NAO), Scandinavian (SCAN) pattern, Tropical North-Atlantic (TNA), East Atlantic (EA), North Tropical Atlantic based on Extended Reconstructed Sea Surface Temperature (NTA\_ERSST), Tropical South Atlantic (TSA), Northern Oscillation Index (NOI), El Niño 4 sea surface temperature index (central equatorial Pacific region) (NINA4), Pacific North American (PNA), Central El Niño Southern Oscillation (CENSO), Western Hemisphere Warm Pool (WHWP), Oceanic Niño Index (ONI), Southern Oscillation Index (SOI), and the Atlantic Multidecadal Sea Surface Temperature (AMMSST). Teleconnection indices were obtained from NOAA (Physical Sciences Laboratory, NOAA/ESRL, 2025), and surge time series from the Coastal Data set for the Evaluation of Climate Impact (CODEC) data set by Copernicus Climate Change Service (C3S) (2022).

We also consider that the EOF and clustering analysis are based on daily maximum storm surges, which include both moderate and extreme surge events. The identified circulation regimes, therefore, characterize coherent variability in daily maximum surge conditions rather than extremes in the strict extreme-value-theory sense. It should be noted that we assume the weather systems associated with moderate and extreme surges share similar large-scale characteristics. We further analyze the surge extremes for each cluster in Sections 3.4 and 3.5. The analysis on moderate storm surges could result in slightly different clusters. To investigate this further, future work could perform experiments with EOF analysis on the 95th percentile threshold, or analysis on block maxima using extreme value theory.

### 3.4. Teleconnections and Circulation Regimes

This section examines the links between leading modes of atmospheric variability and monthly 95th-percentile surge time series across the identified clusters. These correlations indicate potential sources of subseasonal-to-seasonal predictability, but do not by themselves demonstrate predictive skill.

The correlation analysis indicates that large-scale atmospheric patterns are moderately associated with regional surge variability across northwestern Europe. Figure 8 shows statistically significant relationships ( $|r| > 0.05$ ,  $p < 0.05$ ), while all climate indices considered are provided in (Table S2 of Supporting Information S1). We found little evidence of residual serial autocorrelation for the correlations in Figure 8, using the Durbin-Watson

test (Savin & White, 1977). The strongest signals are associated with the Arctic Oscillation (AO) and the North Atlantic Oscillation (NAO), both of which are positively correlated with surge variability in most regions, with the indices typically leading the surge signal by 1 month (Figure 8a). These relationships are strongest in Clusters A1, A2, and A4, while the North Sea (A6) exhibits more moderate correlations. These results are broadly consistent with earlier studies linking atmospheric circulation to storm surge variability (Chafik et al., 2017; Gleeson et al., 2019; Hurrell, 1995).

Positive NAO phases are associated with strengthened westerlies and a northward displacement of North Atlantic storm tracks, conditions that favor enhanced surge activity in exposed shelf and coastal regions. Previous studies have reported NAO-related variability in northwestern European total sea level and extremes (Chafik et al., 2017; Gleeson et al., 2019; Sterlini et al., 2016). Alexander et al. (2005) found strong correlations between the winter NAO and the number of severe storms over Iceland and the UK (A1 and A3 here). For the surge component specifically, Woodworth et al. (2007) found the strongest NAO relationship in the eastern North Sea, corresponding to the eastern part of Cluster A6 identified here, while Wakelin et al. (2003) report winter-mean NAO correlations that reverse sign toward the Celtic Sea and Bay of Biscay, consistent with the inverse response we find in A5. Clusters A3 and A4 may also be influenced by cold-air outbreaks from the Nordic Seas during negative AO phases; however, the positive correlations found here suggest that variability associated with strengthened westerlies dominates the monthly surge signal. In the semi-enclosed Cluster A6, the moderate NAO and AO correlations may additionally reflect wind-driven accumulation of water within the North Sea under persistent onshore flow (Wakelin et al., 2003). While several previously discussed studies considered total sea-level variability, this correlation analysis focuses specifically on atmospheric-driven storm surge variability (Figure 8). Nevertheless, NAO-related sea-level variability on these timescales is thought to arise predominantly through wind stress and pressure forcing associated with large-scale atmospheric circulation changes (Calafat et al., 2012). The dynamical role of wind stress and pressure are further examined in Section 3.5.

In contrast, SCAN is negatively correlated with monthly 95th-percentile surge time series at zero time lag, especially in clusters A2 and A6. Positive SCAN phases are associated with high-latitude blocking that weakens westerlies and reduces surge events, in agreement with previous findings (Chafik et al., 2017; Gleeson et al., 2019). SCAN is especially important in the Norwegian Sea (A2), which is supported by results in Chafik et al. (2017), Gleeson et al. (2019). Together, AO, NAO, and SCAN are associated with much of the observed large-scale atmospheric variability linked to the monthly 95th-percentile surge time series, with a strong link between the basins and the mean position of the westerlies emerging in particular for the AO, followed by the NAO.

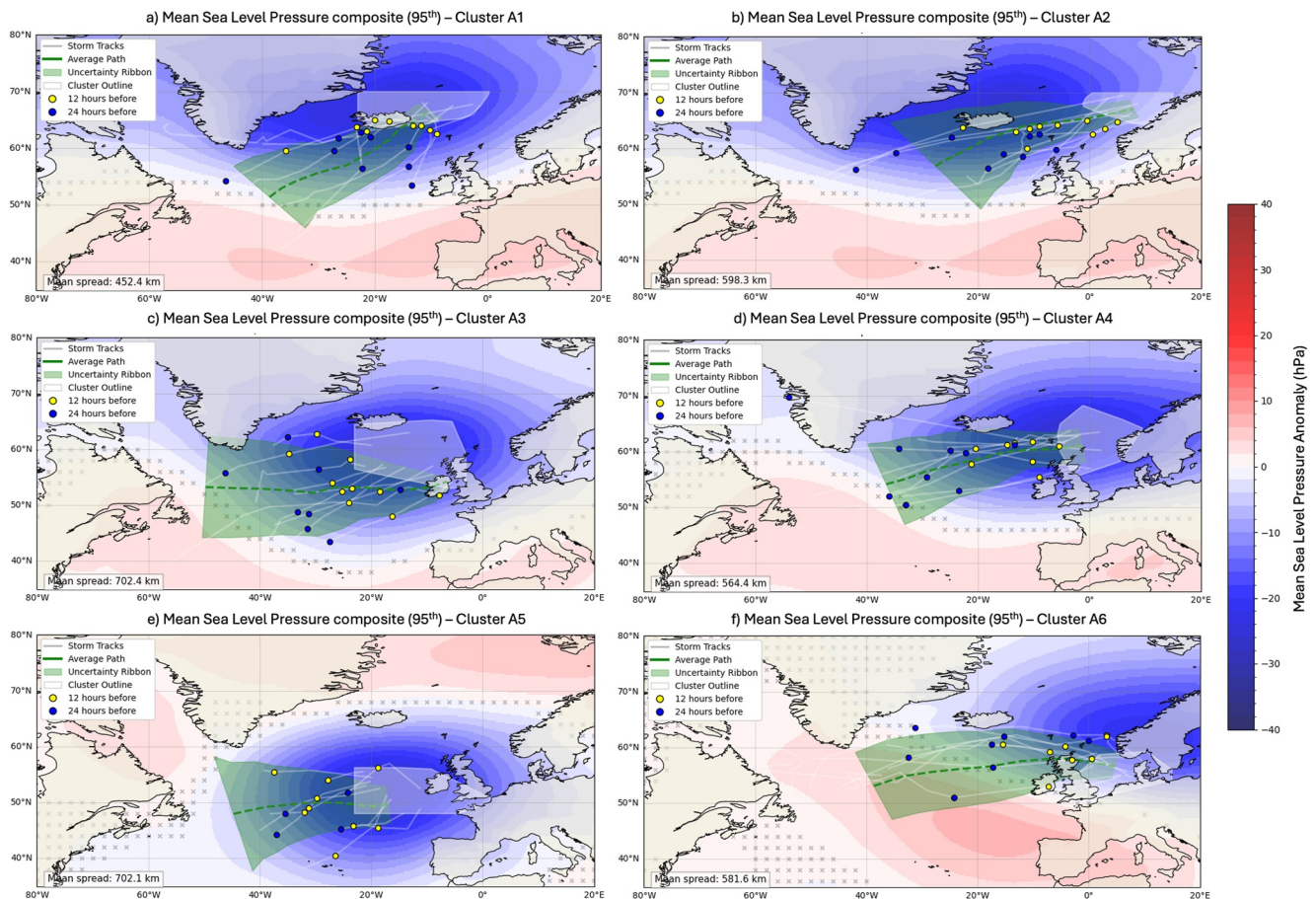
We also find weaker but significant correlations with other indices (Figure 8b). We find significant correlations with the Tropical North Atlantic (TNA), connected to tropical storms at mid-latitudes, with the highest inverse correlations for A1 and A3, and the EA index, the latter having previously been linked to storminess and extreme waves in eastern North Atlantic regions (e.g., A2, A1, and A4 here) (Izaguirre et al., 2011; Seierstad et al., 2007). Overall, these secondary correlations are weaker and should be interpreted with caution. Signals from ENSO-related indices were weak and generally insignificant, in contrast to some earlier studies that reported ENSO impacts on surge components (Muis et al., 2018). We note that our analysis did not consider seasonal dependence or non-stationarity of the teleconnection–surge relationships. Previous work has shown that both can be important, with correlations varying by phase and season (Alexander et al., 2005; Iglesias et al., 2017).

### 3.5. Atmospheric Patterns Analysis

To better understand the dynamical underpinning of the statistical relationships and identify the physical drivers, we next examine the large-scale atmospheric patterns and storm tracks associated with extreme surge days, indexed by the top 5% of the non-detrended and non-deseasonalized cluster-averaged surge series. Consideration is given to the tracks of individual extratropical cyclones, which allow for a more fine-grained analysis of the link between extratropical cyclones and surges.

#### 3.5.1. Mean Sea Level Pressure and Extratropical Cyclones

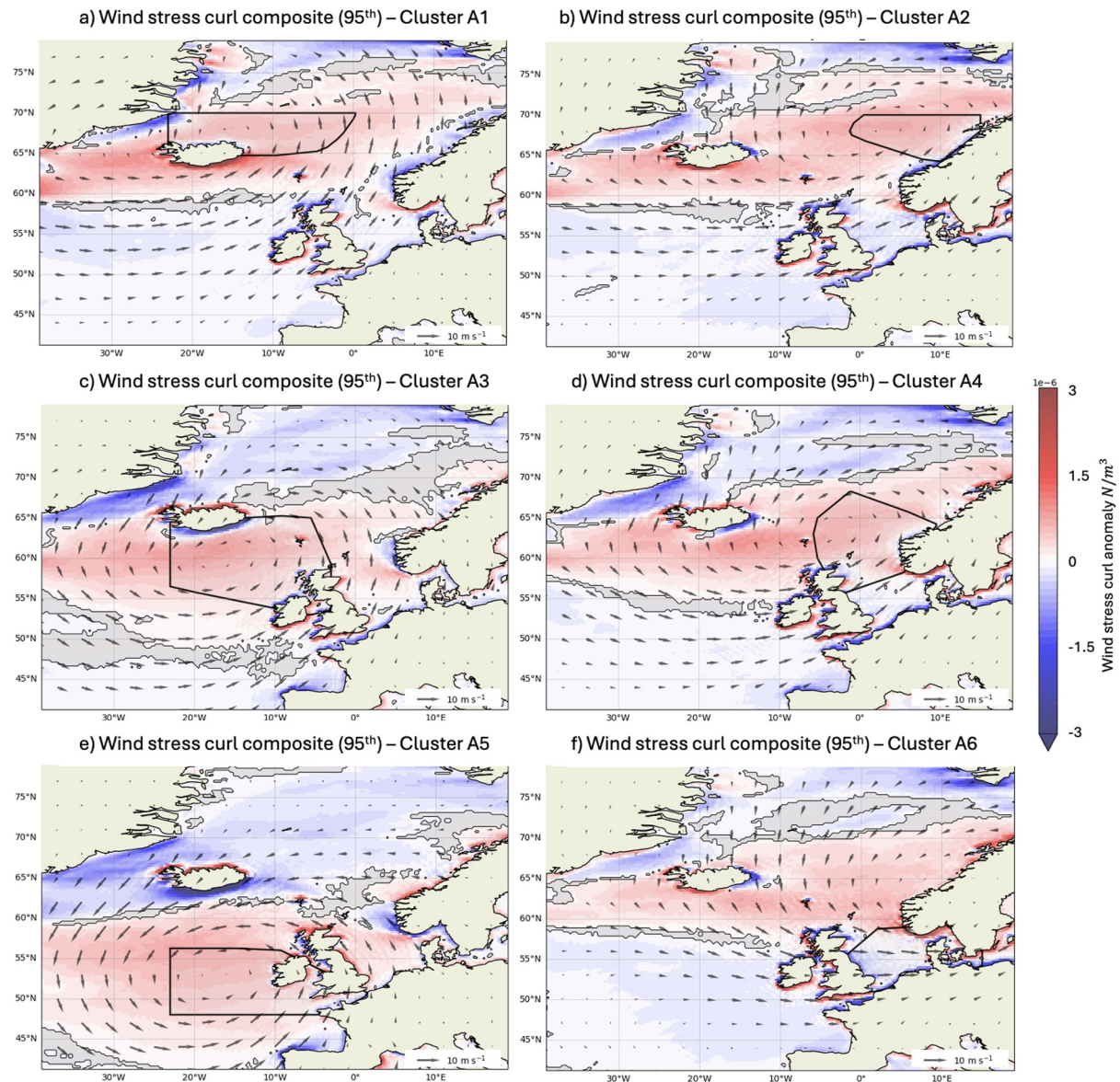
The influence of large-scale circulation and storm tracks was examined using a composite analysis of mean sea level pressure during extreme surge days. For each cluster (Figure 5), daily maximum storm surge levels were likelihood-weighted and averaged, and storm tracks intersecting the clusters were identified (Figure 9).



**Figure 9.** Mean sea level pressure composites for extreme surge days for all clusters, showcasing the average composite difference in sea level pressure during extreme surge (top 5%) and non-extreme surge anomalies. A student's  $t$ -test was used for the composite significance test, where insignificant regions are denoted by a gray cross. Regional extreme surge days, using the 95th percentile, were extracted from the Coastal Data set for the Evaluation of Climate Impact (CODEC) data set by Muis et al. (2020). Mean sea level pressure variables were retrieved from 1950 to 2024 from Hersbach et al. (2023), and were detrended and deseasonalized. The storm tracks, based on pressure depression and maximum vorticity from Sangelantoni et al. (2025).

In Cluster A2, high surges coincide with a marked pressure drop over the Northeast Atlantic, while in Cluster A5 the anomaly is centered west of Ireland (Figures 9b and 9e). These pressure decreases support the interpretation that atmospheric forcing is a major contributor to these surge events, apart from in A6, where weaker pressure-anomaly patterns are observed (Figure 9f). In Cluster A2, the anomaly is paired with mid-latitude high pressure, producing a pressure gradient characteristic of the positive NAO phase like in Dangendorf et al. (2014).

Storm track composites further illustrate distinct pathways. Tracks associated with Cluster A5 tend to originate from lower latitudes (around 50°N), while those for Cluster A2 are more often initiated from higher latitudes (around 60°N). For Cluster A2, many storms originate off the coast of Greenland and in the central North Atlantic, taking a more poleward path. This spatial pattern is consistent with the northward storm-track displacement associated with positive NAO phases, where storm tracks shift northward (Hurrell & Van Loon, 1997). Given the close correspondence between the AO and NAO indices, it also agrees with the positive correlation with the AO, which is characterized by strong westerlies at high latitudes. These storm track signatures are also consistent with earlier studies linking surge variability to storm clustering (Mailier et al., 2006; Malagon Santos et al., 2017). High surge levels in Cluster A5 are more common during autumn, while in other clusters, most extremes occur during winter consistent with Chen et al. (2014), Sterlini et al. (2016). The autumn surges in Cluster A5 may therefore reflect early-season NAO variability influencing mid-latitude extratropical cyclones. For A5, extratropical cyclones originate in the Gulf Stream-Newfoundland region and propagate eastward toward the British Isles, which is characteristic for a zonal flow regime. This may also explain the absence of a strong positive or negative correlation with the NAO, because in a strong negative NAO phase, cyclones would track more



**Figure 10.** Composite differences in wind stress curl, leading to convergent (negative curl, blue) and divergent (positive curl, red) Ekman convergence and divergence, comparing wind stress differences between extreme surge days (top 5%) and non-extreme days. Negative wind stress curl indicates Ekman convergence, which promotes downwelling and an accumulation of surface waters, while positive wind stress curl indicates Ekman divergence, associated with upwelling and surface water removal. Composite positive phases are evaluated for 95th percentile surge days for all clusters, where insignificant regions are denoted by gray shading. Arrows show wind vector direction of zonal and meridional wind speed at 10 m, while color shading indicates the magnitude and direction of the wind stress curl ( $\text{N m}^{-3}$ ). All units, contours, and vectors are scaled across the plots. Results are composited using ERA5 reanalysis wind stress (Hersbach et al., 2023), deseasonalized and detrended, and anomaly significance is calculated using a student's *t*-test.

consistently toward the Mediterranean and thus equatorward of the A5 region, while in a strong positive NAO phase, they would propagate more poleward of the A5 Cluster. Together, these results suggest that storm-track information and climate-mode indices may provide useful predictors for regional storm surge variability.

### 3.5.2. Wind Stress

The role of wind forcing in surge generation was examined by constructing composites of wind stress curl anomalies during extreme surge days, using the 95th percentile. These composites show cyclonic wind patterns near several clusters during high storm surge events (Figure 10), consistent across clusters. This pattern is also aligned with the low-pressure anomalies shown in Figure 9, reflecting the influence of the Coriolis force.

Cyclonic winds are associated with positive wind-stress curl and Ekman divergence, which can promote local surface depression away from coastal convergence zones (Apel, 2013). Away from the centers of the cyclone and against the coastlines, these winds generate regions of Ekman convergence (blue) and drive surface pressure gradients against the coastline where the wind-forced Ekman transports pile up. Convergence is particularly evident along the Norwegian coastline and eastern North Sea (Figure 10b), where alongshore winds drive Ekman transport onshore (Dangendorf et al., 2014; Hermans et al., 2022; Sterlini et al., 2016). This enhances storm surge magnitude and coastal sea level variability (Woodworth et al., 2019). During positive storm surge composites, several clusters show coastal convergence patterns (blue) along nearby coastlines, as can be seen in Figure 10. Positive composite days in Cluster A2 lead to convergence along the northwestern Norwegian coast, as well as the northwest of the British Isles and along the eastern North Sea coast. Figures 10c–10e show convergence along the same regions, but also along the north coast of Spain and south of Iceland.

The higher latitudes of the center of the cyclones for Cluster A3, A4, and A6, compared to A5, are consistent with strengthened westerlies and northward shift of the storm tracks during positive NAO and AO phases (Chafik et al., 2017; Hurrell, 1995), and the stronger correlation with the NAO we found for A1, A2, and A4 (Figure 8a).

Further south of the cyclone centers, negative wind stress curl generates convergence and Ekman transport on synoptic scales. For Cluster A4 (Figure 10d), this leads to strong westward transport north of Iceland and enhanced southward transport south of Iceland. In Cluster A2 (Figure 10b), similar southward Ekman transport anomalies appear as a result of the cyclone, consistent with Marshall et al. (2001). These Figures can be seen in Figures S9 and S10 of Supporting Information S1. Wind stress curl and Ekman transport, however, do not give a quantitative estimation of sea level contribution, and are also not the full description of the wind-driven sea level flux (Wise et al., 2024).

#### 4. Conclusion

This study provides a spatial classification of high-resolution storm surge variability across the northwestern European shelf, combining spatio-temporal EOF analysis with GMM clustering. We identified six distinct regions of storm surge variability on the northwestern European continental shelf (Figure 5), and eight distinct sub-regions in the North Sea (Figure 4), where shallow bathymetry and semi-enclosed geometry strongly shape surge propagation and extremes. The probabilistic nature of the clustering highlights both well-defined surge regimes and transition zones, particularly in the central North Sea, where multiple atmospheric and oceanographic processes interact.

Our analysis shows that the identified North Atlantic regions exhibit heterogeneous links to large-scale atmospheric modes. Surge variability is most strongly associated with the AO and NAO, with a strong positive correlation in most regions (specifically A1, A2, and A4), and with an inverse response from Cluster A5. In contrast, SCAN shows distinct and predominantly negative relationships in northern regions. These regional correlation results are consistent with Seierstad et al. (2007), Mawdsley and Haigh (2016), and Chafik et al. (2017).

Composite analyses indicate that shifts in storm tracks and low-pressure anomalies are associated with regional surge extremes across regions, supporting results by Malagon Santos et al. (2017) and Camus et al. (2021). Wind-stress curl anomalies further clarify the role of coastal convergence in regional surge amplification against coastlines, consistent with studies by Mangini et al. (2021), and Pineau-Guillou et al. (2023), for which we found most coastal convergence on the east coast of the North Sea.

Beyond atmospheric forcing, the spatial clusters are also geographically aligned with major North Atlantic ocean-circulation features. Future changes in the Atlantic Meridional Overturning Circulation (AMOC) could alter oceanographic circulation and currents, such as the Norwegian Atlantic Current and the Icelandic currents, thereby influencing ocean–atmosphere coupling, weather extremes, and the propagation of storm-driven surges (Jackson et al., 2015; Rahmstorf, 2024). This analysis could thus be extended to climate-change scenarios and climate model outputs to explore how the regional surge phenomenology and the clusters may change, for example, by using CODEC's future projections (Muis et al., 2023). By explicitly linking coherent surge regions to non-local physical drivers, this approach also provides a foundation for improved uncertainty quantification and sensitivity analysis in coastal hazard assessments.

Beyond the North Atlantic, applying this clustering framework to other coastal regions could provide new insights into the dominant processes shaping storm surges globally. Future work should also extend the analysis to climate change scenarios to evaluate how regional surge phenomenology and its links to large-scale drivers may evolve in a warming climate.

Furthermore, recognizing the spatial variability of these connections and their non-local drivers provides a basis for advancing the predictive skill of surge models. For example, our coherent clusters provide a useful starting point for distinct regional coastal modeling and process understanding for each individual cluster (e.g., building on work by Nagaraj et al., 2025). These regions can provide the spatial boundaries for regional surge distribution analysis (e.g., Apolola et al., 2025). Lastly, future research could incorporate tidal dynamics, waves and mean sea level rise to assess coastal impact more fully, as surge interactions non-linearly modulate ESLs (Horsburgh & Wilson, 2007; Jacob & Stanev, 2017).

## Abbreviations

|           |                                                                                 |
|-----------|---------------------------------------------------------------------------------|
| ESL       | Extreme Sea Level                                                               |
| CODEC     | Coastal Data set for the Evaluation of Climate Impact                           |
| GESLA     | Global Extreme Sea Level Analysis data set                                      |
| NAO       | North Atlantic Oscillation                                                      |
| SCAN      | Scandinavian pattern                                                            |
| AO        | Arctic Oscillation                                                              |
| EA        | East Atlantic pattern                                                           |
| GMM       | Gaussian Mixture Models                                                         |
| EOF       | Empirical Orthogonal Function                                                   |
| BIC       | Bayesian Information Criterion                                                  |
| WCSS      | Within-Cluster Sum of Squares                                                   |
| TNA       | Tropical North Atlantic                                                         |
| NTA_ERSST | North Tropical Atlantic based on Extended Reconstructed Sea Surface Temperature |
| TSA       | Tropical South Atlantic                                                         |
| NOI       | Northern Oscillation Index                                                      |
| NINA4     | El Niño 4 Sea Surface Temperature                                               |
| PNA       | Pacific North American                                                          |
| CENSO     | Central EL Niño Southern Oscillation                                            |
| WHWP      | Western Hemisphere Warm Pool                                                    |
| ONI       | Oceanic Niño Index                                                              |
| SOI       | Southern Oscillation Index                                                      |
| AMMSST    | Atlantic Multidecadal Sea Surface Temperature                                   |

## Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

## Availability Statement

The CODEC data set by Muis et al. (2020, 2022) used in the surge analysis of this paper can be found at the Copernicus Climate Data Store (Copernicus Climate Change Service (C3S), 2022) (at <https://doi.org/10.24381/cds.a6d42d60>). The time series for the teleconnections were obtained from the NOAA (Physical Sciences Laboratory, NOAA/ESRL, 2025) and they can be found online at <https://psl.noaa.gov/data/>. Individual data links for downloading each climate index can be found in Table S2 of Supporting Information S1. The data set used for analysing windstorm tracks (Copernicus Climate Change Service (C3S), 2025), via <https://doi.org/10.24381/bf1f06a9> is available at the Copernicus Climate Data Store. The ERA5 reanalysis data (Hersbach et al. (2023), via <https://doi.org/10.24381/cds.adbb2d47>) can also be downloaded from the Copernicus Climate Data Store. Bathymetry data were obtained from the GEBCO Compilation Group (2024) via <https://doi.org/10.5285/1c44ce99-0a0d-5f4f-e063-7086abc0ea0f>. Code can be found on the Zenodo repository (Blok et al., 2026) via <https://doi.org/10.5281/zenodo.20342590>.

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