

# Clustering to characterize extreme marine conditions for the benthic region of the Northeastern Pacific continental margin

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## Key Points:

- A generalizable method for characterizing ocean extremes was developed and applied to an Eastern Boundary Current environment.
- Climate indices are predictive of extreme conditions for the Northeastern Pacific continental margin.
- Multiple stressor extremes are rare, but are increasing in some regions, with most of involving compound extremes of oxygen and acidity.

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## Abstract

Anthropogenic CO<sub>2</sub> emissions lead to ocean warming, deoxygenation and acidification. Superimposed on the long-term trends are episodic extremes of temperature, oxygen, and acidity. Here we present an innovative method for assessing single and multiple stressor extremes using a high-resolution regional model of the Northeastern Pacific Ocean. We use an unsupervised clustering approach to identify regions with similar habitat characteristics near the seafloor, define extreme thresholds seasonally using a fixed baseline (1996-2020) within each cluster, and quantify the fraction of ocean waters that exceed these thresholds for both single and compound stressors. Compound extremes (most commonly of O<sub>2</sub> and acidification) are rare but show an increasing trend in some clusters. Potential predictability of occurrence of extremes is demonstrated by correlation with basin-scale climate variability.

## Plain Language Summary

The ocean is becoming warmer, losing oxygen and acidifying as a result of CO<sub>2</sub> emissions. Superimposed on the mean changes are episodic extremes that can have detrimental impacts on ecosystems. To better understand the nature of extreme conditions on the continental margin, we use a statistical approach to characterize these extremes in the recent past (1996-2019).

We introduce a method for characterizing extremes that uses machine learning to divide the data into regions with relatively consistent environmental conditions (temperature, oxygen, acidity), and define the extremes based on the historical statistics of variability of each of these fields. For the Northeast Pacific continental margin, a substantial number of single stressor extremes occur annually. However, coincident extremes of more than one stressor are rare. Local extremes are related to large scale climate variability such as the North Pacific Gyre Oscillation. Long term trends are weak but detectable in some cases.

## 1 Introduction

Global warming, ocean deoxygenation, and acidification are inextricably linked. The ocean has taken up about 30% of anthropogenic carbon emissions and about 90% of the excess heat (Pörtner et al., 2019) which warms and acidifies the ocean and leads to deoxygenation through changes in solubility, stratification, ventilation, and respiration (Keeling et al., 2010; Breitburg et al., 2018). Ocean climate is changing rapidly and episodic extremes can drive changes in ecosystems decades before the mean state reaches that extreme.

Extremes of temperature, oxygen and acidity are projected to increase in the future (Kwiatkowski et al., 2020; Gruber et al., 2021). When these three stressors occur concurrently or consecutively they can have synergistic effects (Gruber, 2011) that impact organisms in ways that exceed the effects of a single stressor in isolation Pörtner et al. (2005). For example, increasing temperature can make species more sensitive to ocean acidification (Pörtner & Farrell, 2008), and oxygen and acidification can impact the thermal tolerances for some species (Pörtner, 2010). Some species will shift their distributions in response to these stressors (Thompson et al., 2023), while others will be unable to.

Episodic occurrences of anomalously warm ocean temperatures, known as marine heatwaves (MHW) have been associated with oxygen and acidification anomalies as solubility declines and stratification increases (Mogen et al., 2022). An analysis of satellite derived sea surface temperatures from the recent past (1982-2016) indicates that marine heatwaves (MHW) are increasing in duration and intensity. Earth system models

project increasing frequency, breadth, intensity and duration of MHWs (Frölicher et al., 2018). A doubling of impacts on species is anticipated by the 2050s (Cheung & Frölicher, 2020).

Marine heatwaves threaten marine life in the North Pacific and are associated with increasing occurrences of harmful algal blooms (Cavole et al., 2016), declines in the nutritional value of key forage fish (von Biela et al., 2019), reduction in stocks of commercially important fish (Cheung & Frölicher, 2020), mass mortality events, and loss of ecosystem services (Smale et al., 2019). The eastern North Pacific is one of the most productive regions in the world ocean (Cushing, 1971) and may be particularly vulnerable to biogeochemical extremes due to upwelling of waters that are low in oxygen and highly corrosive (primarily due to the age of the water). Corrosive ( $\Omega_A < 1$ ) and hypoxic ( $O_2 < 60 \text{ mmol m}^{-3}$ ) water is projected to encroach on the Northeast Pacific continental margin by 2046-2065 (Holdsworth et al., 2021).

Previous studies have divided the shelf by defining bioregions using physical ocean variables and expert knowledge of the prevailing circulation (Zacharias et al., 1998). Rubidge et al. (2016) used machine learning to assimilate biological and environmental data to define ecoregions. They showed that the resulting ecological units represent more distinct species assemblages than the classifications based on expert knowledge. Clustering with machine learning reduces the need for personal interpretation or judgment by defining ecoregions using the data themselves.

This paper introduces a novel method for characterizing individual and compound extremes of temperature, oxygen, and acidification. The approach uses a clustering technique to establish subregions with similar environmental conditions and defines ‘extreme’ thresholds for upwelling and downwelling seasons using a fixed baseline. Assuming that extremes in these unique environmental spaces are influenced by similar processes helps disentangle the mechanistic drivers for this vast and complex region of the shelf. We use the method to analyze output from a high-resolution ocean biogeochemistry model of the Northeast Pacific from 1996 to 2019, restricting our analysis to the benthic layer of the Canadian coastal region, which contains unique ecosystems like glass sponge reefs and economically important shellfish and rockfish habitats. We then examine the occurrence of extreme conditions for both single and compound stressors.

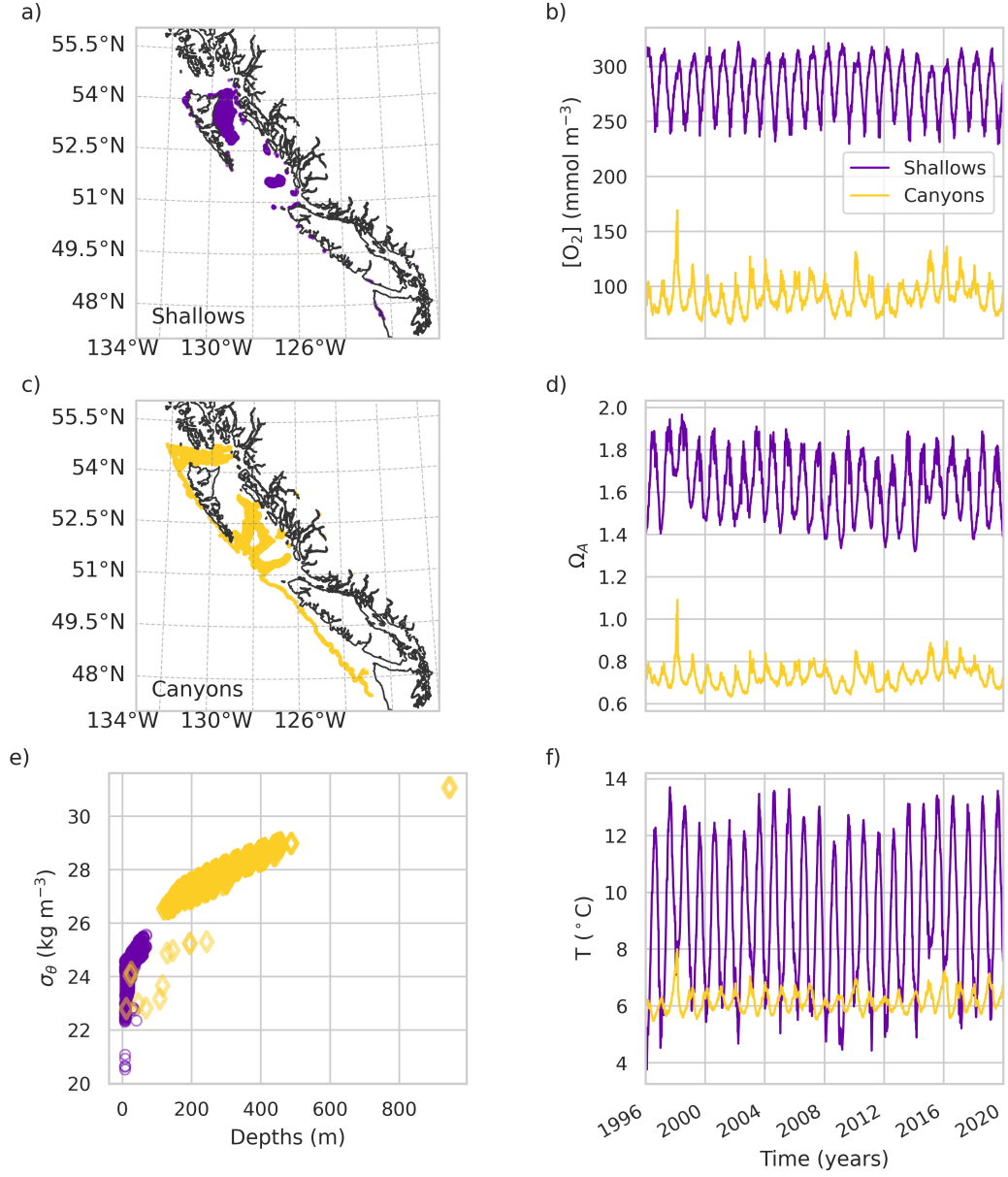
Section 2 describes the regional model and the clustering technique; Section 3 discusses the spatial distribution of extreme thresholds and their evolution over time; Section 4 discusses these results in the broader context of extremes on continental margins and the utility of these findings to ecosystem management; lastly, Section 5 provides an overall summary of the paper and key results.

## 2 Methodology

### 2.1 Northeastern Pacific Ocean Model

The Northeastern Pacific (NEP) model domain spans the Canadian Pacific Ocean east of  $140^\circ\text{W}$  and north of  $45^\circ\text{N}$  (Figure 1 ab, Figure S1). The horizontal resolution is nominally  $1/36^\circ$  latitude and longitude which gives a variable grid spacing between 1.5 and 2.25 km. The model includes the ocean biogeochemistry module known as the Canadian Ocean Ecosystem model (CanOE) (Christian et al., 2022).

The regional ocean model, NEP36-CanOE, is an updated version of the one used in Holdsworth et al. (2021). We added a module for benthic remineralization and phytoplankton and zooplankton parameters (Figure S2) were adjusted to make the community more representative of the Northeastern Pacific continental margin. More details of the model configuration and development can be found in Text S1.



**Figure 1.** Maps of the (a) Shallows and (c) Canyons clusters with (e) density as a function of depth. Spatially averaged time-series of the daily averaged (b) dissolved oxygen, (d) aragonite saturation state, and (f) potential temperature for each cluster. Geographic locations are labelled on Figure S1.

The model was forced with hourly atmospheric forcing from the ERA5 reanalysis (Hersbach et al., 2018); the metpy package was used to convert dew point and pressure to specific humidity (May et al., 2021). At the open boundaries we used the Copernicus Global 1/12° Oceanic and Sea Ice (GLORYS12) Reanalysis (Lellouche et al., 2021) for the physical variables, we used the Global Ocean Data Analysis Project version 2 (GLODAP) (Key et al., 2015; Lauvset et al., 2016) for dissolved inorganic carbon (DIC) and Total Alkalinity (TALK), and World Ocean Atlas 2018 for nitrate plus nitrite ( $\text{NO}_3$ ) and dissolved oxygen ( $\text{O}_2$ ) (Garcia et al., 2019a, 2019b).

The model’s grid spacing is insufficient to resolve locations very near to the shore as well as the narrow straits and channels along the coast. Therefore, we apply a mask to remove the 2 grid cells next to the coast and any channels less than 25 km wide which effectively removes the Salish Sea from our analysis (Figure S1).

The hindcast simulation was extensively evaluated using all of the available ship-sampled data (Department of Fisheries and Oceans Canada (DFO), 2022) (Figure S3), Monthly Isopycnal / Mixed-layer Ocean Climatology (MIMOC) (Schmidt et al., 2013) (Figure S4), and tide gauge observations from 65 stations (Figure S5). More details of the evaluation can be found in supplementary Text S1. The model distributions are similar to those of the ship-sampled observations (Figure S3). We computed several metrics including the Kling-Gupta Efficiency (KGE) and its components (the Pearson correlation  $r$ , the variability ratio  $\alpha$ , and the bias ratio  $\beta$ ) (Kling et al., 2012; Jackson et al., 2019) as well as the signed root mean squared error (RMSE). All of the variables relevant to our analysis were strongly correlated with the observations and perform well compared to the mean observed benchmark ( $\text{KGE} < 0.75$ ) (Table S2). To assess the capability of the simulation to represent extreme conditions, we computed the 10<sup>th</sup> and the 90<sup>th</sup> percentile from these distributions. Extreme values for T, S, DIC, TALK and hypoxia have a relatively low bias (Table S2). Therefore, the simulation is expected to realistically represent extreme marine conditions for each of the three stressors.

## 2.2 Clustering methodology

The benthic Northeast Pacific is a heterogeneous environment; spatial distribution of physical and biogeochemical properties is affected by topography and the large-scale circulation. Thus, a single definition for an extreme is not necessarily appropriate; what is a ‘typical’ value for one sub-region might be considered ‘extreme’ for another. Additionally, defining specific biomes using expert knowledge is challenging due to the complex circulation and the size of the study region. Instead, we use a clustering approach that provides a data driven estimate of regions where the three stressors respond similarly to changes in upwelling/downwelling, biogeochemistry, and circulation.

Clustering is a method used in machine learning to group similar data points together based on certain selected features or input variables. Since we are interested in characterizing T,  $[\text{O}_2]$ , and acidification extremes, the selected features are calculated climatologies of T, apparent oxygen utilization (AOU), and aragonite saturation state,  $\Omega_A$  for all bottom depths less than 1000 m in the model. AOU is used instead of  $[\text{O}_2]$  to eliminate the effect of solubility on oxygen concentration (which potentially overemphasizes T in defining a cluster). While ocean acidification can be considered a ‘multiple driver’ because multiple inorganic carbon parameters are changing (Hurd et al., 2019), we include only  $\Omega_A$  as a variable with important biotic impacts. Each of these is scaled to have zero mean and unit standard deviation. A K-means clustering algorithm (Pedregosa et al., 2011) is then applied to these data to find six distinct clusters whose members have similar relationships among the three variables (Table S3 and Figure S6). Two choices that were made for this study are the number of clusters and the temporal resolution of the data. More details on how these choices were made are given in Text S2.

Visual examination of the clusters (Figure S6) shows that two (d, a) of the six are well-defined regions representing shallow shoals and submarine canyons, respectively (Figure 1 a, c) and referred to as Shallows and Canyons hereafter. We selected these two clusters for detailed analysis, based on their contrasting characteristics, and their ecological relevance; the Canyons and Shallows clusters both contain bioregions with high biodiversity (c.f. the Troughs and Dogfish Bank units in Rubidge et al. (2016) Figure 3). However, other clusters may also be of ecological interest, for example, cluster ‘e’ highlights regions of high species richness for groundfish (c.f. Figure 8 of Thompson et al. (2022)).

From the climatologies, we computed the center for each of the clusters (Table S3). The Shallows cluster has relatively warm temperatures, low AOU (high oxygen), and aragonite supersaturation, while the Canyons cluster has low T, high AOU, and undersaturation (Table S3).

Due to the changes in circulation and life stages of the biota, we examine daily output split into two seasons: an upwelling season (April to September) and a downwelling season (October to March). The boundary between these seasons is the average date of the spring and fall transitions (March 31<sup>st</sup> and October 12<sup>th</sup>) observed between 1991 and 2020 (Boldt et al., 2020).

### 2.3 Defining thresholds for extremes

To define a threshold for what is considered extreme, we rely on the statistics of daily average T,  $[O_2]$ , and  $\Omega_A$ . Here we use  $[O_2]$  instead of AOU, because biotic impacts are related to oxygen concentration.

We implement a relative threshold approach and define a fixed baseline for each regime using the full 24 year time series from January 1996 to December 2019 (Gruber et al., 2021). Because the distributions are asymmetric (complicating the definition of thresholds based on variance), we choose a percentile-based approach to identify thresholds. The thresholds are calculated from the cumulative density function (distributions shown in Figure S7) for each cluster using the 10<sup>th</sup> percentile for  $\Omega_A$  and  $[O_2]$ , and the 90<sup>th</sup> percentile for T (Hobday et al., 2016; Gruber et al., 2021).

## 3 Results

### 3.1 Characterization of the clusters

The Shallows cluster (Figure 1 a) includes the open waters east of Haida Gwaii and some of the shallow banks in Queen Charlotte Sound. The Canyons cluster (Figure 1 b) includes the deep channels of Dixon Entrance north of Haida Gwaii, the troughs of Queen Charlotte Sound and connected waters along the edge of the continental shelf.

The Shallows and Canyons have contrasting environmental conditions. Each cluster displays a strong seasonal cycle (Figure 1 b-d-f); related to seasonal upwelling and downwelling. Compared to the Canyons (263 m average depth), the Shallows (30 m average depth) exhibits a higher seasonal amplitude, particularly for temperature. While this can be partly attributed to their average depth, some depths and isopycnals in the Shallows overlap with the Canyons, which spans a wider range (Figure 1 e).

The thresholds that define extreme conditions during each season, calculated using the criteria for each variable described in section 2.3, are shown in Table 1. For the Canyons, an extreme value for  $O_2$  is close to the widely used criterion for hypoxia that may signify fisheries collapse ( $< 60 \text{ mmol m}^{-3}$ ) (Vaquer-Sunyer & Duarte, 2008), and is associated with aragonite undersaturation; for the Shallows, the oxygen threshold is well above the ‘conservation limit’ of  $\simeq 140 \text{ mmol m}^{-3}$  and occurs in aragonite saturated

and relatively warm waters. In the Shallows, extreme temperatures occur during the summer months when atmospheric temperature is greatest; in the Canyons, warm extreme temperatures occur during downwelling (Table 1). Upwelling during summer brings relatively cool, salty, low oxygen and nutrient rich water to the deep benthic regions of the continental shelf; during winter, downwelling and mixing can propagate surface signals downward.

**Table 1.** The thresholds relative to 1996-2019 (section 2.3) and maximum duration (days) averaged over all of the grid cells within the cluster for extreme events of temperature ( $^{\circ}\text{C}$ ), dissolved oxygen ( $\text{mmol m}^{-3}$ ) and aragonite saturation state for the Shallows (Figure 1a) and Canyons (Figure 1c) clusters.

Cluster	Upwelling Threshold			Downwelling Threshold			Upwelling max duration			Downwelling max duration		
	T	O <sub>2</sub>	$\Omega_A$	T	O <sub>2</sub>	$\Omega_A$	T	O <sub>2</sub>	$\Omega_A$	T	O <sub>2</sub>	$\Omega_A$
Shallows	14.1	241	1.5	10.7	260	1.3	3.4	4.2	6.3	2.5	4.2	6.2
Canyons	6.4	59	0.6	7.1	69	0.6	6.7	6.3	5.4	7.7	7.0	5.6

### 3.2 Occurrence of extremes over time

In the Canyons, two time periods (1999-2003 and 2008-2013) have a large fraction of waters ( $> 40\%$ ) with extreme values of  $[\text{O}_2]$  and  $\Omega_A$  (Figure 2 a, b). These time periods correspond to the positive phase of the North Pacific Gyre Oscillation (NPGO). For temperature, the largest fraction of extreme waters ( $> 50\%$ ) occurs during downwelling in 1998, and during upwelling in 2010, 2016 and 2019.

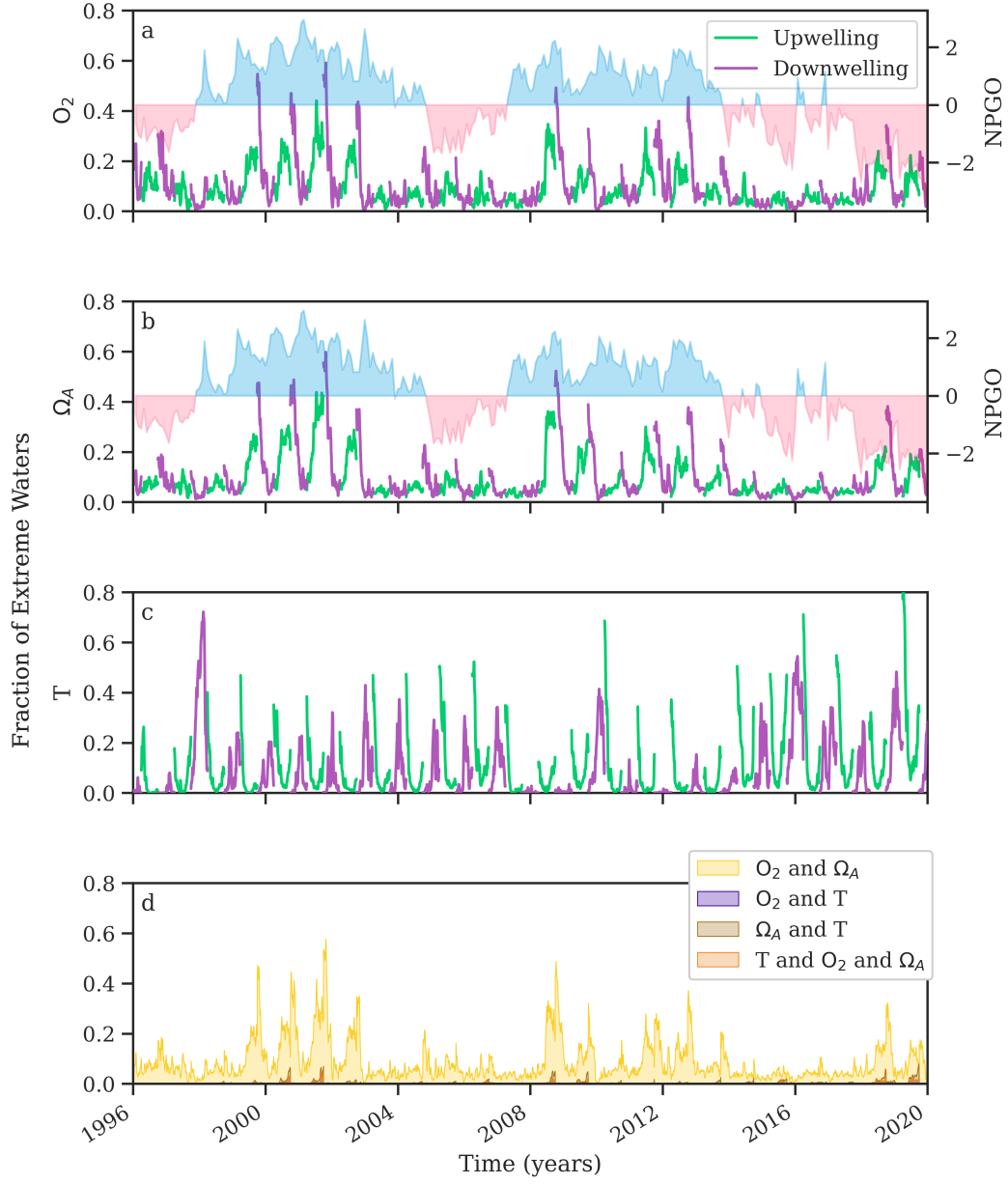
In the shallows, up to 80% of waters experience extreme conditions for  $[\text{O}_2]$  in 1998 during a very strong El Niño and in 2014 during the MHW. The most extreme conditions for  $\Omega_A$  occurred during the upwelling season of 2009 (Figure 3).

For  $[\text{O}_2]$  and T, the most extreme conditions tend to occur at the beginning of the downwelling season when atmospheric temperatures are warmest. While this is partly an artifact of having seasonally defined thresholds, it reflects the interannual variability in the time series.

With the exception of an increase in  $\Omega_A$  extremes in the Shallows ( $0.004 \text{ y}^{-1}$ ), neither cluster exhibits a linear trend in the percentage of extremes (Figures 2, 3, and Text S3). For the Canyons, this may be because the upwelled waters are old and do not contain a signature of recent anthropogenic climate change. In the shallows there may be a trend associated with increasing surface air temperature, but this is damped somewhat by mixing with subsurface waters. In any case, the timescale of the simulation conducted is relatively short compared to the time scales of natural variability, so the anthropogenic trend is not expected to be readily detectable (cf. Christian (2014); Cummins and Masson (2014)).

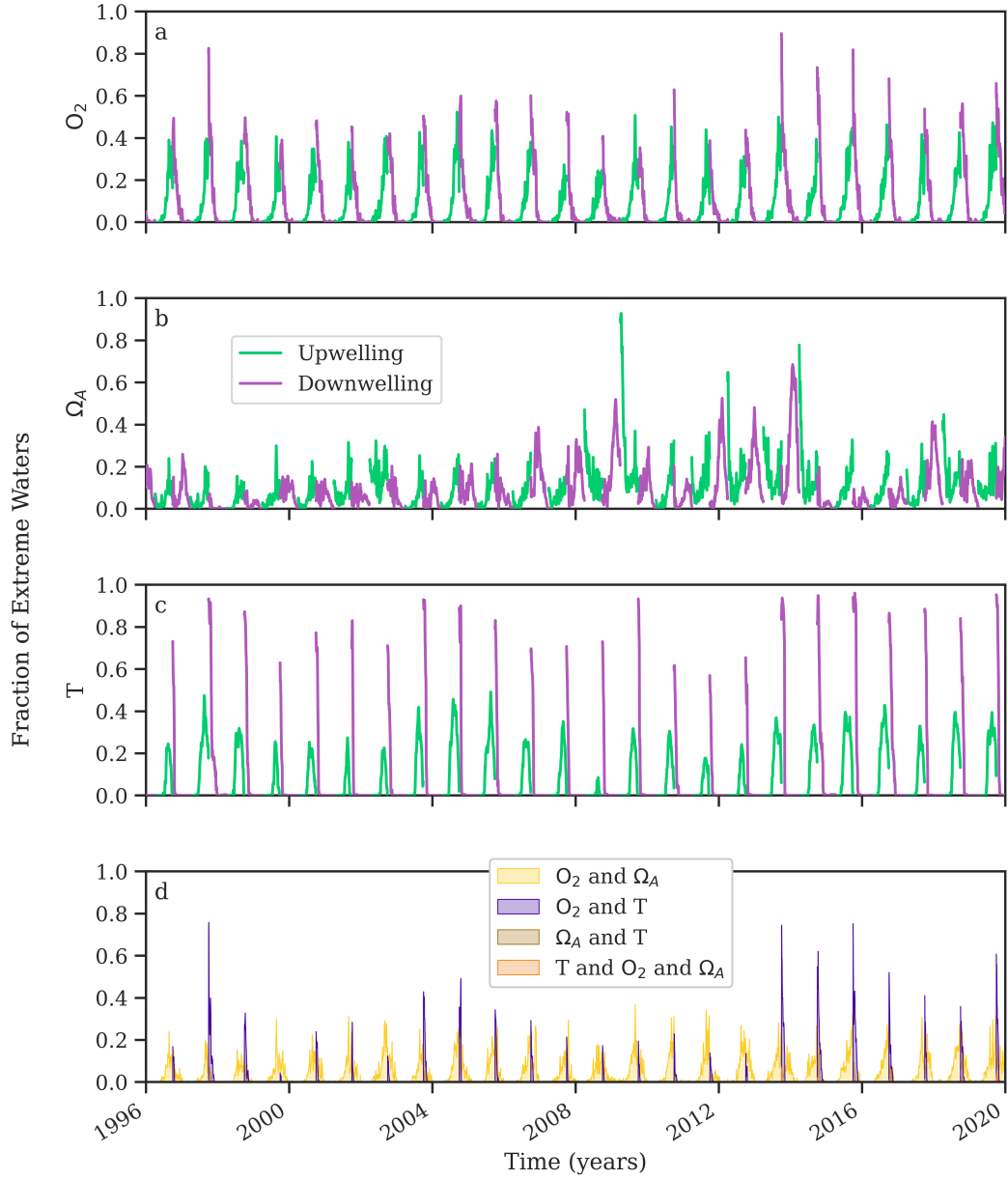
Biota are sensitive to the length of time over which extreme conditions occur in addition to the spatial extent and magnitude. We computed the average duration and the maximum duration of an extreme event over all of the grid cells in each cluster and then average over all of the clusters (Table 1). The average length of an event is around 1.5 days. While T and  $[\text{O}_2]$  events have longer maximum duration in the Canyons,  $\Omega_A$  events have longer maximum duration in the Shallows.





**Figure 2.** The fraction of waters in the Canyons that exceed the relative threshold (Table 1) for (a) dissolved oxygen, (b) aragonite saturation state, (c) potential temperature, and (d) compound stressors. The North Pacific Gyre Oscillation (NPGO) is shown on the secondary axis of (a) and (b) and is colored in red when North-Eastern Pacific waters are warm and blue when they are cold. Discontinuities at the spring and fall transition correspond to the different thresholds for each season. The compound stressors shown in panel (d) are shown individually in Figure S9.





**Figure 3.** The fraction of waters in the Shallows that exceed the relative threshold (Table 1) for (a) dissolved oxygen, (b) aragonite saturation state, (c) potential temperature, and (d) compound stressors. Discontinuities at the spring and fall transition correspond to the different thresholds for each season. The compound stressors shown in panel (d) are shown individually in Figure S10.

Compound extremes (i.e., the occurrence of extreme conditions in two or more stressors at once) can have synergistic effects on marine organisms (Pörtner et al., 2005). The Shallows frequently exhibited compound T and  $[O_2]$  extremes during the downwelling season (Figure 3d and Figure S10b). Yet, the only years for which all three stressors exceeded the thresholds in the Shallows for  $> 5\%$  of waters were MHW years: 2014, the year of the anomalous warming pattern referred to as The Blob, and 2019, referred to as The Blob-2.0 (Amaya et al., 2020) (Figure 3d, Figure S10d). For the Canyons, compound extremes are relatively rare (Figure 2d and Figure S9) with the exception of  $[O_2]$  and  $\Omega_A$  which exhibit the same pattern of variability as the single stressor extremes. Notably, the two periods during which we have a substantial fraction of single and compound extremes for  $O_2$  and  $\Omega_A$  in the Canyons (Figure 2 and Figure S9a) are periods during which the NPGO is positive and is associated with enhanced upwelling in the California Current system (Di Lorenzo et al., 2008).

The other four clusters show similar patterns of variability with very few triple extremes and, for most clusters, less than 5% of waters are extreme before 2014 (Figure S11). Three of the clusters ('b', 'd', 'e') exhibit a statistically significant ( $p < 0.05$ ) trend in triple extremes (Text S3). This result is consistent with Hauri et al. (2024) who characterized extremes for the benthic regions of the shelf in the Gulf of Alaska; they found a greater fraction of waters experiencing compound ( $\Omega_A / O_2$ ) extremes, but the methodologies are not directly comparable. They attributed the increase in extremes at the end of the time series to the secular trends of anthropogenic warming and ocean acidification. The secular trend likely explains the increase in triple extremes for these shallower clusters where the maximum mixed layer depth (MLD) is near the ocean bottom (Text S3).

## 4 Discussion

We introduced a method for characterizing extreme conditions in a regional ocean model. For NEP36-CanOE, daily temporal resolution was sufficient to resolve the extremes (Text S2). While the model was highly correlated with available observations for the relevant variables (section 2.1 and Text S1), it was limited by the fact that we used climatologies for the rivers and did not include the effects of fluvial nutrients. We restricted the environmental conditions used in the unsupervised clustering approach to indices of warming, deoxygenation, and acidification. The two clusters selected for discussion are of ecological importance because of their high biodiversity (Rubidge et al., 2016) and contrasting environmental conditions (Table 1). These contrasting characteristics allow us to distinguish between different mechanistic drivers for marine extremes in the entire domain.

Thresholds defining extremes for each potential stressor were established separately for the upwelling and downwelling seasons because they represent different oceanographic regimes, and coincide with changes in the mean direction of flow of coastal currents (Thomson & Krassovski, 2010). These seasons are relevant to benthic organisms that are adapted to local conditions. Marine organisms may be in different life stages during these seasons, with different tolerance levels depending on life stage (Stachura et al., 2014; Hobday et al., 2016). For example, consider two economically important species from the Shallows and Canyons: Dungeness crab, which experience seasonal vulnerability as a result of their complex life cycle (Berger et al., 2021), and rockfish, whose juvenile abundance is linked to nearshore temperatures in February and March (Ainley et al., 1993; Laidig et al., 2007) and for which coastal downwelling has been shown to influence recruitment (Markel & Shurin, 2020).

The extreme thresholds (Table 1) in the Canyons cluster are closer to established ecological thresholds (Vaquer-Sunyer & Duarte, 2008) which makes this cluster particularly vulnerable. However, ecosystem reorganizations may develop progressively rather

than abruptly because different species have different tolerance levels (Pörtner et al., 2005). Even if the statistical thresholds are not life threatening to a particular organism, they can still have detrimental effects on growth and reproductive success if species are well adapted to their environmental conditions.

Although compound extremes are rare, they are increasing for some clusters. The Canadian northeastern Pacific region shares many ecosystem attributes and physical drivers with other eastern boundary current upwelling systems with similar future projections of warming, deoxygenation and increasing acidification (Bograd et al., 2023). Therefore, recent and potential future increases in compound extremes have global relevance because they present a threat to the ecosystem services that these systems provide.

Compound extremes can be particularly detrimental to organisms because of their synergistic effects (Pörtner, 2010) and further investigation into how these extremes could affect organisms is warranted. Our definition of extremes occurring at the same time and in the same grid cell is potentially too restrictive for mobile organisms. An approach which considers the entire water column (Wong et al., 2024) may be more appropriate for organisms that can move vertically, or laterally to different depths on the seafloor.

The upwelling and downwelling seasons impact the Shallows and Canyons differently, which can be partly attributed to their relative depths (Figure 1). The Canyons are strongly influenced by upwelling waters that are relatively cold and low in oxygen with a low  $\Omega_A$ , and only weakly influenced by surface T changes. The Shallows experience much more temperature variability in response to the seasonally changing atmosphere and are only weakly influenced by upwelled waters. Consequently, the Canyons experience more frequent compound extremes in  $\Omega_A$  and  $[O_2]$ , while the shallows experience more frequent compound extremes in  $[O_2]$  and T (Figs. S9 and S10).

We hypothesize that much of the interannual variability in the percentage of waters that exceed the thresholds (Figs. 2 and 3) can be explained by the strength and length of seasonal upwelling/downwelling in the Canyons, and direct forcing by the atmosphere in the Shallows. There are many factors that contribute to the relative influence of each of these processes on extreme conditions for the cluster and season including the timing of the spring and fall transitions, mixing and stratification of the water column, changes in the California Undercurrent, and coastally trapped waves (Thomson & Krassovski, 2010; Engida et al., 2016; Mogen et al., 2022; Franco et al., 2023; Amaya et al., 2023). Because the clusters are stratified by depth, the relative contribution of upwelling from below and atmospheric forcing from above is influenced by the average depth of the cluster relative to the MLD (Text S3, Table S3).

Correlations between the single stressor extremes and the NPGO, Multivariate ENSO Index (MEI), Pacific Decadal Oscillation (PDO) and Bakun upwelling index provide evidence that changes in upwelling and downwelling and large scale atmospheric forcing drive the variability in extremes (Figure S13 and Text S4). While the only local indicator that we examined was the Bakun index, the correlations (Figure S13) support the conclusion that large scale indicators (NPGO, PDO and MEI) are more predictive of ecosystem change along the continental margin than local indicators (Hallett et al., 2004; Li et al., 2013; Mackas et al., 2013).

## 5 Conclusions

Characterizing the occurrence of extremes in the recent past when they occur in isolation, or in combination is a step towards understanding the risks that they pose to local ecosystems and fisheries. This study presented a simple approach for statistically characterizing extreme marine conditions of high temperature, low oxygen, and high acidification. We applied it to a numerical model of the Northeastern Pacific continental margin, but it can be adapted to other regions and time periods. We used unsupervised clus-

tering to isolate regions with similar environmental conditions and defined the extremes using a relative threshold with a fixed baseline (1996-2020) (Hobday et al., 2016; Gruber et al., 2021).

The analysis of extremes in the Northeastern Pacific demonstrated that the strength of seasonal upwelling/downwelling and direct forcing by the atmosphere strongly influence extreme conditions. Large scale processes (like the NPGO) may be more predictive of extreme conditions of  $[O_2]$  and  $\Omega_A$  than local indicators like the Bakun index and further investigation of these relationships is needed. While a substantial number of single stressor extremes occur annually, compound extremes are rare. Most of the multiple stressor extremes involve coincident  $O_2$  and  $\Omega_A$  extremes, with a greater number in the Canyons than the Shallows. Multiple stressor extremes are increasing for clusters where the mixed layer extends to near the ocean bottom. Under future climate change, compound extremes may become more common, with detrimental effects on ecologically and commercially important species.

## 6 Open Research

The open source code that the ocean model is based on here <https://www.nemo-ocean.eu/> The observational data used to evaluate the model is available online including the ship-sampled data (Department of Fisheries and Oceans Canada (DFO), 2022), tide gauge data (NRCan, 2022) and mixed layer depths (NOAA Pacific Marine Environmental Laboratory, 2021). The model data needed for the analysis can be found here <https://doi.org/10.5281/zenodo.13138494> (Holdsworth et al., 2024a). The python notebooks used for the analysis of the data is found on Github here [https://github.com/ashao/NEP36\\_cluster\\_analysis](https://github.com/ashao/NEP36_cluster_analysis) (Holdsworth et al., 2024b) and will be added to a zenodo repository for permanent storage if this manuscript is published.

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