DTU Aqua
National Institute of Aquatic Resources

Hypoxia effects on stock assessment: A case study of the South-Western Baltic (HypCatch)

Elliot J. Brown, Casper Willestofte Berg, Esther D. Beukhof, Alexandros Kokkalis, Josianne G. Støttrup, Josefine Egekvist, Jonathan Stounberg, Marie Storr-Paulsen, and Anna Rindorf

DTU Aqua Report no. 436-2023

DTU Aqua
National Instiute of Aquatic Resources

Hypoxia effects on stock assessment: A case study of the South-Western Baltic

Elliot J. Brown, Casper Willestofte Berg, Esther D. Beukhof, Alexandros Kokkalis, Josianne G. Støttrup, Josefine Egekvist, Jonathan Stounberg, Marie Storr-Paulsen, and Anna Rindorf

DTU Aqua Report no. 436-2023

Colophon

Title:	Hypoxia effects on stock assessment: A case study of the South-Western Baltic
Authors:	Elliot J. Brown, Casper Willestofte Berg, Esther D. Beukhof, Alexandros Kokkalis, Josianne G. Støttrup, Josefine Egekvist, Jonathan Stounberg, Marie Storr-Paulsen, and Anna Rindorf
DTU Aqua Report no.:	436-2023
Year:	Scientific work finalized November 2023. Report published December 2024
Reference:	Brown, E.J., Berg, C.W., Beukhof, E.D., Kokkalis, A., Støttrup, J.G., Egekvist, J., Stounberg, J., Storr-Paulsen, M. & Rindorf, A. (2023). Hypoxia effects on stock assessment: A case study of the South-Western Baltic. DTU Aqua Report no. 436-2023. National Institute of Aquatic Resources, Technical University of Denmark, 56 pp.
Cover photo:	Cod and plaice. Photo: Esther Savina
Published by:	National Institute of Aquatic Resources, Henrik Dams Allé, 2800 Kgs. Lyngby, Denmark
Download:	www.aqua.dtu.dk/publikationer
ISSN:	1395-8216
ISBN:	978-87-7481-369-9

Preface

This report documents the work carried out in the project *Hypoxia effects on stock assessment: A case study of the South-Western Baltic*, also known as *HypCatch*, which was funded by the European Maritime and Fisheries Fund and the Danish Fisheries Agency (file no. 33113-B-20-177). The project period was from June 2020 to August 2023.

This report includes original research, often in summarised forms, where more details are in preparation for submission to be published in academic journals.

We thank all of the colleagues and diverse working group members who provided discussion and advice that ultimately improved the quality of this work.

DTU Aqua Kgs. Lyngby, November 2023

Elliot J. Brown
Researcher and Project Leader

European Union
European Maritime and Fisheries Fund

Content

Summary

In the 2020 assessments of Atlantic cod (*Gadus morhua*) and European plaice (*Pleuronectes platessa*) stocks from the western Baltic Sea, a marked reduction in numbers of fish caught in the standard survey was observed. Survey reports indicated that this was probably due to widespread hypoxia. Thus, this project HypCatch, was initiated to investigate the effects of hypoxia on cod and plaice from these stocks and to further investigate the observed impacts on fish distribution, the potential mechanisms of impact on the population and small scale fisher's perceptions of how hypoxia in the south-western Baltic Sea impacts upon their decisions, effort and catches.

We describe how different levels of hypoxia severity in the bottom-waters elicit different responses from cod and plaice, in terms of their catchability in the scientific surveys. Cod catchability decreases at moderate levels of hypoxia (between two and four milligrams of oxygen per litre) before rapidly declining at acute levels of hypoxia (below two milligrams of oxygen per litre). Similarly, plaice catch levels decline rapidly under acute hypoxia, however, they appear unresponsive to moderate hypoxia. This finding in the offshore survey was mirrored by increasing (albeit, non-significant) catch rates in coastal monitoring with increasing extents of moderate (cod only) and acute (cod and plaice) hypoxia across the study area. In spite of these responses, we found that accounting for oxygen in the modelled stock indices modified these indices very little, and the subsequent stock assessment outcomes even less. Hence, our recommendation for these stocks is not to include oxygen as a mediating environmental variable in the production of the survey abundance indices.

While oxygen conditions have a minimal effect on the calculation of stock indices and their subsequent use in assessment, the wide spread nature of moderate hypoxia that we document, is likely to have an effect on stock productivity via many potential mechanisms. This report's subsequent chapters describe how fish and fishers' distributions change in response to hypoxia.

First, a more realistic species distribution modelling framework is applied to cod and plaice in the inner Danish waters. This approach, called a soap-film smoother accounts for the complex landmasses and coastline that pepper the inner Danish waters. We document how the models we produce better predict species distributions in space and in response to hypoxic waters, than more traditional approaches.

Similarly, we describe the results of a short survey of small-scale, commercial gill-netters and their interactions with hypoxia. While only 30% of these fishers consider hypoxia in their fishing decisions, nearly 80% of fishers who experienced hypoxic waters moved their gears shallower and closer to land in response. Of those fishers in ICES sub-division 22 whose fishing was impacted by hypoxia in 2019, all noted that there were fewer fish in catches.

While we are currently unable to quantify if such responses to hypoxia are general trends across all small-scale fisheries in the area, this report documents a new, greatly improved method for attributing small scale fisher effort in space, using AIS data via a random forest modelling approach. These methods can be applied in the future to extract catch rates for various

species in different areas and in relation to hypoxic waters, to strengthen further the circumstantial evidence we have of cod and plaice using coastal waters as a refuge from basin-scale hypoxia.

From a collaboration between this project and another, SEAwise, we investigated hypothetical scenarios of impact from hypoxia in the deep basin spawning grounds and in the coastal juvenile habitats and the relative effect these different mechanisms of action have on population productivity. We found that juvenile habitats act as a filter determining future class strength, but that adults aggregating in areas of hypoxia for spawning, are the greatest risk for loss of population productivity. Furthermore, we found that there is a larger scope for the positive effects coming from restoration (reducing hypoxia) than there is for continued negative effects of broad-scale hypoxia.

Finally, we describe how all of these findings were distributed and disseminated amongst working groups with both advisory and scientific tasks.

Dansk Resumé

I bestandsvurderingen fra 2020 af torsk (Gadus morhua) og rødspætte (Pleuronectes platessa) bestandene fraVestlig Østersø blev der observeret en markant reduktion i antallet af fisk fanget i den standardiserede survey. Rapporterne fra surveyet indikerede, at dette sandsynligvis skyldtes udbredt iltsvind. Derfor blev dette projekt, HypCatch, iværksat for at undersøge påvirkningerne af iltsvind på torske- og rødspættebestanden og yderligere undersøge de observerede indvirkninger på fiskedistribution, de potentielle mekanismer for påvirkning af bestanden og småskalafiskeres opfattelser af, hvordan iltsvind i den sydvestlige del af Østersøen påvirker deres beslutninger, indsats og fangster.

Vi beskriver, hvordan forskellige niveauer af iltsvindens alvor i bundvandene udløser forskellige reaktioner fra torsk og rødspætte, når det kommer til deres fangbarhed i de videnskabelige undersøgelser. Fangbarheden for torsk falder ved moderate niveauer af iltsvind (mellem to og fire milligram ilt per liter) før den hurtigt falder ved akutte niveauer af iltsvind (under to milligram ilt per liter). På samme måde falder fangsterne for rødspætte hurtigt under akut iltsvind, men de synes ikke at reagere på moderat iltsvind. Denne observation i den offshore undersøgelse blev afspejlet i stigende (dog ikke signifikante) fangstrater i kystovervågningen med stigende grad af moderat (kun torsk) og akut (torsk og rødspætte) iltsvind over området. Til trods for disse reaktioner fandt vi, at inkludering af ilt i de modellerede bestandsindekser kun ændrede disse indekser meget lidt, og de efterfølgende bestandsvurderingsresultater endnu mindre. Derfor er vores anbefaling for disse bestande ikke at inkludere ilt som en medierende miljøvariabel i produktionen af survey udbredelsesindekserne.

Mens iltniveauer har en minimal effekt på beregningen af bestandsindekserne og deres efterfølgende brug i vurderingen, er det sandsynligt at det udbredte niveau af moderat iltsvind, som vi dokumenterer, kan have en effekt på bestandsproduktiviteten via mange potentielle mekanismer. De følgende kapitler i denne rapport beskriver, hvordan fisk og fiskeres fordeling ændrer sig som reaktion på iltsvind.

Først anvendes en mere realistisk modelramme for artsfordeling på torsk og rødspætte i de indre danske farvande. Denne tilgang, kaldet en 'soap-film smoother' tager højde for de komplekse landmasser og kystlinjer, der præger de indre danske farvande. Vi dokumenterer, hvordan de modeller vi producerer, bedre forudsiger artsfordelinger i rummet og som reaktion på iltsvind, end mere traditionelle tilgange.

På samme måde beskriver vi resultaterne af en kort undersøgelse af småskala, kommercielle garnfiskere og deres interaktioner med iltsvind. Mens kun 30% af disse fiskere overvejer iltsvind i deres beslutninger, flyttede næsten 80% af fiskere, der oplevede iltsvind, deres redskaber til en lavere dybde og tættere på land. Af de fiskere i ICES-underafdeling 22, hvis fiskeri blev påvirket af iltsvind i 2019, bemærkede alle, at der var færre fisk i fangsterne.

Selvom vi i øjeblikket ikke er i stand til at kvantificere, om sådanne reaktioner på iltsvind er generelle tendenser på tværs af alle småskalafiskerier i området, dokumenterer denne rapport en ny, markant forbedret metode til at tilskrive småskalafiskerens indsats i rummet ved hjælp af

AIS-data via en tilgang med 'random forest'-modellering. Disse metoder kan anvendes i fremtiden til at udtrække fangstrater for forskellige arter i forskellige områder og i forhold til iltsvind, for yderligere at styrke det indiciebevis, vi har for, at torsk og rødspætte bruger kystfarvande som en tilflugt fra iltsvind på bassinskala.

Fra et samarbejde mellem dette projekt og et andet, SEAwise, undersøgte vi hypotetiske scenarier for virkning af iltsvind i dybe gydeområder og i kystnære juvenile levesteder og den relative effekt, disse forskellige handlingsmekanismer har på bestandsproduktiviteten. Vi fandt, at juvenile levesteder fungerer som et filter, der bestemmer fremtidig styrke for årsklassen, men at voksne, der samles i områder med iltsvind til gydning, udgør den største risiko for tab af bestandsproduktivitet. Desuden fandt vi, at der er større muligheder for de positive effekter fra genopretning (reducering af iltsvind) end der er for fortsatte negative effekter af bredskala iltsvind.

Endelig beskriver vi, hvordan alle disse fund blev distribueret og udbredt blandt arbejdsgrupper med både rådgivende og videnskabelige opgaver.

1. Background and Motivation for HypCatch

In the assessment of exploited fish stocks, appropriate fisheries independent surveys can be utilised to produce indices of overall stock size and population structure, independent of the fishery data that drive the model. These “tuning fleets”, can be used as raw data or can be modelled to estimate the population size and structure across the entire, non-sampled, stock area (Berg, Nielsen, & Kristensen, 2014). If surveys sampling stations are non-representative of the entire stock area, this can lead to a bias in the tuning index used in the stock assessment. As the marine environment is variable, and fish are mobile, the sampling routine of a given survey may be more or less representative in any given year or season; leading to varying bias in the tuning index for the stock assessment, over time.

In 2020, the Baltic Fisheries Assessment Working Group (WGBFAS) noted that the survey indices for European cod (*Gadus morhua*) and European plaice (*Pleuronectes platessa*) in quarter four of 2019 were extremely, and unexpectedly, low (ICES, 2020). These low values did not match the two survey results immediately adjacent in time, namely the quarter 1 surveys of 2019 or 2020, nor did they match trends in the observed catch rates from the commercial fisheries. After manual consideration of oxygen maps provided by German survey vessel reports (Velasco, 2019), it was decided to leave the data for the 2019 quarter four, out of the stock assessments and to consider them erroneous. However, the question remained, why were the plaice and cod not observed in this one quarter’s survey, while they were present in all other sampling methods? There are two suitable hypotheses based on horizontal or vertical distribution shifts. First, given the surveys operate in waters of a minimum of 20m depth, that during deep water hypoxia, the fish move horizontally into shallower areas to avoid the hypoxia and thus avoid being sampled in the survey. The second hypothesis is that the fish move upward in the water column to above the hypoxic layer, which is also above the operational depth of the survey trawl gears, thus avoiding both the hypoxia and being sampled in the survey.

The primary aim of HypCatch was to investigate how oxygen concentration (hypoxia) in the south-western Baltic Sea effects plaice and cod capture rates in surveys and if this effect can be mediated to reduce the impact this variable capture rate has on the outcomes of stock assessments.

Secondary aims of HypCatch were to:

1) Model and map distribution shifts of cod and plaice using optimal data sources and improved methodology, to investigate the horizontal distribution shift hypothesis.
2) Investigate the catch rates of coastal fishers in response to broad scale, bottom water hypoxia.
3) Document how small scale, gill net fishers identify and respond to hypoxia.
4) Compare the mechanisms by which basin scale hypoxia at spawning time could impact population dynamics of cod and plaice.
5) Disseminate these findings directly to WGBFAS and other relevant ICES working groups to enhance their operational relevance.

2. Operational Consideration of Hypoxia in Stock Assessments

The inclusion of environmental drivers of fish stock productivity or observability in tactical fisheries advice requires that data on environmental conditions be available to stock assessments. In the context of HypCatch, data on oxygen conditions of bottom waters must be available at the same time as survey data and fisheries catch data, ahead of the annual WGBFAS meeting in spring. Furthermore, these data must be universally accepted as valid, by all stakeholders and reliably produced on the same time scale that the stock assessments are made.

Methods to incorporate the data on environmental drivers that are available, into stock assessments are sparse and not routinely incorporated into assessments that provide advice. Many approaches use the output of stock assessment models and correlate the unexplained variation from the fisheries models with observed environmental phenomena (Derhy, Macías, Elkalay, Khalil, & Rincón, 2022). This approach can provide further understanding of the ecological context the fishery is operating in but does not produce a unified model accounting for environmental drivers and fisheries mortality in population dynamics, which would be suitable for providing tactical fisheries advice. A promising avenue of research are spatially explicit state-space population models that can model abundances in space and how these interact with fisheries to make more spatially explicit advice (Olmos et al., 2023). However, while these models could potentially utilise environmental drivers in the estimation of spatial abundance, this has not yet been published, let alone adopted to provide operational advice. Alternatively, using known relationships between environmental drivers and key population dynamic rates (e.g. growth, mortality, fecundity) to dynamically redefine biological reference points can make the assessment of fishing mortality relative to stock size more appropriate for the current environmental conditions (Bessell-Browne et al., 2022). However, this approach relies on strong evidence for the relationships between the environment and population dynamics, in the absence of harvesting. This reliance may be just as much of an assumption as that of current practices, where the unfished biomass is either modelled or taken as the largest value in recorded history. A method that has not been investigated is the incorporation of environmental drivers into the spatial models that produce age-based stock indices to be utilised as tuning fleets in stock assessments.

In this chapter, we investigate how oxygen concentration (hypoxia) in the south-western Baltic Sea affects plaice and cod capture rates in surveys and if this effect can be mediated to reduce the impact this variable capture rate has on the outcomes of stock assessments. First, we review and evaluate available bottom-water, oxygen concentration data sources, before selecting the most appropriate source for operational use. We then incorporate these oxygen data into the models producing the stock indices, and investigate their effects on the indices. Subsequently, we utilise the oxygen-mediated indices in standard stock assessment models and compare the overall effects on the estimated stock size and status.

2.1 Environmental Oxygen Data and Indices

In our review of available oxygen data for the areas covering the stocks of interest, namely European plaice in the Kattegat, Belt Seas and SW Baltic Sea, as well as Atlantic cod from the SW Baltic Sea, we found two different types of data. The first were databases of observations and the second were products of coupled hydro-biogeochemical model runs. For each of these data types we found examples being held at sub-national, national, regional and European scales with various levels of availability (Table 1). While model output data from the Swedish Meteorological Institute appeared promising, the stated rates of update were unreliable, access to the full time series was limited through their own data portal, and attempts to contact the team responsible for the data were unsuccessful. Via the European data portal, Copernicus, data from the same underlying models were available for a longer period back in time, but without any planned updates stated. Furthermore, sources of assimilated data for any of the process-based models could not be determined and thus, no independent observations of bottom water oxygen could be selected for validation of these model outputs. Based on the inability to validate them and the limited availability of both existing data and future updates, the decision was made to utilise a database of raw observations to build our own statistical model of bottom-water oxygen concentrations. The most complete data source was hosted by ICES. This source included all observations in the HELCOM database (mostly data from continuous logging), together with various other observations of oxygen from regular surveys and sporadic projects.

Table 1. Sources and descriptions of considered bottom water oxygen concentration data.

Source	Datatype	Resolution	Availability	Updates
Christian-Albrecht University	Coupled hydro-biogeochemical model output	0.5 degree grid squares	Upon Request / Collaboration	Irregular and project funded
Danish Meteorological Institute	Coupled hydro-biogeochemical model output	Unknown	Delays to becoming public	Unknown for publicly available data
DHI	Coupled hydro-biogeochemical model output	Various scales	Commercial License or funded project partners	Project funded
Swedish Meteorological Institute	Coupled hydro-biogeochemical model output	Various scales down to 0.5 degree grid	Publicly available hind- & forecasts	Regular updates biannual or annually
National Institute of Aquatic Resources, DTU	Observations	Semi-regular samples	Available	After Surveys
HELCOM	Observations	Database of sporadic samples collected ad-hoc	Available	Unknown
ICES	Observations	Database of sporadic samples collected ad-hoc	Publicly available	Upload schedule according to data calls matching stock assessments

The ICES database (data.ices.dk) was used to download high-resolution bottom oxygen data mainly from buoys that measure continuously through the year. This data source was chosen because it is updated regularly, thus ensuring that the newest oxygen data would be available in time for the Baltic stock assessments in spring.

These data could not be used directly, because we need bottom oxygen data matching the time and position for the trawl positions. A spatio-temporal model for bottom oxygen was therefore constructed to be able to interpolate the oxygen concentration at any point in time and space.

The oxygen model was a generalized additive model that included time, geographical coordinates, time of year, depth and distance to the North Sea, as explanatory variables including interactions. The model was fit to data from the years 1991 to 2021 in ICES areas 21-25 (Figure 1).

Some reservations should be taken regarding the very low oxygen values in the years 2014 and 2015. After the analysis had been completed, a strange downwards jump in the data for several stations was noticed over the transition from 2013 to 2014 and a similar upwards jump up over 2015-2016 transition. The Danish Environmental Protection Agency (*Miljøstyrelsen*), who is responsible for collection of these data, was contacted to inquire about this data anomaly, but their response was that they were not aware of any data problems and further analysis was needed to confirm if there was a problem. This further analysis was outside the scope of this project and our group's expertise. This data source remains the most complete and readily available source for operational consideration of oxygen conditions within fisheries assessments.

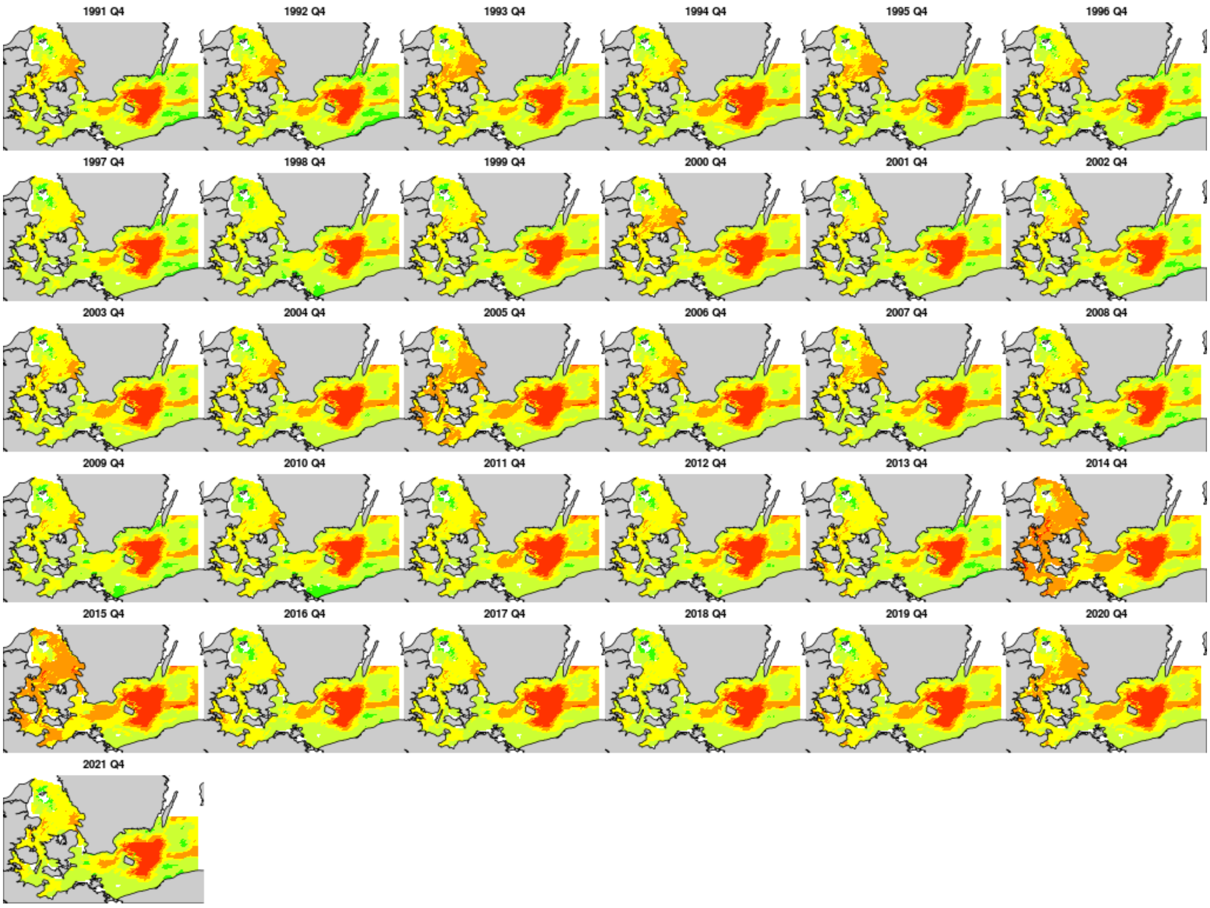

Figure 1. Estimated bottom oxygen concentration. Red colour indicates acute hypoxia (< 2 mL/L), orange is moderate hypoxia (2-4 mL/L) while yellows and greens are considered normoxic, such that they are above the levels commonly reported to impact upon fish physiology.

2.2 Oxygen Mediated Stock Indices

Our next step was to utilise these estimated bottom-water oxygen data in generating standardized abundance indices. In standardised, benchmarked procedures for both cod and plaice, raw catches from the BITS survey are converted to stock abundance indices using spatially explicit generalized additive models (Berg et al., 2014). Our approach was to include the estimated bottom-water oxygen concentrations as an explanatory variable in these index models, to account for the fact that fish may move out of these hypoxic waters. In general, no effect of bottom oxygen was found in quarter 1 due to very limited hypoxia at this time of year, so in the following we focus only on trawl survey data from quarter 4.

Cod catches appear to decrease gradually with oxygen. Where oxygen concentrations are above 6 $mL.L^{-1}$, oxygen has little effect on cod catch rates. Below 6 $mL.L^{-1}$, however we see a negative impact of oxygen on catches until a small plateau within the moderate hypoxia range (around 3 $mL.L^{-1}$), after which there is a substantial decline in catches as conditions enter severe hypoxia (Figure 2). The complex effect of oxygen on cod catches through moderate hypoxia may be due to cod's behaviour, where individuals primarily reside above the hypoxic layer but undertake frequent feeding forays down into the hypoxic waters (Casini et al., 2016; Teschner et al., 2010). This would reduce their interaction with bottom trawling gears by reducing the time any given individual spends in the depth range being fished but does not remove all risk of capture.

Initial results indicated that for plaice there is a sharp decline in CPUE when oxygen concentration drops below 2 $mL.L^{-1}$, with very little response to the ranges of moderate hypoxia (2-4 $mL.L^{-1}$;Figure 2). This sharp decline was, however, only apparent when area 25, which includes the persistently hypoxic Bornholm basin, was included in the analysis. The difference in detecting an oxygen effect between the inclusion or exclusion of subdivision 25 exemplifies the effect of spurious correlations in some statistical models. The abundances of plaice in subdivision 25 are low due, primarily, to the salinity conditions. This happens to coincide with the Bornholm basin with the largest magnitude, breadth and persistence of hypoxia across the study area. This co-occurrence of low oxygen and low plaice abundance drives this correlation detected in our initial model, in spite of the spatio-temporally explicit nature of the model specification. Contrastingly to this correlation, the highest catch rates of plaice in the south-west Baltic were actually found in the years 2014 and 2015 where oxygen concentrations were at the lowest point in the time-series, in what is considered moderate hypoxia (mostly in the 2-4 mL/L range). However, note the reservations made in section 1.1 about these two years' oxygen data. This indicates that unlike cod, plaice do not avoid areas with moderate hypoxic conditions but may respond strongly to severe hypoxia.

The contrast in observed catches of plaice and cod responses to bottom water hypoxia suggests alternative coping strategies. These observed trends across the stocks correspond to documented individual responses and behaviours. In plaice, such individual responses to moderate hypoxia include downregulating activities, such as a reduction in movement, feeding and even ventilation (Petersen & Pihl, 1995; Steffensen, Lomholt, & Johansen, 1982). In cod, field studies have documented the aforementioned avoidance of bottom water hypoxia with periodic forays into the hypoxic zones (Neuenfeldt, Andersen, & Hinrichsen, 2009; Neuenfeldt et al., 2020).

With the combination of our observations and the literature on individual responses, we accept the null hypothesis, that plaice were not excluded from the survey area in the south western Baltic sea by hypoxia in 2019. Thus, the reasons for such low catches in the surveys remain unknown. However, with the clear response of cod, we reject the null hypothesis and accept that hypoxia in bottom waters reduces cod catchability in the surveys. From these observations we cannot detect if this reduced catchability is due to a reduction in actual abundance, if the stock has moved out of the survey area (horizontally), or if individual probability of interaction with bottom gears has changed due to holding different positions in the water column (vertically).

Because plaice only responded to severe hypoxia, and these conditions were rare or absent across the stock area (ICES subdivisions 21 – 23), the real effect of oxygen on plaice catchability in the survey was negligible. Hence, further analyses are only reported for cod.

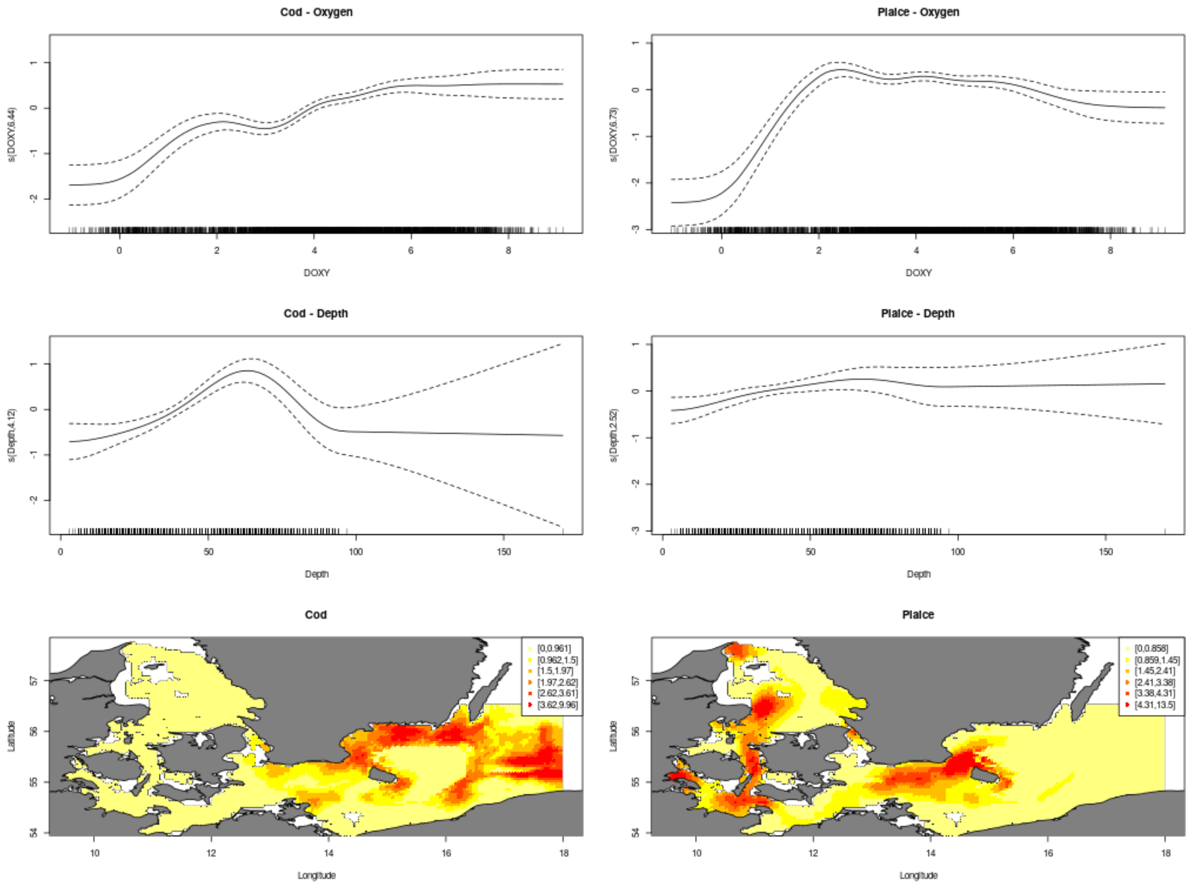

Figure 2. Estimated oxygen effects (top row), depth effects (middle row), and average spatial distribution in Q4 (bottom) for cod (left) and plaice (right).

Independent of the mechanism by which cod catchability in the survey is affected by hypoxia, the impact on survey indices can be mediated by utilising the same model that describes these effects. Model based indices are calculated by summing expected CPUE (predicted from the distribution model) over a fixed grid of virtual trawl positions using a set of fixed reference conditions (e.g. gear, vessel etc.). If oxygen concentration is known in the entire grid in every year and the relationship between CPUE and oxygen has been established, predictions can be made with higher accuracy in locations where observations (trawl samples) were not actually made. In practice this means that, if the chosen survey sampling positions were, by chance, all located in areas with low in oxygen conditions compared to the overall oxygen conditions across the stock area, then the resulting indices would be biased downwards, unless oxygen is included in the model. By including oxygen, we can compensate for the varying oxygen conditions across the stock area, independent of where the observations (trawl samples) were made in any given year. The resultant indices are more representative of the total abundance across the study area, rather than changing the total abundance estimated, by accounting for catchability under different oxygen conditions.

For cod, the inclusion of oxygen in the model producing the stock indices, increased estimates of the stock index for individual ages in different years (Figure 3). These increases were relatively minor and for the majority of years and ages, the indices remained well aligned, whether oxygen was included or not. The role of the oxygen mediated index is illustrated when we plot the oxygen conditions at our virtual grid locations, used for generating the index, alongside the difference between the standard index and the oxygen mediated one (Figure 4). Here we can see that when oxygen conditions are lower across the "sampled" area, the oxygen mediated indices estimate a larger biomass than the standard one (hence, the difference in standard minus oxygen indices is negative).

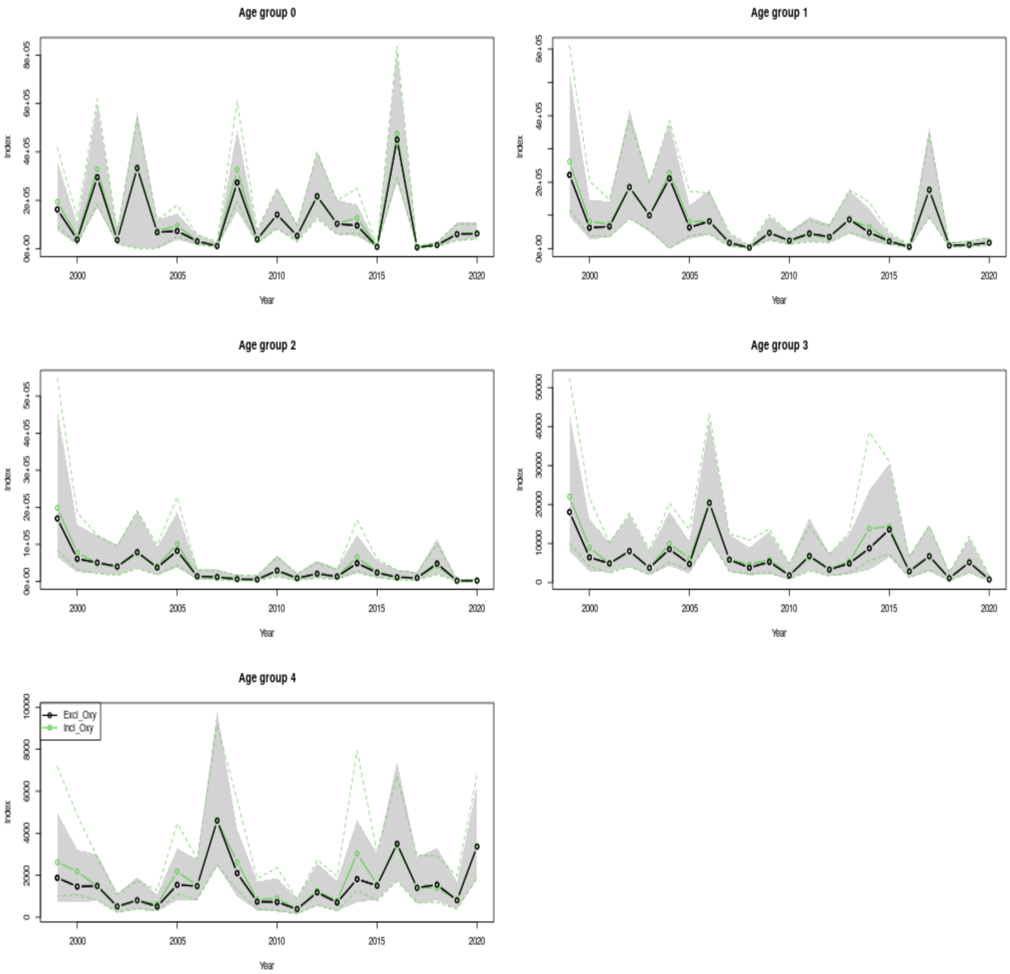

Figure 3. Stock indices for Atlantic cod in the south western Baltic Sea, estimated from models of stock distribution that either did (green) or did not (black) incorporate oxygen concentrations into the model. The baseline model is based on Berg et al. (2014) while the oxygen model is a simple extension of that method.

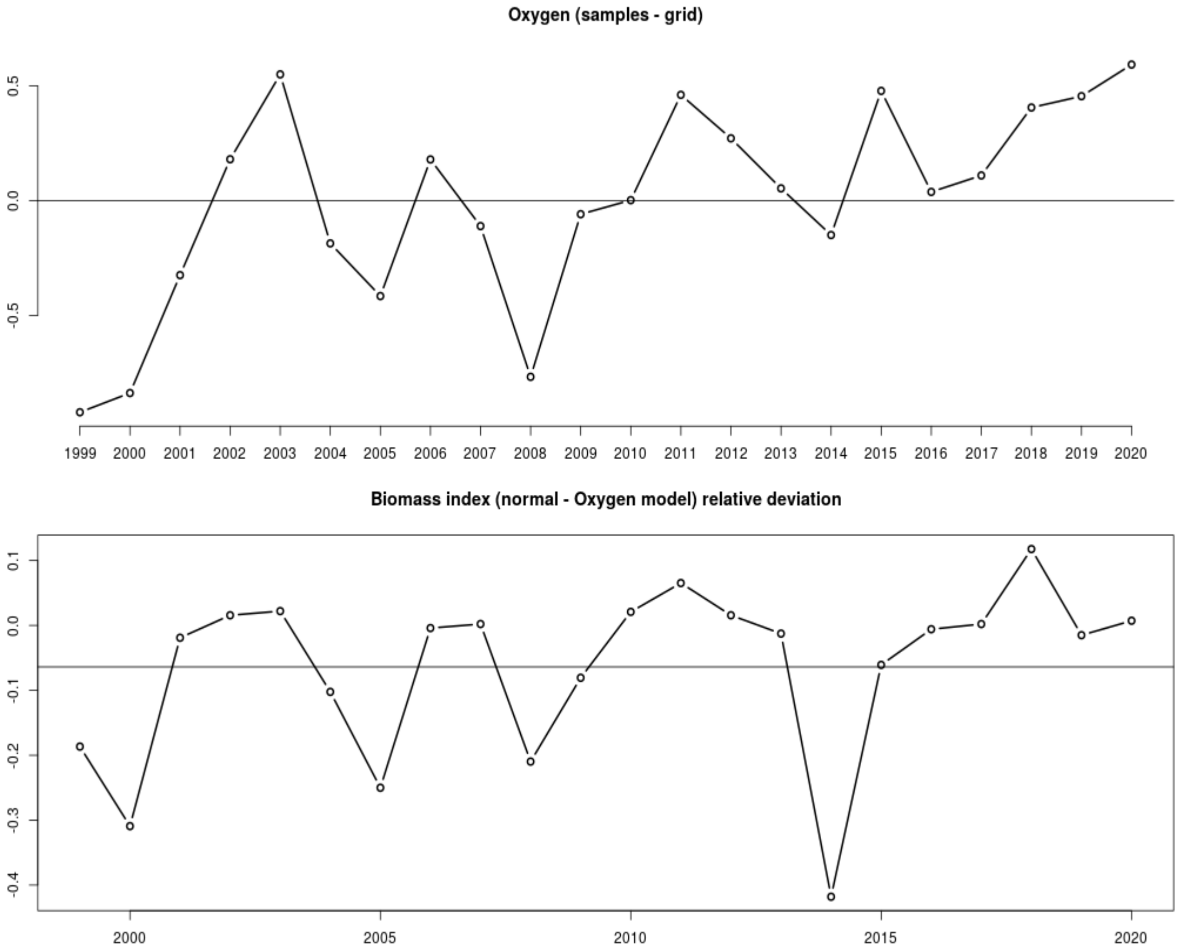

Figure 4. Modelled oxygen conditions (top) and difference in predicted biomass from the standard and oxygen based indices (standard-oxygen) over the period 1999 to 2020.

In the following section we investigate how modified stock indices that account for the reduced catchability due to hypoxia, impact upon estimates of population size in stock assessment models.

2.3 Assessments with Oxygen mediated Stock Indices

The modified stock indices that accounted for oxygen concentrations, described above, were employed in the standard stock assessment models from 2021. Unsurprisingly, given their lack of response to moderate hypoxia, the modified stock index had little to no impact on the assessment of population size (spawning stock biomass) or the subsequently derived fishing pressure for plaice in the southwestern Baltic Sea. Thus, we continue by reporting only results for cod.

We compare the stock assessment model run with the original stock index, from the spatio-temporal only model, to the run where we replace the standard index with the oxygen-mediated one. Here we find only minor differences in the estimated spawning stock biomass, fishing mortality and catch (Figure 5). These differences are all well within the confidence limits across the whole time series. Thus, the impact of including oxygen mediated stock indices is negligible on the assessment of western Baltic Cod.

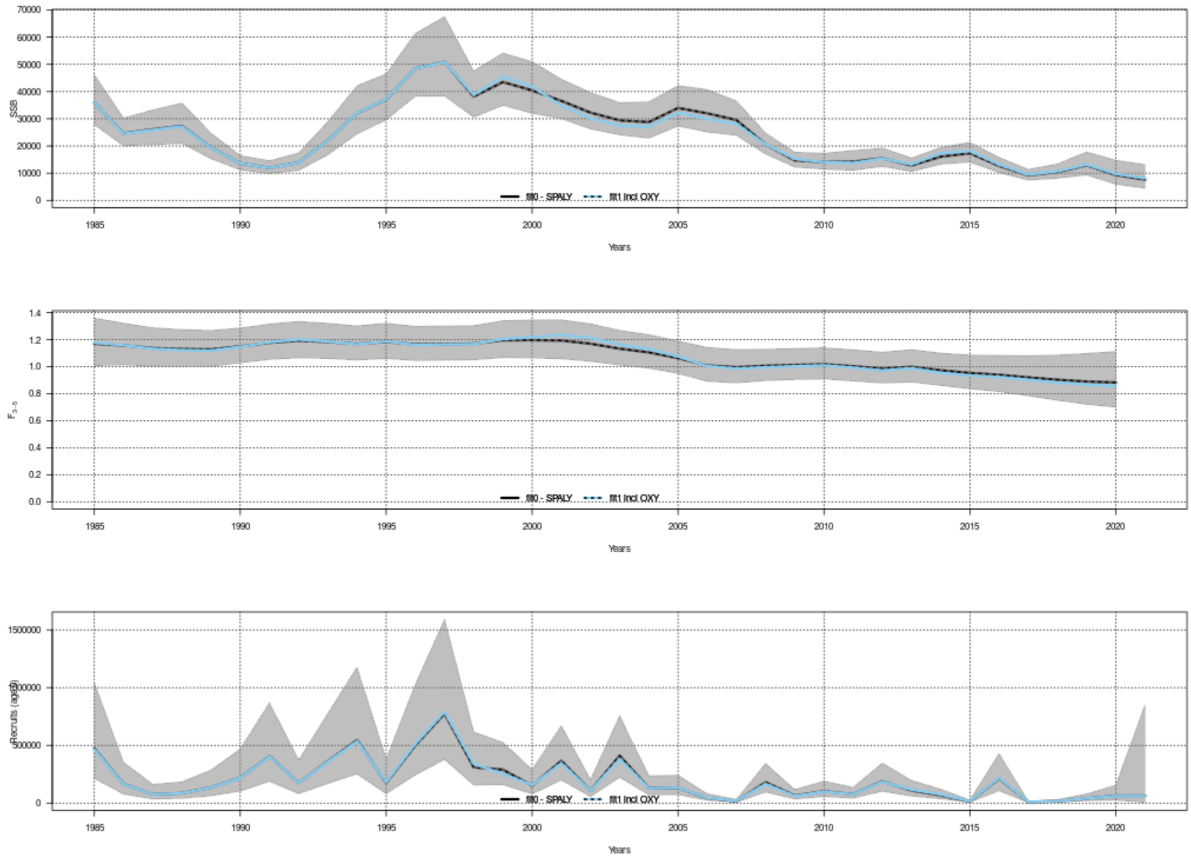

Figure 5. Assessment model estimations of spawning stock biomass (top), fishing mortality (middle), and catches for Cod (Gadus morhua) in subdivisions 22–24. Lines represent the accepted standard assessment methodology in 2021 (black line & grey ribbon), and the same methodology but utilising oxygen mediated stock indices (light blue line).

2.4 Conclusions

We found that the anticipated effects of basin scale hypoxia on survey catchability and assessment accuracy were negligible and that accounting for the moderate hypoxia in survey indices is unnecessary for cod and plaice in the western Baltic Sea. In this attempt to generate an operationally feasible approach to improve stock assessments of cod and plaice, we found that plaice remain well represented in the surveys for the western Baltic, Kattegat and the Belt Seas, where severe hypoxia is rare and they appear to tolerate and remain in areas of moderate hypoxia. We also found that cod appear to have a two-stage reduction in catchability as oxygen decreases from normoxia to moderate hypoxia and then on to acute hypoxia.

While these environmental conditions have a minimal effect on the calculation of stock indices and their subsequent use in assessment, the wide spread nature of the moderate hypoxia is likely to have an effect on stock productivity via many potential mechanisms, some of which are explored further in this report.

3. Underlying Distribution Shifts Associated with Hypoxia

In the previous chapter, we restricted our data sources and methodologies to only those that could be reliably updated and repeated, year-in and year-out, in accordance with standard stock assessment and advisory procedures. In this chapter, we utilise three different sources to investigate changes in cod and plaice distribution in relation to hypoxia, namely unconstrained species distributions models, comparing coastal indices from recreational catches relative to the magnitude of basin scale hypoxia, and fishers' experiences. Furthermore, we also document the improvements made to methods of identifying fishing activities in small scale gill-net fleets that aren't captured in data derived from vessel management systems.

3.1 Improved Species Distribution Models

3.1.1 Background

Species distribution models (SDMs) are commonly used to statistically assess the relationships between the occurrence or abundance of species with the environment. An important application of SDMs is predicting species' occurrence or abundance in space and time, which is especially useful in large areas where monitoring programs have limited coverage.

The distribution of species is often constrained by environmental conditions. In some cases, such conditions are linked to the topographic features of the land- or seascape (e.g. islands, mountains, valleys, rivers, channels). This complexity is often not addressed in SDMs, conversely it is assumed that predictions in space can be made following the shortest distance between two points. For marine and coastal species, this means that predictions are sometimes made across land, following the shortest distance, instead of around islands or peninsulas, leading to potentially unrealistic predictions of occurrence or abundances close to land.

Several methods have been developed to deal with complex topographies and boundaries in SDMs. One of them is the soap-film smoother (Wood, Bravington, & Hedley, 2008) implemented for Generalized Additive Models (GAMs). As the name suggests, like the formation of a bubble from a soap film, this smoother only smooths within a pre-defined boundary area, ensuring that no smoothing across boundaries occurs. Other recent methods are geodesic low rank Thin Plate Splines (Wang & Ranalli, 2007), Complex Region Spatial Smoother (Scott-Hayward, Mackenzie, Ashe, & Williams, 2015; Scott-Hayward, Mackenzie, Donovan, Walker, & Ashe, 2014) and barrier models (Bakka, Vanhatalo, Illian, Simpson, & Rue, 2019).

This study focusses on modelling the distribution of two commercially important species – plaice and cod – in the Kattegat, Belt Seas and western Baltic Sea. The area is characterized by several larger and smaller islands and some complex coastlines. Our aim was to compare the predictive ability of SDMs of plaice and cod with and without accounting for this topographic complexity in SDMs.

3.1.2 Data Sources

To model fish distributions in space and in relation to their environment we needed data on fish abundances and environmental conditions, or hydrographic data, across both space and time. Thus we utilised two sources of data, one for fish abundances and another for environmental conditions. Furthermore, the main focus of our interest was in the western Baltic, including ICES subdivisions 22, 23 and 24, for both species, as well as SD 21 for European plaice (Figure 6 and Figure 7). We therefore expanded the model domain to include ICES subdivisions North and East of this domain, to reduce the edge effects in the model predictions over the areas of interest.

Abundance data of cod and plaice were extracted from DATRAS (https://datras.ices.dk/) from the North Sea International Bottom Trawl Survey (IBTS) and the Baltic International Trawl Survey (BITS). The IBTS covers the first (Q1) and third quarter (Q3), whereas the BITS covers Q1 and the fourth quarter (Q4). The IBTS commenced in the 1960s and BITS in the 1990s. The study area for model fitting were limited to subdivisions 20 to 25 for plaice, and subdivisions 20 to 24 for cod. Survey data were processed using the R package 'DATRAS' (https://github.com/DTUAqua/DATRAS).

Adult and juvenile fish often occur in different habitats (e.g. adults inhabiting deeper, offshore waters compared to juveniles) and the catchability of juvenile cod and plaice is lower in the surveys than for adult fish. Hence, we focused on modelling the distribution of adult fish. Maturity proportions at age were estimated through maturity ogives from the respective stock assessments in the study area. Counted fish were split into spawning and non-spawning fish based on these maturity proportions by age that were averaged across the entire period with data available.

Final survey datasets of plaice and cod used for modelling consisted of 11,372 and 7,326 unique hauls, respectively. The years covered were from 1993-2020, to match the availability of environmental data.

Unlike our work on the Operational Consideration of Hypoxia in Assessments, we were not limited to environmental data that would be updated in an operationally relevant manner, and thus we selected to use a different source of data for the physical conditions at the seafloor. Here we used model output from a coupled hydro-biogeochemical model retrieved via the Copernicus data portal (E.U. Copernicus Marine Service Information (CMEMS), 2023). Daily means of the hydrological conditions at the lowest modelled layer were extracted from the full model dataset, to represent the average daily conditions at the sea floor. These grids of two square kilometres were utilised directly for predicting species distribution, however, to estimate models of distribution, the conditions at the sea floor were predicted at the mid-point of every haul selected from the DATRAS dataset, by means of a linear interpolation from the nearest four points.

During model fitting, depth measured during the survey was used as predictor variable. Missing values (for 0.21% of the data) were interpolated via a GAM that modelled survey depth (log-transformed) against longitude and latitude.

To have bathymetry information at a finer resolution for predictions, depth was extracted for each cell of the prediction grid from the GEBCO 2023 grid (https://download.gebco.net/). For all other environmental variables, daily values for 2019 were extracted for each cell on the prediction grid. Next, daily values from the survey period were selected for each quarter separately, and subsequently averaged to obtain one single value per variable per cell to represent the environmental conditions by quarter for the prediction grid in 2019.

3.1.3 Approaches and Methods

Details regarding the technical approaches, are in preparation for submission to a peer-reviewed journal..

To compare between methods that account for coastal barriers and standard approaches, we fit GAMs of species distribution in relation to environmental variables and space with two different spatial smoothers, namely a soap-film smoother and a standard tensor product of northings and eastings. Models were fit in *R* (R Core Team, 2021) using the package *mgcv* (Wood, 2011).

The standard model can be described as:

Number of plaice ~ s(x,y) + s(Depth) + s(Salinity) + s(Temperature) + s(Oxygen) + Survey + Quarter + re(Year) + offset(log(Haul duration))

Where ‘s’ represents a smoothing function, which in the case of the spatial term (denoted x,y), is either a soap film or tensor product smoother. For the environmental predictors the “s” smoother is a thin plate regression spline. The prefix ‘re’ represents a random effect, which applies only to “Year”.

Each of the spatial smoothers require user defined limits to the degrees of freedom the smoother is allowed. In the case of the standard tensor product, we employed the default limit, which is defined as 5^d, where d is the marginal basis dimension, i.e. two; one dimension each for northings and eastings. This results in 25 knots being the limit for the tensor product smoother. The soap-film smoother is a bit more demanding, requiring the limits to freedom to be specified for each “island” and the bounding coastline, independently, as well as some form of dispersed grid or allocation of knots across the space that is relevant for the model. Through a series of sensitivity tests, we selected dimension constraints based on the complexity of the coastline for each “island” independently. This was based on a rounded square-root of the number of vertices. The resultant knots assigned to the various coastal features were: 14, 4, 7, 3, 5, 2, 2, 4, 3, 4, 3 , 2, 3, 2. Furthermore, we selected a “combined density” grid of knots, which has lower densities of knots in the more open water areas of the study area, and higher densities of knots through the geographically complex Danish straits (Figure 6 and Figure 7).

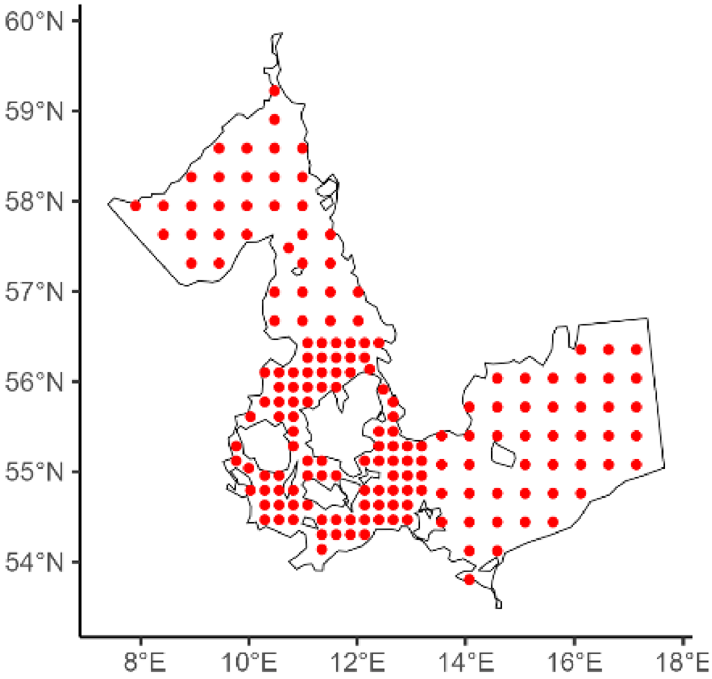

Figure 6. Grid of combined density knots provided to the soap-film smoother across the study domain for European plaice. The higher density of points through the Danish straits was selected to allow greater model flexibility around the complex coastal geography.

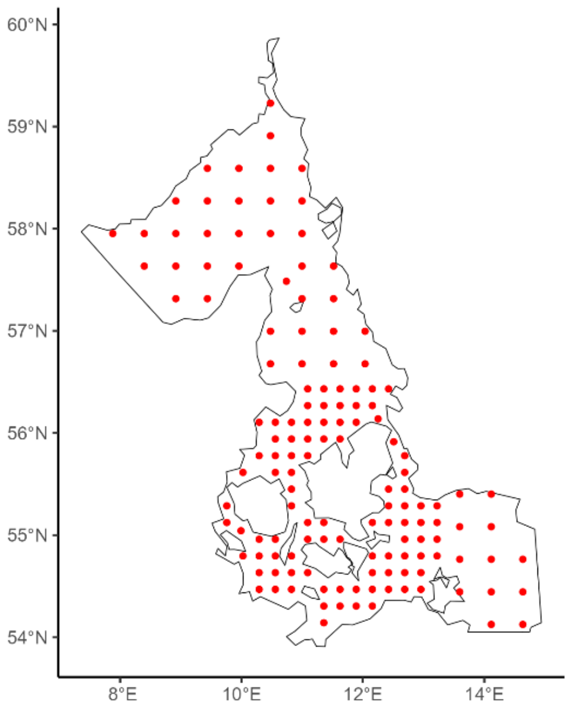

Figure 7. Grid of combined density knots provided to the soap-film smoother across the study domain for Atlantic cod. The higher density of points through the Danish straits was selected to allow greater model flexibility around the complex coastal geography. The model domain was reduced compared to that of plaice to exclude areas dominated by the eastern Baltic cod; a different ecotype with different responses to environmental conditions.

To ensure appropriate model fits within each of these methods, we investigated two response distributions (negative binomial and tweedie) and determined the most appropriate "freedom" (basis dimension) for the smoother of each environmental covariate. Model fits and the suitability of basis dimension for each smoother were evaluated by interrogating standardised model residuals using the package DHARMa (Hartig, 2018), and evaluating the effective degrees of freedom, k-index and p-values, together with an assessment of the Akaike Information Criterion (AIC) from the *mgcv* function *gam.check*.

Once the best models were selected from within each combination of smoothing method (soap-film and tensor) and response distribution (negative binomial and tweedie), repeated random subsampling cross-validation was used to investigate these final models' predictive capability. For cross-validation, 20 iterations were run during which 80% of the data were randomly selected to fit the model. The re-fitted model was then used to predict the remaining 20% of the data. The following statistics of the full model and the 20 fitted sub-models were calculated:

- R^2: represents the correlation between observed and predicted values (the higher the better)
- Root mean squared error (RMSE): represents the scaled difference between observed and predicted values (the lower the better).
- Mean absolute error (MAE): mean of the actual difference observed and predicted values.
- Bias: measure of how large consistent inaccuracies in predictions are, relative to observed values (the lower the better).

For each species the best model with a soap film smoother and the best model with a standard tensor smoother were selected (four models total) to predict abundance across each of the quarters for the year 2019.

3.1.4 Results

Plaice
For plaice, the best values for the basis dimension (maximum smoother freedom) for all environmental covariates was the same between models with standard tensor spatial smoothers and those with the soap-film smoothers.

The tweedie distributions provided the best predictions (over the negative binomial) in cross validation for both the standard tensor spatial smoother and the soap-film smoother, across all metrics (Figure 8).

Comparing the two methods of spatial smoothing (both Tweedie distribution), a higher percentage of deviance was explained (58.6% vs. 48.1%) and correlation between observed and predicted values (R^2=0.29 vs. 0.19) are observed for the soap film model. In addition, the predictive error is lower for the soap film model than for the tensor product model (RMSE=132 vs. 139). For both the tensor smoother and the soap film smoother, predictive bias is low and not dissimilar to one another (Figure 8).

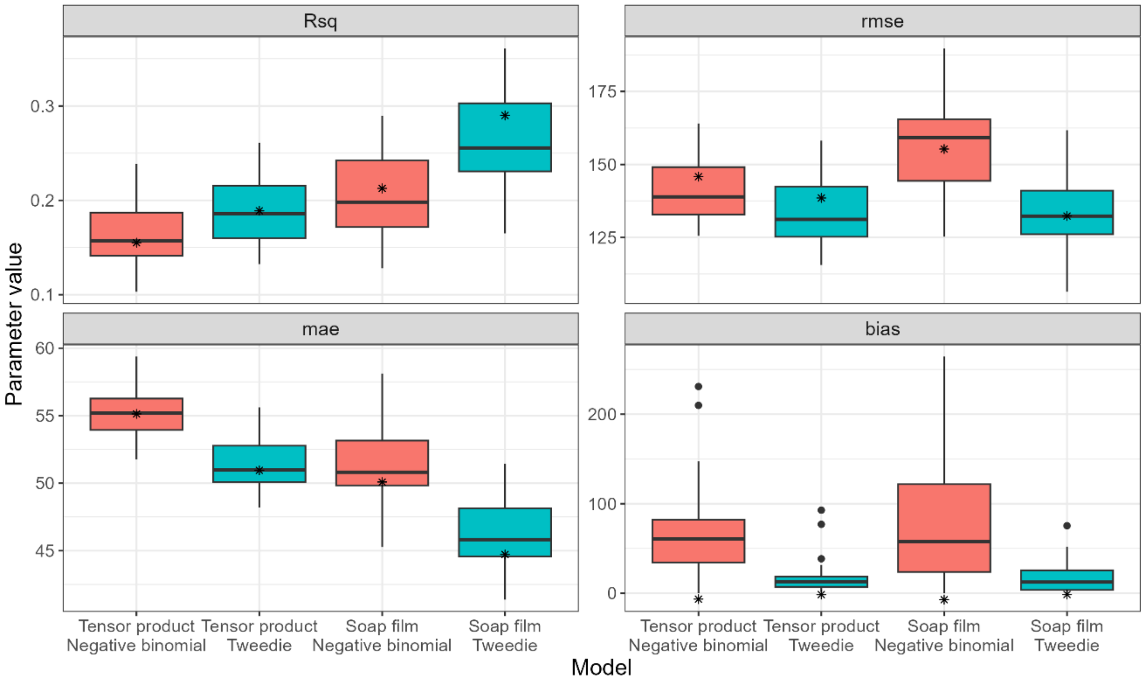

Figure 8. Cross-validation statistics across the 20 iterations for models with tensor product or soap film smoother for plaice that were considered as the best model with either negative binomial (red) or Tweedie distribution (blue). Asterisk indicates value of the full model. Rsq = R-squared, rmse = root mean squared error, mae = mean absolute error.

The partial response plots of the final GAMs with tensor product (Figure 9) and soap film smoother (Figure 10) suggest that models captured similar effects of the environment on plaice abundance. While keeping all other environmental variables constant, depths greater than ~50m generally have a negative effect. Conversely, temperature has a generally positive effect, up to 14-15 ºC. Due to few data points at very low oxygen concentrations (negatives representing oxygen debts from the hydro-biogeochemical model output), the model displays large uncertainty around the effect of oxygen on plaice abundance. Yet, both models indicate increasing negative effects on abundance as oxygen decreases from positive values towards zero (hypoxia). Salinity seems to have a minor effect on plaice abundance, yet the soap film GAM identified a slight negative relationship.

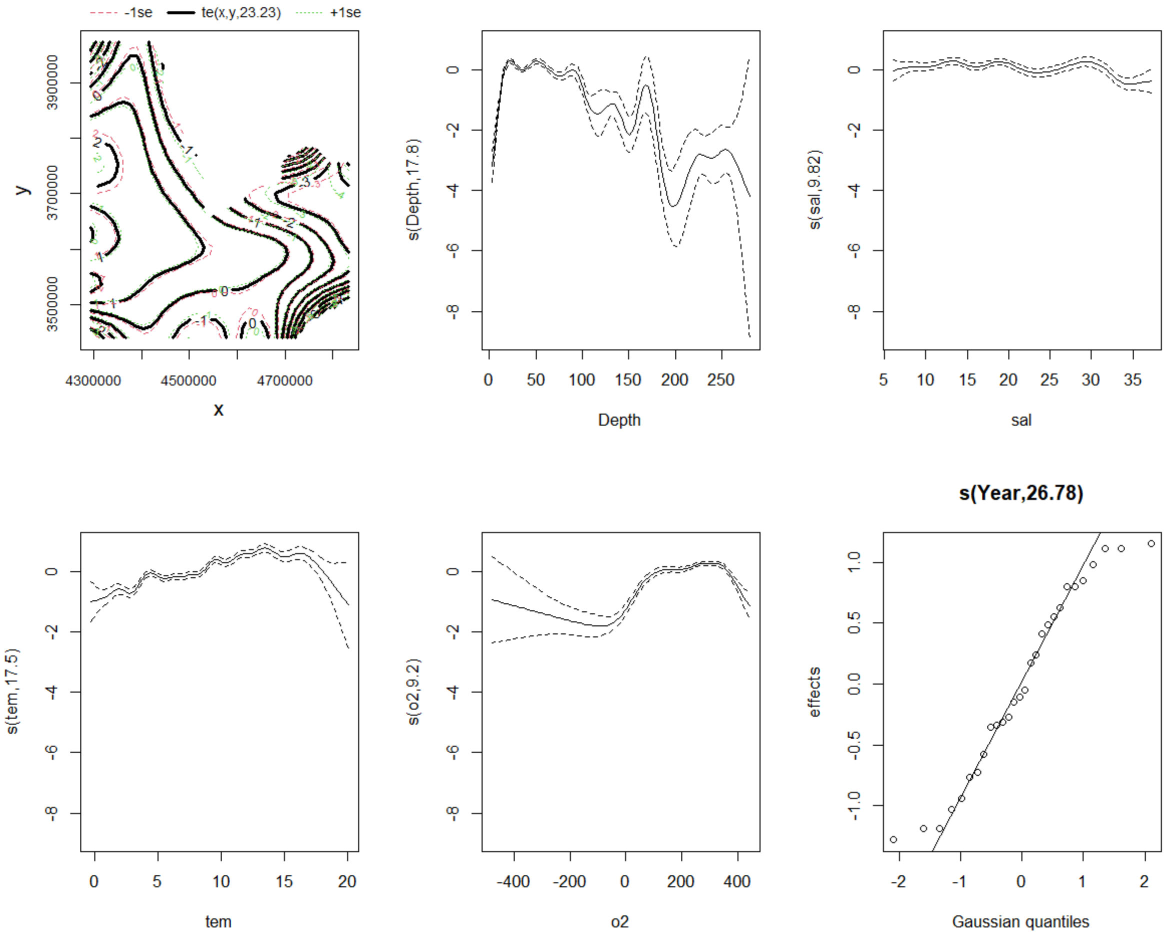

Figure 9. Partial response plots of final GAM with tensor product smoother for plaice. Each panel shows the effect of a given smoother, in the situation where all other variables are held constant at the mean, and are top: Spatial tensor product smooth, depth, and salinity. Bottom: Temperature, oxygen concentration, and the distribution of the random effects of year.

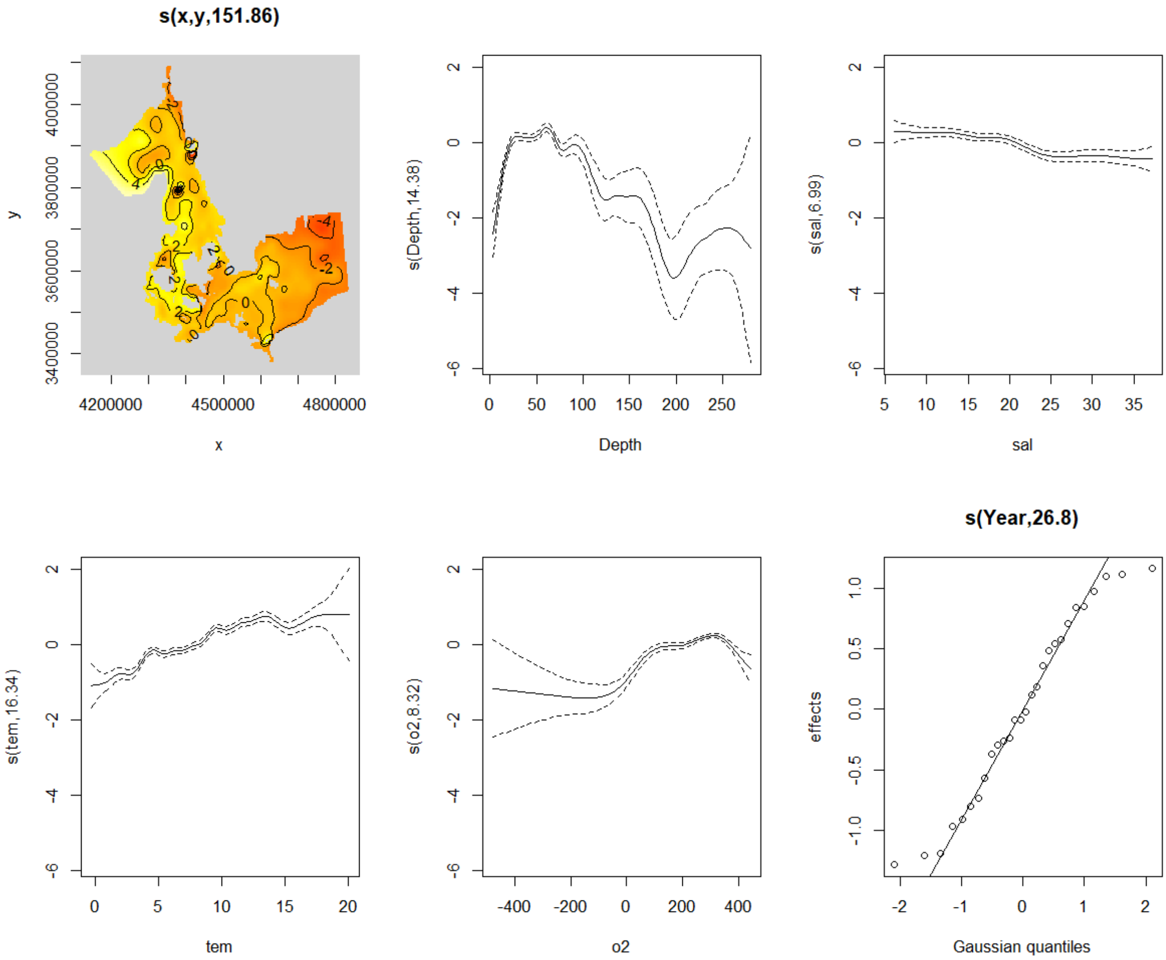

Figure 10. Partial response plots of final GAM with soap film smoother for plaice. Each panel shows the effect of a given smoother, in the situation where all other variables are held constant at the mean, and are top: Spatial soap film smoother, depth, and salinity. Bottom: Temperature, oxygen concentration, and the distribution of the random effects of year.

The predicted number of spawning plaice by the tensor product and soap film smoother model show generally similar spatial patterns, with high abundances in the Belt Seas around the island Funen and in the western Kattegat (Figure 11). Predicted values are on average slightly higher for the tensor product model than for the soap film, yet the soap film model predicts the highest, absolute peaks of abundance (Figure 12). It also predicts hotspots located west of Bornholm and Ålbæk Bay (northwestern Kattegat) that are less pronounced hotspots in the tensor product model. Overall, areas of high abundance in the soap film model are relatively condensed, whereas these are more smoothened out in space in the tensor product model.

Standard errors around the predicted values follow the spatial distributions of the predicted values, with the highest errors in areas where highest abundances are predicted (Figure 11). Standard errors of the tensor product model are generally lower than those of the soap film model (Figure 12).

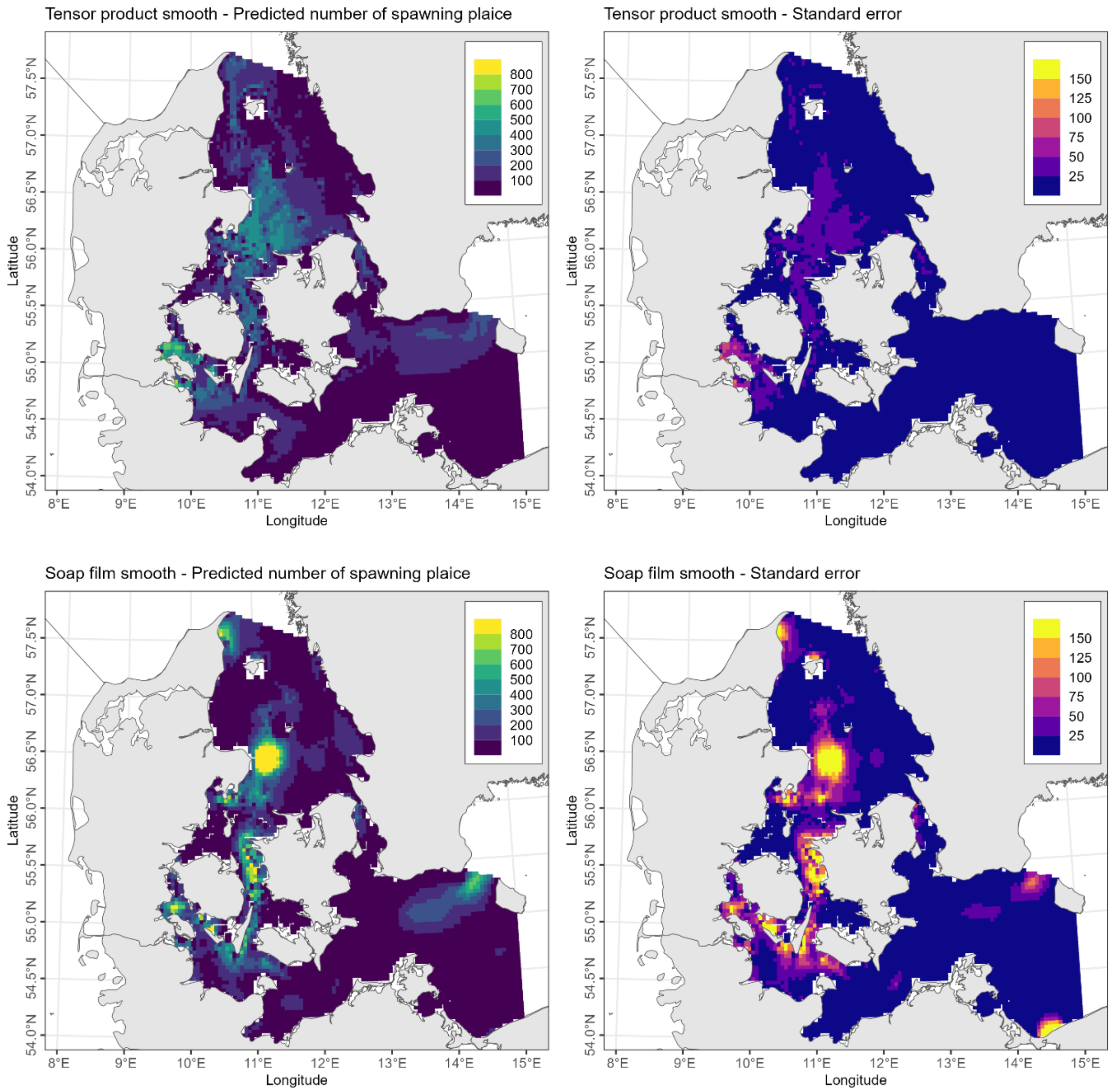

Figure 11. Predicted number of plaice (left panels) and corresponding standard errors (right panels) in Q1 2019, based on the GAM with tensor product (top panels) and soap film smoother (bottom panels).

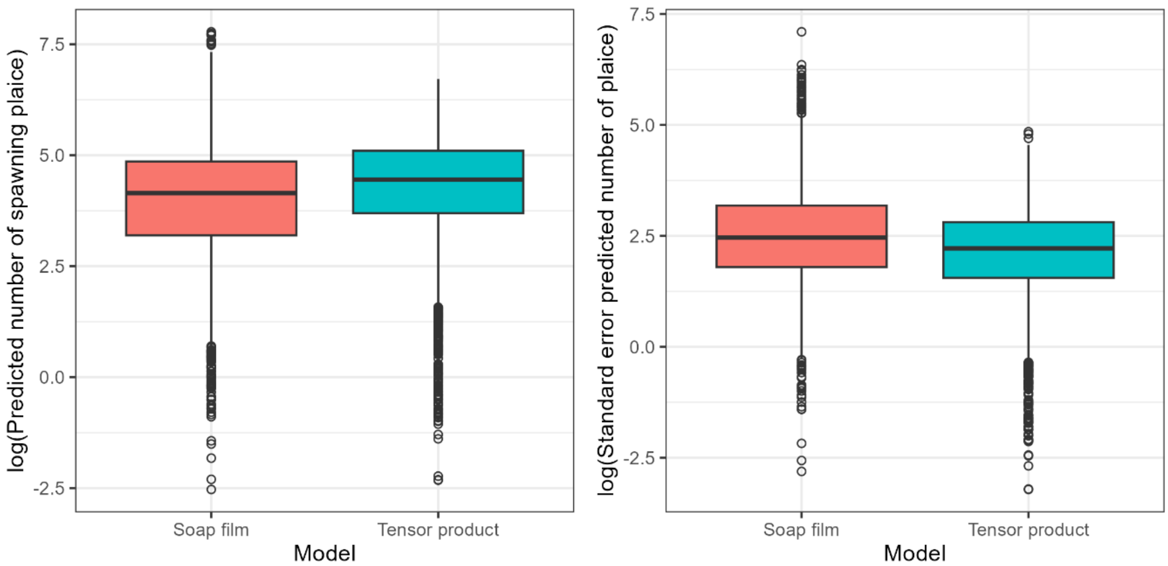

Figure 12. Variation in predicted number of plaice (left) and standard error (right) by the GAMs with soap film and tensor product smoother, Q1 2019. Values have been log-transformed.

Cod

In contrast to plaice, a series of models from the tweedie distribution (with varying freedom given to the smoothers) all performed similarly in terms of model fits and AIC values. However, the negative binomial model had a clear winner in terms of model fit. All of the tweedie distribution based models out performed the negative binomial model in cross-validation, with now substantial difference between the tweedie models themselves (Figure 13). Because of this, the tweedie with the lowest AIC was selected as the final GAM, for further predictions.

While keeping other variables constant, cod abundance peaks in areas with a depth of approximately 100m, decreases with increasing salinity, and peaks at temperatures of 7-8 ºC. Relationships between abundance and oxygen concentration and mixed layer depth are more spurious, due to few data points at very low oxygen concentrations and high mixed later depth values. As was the case with plaice, the nature of the modelled oxygen data includes a few cases of oxygen debt, which in turn make the uncertainties around some of the estimations of oxygen's effect look poor. However, both models indicate increasing negative effects on abundance as oxygen decreases from positive values towards zero (range of hypoxia).

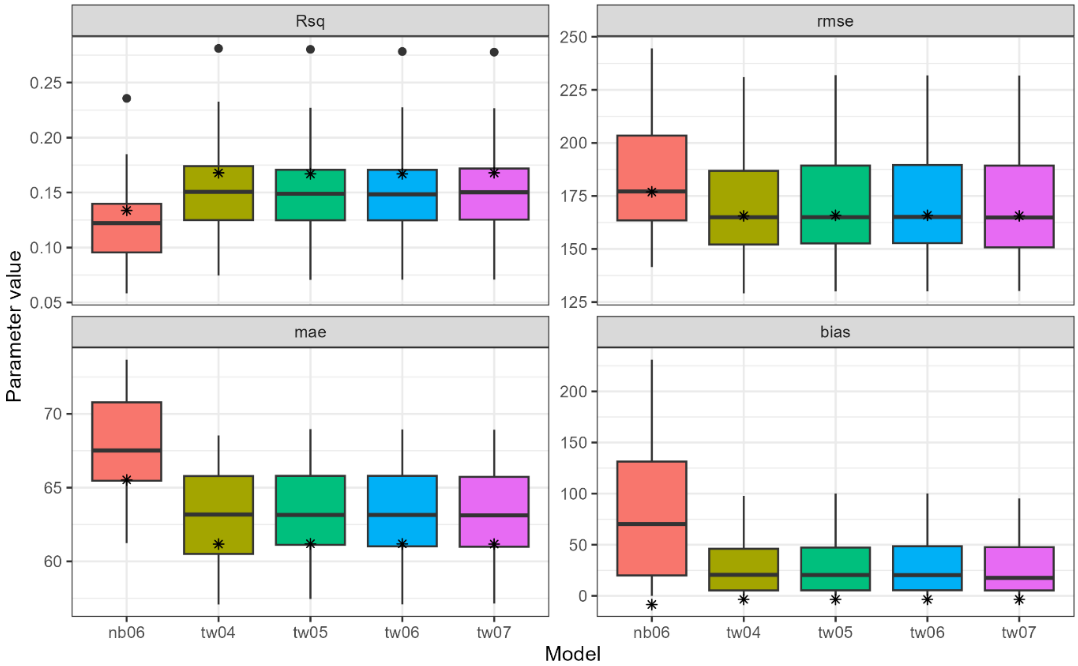

Figure 13. Cross-validation statistics across the 20 iterations for five models with tensor product smoother for cod that were considered among the best models with either negative binomial (nb06) or Tweedie (tw04, tw05, tw06, tw07) distribution. Asterisk indicates value of the full model. Rsq = R-squared, rmse = root mean squared error, mae = mean absolute error.

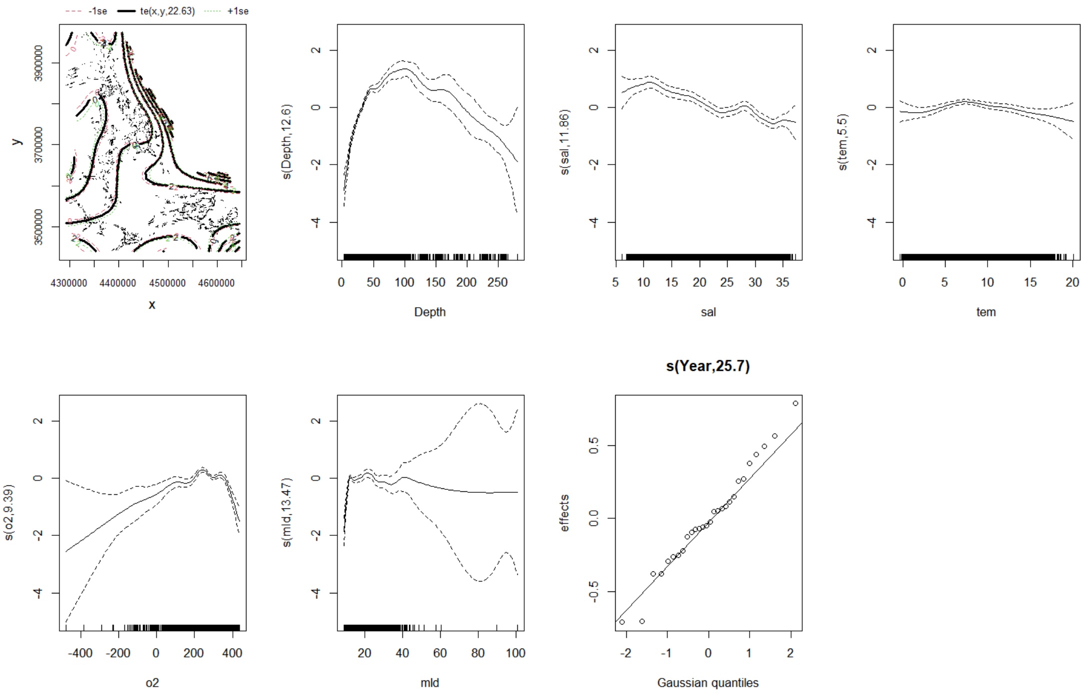

Figure 14. Partial response plots of final GAM with tensor product smoother for cod. Each panel shows the effect of a given smoother, in the situation where all other variables are held constant at the mean, and are as follows. Top: Spatial tensor product smooth, depth, salinity and temperature. Bottom: oxygen concentration, mixed layer depth, and the distribution of the random effects of year.

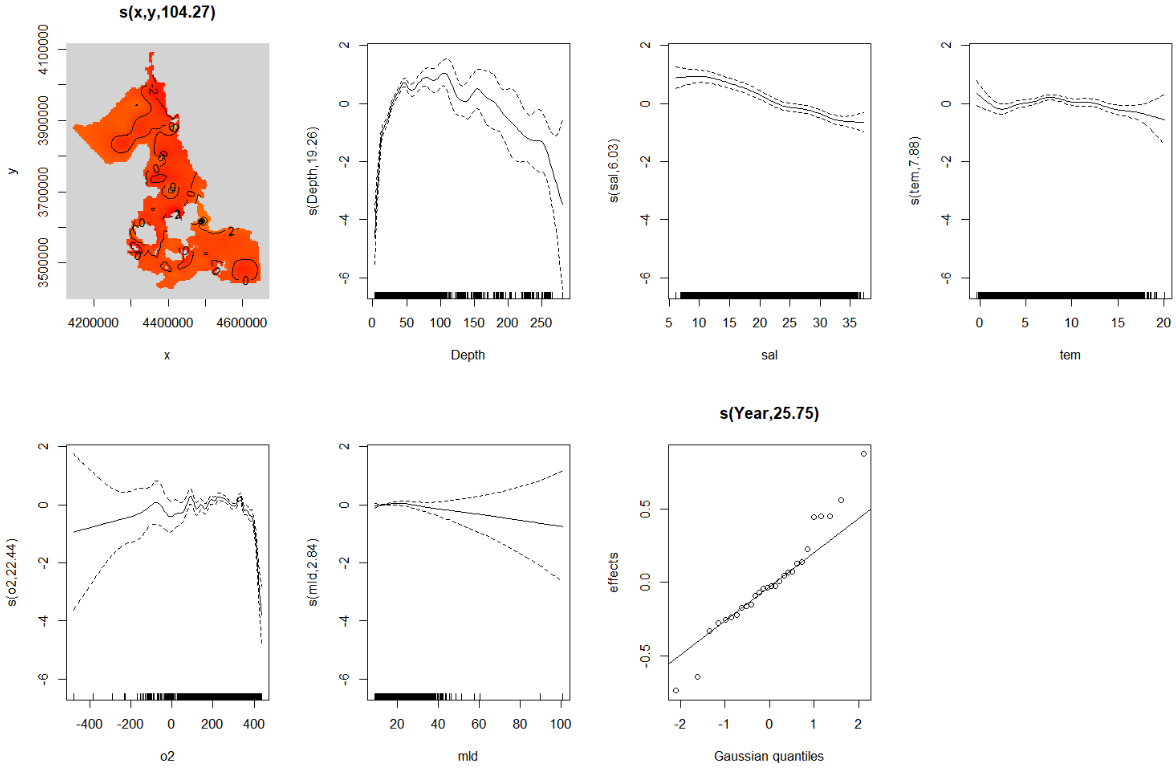

Figure 15. Partial response plots of final GAM with soap film smoother for cod. Each panel shows the effect of a given smoother, in the situation where all other variables are held constant at the mean, and are as follows. Top: Spatial soap film smoother, depth, salinity and temperature. Bottom: oxygen concentration, mixed layer depth, and the distribution of the random effects of year.

The predicted number of cod is highest west of Bornholm for both the tensor product and soap film models, with another common area of intermediately high abundances in the area south of Bornholm (Figure 16). Predictions from the soap film model are also high in the Øresund, between Denmark and Sweden, with an area of very low values of where the island Saltholm is located. However, these high predictions are coupled with high uncertainty, illustrated in the standard errors, especially in comparison to the high predictions and lower standard errors in the area northwest of Bornholm. Predicted abundances by the tensor product model in the Øresund are not as high as the soap film smoother model, but remain high relative to neighbouring areas. Variation in predicted values is overall similar between the two models, with some very high and low outliers for the soap film model (Figure 17).

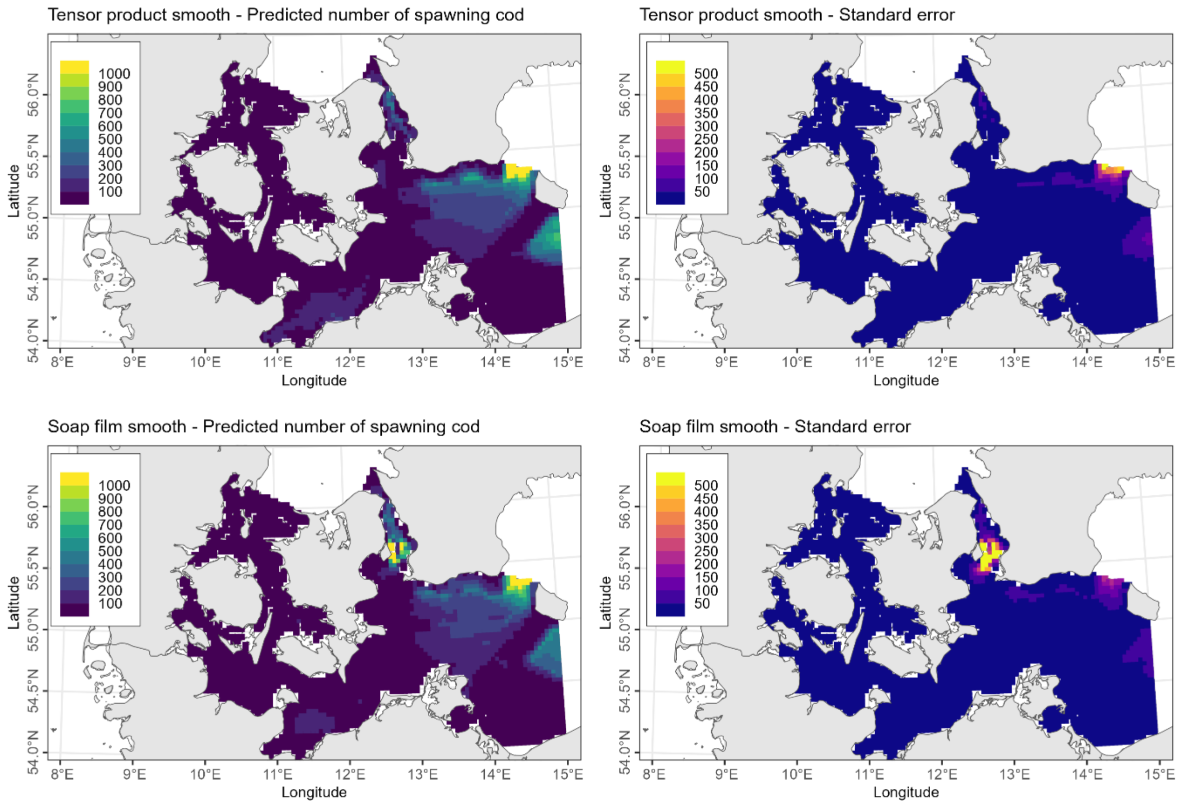

Figure 16. Predicted number of cod (left panels) and corresponding standard errors (right panels) in Q1 2019, based on the GAM with tensor product (top panels) and soap film smoother (bottom panels).

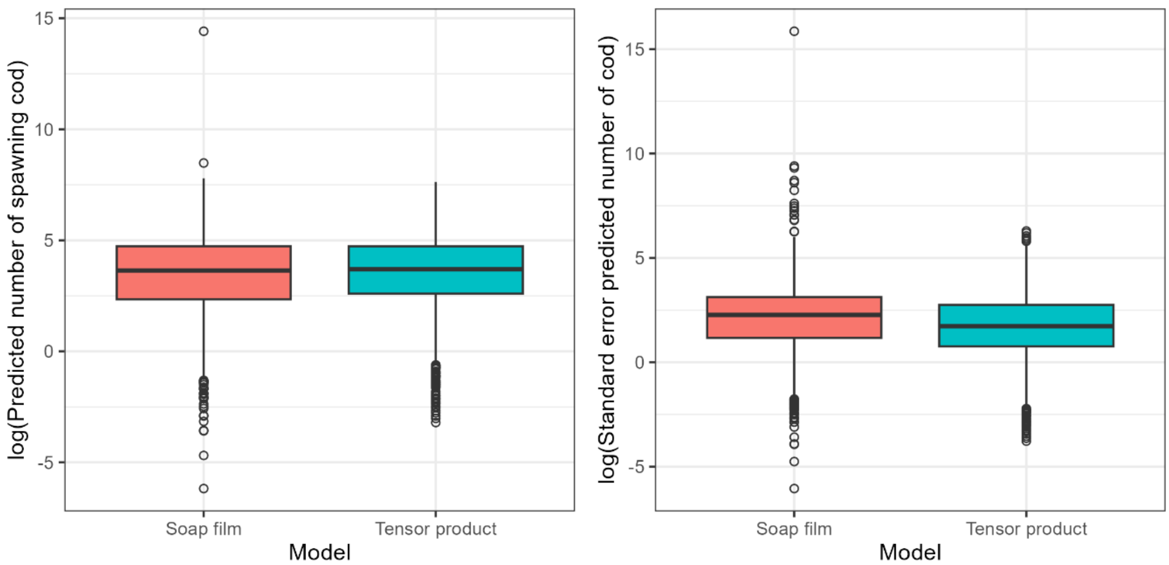

Figure 17. Predicted number of cod (left) and standard error (right) by the GAMs with soap film and tensor product smoother, Q1 2019. Values have been log-transformed.

3.1.5 Conclusions

We have shown that by accounting for the complexities that coastal geography imposes on fish distributions in the southwestern Baltic Sea, we produce better model fits, with better predictive capabilities for distribution models of mature European plaice and Atlantic Cod. Our models that account for the coastal complexity, provide finer scale changes in predicted abundance than both standard approaches and previous studies of these species across the southwestern Baltic Sea and Kattegat (Støttrup et al., 2019). Additionally, the positions of the predicted hotspots from the soap film models fall within the areas of predicted higher abundance from earlier studies (Brown, Kokkalis, & Støttrup, 2019; Støttrup et al., 2019; Ulrich et al., 2017), corroborating the location of these predicted areas of higher density.

With this improved resolution of predictions, we gain visibility of particular situations of predicted higher abundance, like cod in the *Øresund*, plaice in the southern Little Belt, northern Great Belt and *Ålbæk* Bay. This improved resolution may be of use for spatial planning, considering any regulations aimed at protecting vulnerable stocks, or the impacts other regulations may have on fishers' ability to target these species.

Furthermore, without the constraint of using only operationally relevant data sources, as was the case in the section of this report "Operational Consideration of Hypoxia in Assessments", both our conventional spatial approach and our more complex coastal considerations models corroborate the type of relationship that cod and plaice abundances have with oxygen.

We recommend that future projects on fish distribution through the Inner Danish Waters, or other geographically complex water bodies, utilise methods that explicitly account for coastal barriers to distribution, such as the soap film smoother presented here. Furthermore, to make these specific applications of soap film smoothers more readily available to future projects, more work should be done to address the trade-off between the specified knots (coastline and grid) and data availability, as more knots require more positive observations of a species to properly fit.

Finally, future work on the models presented here should consider the temporal stability of the abundance hotspots, in terms of both seasonal (intra-annual) and long term (inter-annual) locations.

3.2 Coastal Catches and Hypoxia

3.2.1 Background

Hypoxia in the Baltic Sea is common in deeper waters where sharp changes in temperature and salinity gradients inhibit oxygen-rich surface water from mixing with bottom waters and where the shallow sills of the Danish straights hamper the inflow of oxygen rich oceanic water to ventilate the deeper basins. While a naturally occurring phenomenon, the severity and extent of hypoxia in the Baltic Sea has been greatly exacerbated by nutrient rich run-off from terrestrial agrigulture, which promotes the over-production of phytoplankton that subsequently die, sink and decompose, removing more oxygen from the deep waters.

Fish responses to hypoxic waters vary, depending on their ability to sense the low oxygen, their general activity levels and their current energy state / capacity. Where fish such as cod and plaice may be present in the deep water basins under normal conditions, they may choose to swim vertically, out of the bottom waters, horizontally to try and get out of the hypoxic area, or alternatively, they may down-regulate their behaviour to reduce their oxygen demands and to tolerate the hypoxia.

In this section, we take the hypothesis that plaice and cod will move horizontally to redistribute themselves to avoid hypoxic areas. As a natural consequence of this, more fish will be present in shallower coastal areas, away from the hypoxic basins, and this will increase the catch rates of coastal recreational fishers.

3.2.2 Data Sources

The majority of species distribution models for fish in the Baltic Sea are derived from either trawl surveys (as described in section 3.1) or commercial fisheries data, the latter of which is often reduced to just the active trawl gears to standardise for effort (Støttrup et al., 2019). These data sources are limited in that the physical sampling is restricted to deeper waters, i.e. deeper than 10m or 20m depth in various areas across the Baltic Sea (ICES, 2017), which prevents vessels operating in near-shore coastal areas. Other sources of coastal fish surveys occur both in Denmark (Pedersen et al., 2023; Støttrup et al., 2018) and around the Baltic Sea (HELCOM et al., 2018; Kraufvelin et al., 2018), however they utilise different sampling methods to the offshore surveys and they differ among themselves. In Denmark, a long running programme of select recreational fishers utilising common gears and methods fishing at select times and reporting catches provides insight into which species are present in coastal catches (Støttrup et al., 2018). These fishers use some combination of standardised fyke nets targeting eel, or gill nets targeting cod, flounder and plaice.

Here in this section, we utilise the mean catch per unit effort of cod and plaice from gill net fishers operating at static locations throughout the Danish part of the south-western Baltic Sea (Figure 18).

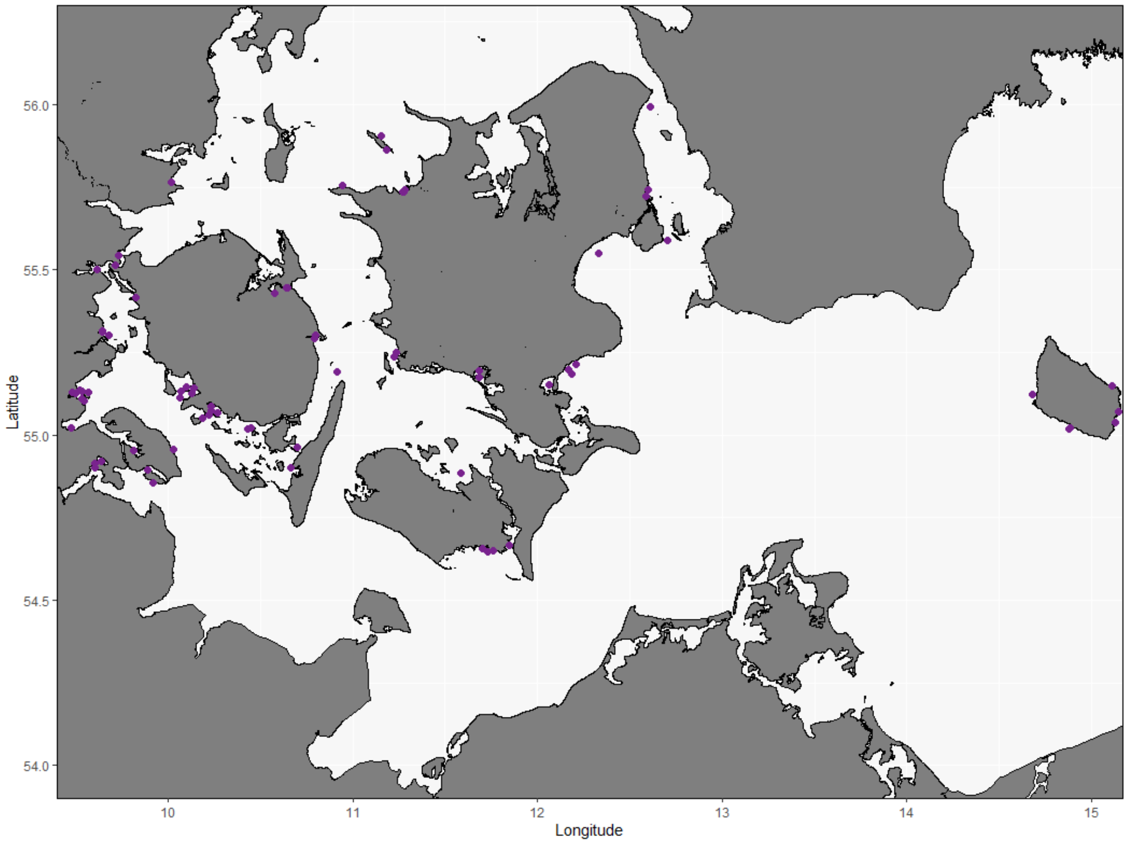

Figure 18. Locations of "KeyFisher" gill net sampling from across the years 2005-2020, utilised in the production of a coastal catch index.

We pair these catch data with indices of the horizontal extent of bottom-water hypoxia across the ICES subdivisions 21-25, which spans the study area. These indices were derived from the statistical model of bottom water oxygen, described in section 2.1, but were limited to those years for which coastal catch data were available (2005 – 2020).

3.2.3 Approaches and Methods

To derive a coastal catch index for cod and plaice, a standardised catch per unity effort for each species was calculated per fishing activity / sampling. This "standardised CPUE", is simply the mean number of individuals at or above the length at 50% maturity caught per hour, multiplied over the standard fishing time, which in the case of gill nets was 12 hours. These indices were then again averaged across the whole study area for each quarter of every year, providing a CPUE of mean number of individuals caught, per sampling activity, across the study area in a given quarter.

To calculate a paired index of the magnitude of hypoxia, we calculated the proportion of the study area that was experiencing either moderate hypoxia (below four $mL.L^{-1}$ of oxygen) or acute hypoxia (below two $mL.L^{-1}$ of oxygen). This proportion was calculated from the number of grid cells across the model domain from the model of section 2.1.

To investigate the relationship between the extent of hypoxia in a given year and coastal fish catches, we built linear models of the coastal CPUE being explained by the hypoxia indices and a stock size indicator (cod; ICES, 2023) or estimated stock size (plaice; ICES, 2022a). We chose to use the estimated indicator/stock size from the most recent stock assessments, instead of accounting for temporal autocorrelation. We do this because we make the assumption that the catch rate of coastal fishers is more likely to be related to the abundance of fish, overall, than to the coastal catch rates in the previous year or years.

To investigate any potential lag-effects of hypoxia, from one year to the next, we employed a lagged-correlation approach. Because the mechanisms by which low oxygen impacts upon a species distribution, or its catchability, vary and are uncertain, we utilised an approach that does not try to establish nor assume, a mechanistic causal relationship. Rather, the underlying assumption is that these two datasets vary together and that the combination of their past state is a better predictor of their future state, than only predicting from each data set independently. This form of time-series correlation is termed “Granger correlation” (Granger, 1969), and models were tested using the function *grangertest* from the R package *lmtest* (Zeileis & Hothorn, 2002). Models with up to three years’ worth of lag on both the hypoxia index and the catch indices were tested. In all cases, both the catch indices and the hypoxia indices had the same amount of lag applied, within each model comparison. The model utilising only the lagged catch index as a predictor of the catch index was used as a baseline. A model utilising both the lagged catch index and the lagged hypoxia index was used as the alternate model. A Wald’s test was used to estimate an F-statistic comparing the fit two models. This was repeated for the three lag years.

3.2.4 Results

Cod coastal catch rates were very variable over the study period and do not readily appear to co-vary with our hypoxia indices (Figure 19). Plaice coastal catch rates were, on average, higher than those observed for cod, with a large peak in the middle of our time series and declining trend, thereafter (Figure 20).

A visual inspection of how cod catch rates varied with concurrent year hypoxia indices suggests some positive association, but with very large uncertainties (). Plaice showed a similar relationship for acute hypoxia but little to no indication of a relationship to the moderate hypoxia index (). Ultimately, these relationships are indicative only, as they don’t account for other major sources of variation such as the previous year’s catch rates (autocorrelation) or more appropriately the overall stock size. Our models of coastal catch rates in response to hypoxia indices and stock size showed no significant correlations between coastal CPUE and the extent of either acute or moderate hypoxia (Table 2).

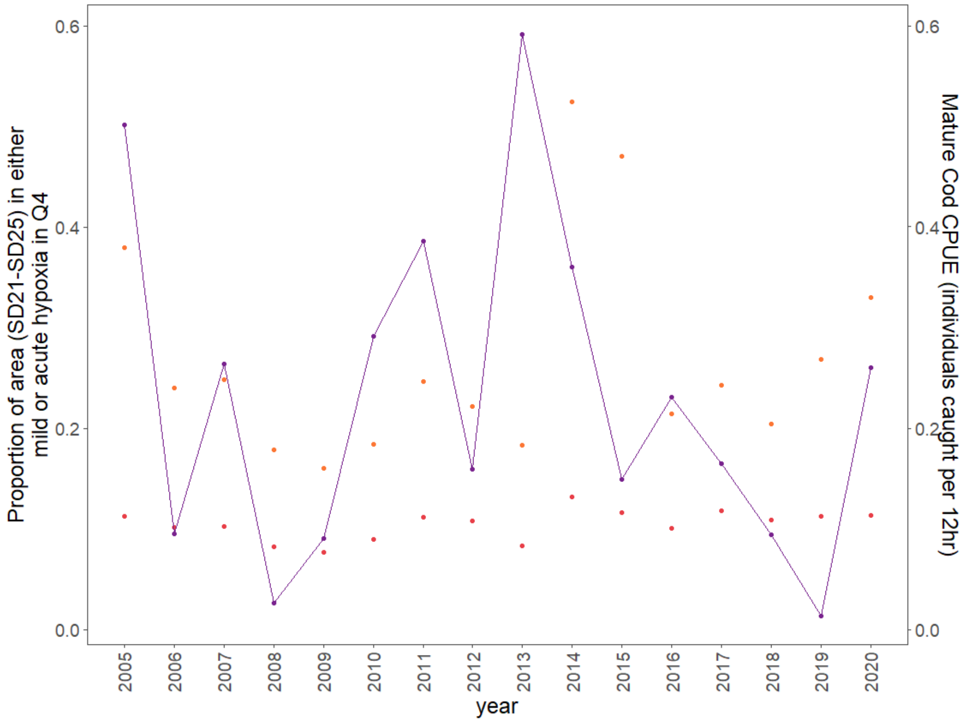

Figure 19. Hypoxia indices as proportion of study area at or below moderate (4 mL.L-1 oxygen; orange circles) or acute (2 mL.L-1 oxygen; red circles) hypoxia in bottom waters in quarter four. Overlain is the coastal catch index for cod, as a standardised catch per unit effort from gill nets across the study area averaged for quarter 4.

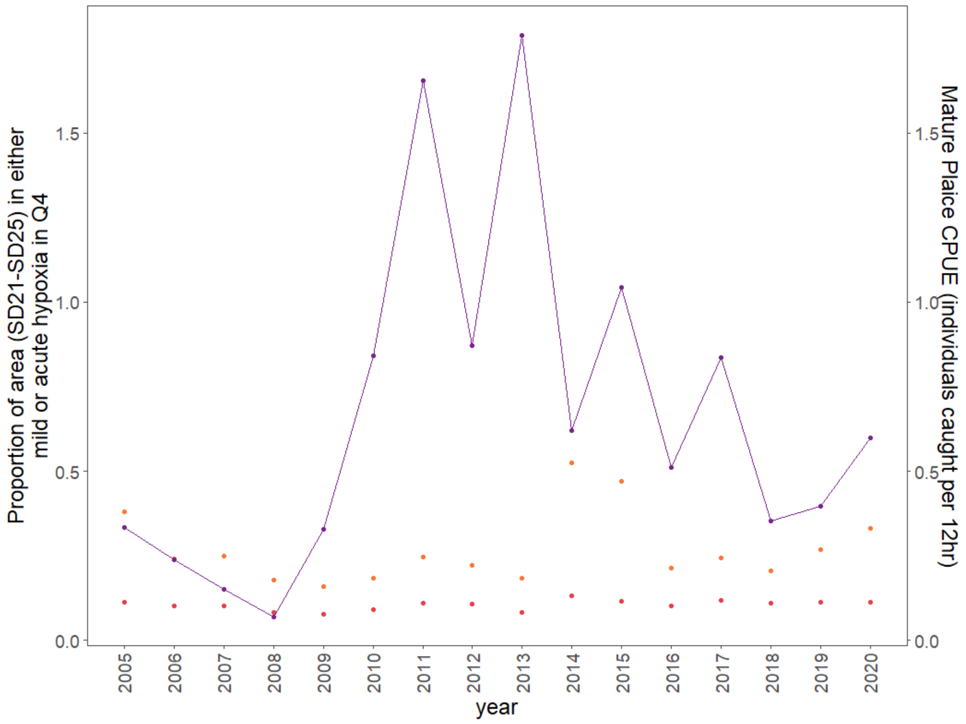

Figure 20. Hypoxia indices as proportion of study area at or below moderate (4 mL.L-1 oxygen; orange circles) or acute (2 mL.L-1 oxygen; red circles) hypoxia in bottom waters in quarter four. Overlain is the coastal catch index for plaice, as a standardised catch per unit effort from gill nets across the study area averaged for quarter 4.

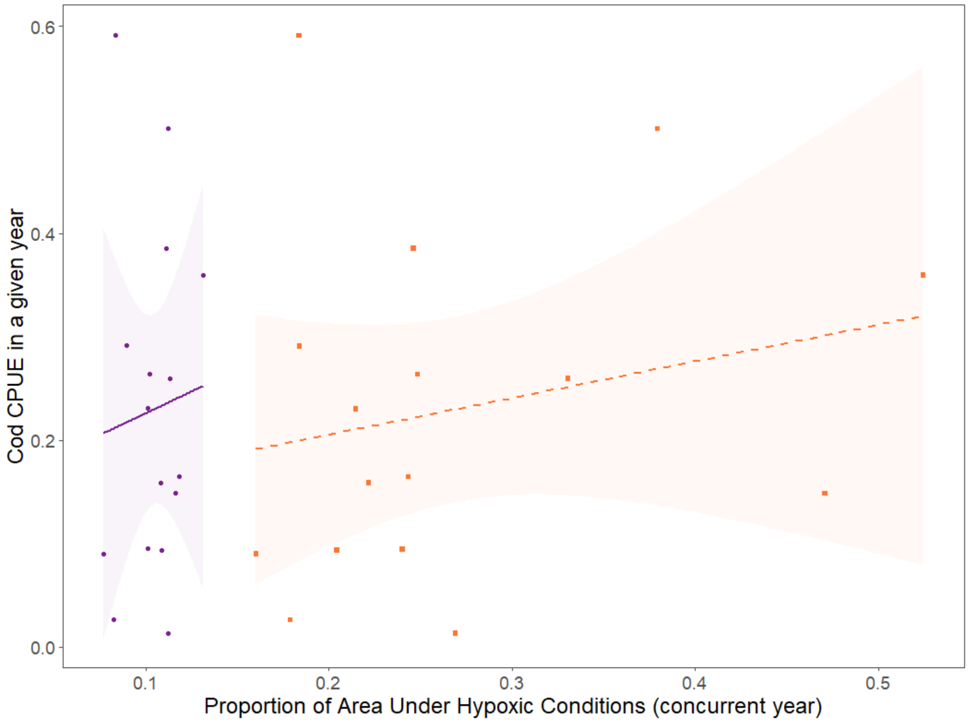

Figure 21. Cod coastal catch rates in response to two different hypoxia indicators, the proportion of the study area at or below moderate (4 mL.L-1 oxygen; orange) or acute (2 mL.L-1 oxygen; purple) hypoxia in bottom waters in quarter four. The trend lines are basing linear regressions and are for visualisation purposes only. For appropriate models and statistical tests see Table 2.

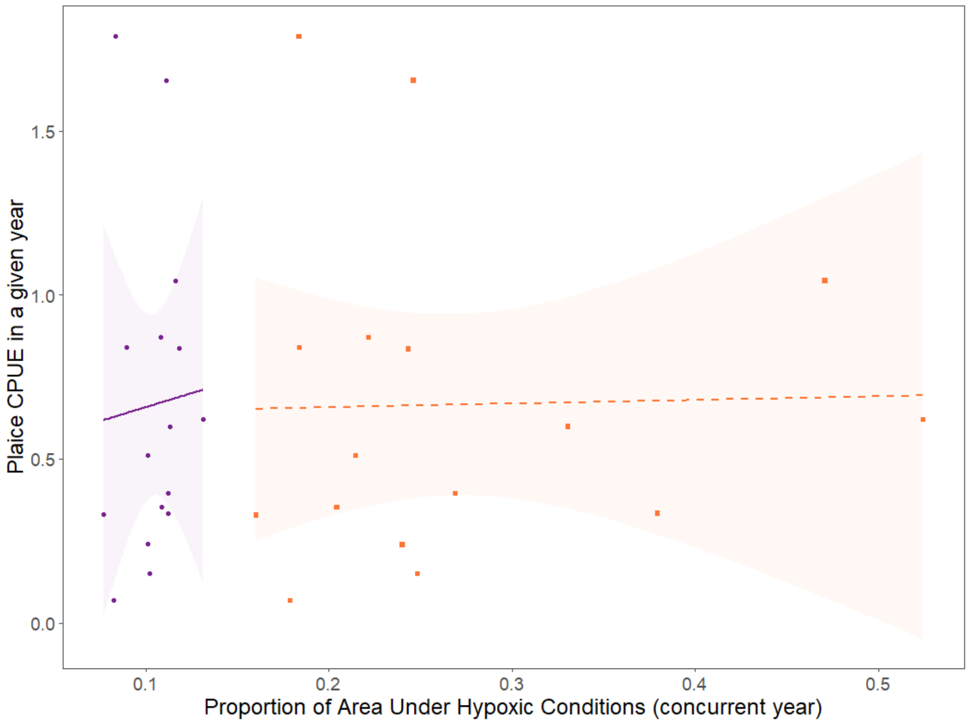

Figure 22. Plaice coastal catch rates in response to two different hypoxia indicators, the proportion of the study area at or below moderate (4 mL.L-1 oxygen; orange) or acute (2 mL.L-1 oxygen; purple) hypoxia in bottom waters in quarter four. The trend lines are basing linear regressions and are for visualisation purposes only. For appropriate models and statistical tests see Table 2.

Table 2. Significance tests on linear regressions of coastal catch indicators against hypoxia and stock size indicators.

Species	Oxygen Indicator	Stock Size Indicator	F-statistic	p-value
Cod	Acute	Relative Biomass	0.159	0.855
Cod	Moderate	Relative Biomass	0.417	0.668
Plaice	Acute	SSB estimate	0.019	0.982
Plaice	Moderate	SSB estimate	0.004	0.996

When investigating potential inter-annual lag effects of hypoxia on coastal catch rates, our visualisations show no significant relationship between lagged, quarter four hypoxia indices and coastal catch rates of either species (Figures 23 – 26). Furthermore, we found no significant improvement in predictive ability of models including any lagged form of hypoxia indices (Table 3).

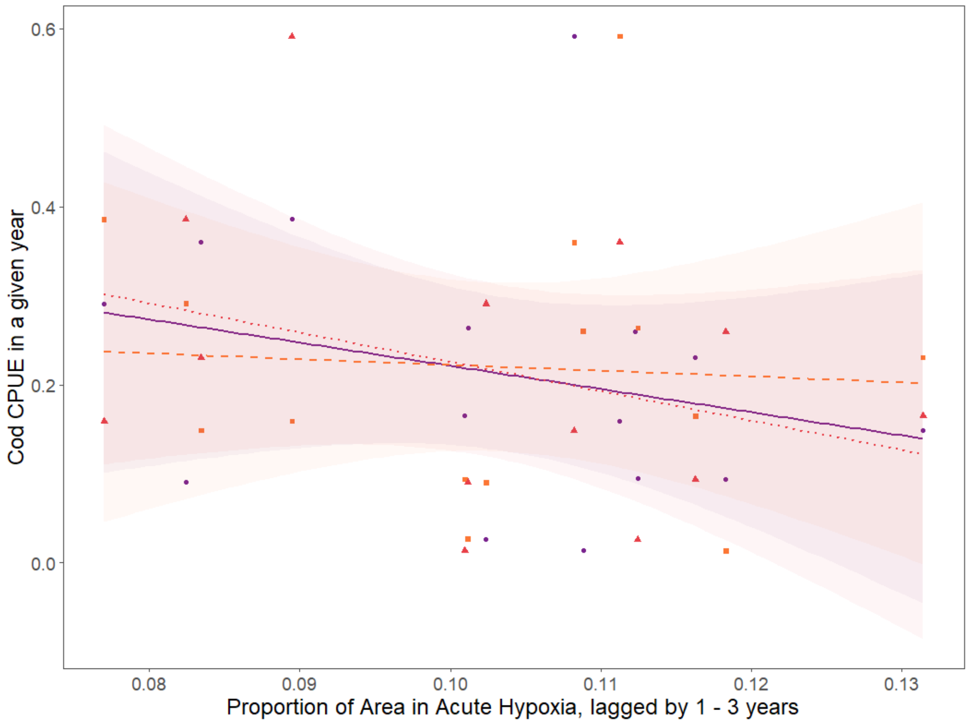

Figure 23. Cod coastal catch rates in response to acute hypoxia extent across the study area. Points represent the data while lines are linear regressions and ribbons are standard errors. Purple is for the hypoxia indices lagged by one year, orange is two years and red is three years.

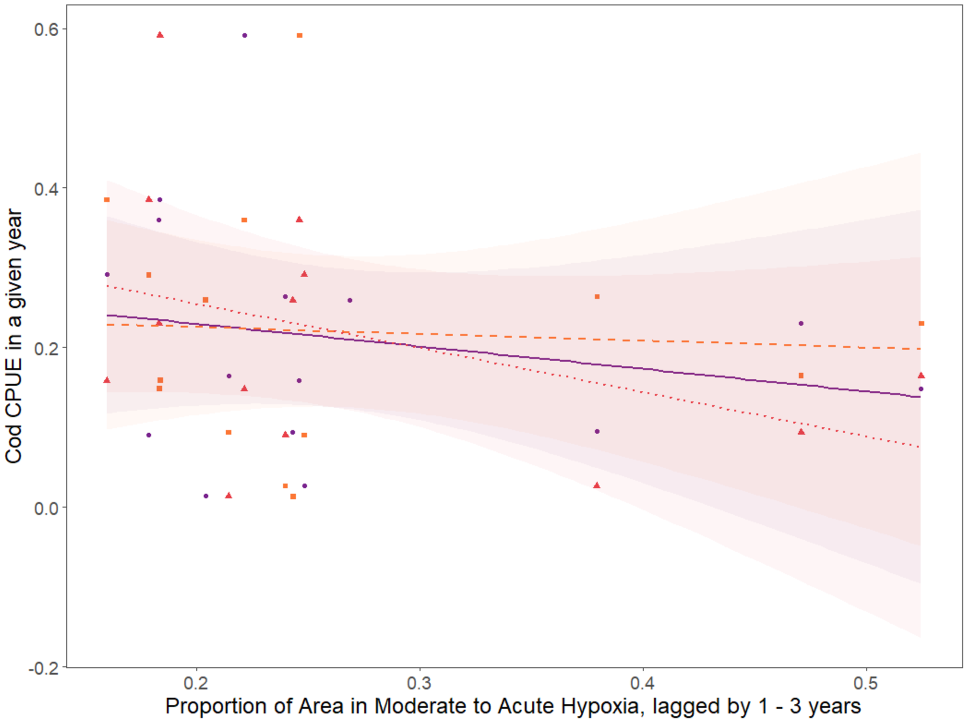

Figure 24. Cod coastal catch rates in response to moderate or acute hypoxia extent across the study area. Points represent the data while lines are linear regressions and ribbons are standard errors. Purple is for the hypoxia indices lagged by one year, orange is two years and red is three years.

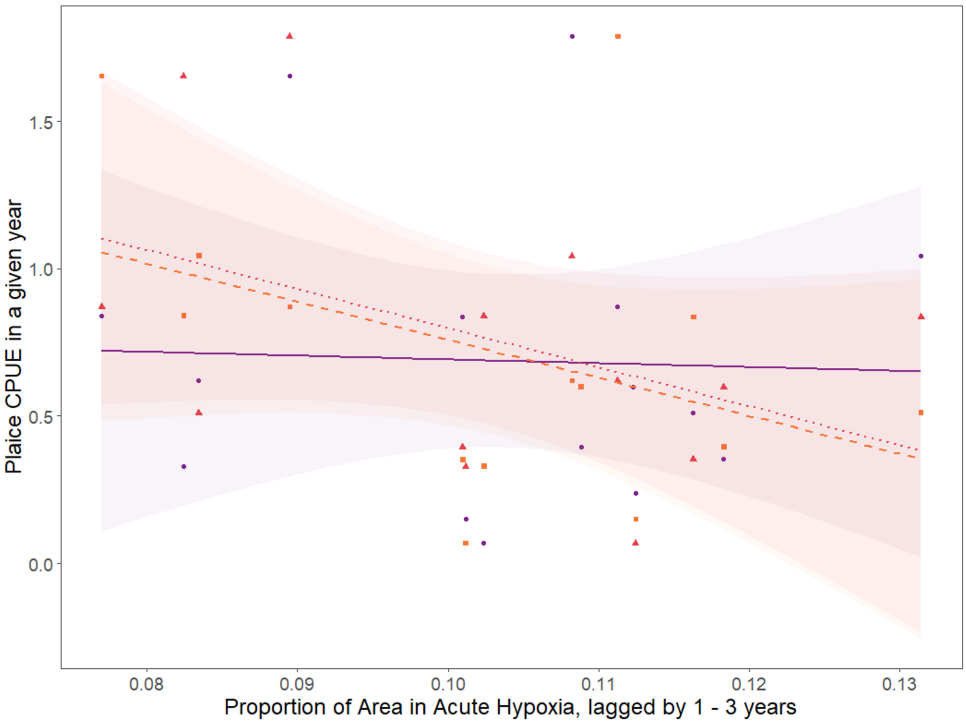

Figure 25. Plaice coastal catch rates in response to acute hypoxia extent across the study area. Points represent the data while lines are linear regressions and ribbons are standard errors. Purple is for the hypoxia indices lagged by one year, orange is two years and red is three years.

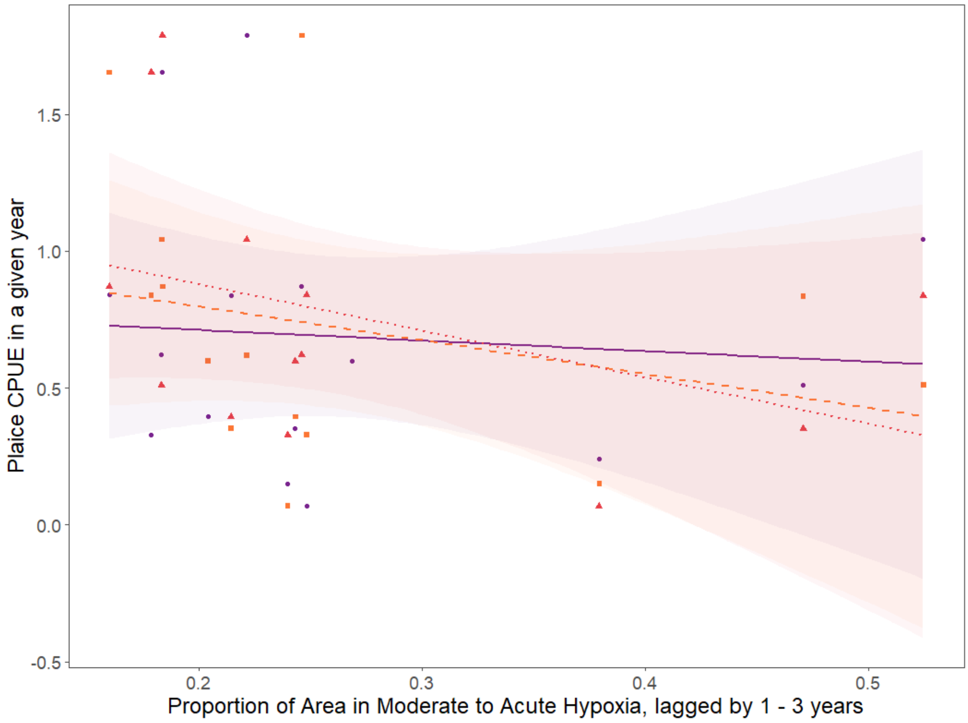

Figure 26. Plaice coastal catch rates in response to moderate or acute hypoxia extent across the study area. Points represent the data while lines are linear regressions and ribbons are standard errors. Purple is for the hypoxia indices lagged by one year, orange is two years and red is three years.

Table 3. Results of a series of Granger correlation tests investigating if lagged hypoxia indices (previous years' quarter four hypoxia index explaining given years' coastal fish catch rates) better predicted cod and plaice coastal catch rates than catch rates with the same lag, alone. In no circumstances were models with lagged hypoxia indices better at predicting coastal fish catch rates.

Species	Oxygen Indicator	Lag (years)	F-statistic	P-value
Cod	Acute	1	0.856	0.373
Cod	Acute	2	0.577	0.581
Cod	Acute	3	0.423	0.744
Cod	Moderate	1	0.561	0.468
Cod	Moderate	2	0.391	0.687
Cod	Moderate	3	0.723	0.574
Plaice	Acute	1	0.048	0.830
Plaice	Acute	2	2.449	0.142
Plaice	Acute	3	0.904	0.492
Plaice	Moderate	1	0.048	0.826
Plaice	Moderate	2	4.899	0.086
Plaice	Moderate	3	2.713	0.438

3.2.5 Conclusions

We detected no significant effect of hypoxia extent on the catch rates of cod and plaice in coastal fish monitoring catch rates; from neither within year comparisons, nor inter-annual lagged effects of hypoxia.

While non-significant, the increases in coastal catch rates with the extent of hypoxia (Figures Figure 21Figure 22) correspond to the results found in section 2. Cod catch rates in the bottom waters of areas where the offshore surveys are undertaken decreased in both moderate and severe hypoxia, while plaice catch rates only declined under severe hypoxia. The converse is true in our observations of coastal catches. This suggests that perhaps our sampling and aggregation are too course, or our sample size is too small, to detect an underlying trend.

To investigate this further, future work should develop the use of modelled indices for coastal catches, in-place of the standardised CPUE we utilised here. This would account for structural changes in the data, such as changes in sampling teams/locations that inevitably happen over years. Furthermore, the development of such modelled indices would facilitate year-round estimations, if there are enough data. Such year-round indices would provide a more temporally resolved data set, which could account for seasonal movements and help to isolate the effects of hypoxia, with variable extent throughout the year.

The use of broad scale indices of extent masks local conditions. In the Little Belt, in particular, this is of importance, where local shallow-water hypoxia and "marine heatwaves" may prevent fish from escaping deep hypoxic water to shallow waters. Utilising more location specific data would account for this dampening effect, however, current models do not predict coastal hypoxia very well and oxygen data are not collected at the same time as the coastal fish sampling.

3.3 Small Scale Fishers' Experiences

Initial plans to run a series of interviews around the country were thwarted by Covid-19 pandemic lock downs and the general inexperience of interviewers and interviewees with utilising online meeting platforms made this an unsuitable alternative. In place of these interviews, a few questions were added to a standard commercial fisher telephone survey run by DTU Aqua. These interviews were undertaken in Danish in the first half of 2021 and were only posed to fishers targeting cod or plaice. The questions were posed as follows:

1) Do you take the locations of hypoxia into consideration when you fish?
    a) If yes, what considerations do you make with regard to hypoxia?
        i) Possible Prompts for examples: Time of year, specific local area characteristics, avoiding specific areas where hypoxia is frequent and common knowledge, specific features you avoid or are attracted to during hypoxic events.
    b) If yes, how do you get information about the location and timing of hypoxic waters?
2) In 2019, there was widespread hypoxia in the area (southwest Baltic Sea). Has this had an impact on your fishery?
    a) If yes, what impact did this have?
        i) Possible prompts for examples: Fished in other areas, reduced effort over the period of hypoxia, lower catches, or lower income for the year.
    b) If yes, have you noticed any changes in the characteristics or features of the fish relative to earlier or later years?

Of the 71 relevant fishers that were interviewed, 29 (41%) responded that they take hypoxia into consideration when fishing. Of these 29 fishers who consider hypoxia, two thirds responded that their fishery was impacted by hypoxia, generally (Table 4). However, just under half reported that hypoxia had an impact on their fishery specifically in 2019; the difference in responses on impact between these two questions is driven by some respondents noting that while hypoxia does have an effect, it was no more noticeable to them in 2019, than in any other year.

Table 4. Numbers of respondents responding to various questions via a telephone survey of relevant fishers. Numbers show only those respondents who consider hypoxia in their fishing practices.

Area Fished	Fishers who took note of hypoxia	Fishers whose fishery was impacted by hypoxia	Did hypoxia have an impact in 2019	
			Yes	No
Isefjorden (SD 21)	4	3	0	4
Øresund (SD 23)	3	2	1	2
Baltic Sea (SD 22)	16	14	11	3
Baltic Sea (SD 24)	6	0	0	6
Totals	29	19	12	15

In response to hypoxia, 79% (15) of fishers whose fishery was impacted (19), moved their gear from originally planned or desired positions. The majority of those who moved gear, moved closer to the shore, into shallower waters, while two respondents tried to position their gear at the edges of hypoxic pockets of water, and one moved their gear to deeper water.

Most fishers learned about hypoxia in their area via first or second hand experience, predominantly hearing about locations from colleagues and friends. The methods given by fishers for the detection of hypoxia in a fishing area were:

1) Dead fish in nets (especially if the dead fish are eel, flounder or gobies).
2) White coatings on the gear's netting components.
3) White spots visible on the seafloor.
4) The smell (hydrogen sulphide).
5) Simply if there are no fish, where fish are expected (including non-target species).

Of the 22 fishers in the Baltic Sea (SDs 22 & 24), 64% (14) noted that their fishing is impacted by hypoxia while only 50% (11) noted a specific impact in 2019. All of those fishers that noted the effects of hypoxia in the Baltic were from SD22, and the percentages of fisher impacted by hypoxia generally and specifically in 2019, rises to 88% and 69%, respectively, when considering only those fishing in SD22 (16). Of those fishers in SD22 whose fishing was impacted by hypoxia in 2019, all 11 noted that there were fewer fish in catches, apparently referring to target species. A few fishers mentioned catching fewer species, or that those fish caught were hauled in dead. One fisher described how fish were absent over the whole summer and only returned in late autumn, while another experienced very thin fish, and another noted that in the years since 2019 (2019 -> Q1, 2021) there remained very few fish.

The reasons given for none of the interviewed fishers from SD24 being impacted by hypoxia, where the shallow depths and close proximity to shore, and the current strength causing mixing in the areas they fish.

The fishers interviewed from SD21, fished out of Isefjord, and thus their experience isn't necessarily representative of fishers across SD21. However, 75% (3/4) of them note that hypoxia impacts upon their fishing, while none of the respondents identified 2019 as a particularly bad year.

Overall, the fishers' experiences from SD22 matched the preliminary results and perceptions coming from operators of the commercial fish surveys and ICES' Baltic Fisheries Assessment Working Group (WGBFAS), while the experiences from other relevant subdivisions did not corroborate these perceptions. This indicates that fishers in the very western part of the Baltic appear more impacted by, or more conscious of hypoxia.

3.4 Improving Small Scale Fleet Effort Detection

3.4.1 Introduction

In lieu of comprehensive interviews of coastal fishers, which were planned but prohibited from being undertaken in a timely manner due to Covid-19 lockdowns, we reallocated effort from asking fishers about their fishing behaviour, to trying to measure it more objectively.

For small fishing vessels (<15m length) without Vessel Monitoring Systems (VMS) installed, attributing effort in space was, until the late 2000s, limited to port or management area from logbooks. With broader adoption of Automatic Identification Systems to aid in navigation and improve safety, and localised regulation to impose position tracking equipment on small vessels (James, 2016) it became possible to link fishing vessel log-books with AIS based position, heading and speed data, in a more representative way. Until HypCatch, AIS position data in Denmark, was utilised by simply applying speed filters for vessels known to utilise specific gears, as there are gear specific speeds that can be associated with setting and retrieving gears. This allowed some broad-scale allocation of effort in space, such that vessels travelling within a specified range of speeds would have that section of the trip marked as a fishing activity (Eastwood, Mills, Aldridge, Houghton, & Rogers, 2007). However, simple speed filters will incorrectly allocate fishing to slow steaming or other activities, and perhaps not attribute fishing if a vessel is setting or retrieving gears in situations outside of the assumed range of speeds (e.g. when working within a strong current) (Deng et al., 2005). Work in other contexts showed that fitting statistical models to the position and movement data, available from sources such as AIS, could improve the identification of fishing activities from small-scale fishers (Mendo, Smout, Photopoulou, & James, 2019).
Therefore, the aim of this section is to improve the identification of fishing activity, distinct from steaming or drifting/processing, from AIS tracks of gill net fishing vessels, from the ICES subdivisions 22 and 23, through the application of a simple machine learning approach.

3.4.2 Methods

Data

Electronic Monitoring data (EM) from various projects run through DTU Aqua were used to inform and validate methods to identify fishing activities. These data include regular information on position and speed, as well as observations of fishing activities made and identified from simultaneous video recordings (ICES, 2022b). These time-stamped fishing activities were used as the ground truth for when a vessel was or was not fishing.

The EM data provided a temporal resolution of 0.1Hz, which was subsequently down-sampled to 0.0167Hz (from one data point per ten seconds, to one datapoint per minute). The setting and retrieving of gear was identified as “fishing”, from the video recordings. The full database of EM data was subset to include only gill net fishers, with clearly defined trips, and only trips that included at least one fishing event. This resulted in 3289 fishing trips, shared among fourteen vessels (Figure 27).

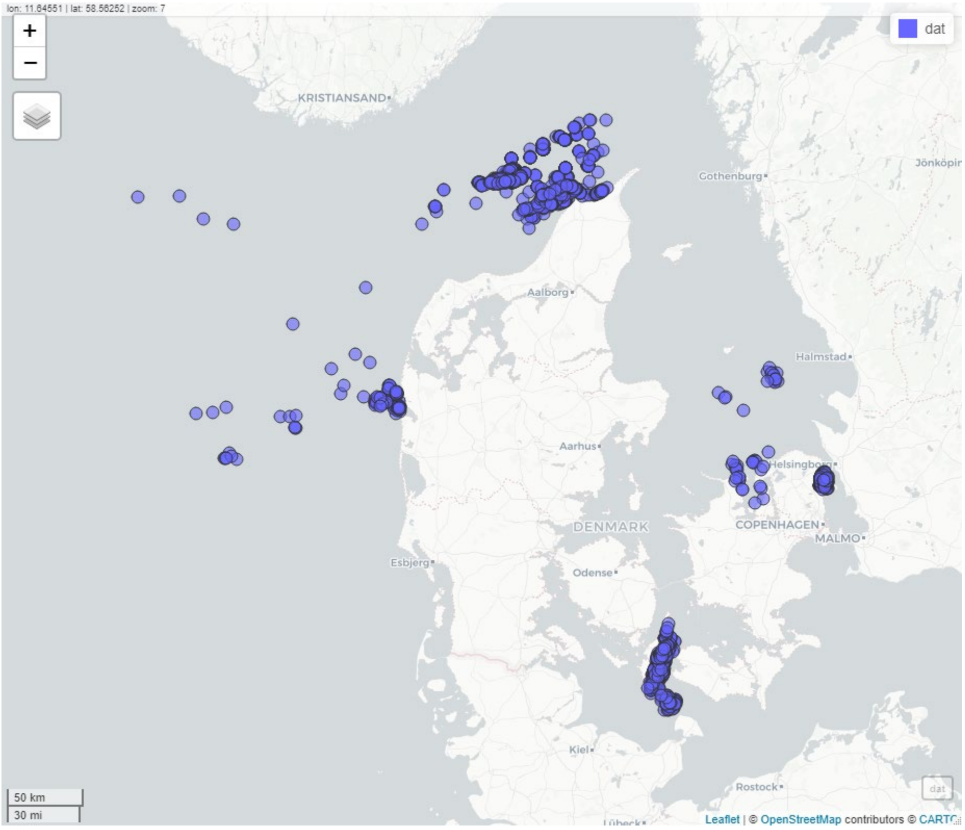

Figure 27. Electronic monitoring data from Denmark showing instances of fishing, in the period 2016-2020, including only gill net fishing vessels, where trips were well defined, and at least one instance of fishing was undertaken.

Baseline method

The baseline method is based on a pure speed filter, which was and remains the current method, at DTU Aqua, for attributing effort in space to small fishing vessel activities. For the gill net fishing vessels in this study, the speed filter considers vessels moving between two to four knots over ground as setting or retrieving gears. A mask is applied to areas in and immediately surrounding ports, to prevent the incorrect attribution of fishing when vessels are manoeuvring into and out of port. This results in tracks that consist of the individual point locations of the vessel over one trip. The trip is defined by a departure from and return to known ports. The individual points have the attributes of the vessel, trip, position and speed. The trip is then allocated into sections of fishing and not fishing, each section containing multiple points, based on the speed attribute of the points. All calculations and attributions were made using the statistical programming language *R* (R Core Team, 2021).

Random forest method

Random forest models were also built in *R* using the package *ranger* (Wright & Ziegler, 2017). Prior to running the models, a series of derived attributes were calculated for the individual points, in addition to those variables that are directly reported as part of the monitoring (i.e. longitude, latitude, speed, course). These included:

- change in absolute heading,
- heading based on change in position (as opposed to reported course),
- acceleration (magnitude not vector),
- a series of distances from the points' nearest nine neighbours,
- moving averages (means) of speed for the last three, four and five points,
- binary value based on being within or outside of the speed filter used in the baseline method.
- Speed relative to trip speed:

$$\frac{point\ speed}{\left({}^{maximum\ trip\ speed}\big/_{mean\ trip\ speed}\right)}$$

Five model specifications were used, based on the inclusion of different explanatory variables (Table 5). The best model selected from these five was then re-fit with a subset of the EM data, including only those vessels operating in the inner Danish waters (ICES subdivisions 21-24). No interaction terms are included in the model specification as the random forest approach utilised considers interactions inherently, in the many-tree nature of the final model. Furthermore, this approach is robust to correlation between explanatory variables.

The model predictions are subsequently processed, to deal with known sources of error. In cases where a non-fishing point is predicted between two (or more) fishing points, the non-fishing point is converted to fishing. This is action was taken because it was observed that these models consistently underestimate fishing activities, and this resulted in points clearly located within a fishing activity being predicted as non-fishing.

Table 5. Explanatory variables used in the construction of the various model fits (M_1 -> 7). The first four variables are reported as part of the data collection, while the remainder are derived from the data.

VARIABLE	M_1	M_2	M_3	M_4	M_5	M_6	M_7
LONGITUDE	X	X	X	X	X	X	X
LATITUDE	X	X	X	X	X	X	X
SPEED	X	X	X	X	X	X	X
COURSE	X	X	X	X	X	X	X
CHANGE IN ABSOLUTE HEADING	X	X	X	X	X	X	X
POSITION BASED HEADING	X	X	X	X	X	X	X
MAGNITUDE OF ACCELERATION	X	X	X	X	X	X	X
NEAREST NEIGHBOUR DISTANCES	X	X	X	X	X	X	X
TRIP IDENTIFIER		X				X	X
3 POINT MOVING AVERAGE, SPEED					X	X	X
4 POINT MOVING AVERAGE, SPEED					X	X	X
5 POINT MOVING AVERAGE, SPEED			X		X	X	X
INSIDE/OUTSIDE SPEED FILTER				X			
SPEED RELATIVE TO TRIP SPEEDS							X

Validation

To select between models, and to compare the models' performance to that of the baseline approach, we compared the predicted fishing/non-fishing state with the observed fishing/non-fishing state from the data extracted from videos taken as part of the EM. To ensure that the model approach would be suitable in situations where it is predicting fishing activities from novel position data, we utilised a k-fold cross validation approach, with a k equal to five. This means that the data are randomly split into five groups with roughly equal numbers of fishing trips in each. The selected model is then re-fit using only four out of the five groups' data. This re-fit model is then used to predict the fishing activities in the fifth group, of which it is now considered naïve. This combination of re-fitting and predicting is repeated five times, such that all of the original trips have had their fishing activities predicted by a re-fit model that was not explicitly fit using the data from that trip. The same five groups are used in the validation across all models.

The inaccuracy of the predictions is measured as the percentage of points that are incorrectly allocated to either fishing or non-fishing. The percentage of points are reported in different ways, including:

- The mean percentage across the five "folds" of cross validation (overall average error).
- The percentage of points in error across all trips (mean trip error and median trip error).
- The minimum and maximum percentage of errors per trip (min trip error and max trip error).
- The number of trips containing fewer than 10% of points that are incorrectly allocated (trips < 10% error).

Visualisation

The maps showing data, trips, observed fishing and predicted fishing were constructed in R using the packages *ggplot2* (Wickham, 2016), *sf* (Pebesma, 2018) with background data from *OpenStreetMap* (openstreetmap.org/copyright).

3.4.3 Results

We found that including many derived variables that represent different aspects of vessel behaviour improved the model predictive ability (Table 6). Iteratively, through the inclusion of an identifier for each trip, moving averages of speed over the last three, four and five points, and a speed relative to trip speeds, we saw decreases in the error rates across all measures of error. The only derived variable that did not improve the models' predictive capacity was the inclusion of the speed filter that is utilised in the baseline approach to categorise, *a priori*, fishing or non-fishing state.

Table 6. Percentage of track points incorrectly allocated to either fishing or not fishing in the EM data when using the baseline speed filter method compared to five-fold cross-validation predictions of the various random forest models.

METHOD	OVERALL MEAN ERROR %	MEAN TRIP ERROR %	MEDIAN TRIP ERROR %	MIN TRIP ERROR %	MAX TRIP ERROR %	TRIPS < 10 % ERROR
BASELINE	34.6	36.1	35.2	1.6	82.1	2.2
M_1	16.9	18.2	17	1.6	75.5	11
M_2	13.2	13.8	12.8	0	52.6	32
M_3	15.2	16.6	15.3	2.9	72.5	19
M_4	15.1	16.6	15.2	1.6	77.5	19.6
M_5	15	16.3	15	2.5	74.5	20.3
M_6	11.9	12.3	11.4	0	50	40.1
M_7	11.7	12.1	11.3	0	48.7	42.1

By applying a post-prediction processing to the model cross-validation predictions, we saw improvement across all models but no change in which models performed better or worse relative to one another (Table 7).

Table 7. Percentage of track points incorrectly allocated to either fishing or not fishing in the EM data when using the five-fold cross-validation predictions of the various random forest models and applying a post-prediction processing routine.

METHOD	OVERALL MEAN ERROR %	MEAN TRIP ERROR %	MEDIAN TRIP ERROR %	MIN TRIP ERROR %	MAX TRIP ERROR %	TRIPS < 10 % ERROR
M_1	16.6	17.7	16.5	0	75.5	13.1
M_2	12.8	13.3	12.3	0	52.6	34.5
M_3	14.7	16.1	14.8	2.2	72.6	21.5
M_4	14.8	16.1	14.8	0	77.5	22.2
M_5	14.5	15.8	14.5	1.6	74.5	23
M_6	11.5	12	11	0	50	43.4
M_7	11.3	11.8	10.9	0	49.6	44.9

The best performing model overall was M_7, with post processing of clearly erroneous individual points. This model utilises all of the explanatory variables except for the speed filter used in the baseline approach. The inclusion of the speed relative to trip speed, in model M_7, made it marginally better performing than M_6, where this derived variable was not included in the model fit, or predictions. The performance of M_7 relative to other models was unaltered by the post-processing of model predictions.

Irrespective of whether the post-processing step was carried out, all models out performed the baseline approach. The worst performing model (M_1, without post-processing) had approximately 18 percentage points lower mean and median error rates than the baseline approach. The best performing model (M_7, with post-processing) outperformed the baseline method in predicting fishing by ~24 percentage points across mean and median error rates. These relative comparisons were consistent for the percentage of trips with fewer that 10% of points allocated incorrectly, where the best model had 45% of trips with low errors, which was 43 percentage points greater than that of the baseline approach.

3.4.4 Discussion

We have documented a method to improve the allocation of small-scale, gill net fishers' fishing effort in space and time, in Danish waters. Independent of the combination of explanatory variables we employed in our models, the random forest modelling approach greatly reduced errors in detecting fishing activities compared to the baseline method.

Our random forest models depart from the standard modelling approaches documented so far in primary literature. Here hidden Markov models based on Bayesian statistics are more commonly employed to "track" vessels in a similar approach to how these tools are applied to track animals (Mendo et al., 2019). They assume some underlying, unobserved variable (fishing activity) that the observed variables are all derived from and consider changes in the state of this unobserved variable relative to time. These assumptions fit the circumstance of categorising fishing vessel activities well, however, when predictive accuracy is the primary focus, rather than understanding mechanisms, machine learning approaches have proven capable. Our random forest approach is a basic implementation of machine learning that can be used for categoriseation, but that requires an awkward use of variables to incorporate temporal shifts. Our use of the random forest approach increases the diversity of tools applicable to the challenge of locating fishing of small-scale fishers. The performatnce of these two methods should be directly compared in future work.

Before comparing these approaches, further tuning of our implementation of the random forest methods is required. Our models utilise many of the default settings for the training phase, which are offered as part of the R-package we employed. Further investigation into the statistical underpinning of these defaults, and potential changes to some settings may make the model fitting more appropriate to our data and situation, which should improve model predictive capacity.

The improved accuracy of allocating fishing effort will benefit studies using these effort data, or their corresponding catch data, to investigate changes in fisheries in response to fine scale or highly resolved environmental, or management changes. For example, these small-scale fisheries data may be paired with improved spatio-temporal resolution of hydrographic phenomena, such as hypoxia and marine heatwaves, to detect impacts upon fisher behaviour and resultant catches, or even to aid in detecting shifts in fish distribution. Furthermore, with the enforcement of more spatial management measures, such as marine protected areas with fishing restrictions or wind energy installations, understanding both the potential impacts on small-scale fishers before implementation, and the actual impacts post-implementation, should inform decisions on where various management measures are implemented. This work has fed into ongoing work among ICES partners and a preliminary version of this work was presented at WKSSFGEO in 2022.

It is therefore recommended that future studies investigating the methods for allocating small-scale fishers' efforts in space should fine tune the random forest model, such that all settings are set to an optimum, and compare predictive capability across modelling platforms. These platforms should not be limited to existing ones, and should consider newer, more complex versions of machine learning (*c.f.* random forest). Furthermore, these approaches should be expanded to cover all methods of fishing rather than only gill-netters.

3.4.5 Conclusion

The allocation of small scale gill net fishing effort based on high-resolution geographic position data should move away from simple speed filters and towards modelled estimations of fishing activity. The random forest model approach that we employed in a Danish context has proven to be a great improvement over the baseline speed filter. While improvements are imminent and alternate approaches exist to be compared against, we should not let perfection be the enemy of the good; that is to say this approach should be adopted, while it is being tuned and improved.

4. Mechanisms of Impact and Life-history Dependent Population Responses to Hypoxia

This work has been accepted for publication in a peer reviewed journal at the time of the publication of this report, thus the details of the work can be found in the open source article: "Champagnat, J., Brown, E. J., Rivot, E., & Le Pape, O. (submitted). Impact of hypoxia on essential fish habitats throughout the life cycle of exploited marine species. ICES Journal of Marine Science.

4.1 Background

In the first section of this report we document how accounting for hypoxia in stock indices has no significant effect on the outcome of stock assessments. However, the frequency and magnitude of hypoxia throughout the southwest Baltic Sea, coupled with the clear negative effect hypoxia has on cod and plaice abundance, begs the question: What are the population level consequences of hypoxia on these species? While no literature has linked hypoxia definitively to population level changes, the indirect effects of hypoxia reducing food availability have been described (e.g. Casini et al., 2016; Neuenfeldt et al., 2020; Teschner et al., 2010). The impact of the extent of hypoxia on egg and larval survival has been considered (Hinrichsen, Hüssy, & Huwer, 2011; Petereit, Hinrichsen, Franke, & Köster, 2014), however, the interaction was based on proportions of simulated egg releases in hydrodynamic models, and not linked to subsequent population development.

The work we document here was initiated by HypCatch, including hosting a PhD student from *L' Institute Agro* at DTU Aqua for one month. Subsequently, this evolved into a collaboration with partners in the Horizon 2020 project SEAwise (https://seawiseproject.org/). The main aim of this work was to simulate life-cycle models with separate spawning, egg and juvenile life-history phases, and to investigate how changes in survival at these different life-history stages due to exposure to hypoxia, ultimately effect population productivity. We hypothesised two scenarios based on spawner interactions with hypoxic waters in spawning grounds: 1. a higher mortality of eggs that are spawned in less favourable habitats and 2. a higher mortality of spawners trying to access regular spawning grounds (Figure 28).

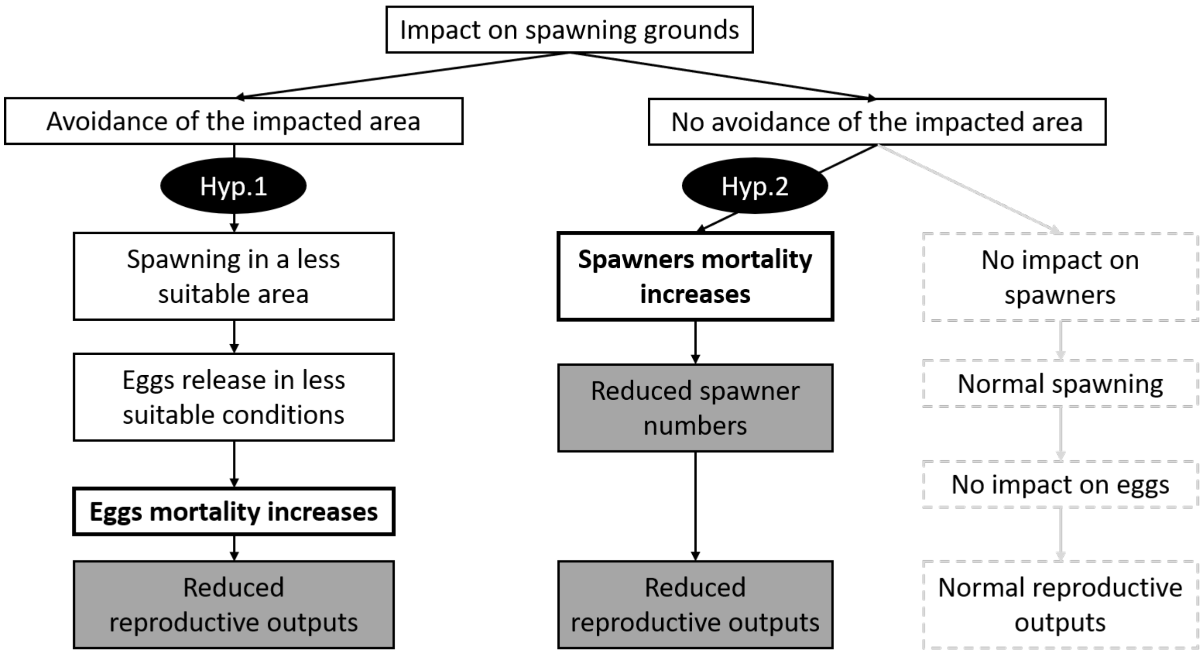

Figure 28. Diagram of the hypothetical consequences of impacts of hypoxia/anoxia on spawning grounds taken from (Champagnat, Brown, Rivot, & Le Pape, n.d.). Black and solid line emphasize the two hypothesised mechanisms of action. Bold text indicates the model parameters modified by the scenario. Grey shaded shapes highlight the consequences at the population scale. Shapes outlined in grey dashed lines display less likely mechanisms of action, with unclear consequences, not investigated in this study. Figure taken from (Champagnat, Brown, et al., n.d.).

4.2 Methods

The potential impact of hypoxia in spawning habitats on population dynamics and productivity was assessed with a deterministic life cycle model, structured by stage and age (Champagnat, Rivot, & Le Pape, n.d.). This model considers a single closed population with unique but distinct spawning and juvenile habitat areas, linked by a defined egg and larval stage. The model was parameterised for three species, namely, European plaice, Atlantic cod and Atlantic herring. The population and life-history parameters necessary for the model were predominantly taken from *FishLife* (Thorson, 2020), but in the few circumstances these weren't available, they were retrieved from the most appropriate primary literature found.

4.3 Results

The three species responded in differing degrees to the two hypothesised mechanisms of the impact of spawning ground hypoxia. Generally, hypoxia impacting upon eggs (hypothesis 1) brought about the smallest changes in three stock productivity metrics, namely catch at MSY, fishing pressure to achieve MSY, and the SSB at MSY (Figure 29). Where spawners themselves experienced increased mortality due to inflexibility in selecting appropriate spawning areas (hypothesis 2), we found the largest effects on stock productivity. A third scenario, investigating the impact upon coastal juveniles, while out of scope for the current report, was found to result in intermediate effects on population productivity.

The magnitudes of the positive effects of restoration on spawners were all greater than the negative effects of habitat degradation for each species.

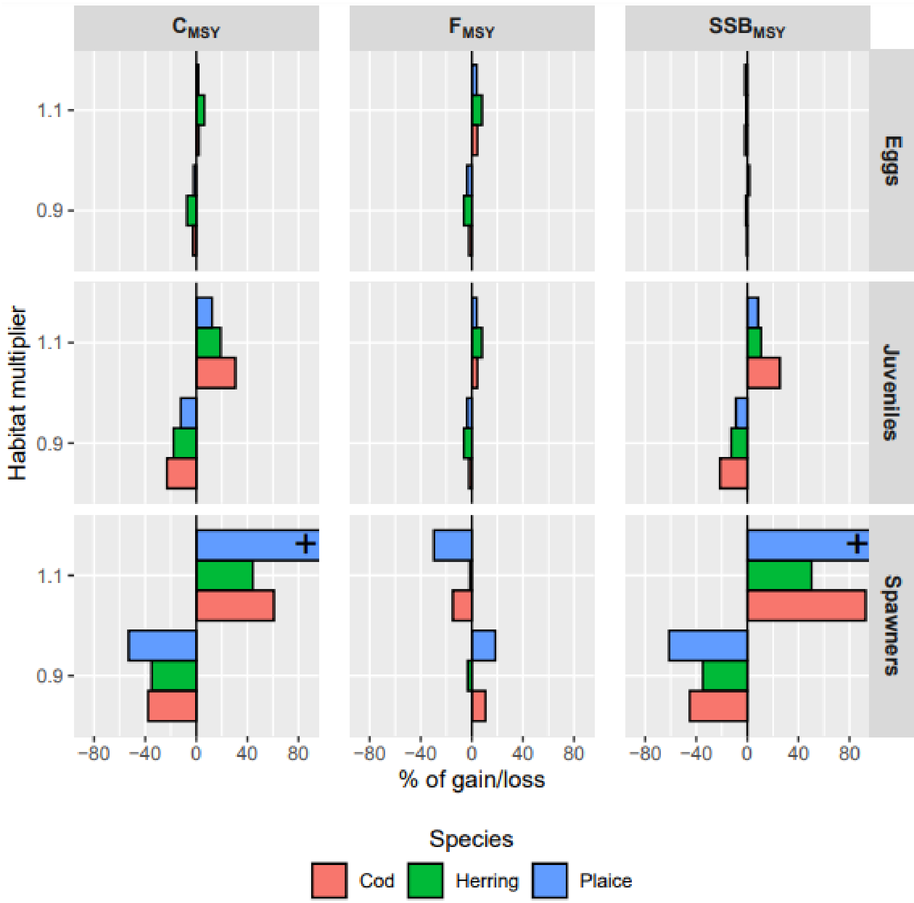

Figure 29. Marginal effects of the three habitat scenarios (rows) on the value of C_MSY (left column), F_MSY (middle column), and SSB_MSY (right column) for the three-example species (European plaice: Blue, Atlantic cod: Green, and Atlantic herring: Orange) under situations of habitat degradation (Habitat multiplier = 0.9) and restoration (habitat multiplier = 1.1). The stars indicate out of the graph high values obtained for plaice in spawners scenario (140% for left panel, 246% for the right one). Figure taken from (Champagnat, Brown, et al., n.d.).

4.4 Conclusions

Different species exposed to the same stressors at the same life-history stages will respond to lesser or greater extents, due to their life-history traits. Plaice, being long lived and maturing relatively young, have a larger life-time exposure to hypoxic spawning grounds under our second hypothesis, that spawners do not change spawning habitat to avoid hypoxic waters.

Because of the large mortality associated with metamorphosis and the shift from egg/larval habitats to new juvenile habitats, increased mortality on eggs that are spawned in unfavourable habitats (hypothesis one) has the lowest impact on stock productivity across all mechanisms of action. However, this effect of mortality on eggs, is largest for Herring, whose recruitment is more tightly coupled to reproductive output.

Not shown here, but analysed was the impact of combined exposure to hypoxia in juvenile habitats, together with either eggs being spawned in lower quality areas (hypothesis one) or adults not avoiding hypoxia during spawning (hypothesis two). These cumulative effects were not additive, but they did not differ greatly from the summed individual effects.

Interestingly, reducing the impact of hypoxia (i.e. habitat restoration) had a larger impact on population productivity for all three species, than did degradation. This shows that the scope for benefit is large for the reduction of impacts across all three life-history stages examined here.

5. Dissemination and Impact

A major focus for HypCatch was to ensure that the approach was accepted by scientific advisory groups and the results shared in a manner that increased the likelihood that the methods be adopted into advisory processes. The plan for achieving this was repeated interaction with the relevant ICES advisory group, the Baltic Fisheries Assessment Working Group (WGBFAS) during the project lifetime, as well as ad-hoc presentation and participation in other relevant working groups or workshops, to share our approach and findings.

As the main conclusion from the section on operationalising oxygen mediated stock indices was that accounting for oxygen in stock indices had a negligible impact on the indices and the assessment overall, we did not advocate for a change in the methods for the assessment of the two stocks under study. Below we document both the process of engaging with the assessment working group and the broader dissemination to other scientific groups.

5.1 Dissemination to Advisory Groups

The primary focus for dissemination to advisory groups was the ICES WGBFAS, due to the two stocks of interest. In May of 2021, the project plan was presented to WGBFAS in plenary and feedback was received from the meeting participants on our proposed approaches. The presentation was given by Elliot John Brown, while Marie Storr-Paulsen and Casper Berg were present and contributed both broader context and more details for the group during discussion. There was general agreement that the approach of accounting for oxygen variation in survey indices was appropriate and relevant to the problems that the group had observed the year before in the indices for plaice and cod.

In April of 2022, the working group's agenda was overbooked and therefore, due to our conclusion to not propose any changes, only an informal presentation of the results from chapter 2 was made to working group members with specific interest in the western Baltic cod and plaice stocks, which we addressed.

5.2 Dissemination to Scientific Groups

In October of 2021, the methods, approaches and results of chapter 2 were presented to the ICES Working Group on Improving use of Survey Data for Assessment and Advice (WGISDAA) by Casper Berg. This group was generally open to the approach but could not provide any further insights on alternate approaches for modifying the stock indices in accordance with oxygen levels. There was some discussion of the use of this approach in other contexts, with different environmental drivers than oxygen.

In November of 2021, the approach and findings of chapter 2 were presented and contrasted with both chapter 3 and other external projects to the ICES/HELCOM Workshop on Ecosystem Based Fisheries Advice for the Baltic (WKEBFAB) by Elliot Brown. The presentation used HypCatch as an example of preparing methods suitable for tactical advice, as opposed to strategic advice.

In November and December of 2021, HypCatch funded the chairing and further Danish participation in the ICES Workshop on Geo-Spatial Data for Small-Scale Fisheries (WKSSFGEO) where the data used in chapter 3.4 were presented and the proposed analytical approach was presented and discussed. Feedback from the group was very helpful in shaping the approach and a code sharing repository was subsequently established to aid in collaboration and improvement of methods for utilising small scale fishery data across Europe. Members of the group have since collaborated outside of the workshop to produce articles on various methods, complimentary to those described in chapter 3.4.

In June of 2022, an early approach and preliminary results from chapter 4 were presented to the ICES Working Group on the Value of Coastal Habitats for Exploited Species (WGVHES). This presentation was made by Juliette Champagnat, a PhD student who visited DTU Aqua in 2021 to initiate this work. Elliot Brown was present for further elaboration on the context of the study during the discussion. Feedback from the working group initiated further lines of enquiry and improved the overall work.

References

Bakka, H., Vanhatalo, J., Illian, J. B., Simpson, D., & Rue, H. (2019). Non-stationary Gaussian models with physical barriers. *Spatial Statistics*, *29*, 268–288. https://doi.org/10.1016/j.spasta.2019.01.002

Berg, C. W., Nielsen, A., & Kristensen, K. (2014). Evaluation of alternative age-based methods for estimating relative abundance from survey data in relation to assessment models. *Fisheries Research*, *151*, 91–99. https://doi.org/10.1016/j.fishres.2013.10.005

Bessell-Browne, P., Punt, A. E., Tuck, G. N., Day, J., Klaer, N., & Penney, A. (2022). The effects of implementing a 'dynamic B0' harvest control rule in Australia's Southern and Eastern Scalefish and Shark Fishery. *Fisheries Research*, *252*(November 2021), 106306. https://doi.org/10.1016/j.fishres.2022.106306

Brown, E. J., Kokkalis, A., & Støttrup, J. G. (2019). Juvenile fish habitat across the inner Danish waters: Habitat association models and habitat growth models for European plaice, flounder and common sole informed by a targeted survey. *Journal of Sea Research*, *155*, 101795. https://doi.org/10.1016/j.seares.2019.101795

Casini, M., Käll, F., Hansson, M., Plikshs, M., Baranova, T., Karlsson, O., … Hjelm, J. (2016). Hypoxic areas , density-dependence and food limitation drive the body condition of a heavily exploited marine fish predator Subject Category : Subject Areas : *Royal Society Open Science*, *3*(10), 160416. https://doi.org/10.1098/rsos.160416

Champagnat, J., Brown, E. J., Rivot, E., & Le Pape, O. (n.d.). Impact of hypoxia on essential fish habitats throughout the life cycle of exploited marine species. *ICES Journal of Marine Science*.

Champagnat, J., Rivot, E., & Le Pape, O. (n.d.). Response of marine fish population productivity to juvenile habitat modifications depends upon life histories. *Fish and Fisheries, Submitted*.

Deng, R., Dichmont, C., Milton, D., Haywood, M., Vance, D., Hall, N., & Die, D. (2005). Can vessel monitoring system data also be used to study trawling intensity and population depletion? The example of Australia's northern prawn fishery. *Canadian Journal of Fisheries and Aquatic Sciences*, *62*(3), 611–622. https://doi.org/10.1139/f04-219

Derhy, G., Macías, D., Elkalay, K., Khalil, K., & Rincón, M. M. (2022). Stochastic Modelling to Assess External Environmental Drivers of Atlantic Chub Mackerel Population Dynamics. *Sustainability (Switzerland)*, *14*(15), 1–19. https://doi.org/10.3390/su14159211

E.U. Copernicus Marine Service Information (CMEMS). (2023). *Baltic Sea Biogeochemistry Reanalysis*. https://doi.org/10.48670/moi-00012

Eastwood, P. D., Mills, C. M., Aldridge, J. N., Houghton, C. A., & Rogers, S. I. (2007). Human activities in UK offshore waters: An assessment of direct, physical pressure on the seabed. *ICES Journal of Marine Science*, *64*(3), 453–463. https://doi.org/10.1093/icesjms/fsm001

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*, *37*(3), 424. https://doi.org/10.2307/1912791

Hartig, F. (2018). DHARMa: Residual diagnostics for hierarchical (multi-level / mixed) regression models. CRAN.R-project. Retrieved from https://cran.r-project.org/web/packages/DHARMa/vignettes/DHARMa.html

HELCOM, Olsson, J., Naddafi, R., Brown, E. J., Lejk, A. M., Smoliński, S., & Bergström, L. (2018). *Status of coastal fish communities in the Baltic Sea during 2011-2016 - The third thematic assessment*. Helsinki, Finland. Retrieved from http://www.helcom.fi/Lists/Publications/Status-of-coastal-fish-2018-HELCOM-report.pdf

Hinrichsen, H.-H., Hüssy, K., & Huwer, B. (2011). *The impact of hydrodynamics and* *hydrography on western Baltic cod early life stage survival* (ICES CM). Copenhagen. Retrieved from http://orbit.dtu.dk/fedora/objects/orbit:39231/datastreams/file_6222565/content

ICES. (2017). *SISP 7 BITS Manual for the Baltic International Trawls Surveys*. Retrieved from http://doi.org/10.17895/ices.pub.2883

ICES. (2020). Baltic Fisheries Assessment Working Group (WGBFAS). ICES Scientific Reports., *2*(45), 653. https://doi.org/10.17895/ices.pub.6024

ICES. (2022a). *Plaice (Pleuronectes platessa) in subdivisions 24 – 32 (Baltic Sea , excluding the Sound and Belt Seas)*. https://doi.org/10.17895/ices.advice.19453550

ICES. (2022b). *Workshop on Geo-Spatial Data for Small-Scale Fisheries (WKSSFGEO)* (Vol. 4). https://doi.org/10.17895/ices.pub.10032

ICES. (2023). *Cod (Gadus morhua) in subdivisions 22 –24 , western Baltic stock (western Baltic Sea)*. https://doi.org/10.17895/ices.advice.21820494.v1

James, M. A. (Ed.). (2016). *fishPi - strengthening regional co-operation in fisheries data collection*. Marine Alliance for Science and Technology for Scotland (MASTS).

Kraufvelin, P., Pekcan-Hekim, Z., Bergström, U., Florin, A.-B., Lehikoinen, A., Mattila, J., … Olsson, J. (2018). Essential coastal habitats for fish in the Baltic Sea. *Estuarine, Coastal and Shelf Science*, *204*, 14–30. https://doi.org/10.1016/j.ecss.2018.02.014

Mendo, T., Smout, S., Photopoulou, T., & James, M. (2019). Identifying fishing grounds from vessel tracks: Model-based inference for small scale fisheries. *Royal Society Open Science*, *6*(10). https://doi.org/10.1098/rsos.191161

Neuenfeldt, S., Andersen, K. H., & Hinrichsen, H. H. (2009). Some Atlantic cod Gadus morhua in the Baltic Sea visit hypoxic water briefly but often. *Journal of Fish Biology*, *75*(1), 290–294. https://doi.org/10.1111/j.1095-8649.2009.02281.x

Neuenfeldt, S., Bartolino, V., Orio, A., Andersen, K. H., Andersen, N. G., Niiranen, S., … Casini, M. (2020). Feeding and growth of Atlantic cod (Gadus morhua L.) in the eastern Baltic Sea under environmental change. *ICES Journal of Marine Science*, *77*(2), 624–632. https://doi.org/10.1093/icesjms/fsz224

Olmos, M., Cao, J., Thorson, J. T., Punt, A. E., Monnahan, C. C., Alglave, B., & Szuwalski, C. (2023). A step towards the integration of spatial dynamics in population dynamics models: Eastern Bering Sea snow crab as a case study. *Ecological Modelling*, *485*(August). https://doi.org/10.1016/j.ecolmodel.2023.110484

Pebesma, E. (2018). Simple Features for R: Standardized Support for Spatial Vector Data. *The R Journal*, *10*(1), 439–446. https://doi.org/10.32614/RJ-2018-009

Pedersen, E. M., Schiønning, M. K., Kokkalis, A., van Deurs, M., Pedersen, M. I., Brown, E. J., … Støttrup, J. G. (2023). *Registrering af fangster med standardredskaber i de danske kystområder. Nøglefiskerapport 2020-2022. DTU Aqua Report nr. 428-2023*. Retrieved from https://www.researchgate.net/publication/374117647_Registrering_af_fangster_med_standardredskaber_i_de_danske_kystomrader_Noglefiskerrapport_for_2020-2022_Registration_of_catches_with_standard_gear_in_the_Danish_coastal_areas_Key_Fishery_Report_for_20

Petereit, C., Hinrichsen, H.-H., Franke, a., & Köster, F. W. (2014). Floating along buoyancy levels: Dispersal and survival of western Baltic fish eggs. *Progress in Oceanography*, *122*, 131–152. https://doi.org/10.1016/j.pocean.2014.01.001

Petersen, J. K., & Pihl, L. (1995). Responses to hypoxia of plaice, *Pleuronectes platessa*, and dab, *Limanda limanda*, in the south-east Kattegat: distribution and growth. *Environmental Biology of Fishes*, *43*(3), 311–321. https://doi.org/10.1007/BF00005864

R Core Team. (2021). R: A Language and Environment for Statistical Computing. Vienna, Austria. Retrieved from https://www.r-project.org/

Scott-Hayward, L. A. S., Mackenzie, M. L., Ashe, E., & Williams, R. (2015). Modelling Killer

Whale Feeding Behaviour Using a Spatially Adaptive Complex Region Spatial Smoother (CReSS) and Generalised Estimating Equations (GEEs). *Journal of Agricultural, Biological, and Environmental Statistics*, *20*(3), 305–322. https://doi.org/10.1007/s13253-015-0209-2

Scott-Hayward, L. A. S., Mackenzie, M. L., Donovan, C. R., Walker, C. G., & Ashe, E. (2014). Complex region spatial smoother (CReSS). *Journal of Computational and Graphical Statistics*, *23*(2), 340–360. https://doi.org/10.1080/10618600.2012.762920

Steffensen, J., Lomholt, J., & Johansen, K. (1982). Gill ventilation and O2 extraction during graded hypoxia in two ecologically distinct species of flatfish, the flounder (*Platichthys flesus*) and the plaice (*Pleuronectes platessa*). *Environmental Biology of Fishes*, *7*(2), 157–163. Retrieved from http://link.springer.com/article/10.1007/BF00001786

Støttrup, J. G., Kokkalis, A., Brown, E. J., Olsen, J., Kærulf Andersen, S., & Pedersen, E. M. (2018). Harvesting geo-spatial data on coastal fish assemblages through coordinated citizen science. *Fisheries Research*, *208*(October 2017), 86–96. https://doi.org/10.1016/j.fishres.2018.07.015

Støttrup, J. G., Kokkalis, A., Brown, E. J., Vastenhoud, B., Ferreira, S., Olsen, J., … Dinesen, G. E. (2019). *Essential Fish Habitats for commercially important marine species in the inner Danish waters Essential Fish Habitats for commercially important marine species in the inner Danish waters*.

Teschner, E. C., Kraus, G., Neuenfeldt, S., Voss, R., Hinrichsen, H.-H., & Köster, F. W. (2010). Impact of hypoxia on consumption of Baltic cod in a multispecies stock assessment context. *Journal of Applied Ichthyology*, *26*(6), 836–842. https://doi.org/10.1111/j.1439-0426.2010.01485.x

Thorson, J. T. (2020). Predicting recruitment density dependence and intrinsic growth rate for all fishes worldwide using a data-integrated life-history model. *Fish and Fisheries*, *21*(2), 237–251. https://doi.org/10.1111/faf.12427

Ulrich, C., Hemmer-Hansen, J., Boje, J., Christensen, A., Hüssy, K., Sun, H., & Clausen, L. W. (2017). Variability and connectivity of plaice populations from the Eastern North Sea to the Baltic Sea, part II. Biological evidence of population mixing. *Journal of Sea Research*, *120*, 13–23. https://doi.org/10.1016/j.seares.2016.11.002

Velasco, A. (2019). *Baltic International Trawl Autumn Survey (BITS) in der Arkona See und in der Mecklenburger Bucht (ICES SD 24+22)*. Rostock.

Wang, H., & Ranalli, M. G. (2007). Low-rank smoothing splines on complicated domains. *Biometrics*, *63*(1), 209–217. https://doi.org/10.1111/j.1541-0420.2006.00674.x

Wickham, H. (2016). *ggplot2: elegant graphics for data analysis*. New York: Springer-Verlag. Retrieved from http://ggplot2.org

Wood, S. N. (2011). Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society. Series B: Statistical Methodology*, *73*(1), 3–36. https://doi.org/10.1111/j.1467-9868.2010.00749.x

Wood, S. N., Bravington, M. V., & Hedley, S. L. (2008). Soap film smoothing. *Journal of the Royal Statistical Society. Series B: Statistical Methodology*, *70*(5), 931–955. https://doi.org/10.1111/j.1467-9868.2008.00665.x

Wright, M. N., & Ziegler, A. (2017). {ranger}: A Fast Implementation of Random Forests for High Dimensional Data in {C++} and {R}. *Journal of Statistical Software*, *77*(1), 1–17. https://doi.org/10.18637/jss.v077.i01

Zeileis, A., & Hothorn, T. (2002). Diagnostic Checking in Regression Relationships. *R News*, *2*(3), 7–10. Retrieved from https://cran.r-project.org/doc/Rnews/

Acknowledgements

Juliette Champagnat, PhD, Institut Agro Rennes-Angers
Thank you to Juliette for visiting us at DTU and for undertaking a chapter of her thesis on hypoxia effects on different species in the south-western Baltic Sea. Juliette’s work makes up one chapter of this report.

Olivier LePape, Professor, Institut Agro Rennes-Angers
As Juliette’s main supervisor and a major contributor to the chapter on the mechanisms of hypoxia effects on various species.

Etienne Rivot, PhD, HDR, Institut Agro Rennes-Angers
As a major contributor to the chapter on the mechanisms of hypoxia effects on various species.

Jasmin Ann-Christine Thomassen, DTU Aqua
For translation assistance with the Danish summary

Karin Stubgaard, DTU Aqua
For editing, guidance and the final touches on this report.

Hanne Maria Jacobsen, DTU Aqua
For assistance in all things project related.

Technical
University
of Denmark

DTU Aqua
Henrik Dams Allé
DK-2800 Kgs. Lyngby

www.aqua.dtu.dk