Distribution change of *Orcinus Orca* in the North-East Atlantic caused by overfishing and sea-surface temperature change

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Förändringar i utbredningen av Orcinus orca i nordöstra Atlanten till följd av överfiske och förändringar i havsytans temperatur

Bachelor's degree thesis, 15 credits in *Physical Geography and Ecosystem Science*
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Abstract

This study investigates the effects of overfishing and sea-surface temperature changes on the distribution of *Orcinus Orca* in the North-east Atlantic and aims to evaluate which factors contribute the most to these shifts in orca presence. As apex predators, killer whales can have a great impact on ecosystems and food webs, and a migration to polar ecosystems could have big impacts on arctic systems and food availability for local species and indigenous peoples. Orca occurrence data from OBIS Sea map was used to analyze orca distribution from 1980 to 2024. Additionally, fish stock data for Atlantic herring and Atlantic mackerel and SST data and chlorophyll-a concentration was compared to the estimated "Orca population". A big emphasis was put on assessing and eliminating observer bias.

Findings of this study include a distribution shift of killer whales in the region primarily in connection to Atlantic herring and mackerel stock migration. The observed trends of the factors "Orca population", Atlantic herring and mackerel stocks and of chlorophyll-a distribution are consistent with SST and a changing climate.

In conclusion, these changes force a shift in orca distribution and could cause a new distribution in overall areas of high marine productivity.

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Glossary

Apex predator: species with no natural predators

Pod: a group of orcas

NOrcas/GBT: number of orcas seen per grid box trip

Echolocation: biological sonar system used by orcas to navigate and hunt

OBIS sea map: Ocean Biogeographic Information System – Spatial Ecological Analysis of Megavertebrate Populations

ICES: international council of the exploration of the seas

NOAA: National Oceanic and Atmospheric Administration

SST: sea-surface temperature

SSB: Spawning stock biomass

Blim: Biological limit biomass

F: fishing mortality

FMSY: fishing mortality at maximum sustainable yield

1. Introduction

1.1 The killer whale

The killer whale or orca is the apex predator of the ocean. There is only one species of killer whales – *Orcinus Orca* - which exists in every ocean of the world (Ford, 2009). They are highly social animals who live in a matriarchy with maternal descendents and extended relatives to form pods of around 20 individuals. The oldest female Orcas can reach an age of 80-90 years, with the average female living 50 years. Males reach a mean age of 30 years, but have been shown to reach 50-60 years in some cases. In all their life, Orcas stay close to their mothers or other relatives and are rarely seen alone (Ford, 2009).

Foraging also happens within pods and hunting techniques depend on the prey and population. Orcas are skilled hunters, that use techniques like tail lobbing, bubble blasts and simply their strength to drive prey to exhaustion (Ford, 2009). Records have shown that orcas even hunt the oceans other apex predator, the great white shark (*Carcharodon carcharias*). Not only do they manage to kill them, but they scare them away to a degree where the sharks desert the area they had been in before the attack for weeks or months after the attack (Towner et al., 2022).

Orca migration is researched little and migration patterns therefore poorly understood. It is known that Orcas cover great distances, of hundreds to several thousands of kilometers (Dietz et al., 2020). Moreover, there are factors such as prey abundance that impact orca migration and Similä (1996) found that orca distribution is highly dependent on one of its main food sources, Atlantic herring.

The size of orca populations is difficult to estimate, which gives great uncertainty in monitoring how orcas respond to changes in their environment. Similä (1997) estimated a population of around 450 individuals off the coast of Norway and Jourdain et al. (2021) estimated the population size in the same area to be around 700 in the early 90s, 1061 animals in 2015 and around half of that (513) in 2018. This gives an insight into the quantitative changes of at least the Norwegian orca population.

Additionally, it is known, that before the 1980s, orcas were hunted by humans because they outcompeted fisheries. In Norway, 56 animals were killed between 1938-1981 and in the late 1970s to mid-1980s, hunting grounds shifted to Icelandic waters, where at least 50 killer whales were killed (Ford, 2009).

While only one species of Orcas exists, a distinction can be made between several orca populations each having a preferred geographical range and main type of prey (Blanc & Martínez-Rincón, 2023; Ford, 2009; Remili et al., 2023). These specializations make orcas vulnerable to habitat loss from human influence and increasing ocean temperatures, and overexploitation of food sources.

1.2 Overfishing

There are two main types of orcas: transient or "mammal-eating" and residents, which eat fish (Ford, 2009). The prey of the resident orca population of the north-east atlantic mainly consists of Atlantic herring *(Clupea harengus)* and Atlantic mackerel *(Scomber scombrus)* (Remili et al., 2023). Changes in stock, spatial and seasonal distribution of these species, will therefore directly influence orca distribution patterns (Jourdain et al., 2021). An 800-km poleward shift of herring along the Norwegian coast has been observed by Slotte et al. (2025) and exemplifies how prey distribution could change in the future. Both Atlantic herring and mackerel are pelagic species that travel great distances along the Atlantic coast every season to reach spawning and feeding grounds. These migratory routes are temperature linked, driving migration in summer and early autumn further north and into warmer waters in the south during winter (Cho et al., 2005; Jansen and Gislason, 2011).
Overfishing however, is probably the biggest human influence which impacts orcas. Due to their limited specialization of foraging strategies and prey range, which are inherited over generations, killer whales are not able to adapt as rapidly to changes in food availability as necessary with current overfishing patterns (Ford et al., 2009). Chlorophyll-a concentration is another temperature dependent factor and since phytoplankton sits at the base of marine food webs, it is used as the primary productivity proxy and can indicate overall energy availability for all higher trophic levels (Behrenfeld et al., 2006).

1.3 A changing climate and the Atlantic Ocean

Since the 1880s, but more intensively from the 1950s, ocean temperatures have been increasing all over the planet and ice caps have been melting at an alarming rate (Venegas et al., 2023). The arctic is warming faster than any other place on earth with a yearly temperature increase four times higher than the global average (Rantanen et al., 2022). Kim et al. (2023) predicts that arctic summers will be ice-free by the middle of the 21st century which can lead to a higher presence of orcas in polar waters which were previously blocked by ice (Higdon & Ferguson, 2009).

Orcas have been found to show temperature preferences, which lead to greater densities in specific areas. Blanc & Martínez-Rincón (2023) found one suitable spot to be the North-east Atlantic and Arctic area (NEAA). They elaborate that the suitability for some regions is reserved for specific season, indicating a response to both seasonal changes in prey abundance and temperature. The Barents sea for example is occupied by killer whales primarily from January to March and July to September, as can be seen by figure 5, with higher densities in summer and autumn. The arctic ocean is very suitable until Severney Island, north of Russia. The highest Orca probabilities are found in areas of 5-15 °C in spring and 10-20°C in summer (Blanc & Martínez-Rincón, 2023).

The north-east Atlantic was chosen as the area of interest because it is a highly complex system that is predicted to undergo major changes under the current rate of climate change. For example, the Atlantic meridional overturning circulation (AMOC), which is a major tipping element in climate predictions, has been recently estimated to collapse in the middle of this century, much earlier than previously thought (Ditlevsen and Ditlevsen, 2023). Higher freshwater levels from melting ice in the arctic will affect ocean circulation in the Atlantic which can lead to higher precipitation levels and more extreme weather events. Less ice, will reduce the albedo effect of the entire planet and accelerate global warming even more (Haine et al., 2023).

This is a major disruption and will not only negatively impact the Atlantic Ocean and its inhabitants but will have severe consequences on humans in the North Atlantic region, especially indigenous groups which rely on the oceans as their main food source.

1.4 Methods of observation

Orca occurrence data was used from the Ocean Biogeographic Information System (OBIS-Seamap), an interactive online database to record sightings of marine mammals and other aquatic animals and birds (Halpin et al., 2009). This tool, started at Duke University, collects, analyses and visualizes sightings from organizations, institutions and citizen scientists from all over the world. Orca occurrence data from 13 different datasets from 1980 to 2025 are the foundation of this study. This time span can give a good insight into the state of fish stocks and human pressures on them throughout the decades and also show climatic changes.

1.5 Motivation and Hypothesis

Orcas are classified as “data deficient” on the IUCN red list (Reeves, Pitman & Ford, 2017). Even though they are at the top of every aquatic food web and have great top-down influences, which makes them a key species to study to understand how food webs will change in future climates, we don’t know enough about them. Over time, Orcas have had the status of hellish creatures of the sea, aqua park attractions and ruthless killers, yet there are no records of them ever purposely hurting humans. Humans on the other hand, have hunted and killed Orcas, have taken their prey in unsustainable amounts and fundamentally changed the ecosystems of these fascinating creatures. Human induced climate change will likely only make matters worse in the future. It is important to study how anthropogenic activities affect species which occupy such a critical position in the food web, as disturbances affecting orcas, are likely to propagate across all trophic levels and change ecosystem structures.

Therefore, it is the aim of this study to evaluate orca occurrence data and test whether:

a) There is a spatial distribution change in the orca population of the north-east Atlantic and
b) If these changes are caused primarily by overfishing or sea-surface temperature changes from increasing ocean temperatures.
c) Additionally, this study aims to assess, whether occurrence data can be a valuable source to evaluate connections between SST temperature changes, Chlorophyll-a distribution and overfishing of Atlantic mackerel and herring.

2. Data and Methods

2.1 Orca analysis

As the base dataset, Orca occurrence data from OBIS sea map was downloaded for the studied area and imported into ArcGIS Pro. The area was defined in OBIS sea map and only publicly available datasets were downloaded. The coordinate system ETRS 1989 LAEA was chosen for all maps as the suitable projection for the area. A fishnet grid (50x50km) was added to divide the study area into grid cells with an equal area of 25,000 km^2. All maps and calculations for the maps were made in ArcGIS Pro (Esri, 2024 – version 3.4.0).
To calculate the "Orca frequency", the layer was divided into the respective decades, 1980s, 1990a, 2000s, 2010s and 2020s and orca occurrences per grid per decade were counted in ArcGIS Pro. To normalize this frequency within the decade, it was divided by the whole number of sightings of the decade. This was then multiplied by 100 to show the percentage of sightings that each grid contains of that respective decade. This calculation was made for each grid cell for all decades.

$$Orca\ Frequency = \frac{N\ Orca\ sightings}{Total\ N\ sightings\ in\ decade}\ x\ 100$$

To further eliminate the observational bias that is influencing the spatial distribution of the data, the orca dataset was compared to a larger dataset of orca occurrence data plus sightings of 5 common marine mammals in the area: the common minke whale (*Balaenoptera acutorostrata)*, the sperm whale (*Physeter macrocephalus)*, the humpback whale (*Megaptera novaeangliae)*, the fin whale (*Balaenoptera physalus*) and the white-beaked dolphin (*Lagenorhynchus albirostris*). This data was also retrieved from OBIS for the same area and time span and analyzed in ArcGIS Pro. Choosing common marine mammals increases the chance of an observation being made and recorded. This helps estimating the effort which can be described as the number of observational trips that were taken, where something was observed. This is essential, because trips with no observation for Orcas are not recorded and therefore true effort and population density cannot be estimated properly. To visualize this, the number of orca observations per grid cell per decade was divided by the effort of the big marine mammal dataset for each decade. This defines the "total effort" as the unique number of days per decade that each grid cell was visited and any observation at all recorded. This calculation was repeated for all grid cells for all decades.

$$N\ Orcas\ seen\ per\ grid\ box\ trip = \frac{N\ Orca\ sightings}{Total\ Effort}$$

The "Orca frequency", the total effort and the N Orcas seen per grid box trip (NOrcas/GBT) was then visualized as maps in ArcGIS Pro. The continent layer was retrieved from the ArcGIS Pro living Atlas and is available under the name "NLW_v3_Continents".
The seasonal distribution of NOrcas/GBT uses the same methodology and calculations in ArcGIS Pro with the addition of seasonality which results in NOrcas/GBT per grid box per

decade per season. Seasons are defined as Spring (1) which consists of the months March, April, May and Summer (2); June, July, August and so on.
For the "orca population" estimation graph, NOrcas/GBT were spatially joined to raw orca sightings and their dates and then the average NOrcas/GBT was calculated for each year.

For the large-scale comparison of the total effort and the N Orcas seen per grid box trip, a new fishnet grid was created with an area of 62,500 km^2 (250x250km) per grid cell. The data from the original grid was summarized within the big grid cells to visualize the large-scale trend of effort and orca distribution.
Some lines of Python code to edit attribute tables in ArcGIS Pro were written or improved with the help of generative AI (ChatGPT).
For further analysis, the distance of each grid cell to the closest coastline and its latitude were calculated within ArcGIS Pro and the data was then imported into Microsoft Excel. After reviewing the maps and the raw data, it was decided to eliminate the 2020s from any further analysis, as the distribution of data had drastically changed because of a different observer effort.
In Microsoft Excel, line graphs and boxplot diagrams were created with the data from ArcGIS Pro. For some graphs, the data was smoothed with a centered moving average of 5 years (see indication in figure description) and a linear correlation calculated.

2.2 Overfishing

For the analysis and visualization of overfishing, data from the international council of the exploration of the seas (ICES) was downloaded for the her.27.1-24a514a Atlantic herring and mac.27.nea Atlantic Mackerel population for following factors: Catch (in tons), fishing mortality (F) (per year) Spawning stock biomass (SSB) (tons) Catch advice (tons), fishing mortality at maximum sustainable yield (FMSY) (per year) and biological limit biomass (Blim) (t). FMSY and Blim are constant values, all other factors were downloaded for the periods 1988-2024 (Herring) and 1998-2024 (Mackerel). From these, the indices "Management performance" (Catch/Quota), "Stock health" (SSB/Blim) and "biological sustainability" (F/FMSY) were calculated and visualized as line graphs of the 5-year moving average in Microsoft Excel.

2.3 Sea-surface temperature and Chlorophyll-a

Finally, the environmental aspects of Sea-surface temperature (SST) and Chlorophyll-a were analyzed. For SST, the study area was defined in Google Earth Engine (GEE) (Gorelick et al., 2017) as longitude 30°W to 30°E and latitude 43°N to 80°N. The dataset "NOAA Optimum Interpolation Sea Surface Temperature dataset (OISST v2.1)" (Huang et al., 2020) was obtained from the national Oceanic and Atmospheric Administrataion (NOAA) for the time period 1982-2024. The data was processed within the script in GEE and was converted from scaled integers to degrees Clesius with a scaling factor of x0.01. The data was also aggregated into annual means and spatially avergaed over the study region to reduce seasonal variability and highlight long-term trends. To get a single SST value per year that is representative for the whole region, a mean reducer was applied across all pixels in the defined area polygon. The final dataset consisting of the years 1982-2025 and a mean regional SST (°C) were exported as CSV to Google drive and then imported into Microsoft Excel for visualisation and correlation analysis.

Chlorophyll-a data processing was done for the same area and a temporal coverage of 1997-2024. The dataset "Global Ocean Colour plankton product" from Copernicus marine Service – Plymouth Marine laboratory (Copernicus Marine Services, 2023) with a spatial resolution of ~4km was used as a proxy for phytoplankton biomass and marine primary productivity (mg/m^3).

Data processing of the NetCDF file was done using Python (IDLE Shell 3.14.5) where a spatial averaging across latitude and longitude and for each year was applied and the gridded satellite data converted to a regional time series. The output CSV file included years and mean Chlorophyll-a (CHL) data. In addition to Python, Xarray was used for NetCDF handling and pandas for aggregation.

The scripts (available upon request) for SST in Google Earth Engine and Chlorophyll-a in Python were written with the help of generative AI (ChatGPT).

The two final datasets were visualized as line graphs in Microsoft Excel as 5-year moving averages and linear correlations between the two factors and previous datasets were calculated as well.

2.4 Data

Table 1: Overview of the datasets that were used.

Data	Source	Citation
Orca sightings	OBIS sea map	(Halpin et al., 2009). See references for all datasets in Appendix A.
Continent layer	ArcGis Pro Living atlas	NLW_v3_Continents (Esri, n.d.)
SST change	NOAA	NOAA Optimum Interpolation Sea Surface Temperature dataset (OISST v2.1) (Huang et al., 2020)
Chlorophyll-a	Copernicus	Global Ocean Colour plankton product (Copernicus Marine Services, 2023)
Overfishing	ICES	Atlantic herring: her.27.1-24a514a (ICES, 2025), Atlantic Mackerel: mac.27.nea (ICES, 2025)

3. Results

3.1 Orca distribution and effort distribution analysis

Figure 1 visualizes the shift in the raw orca sightings and the "Orca frequency" over time. After the 1980s, an expansion in spatial distribution is visible until the 2000s, whereafter the spatial distribution decreases again and nearly fully concentrates itself along the coastline in the 2020s. It can also be seen that distribution concentration is relatively similar in the first four decades, with slightly higher abundance along the coastlines. In contrast, the concentration of "Orca frequency" is much denser in much fewer points in the 2020s with some cells containing over 20% of the sightings of the entire decade.

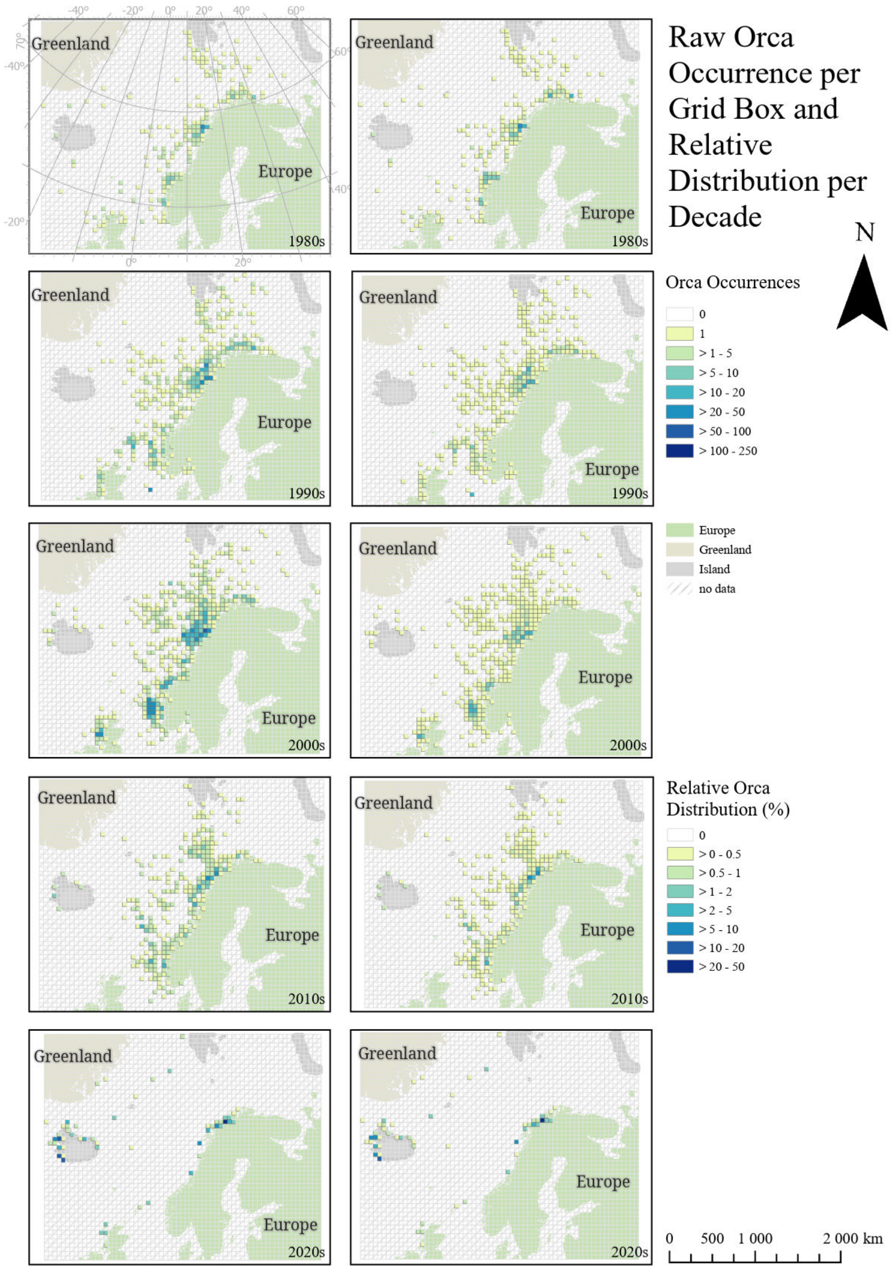

Figure 1: Showing the raw orca sightings per decade per cell (column 1) and "Orca frequency" calculated from N sightings in one grid cell/ N sightings for the whole decade (column 2). "Orca frequency" shows relative percentage per grid cell of entire decade. Continent layer: see data table (applies for all following maps). Missing grid cells showed no observations at all in the respective decade (applies for all following maps). Coordinate system EST89 LAEA Europe (applies to all following maps).

Figure 2 shows how the "total effort” is distributed in the studied area. It shows the effort of the sightings for 6 marine mammals, including orcas to better understand the observational bias of the “Orca frequency”. The pattern of expansion and contraction is similar to that in figure 1, with an increase until the 2000s, then a slight decrease in the 2010s and a near total contraction to the coastlines in the 2020s. Additionally, the effort distribution is much more concentrated between northern Norway and Svalbard than it is in figure 1. Generally, it can be seen that hot spots of effort do not necessary correspond to hotspots of orca sightings. A clear takeaway from both figure 1 and 2 is that data collection around Iceland probably started earliest in the late 1980s or beginning of the 1990s. Finally, the effort distribution covers a much bigger area, which suggests that this dataset can give us a good insight into “zero data” for orca distribution and therefore more accurately describe orca distribution patters.

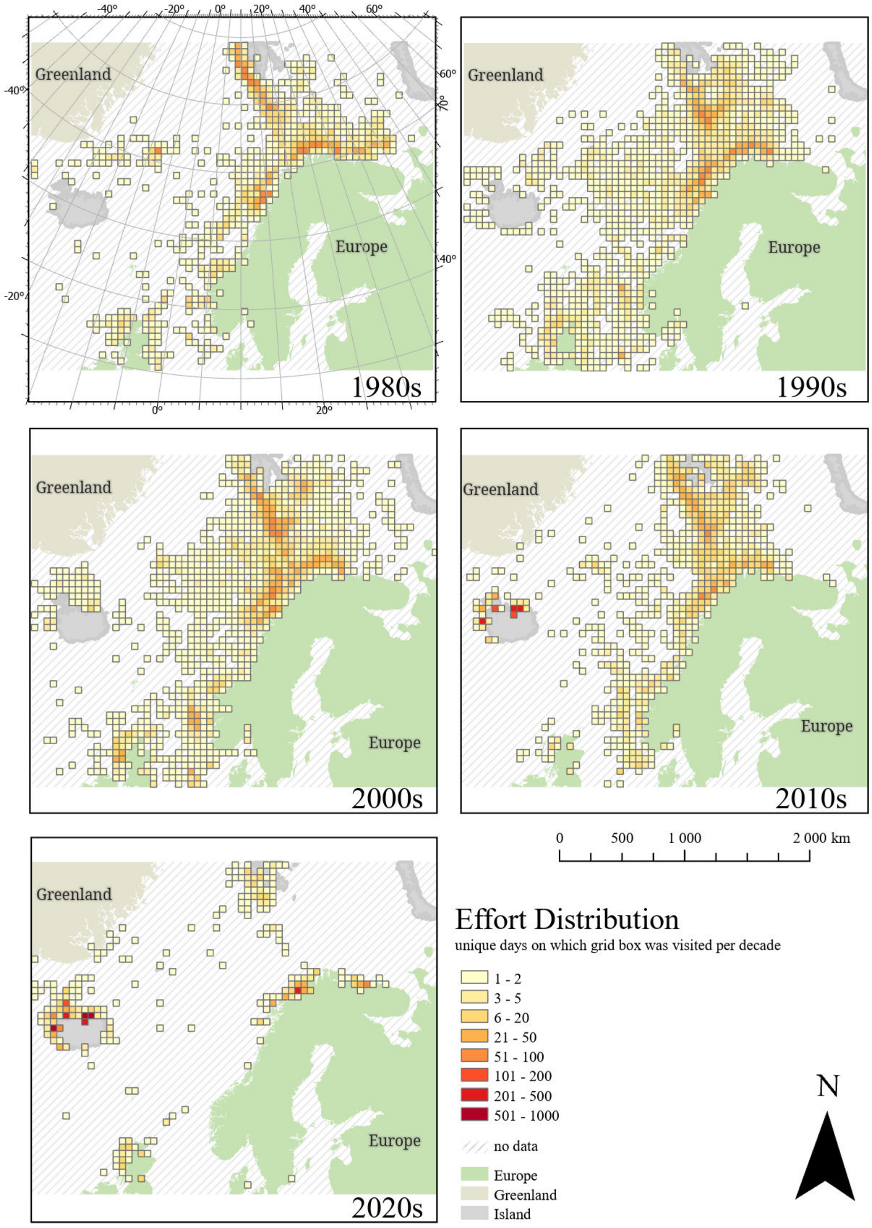

Figure 2: Showing the distribution of total effort (unique number of days per decade that grid box was visited and any observation at all recorded).

A combination of figure 1 and figure 2 can be seen below in figure 3, which shows the number of orcas seen per grid box trip (NOrcas/GBT) in relation to the total effort, which is the number of unique days that a grid box was visited per decade. It shows that in all decades, the effort went beyond the majority of NOrcas/GBT and that therefore, a large part of the North-east Atlantic orca population was within the covered area. It is important to note, that there are nearly no observations along the coast of Greenland and between Iceland and the UK, so these areas are impossible to assess. A pattern of spatial preference can be derived from this figure, which places orcas primarily along the coast and off the coast of Norway, up to waters south of Svalbard. A slight shift into higher latitudes in the 2010s can also be seen, with higher concentrations of NOrcas/GBT at higher latitudes compared to previous seasons.

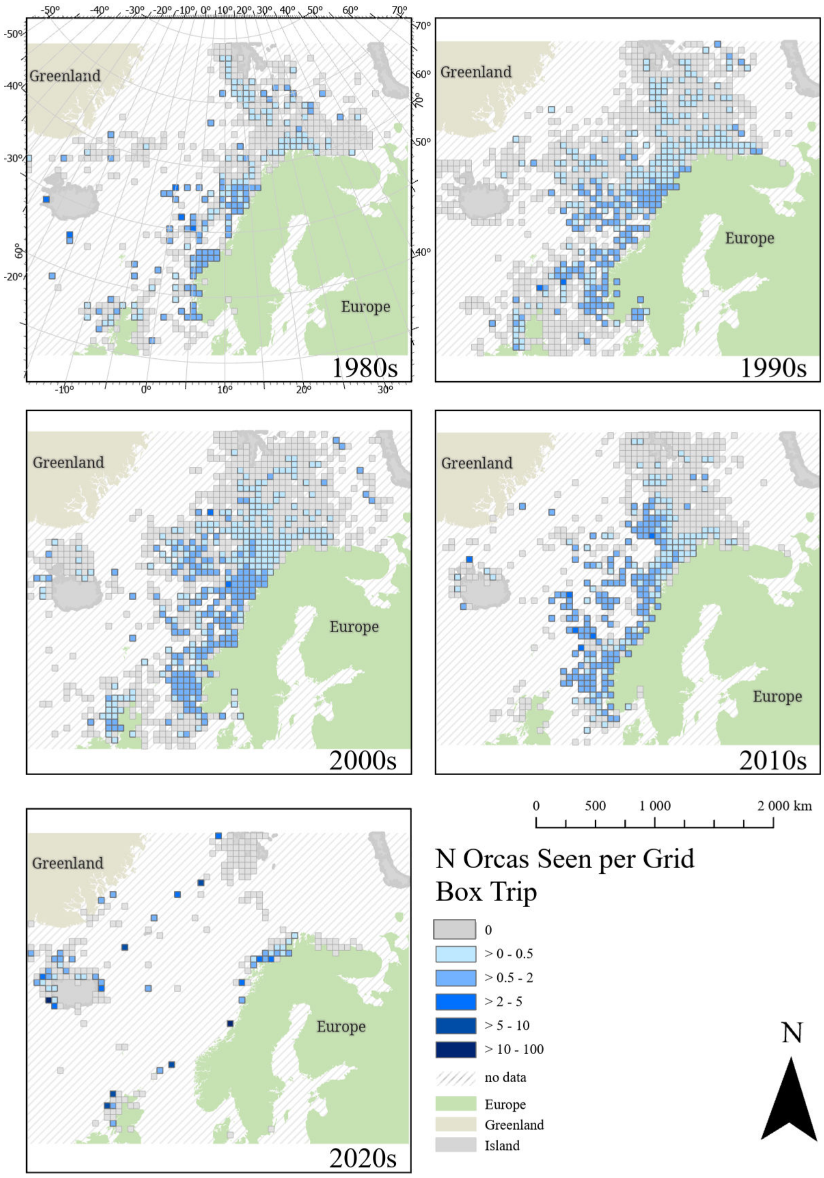

Figure 3: N orcas seen per grid box trip which is proportional to the probability of seeing an orca, which is estimated to be proportional to the population density. Effort is derived from the number of unique days per decade that the grid cell was visited and something observed.

Table 2: Quantification of variable shown in the figures above to give an insight into Orca and effort distribution.

	Total Effort (unique days per decade)	Total Number of 6 Marine Mammals	Total Number of Orca sightings	Highest orca sighting probability in decade	Number of grids with any observation	Effort but no Orca seen
1980s	2002	2789	405	4	558	369
1990s	4640	7130	954	4	955	612
2000s	5610	8835	1556	3,67	940	557
2010s	3954	7325	747	5	625	356
2020s	4165	13189	796	20,34	218	164
mean	40474. 2	7853. 6	891.6	7.4	659.2	411.6

Yearly number of Orca sightings can be found in Appendix B.

Table 2 gives background information on the three figures above. It contradicts the visual trend that one could assume from effort distribution. In fact, while it looks like the effort reaches a low point in the 2020s, that is not the case at all and in the 4 surveyed years within that decade, the total effort is higher than in the decade before. The same is true for the total number of marine mammal sightings (of the 6 chosen species), which is by far the highest in the current decade. The "highest orca sighting probability" supports the trend that can be seen above: the spatial distribution is at its lowest but the density of NOrcas/GBT is the highest. The numbers for effort without any orca sightings in the 2020s suggest, similarly to the spatial distribution of effort in figure 2, that a change in effort and likely observational bias play a part in the distribution of the data and orca sightings.

Important to note is that one key dataset (Hartvedt, 2020) stopped recording orca sightings in 2015. This explains the drop in overall sightings (Appendix B, table 6) and could also account for the significant change in observer concentration.

This visualization of NOrcas/GBT and total effort help visualize the large-scale trend of orca and effort distribution. It clearly shows a high effort concentration in the north of Norway and especially in later decades around Iceland. Except for the 2020s and a sudden shift around Iceland, the effort concentration changes less than the NOrcas/GBT concentration which varies more between the decades. Effort density and orca density do not necessarily align, with higher NOrcas/GBT density further south than the areas of intense effort. In the 2010s, a high density shift slightly northwards can be observed.

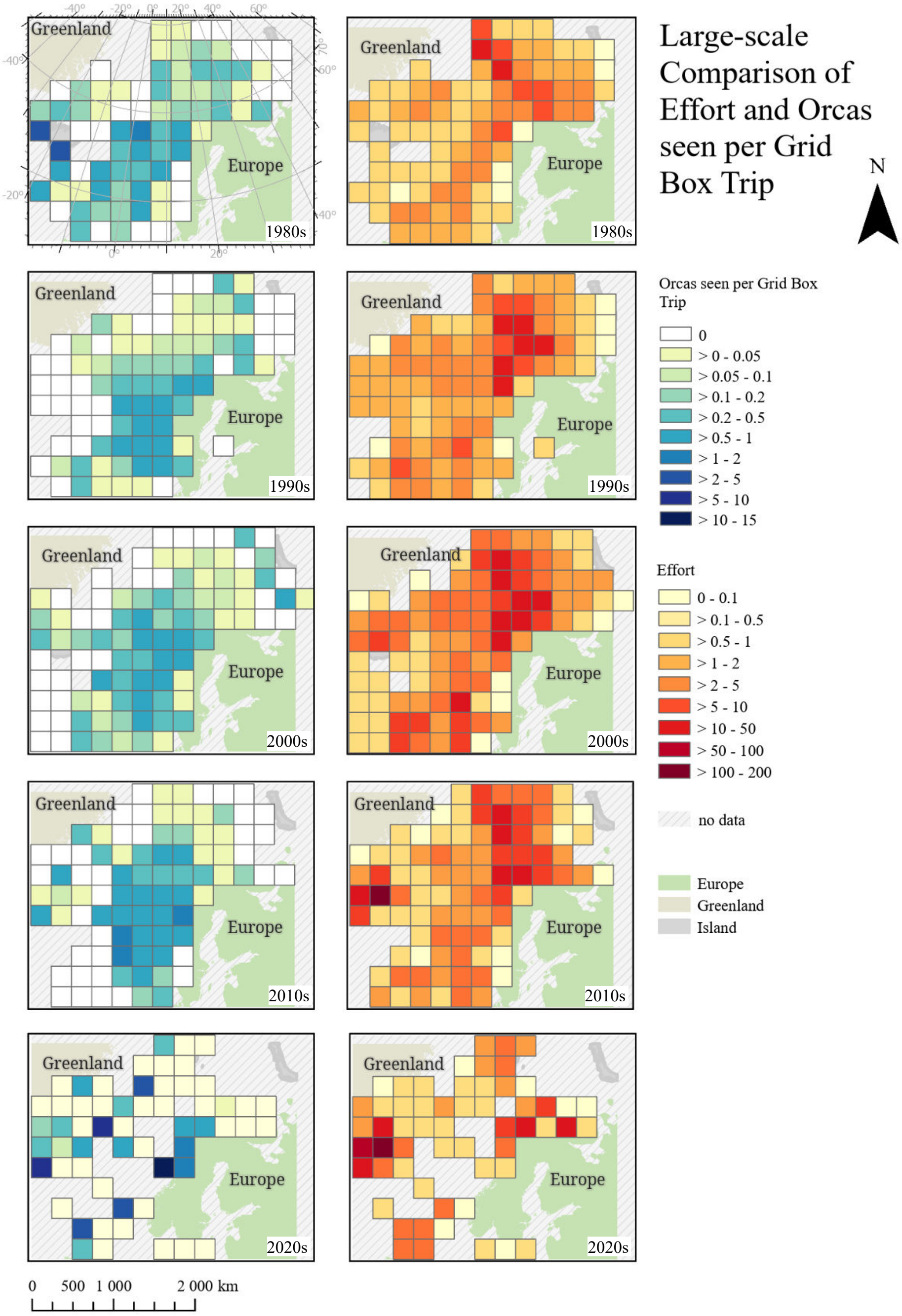

Figure 4: NOrcas/GBT and total effort data from original grid cells summarized within a larger fishnet grid to show large-scale distribution trends.

To conclude, patterns of high effort and NOrcas/GBT do not overlap and while effort distribution stays similar, NOrcas/GBT changes more each decade. The 2020s seem to be an exception influenced strongly by observational methods.

3.2 Distribution analysis by latitude and distance to coast and analysis of observational bias

Figure 5 shows that the NOrcas/GBT, which is used as an orca population density estimate for the region, was highest at nearly all latitudes in the 2010s. In the 1980s, the NOrcas/GBT was second highest at degrees of latitude 59-69 and then went down to be the lowest at 73 degress and the highest from 77 degrees and higher. The distribution of the 1990s and 2000s stayed similar over the whole area, except between 69-75 degrees, when the 2000s distribution was slightly higher. Overall, the highest densities and therefore the area with the largest density of orcas can be found between 59 and 69 degrees of latitude, which translates to nearly the entire length of Norway, from Oslo to the northern most parts. There is no significant shift of any decade noticeably north or south, but rather a change in density.

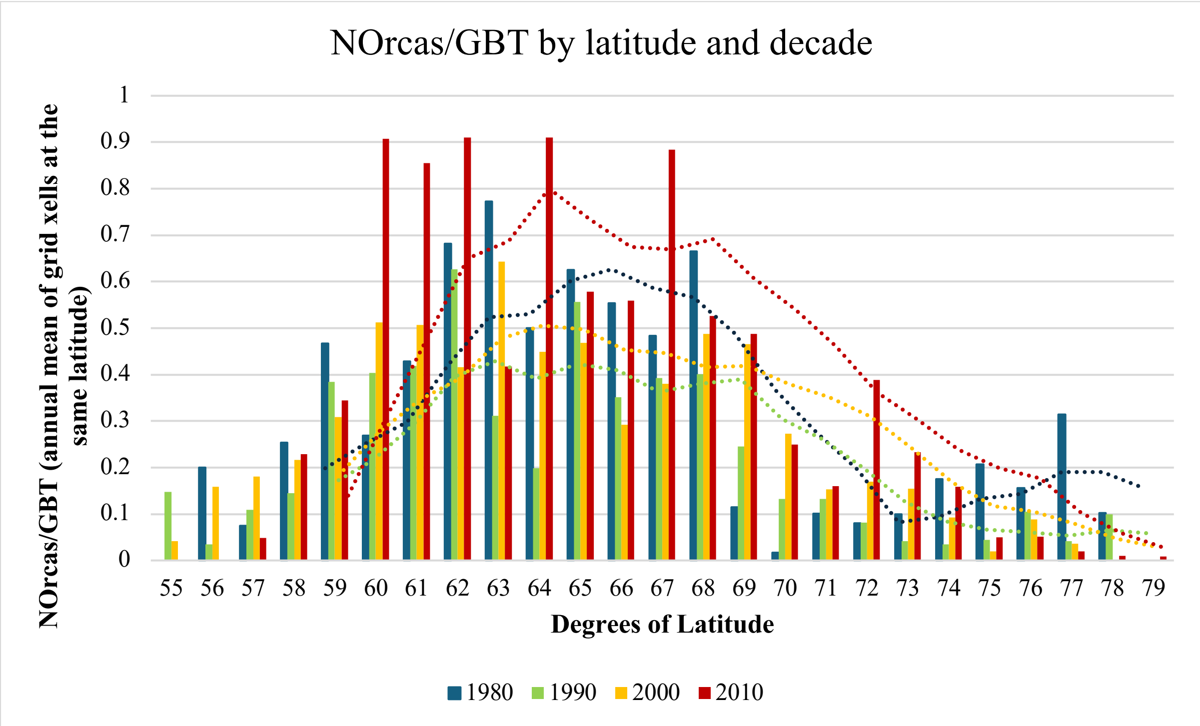

Figure 5: The number of NOrcas/GBT, which is estimated to be proportional to the local Orca population density, for each decade at different latitudes. Moving average trendline with a period of 5 years.

Below, figures 6 and 7 give better insight into the spatial distribution of NOrcas/GBT and total effort specifically in relation to the distance to the nearest coastline. It shows that effort goes beyond the area where orcas were seen in the 1990s and 2000s and that the opposite is the case for the 1980s and 2010s: higher concentrations of orcas were observed further away from the coast than the effort concentration. The median distance to coast of sightings in all decades stays well below 100km distance, while effort expands to medians between 80-120km off the coast. This could indicate a stronger observer bias in the 1980s and 2010s compared to the two decades in between.

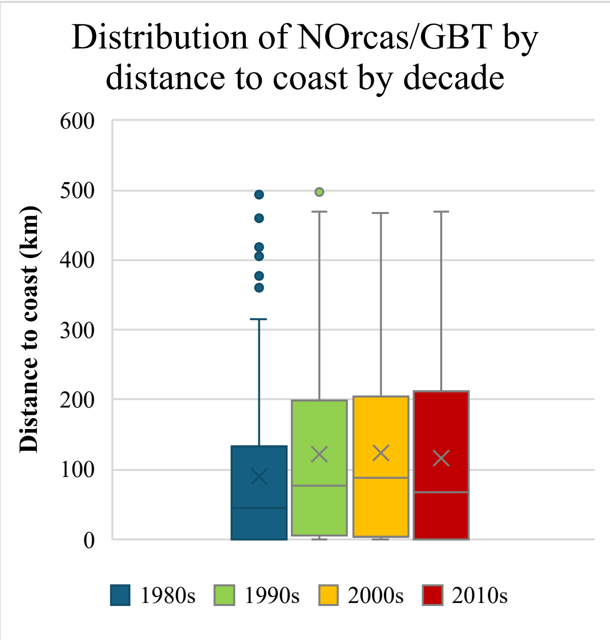

Figure 6: Distribution of NOrcas/GBT in relation to distance to nearest coastline (km) for all decades. The boxplot diagrams show percentiles of the data: 50% (25-75) are within the box, and whiskers show the first and last 25%. Outliers are shown as individual points outside the last 25%. The line in the box represents the median and the x represents the mean.

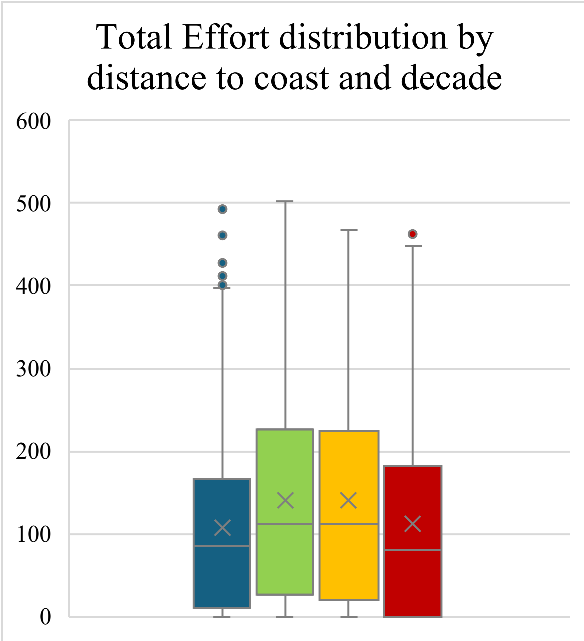

Figure 7: Distribution of total effort in relation to distance to nearest coastline (km) for all decades. Plotted as in see fig. 6.

The NOrcas/GBT distribution by distance to coast and decade is a clear opposite of the effort distribution in figure 9. It also clarifies what is harder to see from just looking at the maps. While the maps suggest that highest concentrations are situated along the coastline (just like the effort), it is obvious here that high concentrations of NOrcas/GBT are also located at bigger distances between 350-450km off the shore. Some high concentration points in the 1980s are at 200 and 350km distance, at 350km distance in the 2000s and at 350 and 450km distance in the 2010s. In combination with figure 6, it can be assumed, that these high concentrations are rare though and that stable distribution ends at around 150km off the nearest coastline. Distributions in the 1990s stay relatively stable over distance.
Figure 9 clearly represents what can be seen in figure 2 and figure 7; Effort increases with nearness to the coastline which is nearly the opposite of what can be seen in figure 8. The figure also shows that effort in the 2010s was the lowest at all distances. In contrast, the effort concentration in the 2000s, was highest nearly everywhere, but Table 1 shows, that the overall effort was low. This could mean that the effort concentration in 2010s was distributed most evenly. The other decades each follow a similar pattern of high distribution up to 50km off the coast and then a steady decline except for a slight increase at 450km distance in the 2010s.

Norcas/GBT by distance to coast and decade (fig. 8) and effort by distance to coast and decade (fig.9)

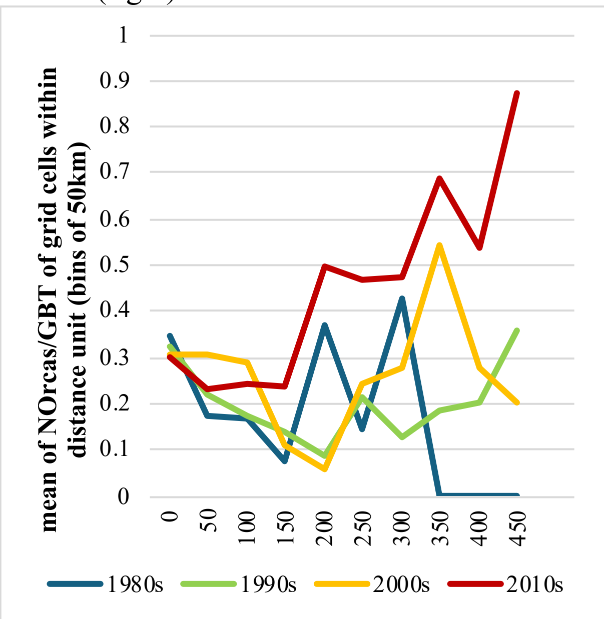

Figure 8: NOrcas/GBT per grid box trip in relation to distance to coast (km) for all decades.

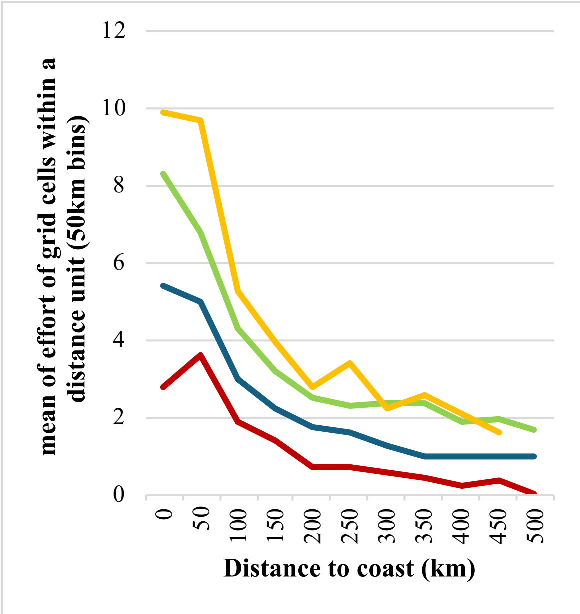

Figure 9: Showing the Effort in relation to distance to coast (km) for all decades.9

In summary, there is no significant shift of orca distribution north or south. Effort distribution and NOrcas/GBT show near opposite trends in relation to distance to coast which indicates a low observer bias.

3.3 Seasonal analysis

Seasonal distribution of NOrcas/GBT and total effort are similar in spring and autumn, where the concentration is highest along the coastlines. There is a slight shift northward in autumn of the 2010s, where the effort and density seem to be higher than in any other season and decade. The distribution is largest in summer, where a much higher area is covered and the opposite is true for winter, where the smallest area was visited and observations made. An overall increase of observations and effort for all decades, except maybe summer where it seems to be similar, from the 1980s to 2010s can be seen. The low data availability for winter in the 1980s makes it hard to compare, but the concentration of NOrcas/GBT is notably further north, with a hotspot in northern Norway in the winter of the 2010s.

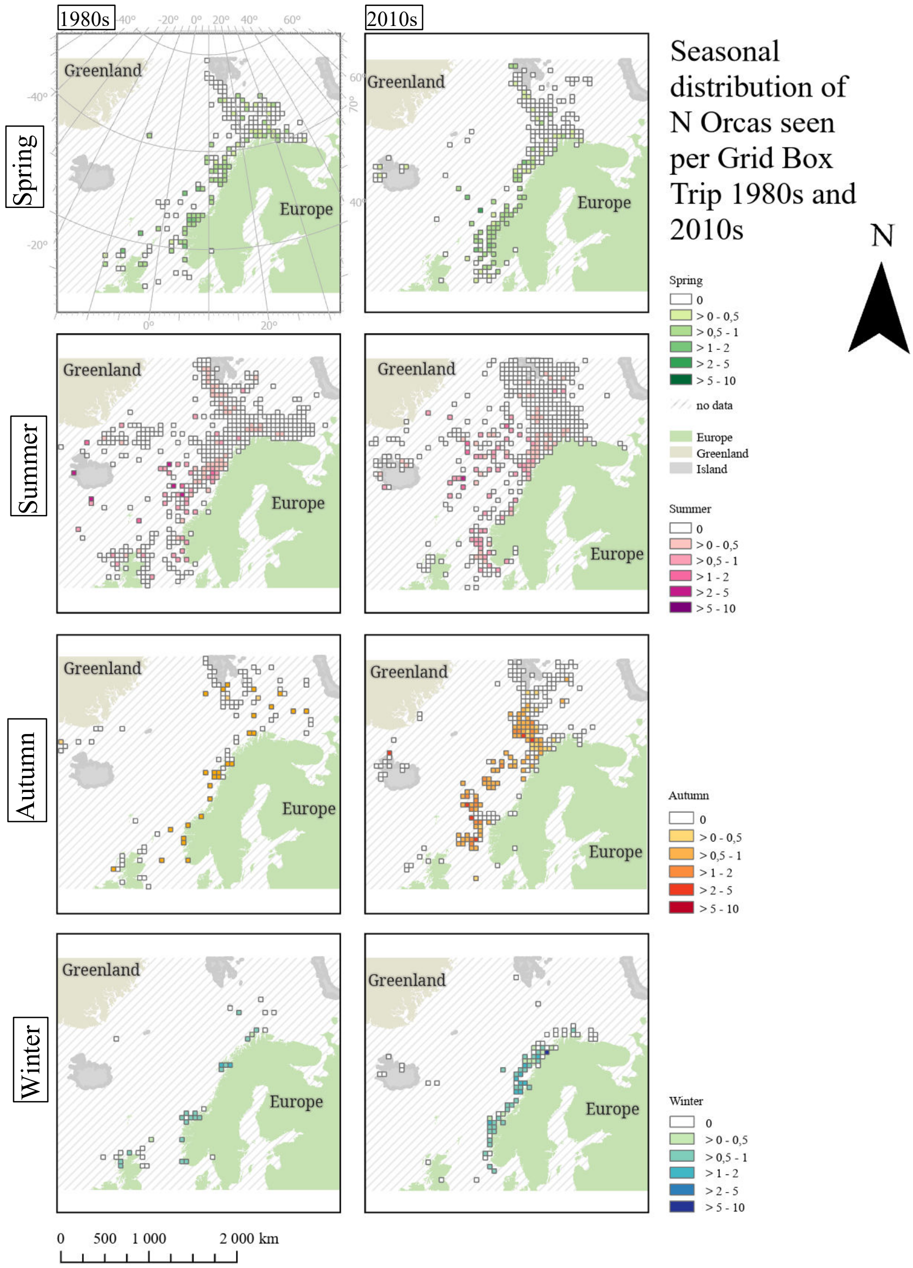

Figure 10: Showing NOrcas/GBT trip from the 1980s and the 2010s by season. One color per season as can be seen in the seasonal figures below.

Figures 11 and 12 below reflect the trends that are visible in the maps above (fig.10). Concentrations further away from the coast and in highest latitudes are biggest in autumn in both decades. Except for winter in the 2010s which shows a big increase in mean latitude, and spring which shows a decrease, the mean of summer and autumn stay similar, however the median increases in the 2010s compared to the 1980s.

Distribution of NOrcas/GBT by distance to coast (fig.11) and latitude (fig.12) by season for the 1980s and 2010.

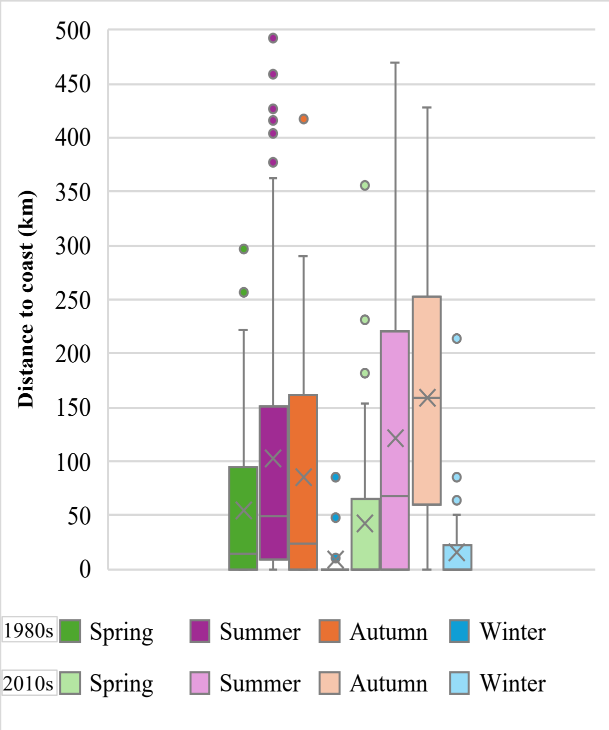

Figure 11: NOrcas/GBT distribution of distance to coast by season for the decades 1980s and 2010s. Plotted as in see fig. 6. Colors relate to 4 seasons in the map above.

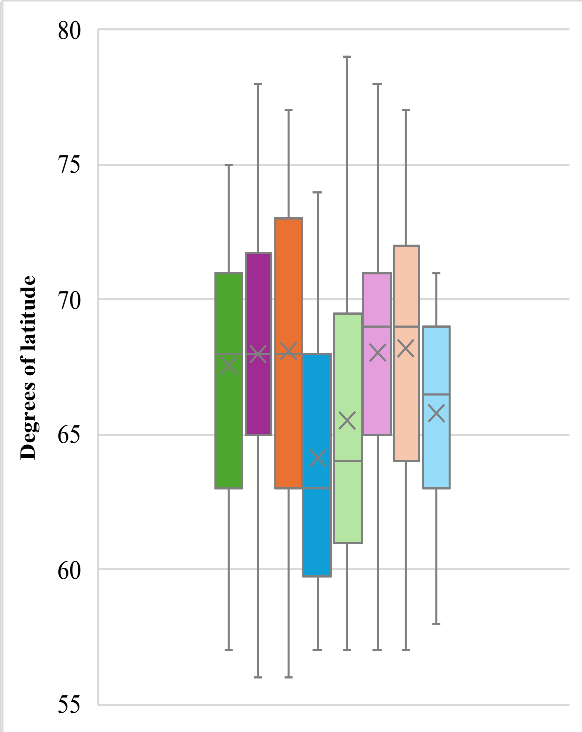

Figure 12: NOrcas/GBT distribution of latitude by season for the decades 1980s and 2010s. Plotted as in see fig. 6

Figure 13 shows similar results, notably with the highest concentration of NOrcas/GBT at ~250km off the coast in autumn 2010, which are visible as two red dots in the map (figure 10). Figure 14 suggests a strong preference for latitude in the summer months around 70 degrees. Figures 11, 13 and 14 indicate that data availability for both winter seasons and the 1980s autumn season was much lower compared to the other decades and seasons.

Distribution by distance to coast (fig.13) and latitude (fig. 14) by season for the 1980s and 2010s

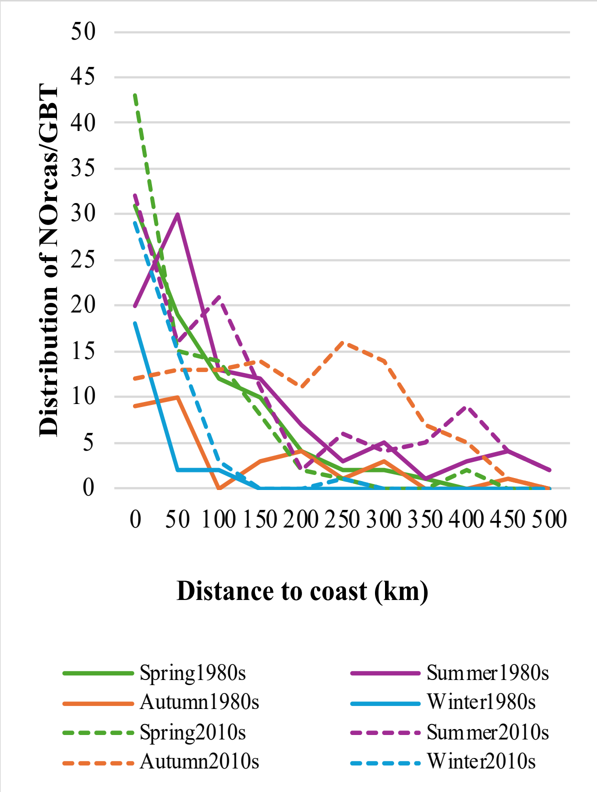

Figure 13: Seasonal distance to coast of NOrcas/GBT in the 1980s and 2020s.

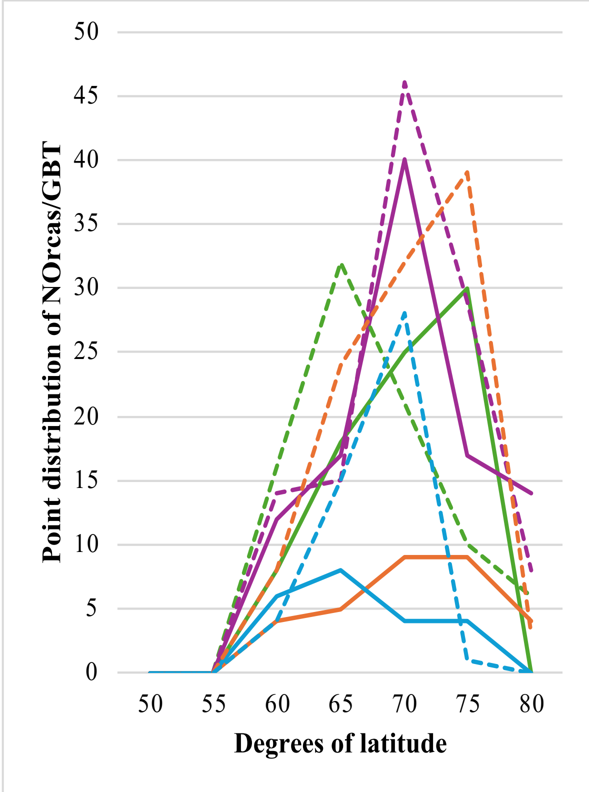

Figure 14: Seasonal distribution of NOrcas/GBT by latitude for the 1980s and 2010s.

Seasonal effort distribution by distance to coast is quite similar to that of NOrcas/GBT (fig.11). The biggest differences are in distance to coast in autumn in the 2010s, where effort is higher closer to the coasts than NOrcas/GBT which barely concentrated along the coast. The effort distribution in autumn 1980s covered a much smaller area from the coast than NOrcas/GBT, which indicates lower observer bias than in other seasons.

Distribution of effort by distance to coast (fig.15) and latitude (fig.16) by season for the 1980s and 2010s.

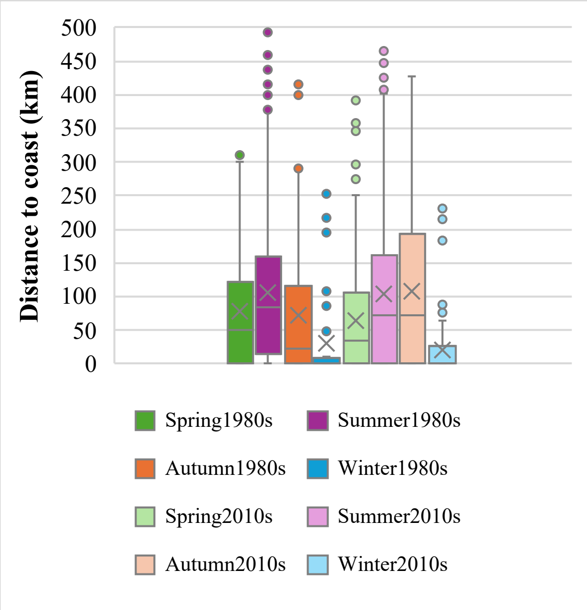

Figure 15: Effort by distance to coast (km) for all seasons in the 1980s and 2010s. Plotted as in see fig. 6

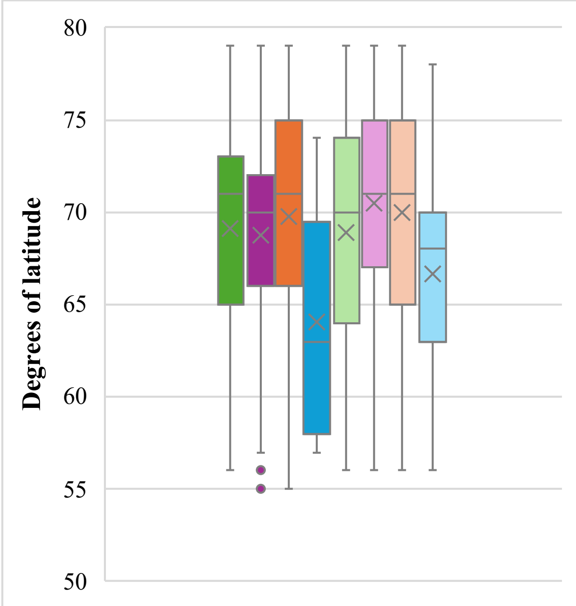

Figure 16: Effort by degrees of latitude for all seasons in the 1980s and 2010s. Plotted as in see fig. 6

In summary, there is a strong distribution difference between the seasons and a strong observer bias was found for winter of both decades and the autumn of the 1980s.

3.4 Overfishing

To quantify the factor of overfishing, three indices were calculated and compared. These are the management performance, biological sustainability and stock health. The management performance describes the actual amount of catch in tons divided by how many tons of each species should be fished each year (ICES quotas). If this exceeds 1, more fish was fished than was advised to be sustainable. The biological sustainability is the fishing mortality divided by the fishing mortality at maximum sustainable yield. If F exceeds FMSY, the fishing pressure is too high, and overfishing occurs. Lastly, stock health is estimated by dividing the stock spawning biomass by the biological limit biomass. If Blim is higher than SSB, the stock is depleted, and the population may not be able to replenish itself reliably. The stock is at a risk of collapse (Silvar-Viladomiu et al., 2022).

From the results in Table 2, it can be concluded that Atlantic mackerel has been overfished much more than the Atlantic herring population. All indices are higher/worse for the mackerel species. Advice from ICES, which was to allow 0 tons of catch of mackerel in 2021, reflects that. While the biological sustainability and stock health for herring are better and stay below 20%, catch numbers still outnumber advice in two thirds of recorded years which cannot be sustainable over long periods of time.

Table 3: Summary of the ICES data for Atlantic herring (1988-2024) and Atlantic mackerel (1998-2024) and the results of indices calculations for overfishing assessment.

	Management performance (Catch/Quota) (t)	Biological sustainability (F/FMSY)	Stock health (SSB/Blim)
Mackerel *(Scomber scombrus)*	All years exceed the recommended amount of catch	Overfishing in 52% of recorded years	Stock depleted in 33,3% of recorded years
Times factor 1 (min – max)	1.03322181 (2000) - 56.0707028 (2021)	0.55218639 (2019) - 1.96242565 (2003)	0.67428221 (2002) - 3.53721809 (2014)
Herring *(Clupea harengus)*	Exceedance in 66,6% of the years	Overfishing in 16,2% of recorded years	Stock depleted in 10,8% of recorded years
Times factor 1 (min – max)	0.8 (2000) - 104448 (1992)	0.4 (1988) - 1.5 (2000)	0.5 (1988) - 3.4 (2007)

Figure 17 visualizes the three indices and compares them to the estimated "Orca population" (NOrcas/GBT). For both the "Orca population" and herring stock health, a sharp increase starting in the early 1990s can be seen, followed by a slight dip in the early 2000s, where mackerel stock health is also at its lowest. After that, herring and mackerel stock health steadily rises again until the late 2000s and middle of the 2010s respectively. The "Orca population" drops steadily from 2004 to 2018 except for a plateau from 2009-2013. After 2018, it rises again. The drop in the late 2010s can be explained by the raw data, which has by far the lowest sightings from 2016-2019 (see appendix B, table 6) probably because one institute (Hartvedt, 2020) stopped recording data in 2015.

Correlation coefficients in table 3 show that overall connection between stock health in Atlantic herring and mackerel is weak, meaning they don't respond to changes in their environment synchronously. However, their slope correlation, is more significant, suggesting that the decrease in stock health of one, often coincides with improving stock health in the other.
The statistical significance of mackerel to orcas is much higher than that of herring to orcas. It seems when herring stocks are healthier, orcas become more abundant and oppositely, when the "Orca population" rises, mackerel stock health falls. Comparing the indices stock health and biological sustainability shows a strong significance for both species (Herring: 0.6, mackerel -0.9), which means that poor biological sustainability is closely linked with and may cause declining stock health. A strong correlation between mackerel stock health and management performance show that conservation efforts can have positive effects on stock health. The biological sustainability of mackerel, which can be used to calculate if overfishing is occurring, is strongly related to orca abundance, indicating that healthy fishing numbers correlate to a healthier, more abundant "Orca population".

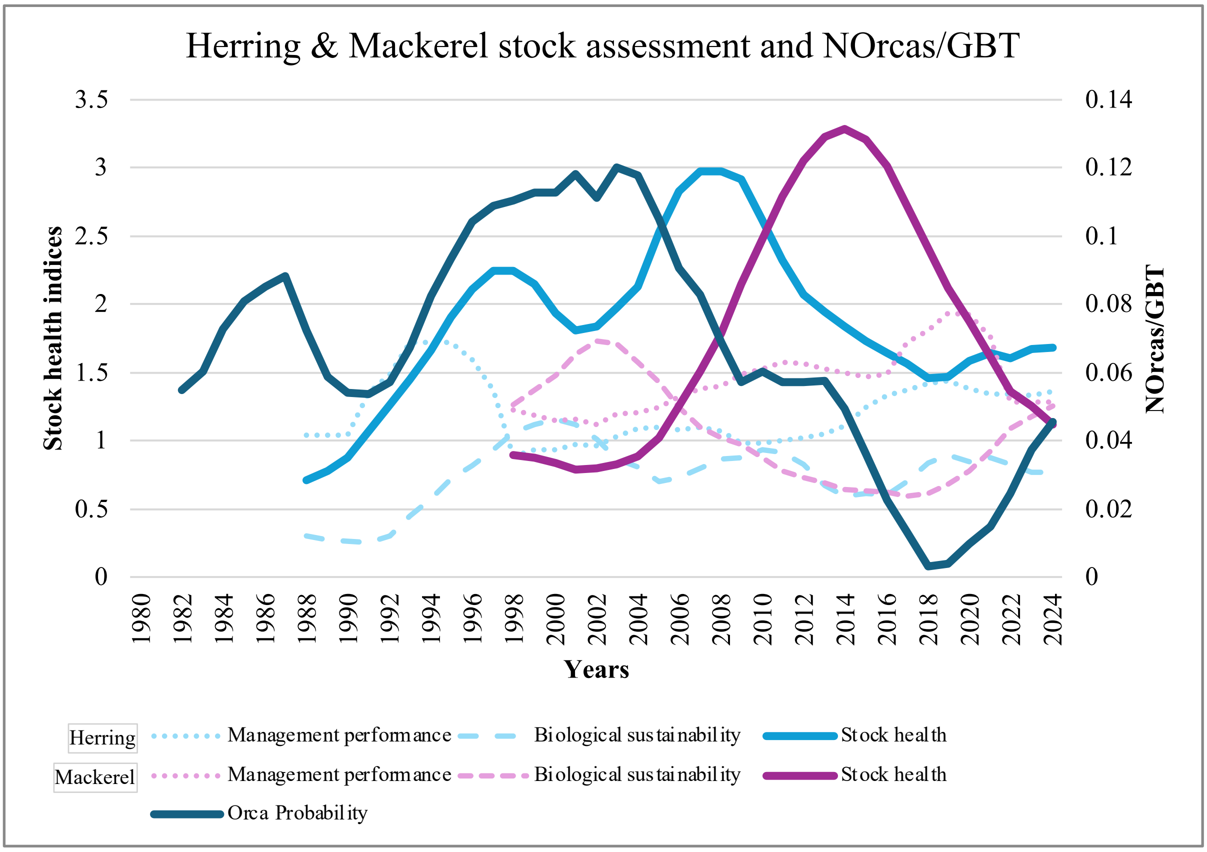

Figure 17: Comparing biological sustainability, stock health and management performance of Atlantic herring (Clupea harengus) and Atlantic mackerel (Scomber scombrus) to NOrcas/GBT. Data is smoothed with a 5-year moving average.

Table 4: Correlation coefficients for 5-year moving avergae of Atlantic herring stock health and Atlantic mackerel stock health between the 5 year-moving average of eachother, the correlation between the slopes (comparing incline and decline) of eachother, correlation to 5-year moving average of NOrcas/GBT, correlation between slope of NOrcas/GBT and correlation to 5-year moving average of the biological sustainability and 5-year moving average of management performance. Lastly, the biological sustainability of herring and mackerel is correlated to the 5-year moving average of NOrcas/GBT.

	Each-other	Each-other slope	Orca	Orca slope	Biological sustianability	Management performance	Orca and biological sustainability
Atlantic Herring Stock health	-0.14	-0.67	0.37	0.13	0.6	-0.3	0.3
Atlantic Mackerel Stock health	-0.14	-0.67	-0.63	-0.75	-0.9	0.65	0.84

To summarize, a significant relationship was found between all mackerel and herring indices to Norcas/GBT, but Norcas/GBT respond more to this mackerel species than the chosen herring species.

3.5 Sea-surface temperature and Chlorophyll-a

With a peak around 2013, figure 18 shows a steady incline in SST. Chlorophyll-a goes up steadily, then it flattens to a platueau from 2010 to 2014, then goes down in 2015 and up again until the beginning of the 2020s, just to go down once more. Especially from 2006, there is a clear pattern of SST going up and chlorophyll-a going down as a response and the other way around; when SST goes down, chlorophyll-a concentrations increase. Similarly, in figure 19, from the late 1990s, the "Orca population" and SST rise at the same rate and then in 2005 they move in opposite directions. SST continues to rise while Norcas/GBT falls drastically until 2010, after which it recovers slightly.

5-year moving average of Sea-surface temperature (SST) & Chlorophyll-a concentration (fig. 18) and 5-year moving average of SST and Norcas/GBT (fig. 19)

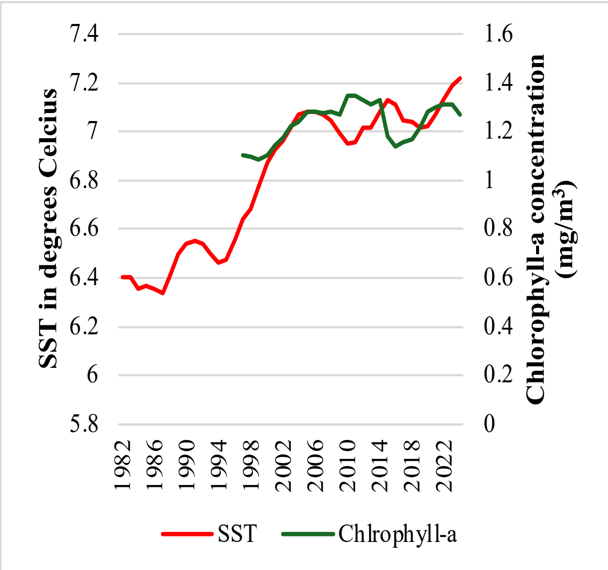

Figure 18: 5-year moving average of annual mean of SST and Chlorophyll-a (mg/m³) concentration from 1982-2024.

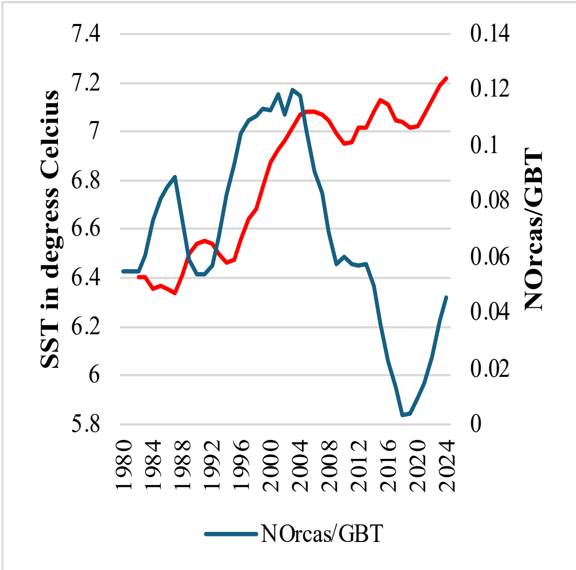

Figure 19: 5-year moving average of annual mean of SST and NOrcas/GBT from 1980-2024.

Figures 20 and 21 visualize the patterns of SST and chlorophyll-a overtime in comparison to stock health of Atlantic herring and mackerel. The pattern in figure 20 is similar to that in figure 19 – both orcas and fish rise to the high point at a temperature around 7.1 °C and then fall drastically.

Looking at figure 18, one can see that even chlorophyll-a concentration, which is used as a primary productivity proxy for marine environments, reaches its highpoint at approximately 7.1 °C. Herring and mackerel stock health and chlorophyll-a concentrations rise simultaneously, then peak around the same time and then all fall (fig. 21).

The "Orca population" falls steadily from 2004 but then slows down to a plateau at the same time (2009 -2014) at which chlorophyll-a concentration peaks (fig. 22). The peaks of all three species align or seem to respond to the peak in chlorophyll-a concentration and they all peak at a temperature of around 7.1°C.

Since the SST temperature is averaged for the whole area, the temperatures are much lower than that in areas of high orca density, so no actual preference can be derived from these figures but rather a response to an increase in temperature.

An important distinction to be made, is that stock health does not translate directly to number of fish in the ocean, so it is not ideal to view it as a direct link in the food chain since it is altered heavily by human influence. This could be a reason for the low correlation coefficients (table 5).

Chlorophyll-a concentration and "Orca population" on the other hand, stand at the beginning and end of the food chain respectively and therefore, changes in chlorophyll-a concentration should ripple through the entire food web and consequences should show in "Orca population" too. NOrcas/GBT shows a negative correlation to SST and chlorophyll-a, meaning a rise in these factors causes a decline in "Orca population".

Unfortunately, the data availability for chlorophyll-a and also mackerel is limited, and long-term trends are hard to assess.

5-year moving average of SST (fig. 20) and Chlorophyll-a concentration (fig. 21) and stock health of Atlantic herring and mackerel.

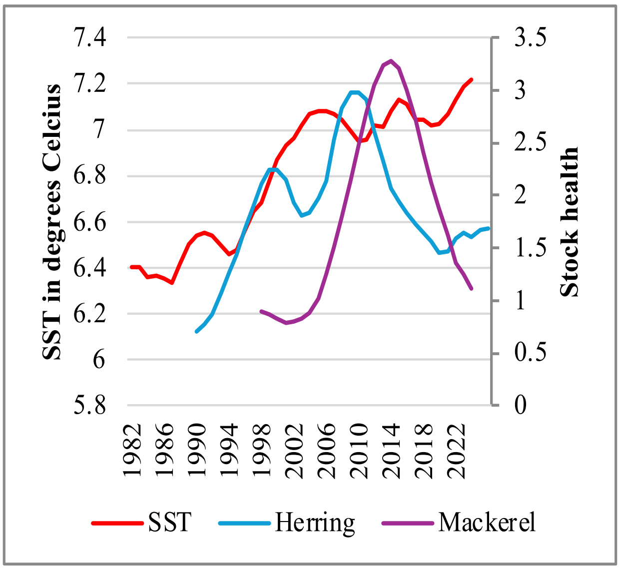

Figure 20: 5-year moving average of annual mean SST and stock health of Atlantic herring and Atlantic mackerel from 1982-2024.

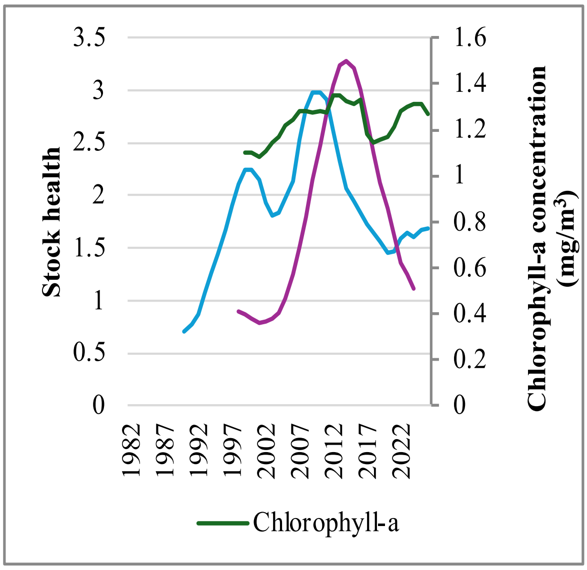

Figure 21: 5-year moving average of annual mean Chlorophyll-a (mg/m³) concentration and stock health of Atlantic herring and Atlantic mackerel from 1982-2024.

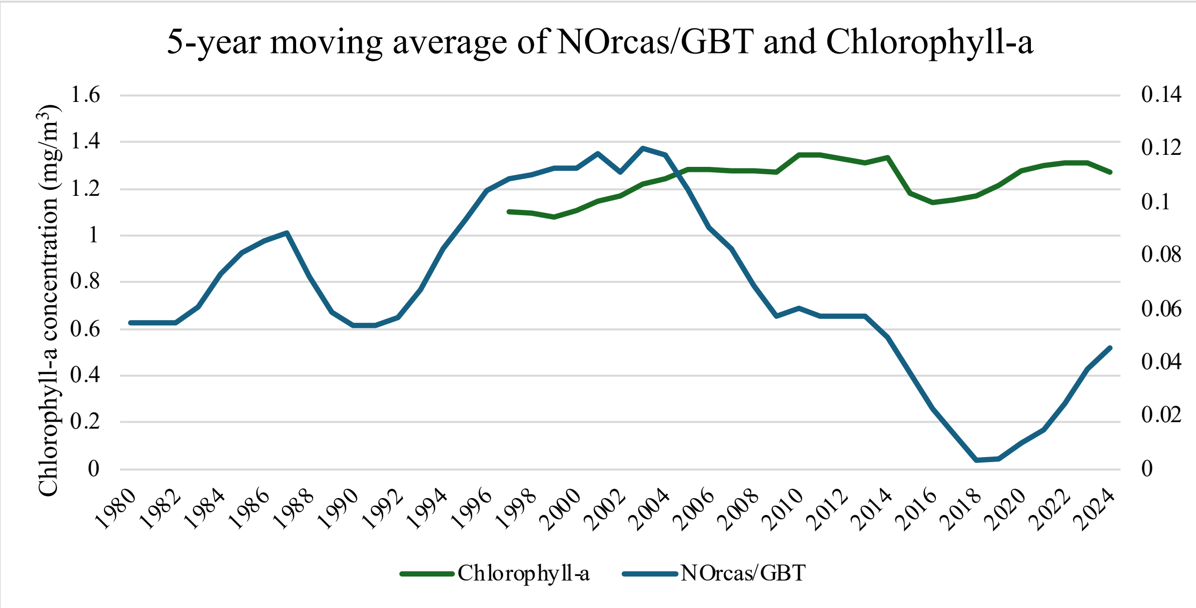

Figure 22: 5-year moving average of annual mean Chlorophyll-a concentration (mg/m³) and NOrcas/GBT.

Table 5: Correlation coefficients for 5-year moving averages of SST and Chlorophyll-a, each with the 5-year moving average of the other, Atlantic mackerel, Atlantic herring and NOrcas/GBT.

	eachother	Herring	Mackerel	Orca
SST	0.6	0.4	0.25	-0.3
Chlorophyll-a	0.6	0.27	0.34	-0.34

In summary, the connection between SST and chlrophyll-a concentration is significant and mackerel, herring and orcas respond to both changes in chlorophyll-a concentration and SST changes. The relationship is less significant than those found in section 3.4 (Overfishing).

4. Discussion

4.1 Distribution of orcas and distribution of effort

Considering the hunting of orcas before the 1980s (see section 1.1), this explains why the population size and therefore the number of sightings is low in the 1980s, as can be seen in table 1 and figure 15. It then has time to recover and rise to a high in the 2000s (Table 1) and also to spread over a larger area (figure 1 and 3). The same decrease in orca numbers that Jourdain et al. (2021) explains, is visible in both the maps and figure 15.

Orcas and the majority of aquatic animals are found in temperate, coastal waters, with a high level of marine productivity (Forney and Wade, 2006). One of these places is along the coast of Norway, which is one explanation for the great density of orca sightings (fig. 1, 3, 4) that can be seen within the first 100km from the nearest coastline (median distance for all decades, fig. 6). This area is also characterized by high chlorophyll-a concentrations, which thrive in colder, nutrient-rich waters, brought to the surface by ocean currents and along shorelines (NASA Earth Observatory, 2018).

In figure 8, we can see that there are more high-density spots away from the coast in the 1980s and 2010s and a trend towards the coastlines in the decades in between. This could be linked to a boom in the whale watching industry starting in the 1990s (Hoyt and Parsons, 2014) which would increase sightings by the coast but also an interest in studying these animals and therefore a possible effort further away from coastlines and commercial tourism.

Keeping in mind the northeast shipping passage (Nong et al., 2018) south of Svalbard, along the coast of Norway and between Iceland and Scotland, a rough channel that aligns with the passage is visible in all maps. Especially in the effort map (fig. 2), off the northcoast of Norway and south of Svalbard, the effort seems pretty strong and equal in that area, except for middle points between the two countries, where effort and sightings are much lower than in surrounding areas. In other maps too, a near empty or low sighting/effort line can be followed down south between the United Kingdom and southern coasts of Iceland. This could well be a combination of distance to coast and high presence of large ships, but the majority of high density spots of observations and effort lie outside this shipping channel.

It is important to keep in mind that all these explanations can be true and probably play a part, but another factor that cannot be forgotten is the observer bias. From figures 2 and 9, while orcas might have been along the coast in great numbers, so were the observers that recorded these sightings. This study focused on analyzing and eliminating observer bias as much as possible. This shows in the median effort distance (fig. 7) which goes beyond that of orca sightings. From the effort hotspots (fig. 2) and figures 8 and 9, which show that orca sightings do not align with the effort in relation to distance to coast, we can see that high effort does not equal high numbers of orcas and at times the opposite is true – low effort recorded higher densities. This is a good clue that observational bias was assessed and to some degree eliminated. However, a clear indicator of observer bias is the sighting density around Iceland, with sightings suddenly appearing in the 2000s/2010s which were nearly non-existent before that. This shows that monitoring around the island in the available dataset started much later than in Norway for example. The observer bias was also found to be especially strong in the seasonal analysis for the two winter months and autumn in the 1980s (figs.10, 11, 15).

Natural orca migration is under researched so the areas that orcas travel to outside this area are hard to pinpoint. It is sensible to assume that there are many more orca sightings both within and outside the studied area that are not recorded or not part of this dataset.

4.2 Overfishing and the impact on orcas

The results in figure 15 and in table 4, show that orcas are linked to and dependent on key prey species, which makes them susceptible to changes in prey abundance. This study found that the link between NOrcas/GBT and Atlantic mackerel was statistically more significant than that to Atlantic herring. The figure also shows a peak in “Orca population’ before a peak in Atlantic Mackerel and Herring. This is unusual for predator-prey interactions, but it could be due to several factors, like stock health estimates could lag behind the actual maximum amount of stock size. Another theory is presented by Cortez and Weitz (2014) which argue that a peak in predators could precede a peak in prey because of coevolution. If orcas show a high hunting success and eliminate weaker individuals first, prey species could adapt. Prey abundance could also lag behind because it is more strongly influenced by other environmental factors.

Slotte et al. (2025) shows that Atlantic herring migrate seasonally to spawning and feeding grounds: down the coast of norway in spring, into open waters north of Iceland (further off the coast of Norway: fig 11.), circeling to the north of Norway in summer, where they stay in autumn (highest latitude: fig. 12) and then spend the winter close to the Norwegian coast. The same pattern is clearly visible on figure 10, which supports that orcas follow seasonal migration of atlantic herring.
Under increasing ocean temperatures, these patterns have been shown to change and herring populations might face reproductive stress (Gröger et al., 2024) and shift their spawning grounds further north (Slotte et al. 2025). Spawning distribution of Atlantic mackerel has also shifted northwards in response to global warming (Bruge et al., 2016). Figure 20 also shows a temperature preference for both fish species. Chandelier and Kiszka (2026) found that dolphins and porpoises, which are among transient killer whale prey will expand their range into subpolar waters by 2100.

Additionally, the EU states in its “Common Fisheries Policy” that all fleets of its member states have to end overfishing by the year 2020. In 2018, 40% of stocks were still overfished (Froese et al., 2020). Atlantic herring was overfished in 16,2% of the recorded years and mackerel in more than half of the years during 1998-2024 (table 3).
Currently, mackerel catch is still exceeding quotas with a catch advice of 174357 tons for 2026 and a total catch of 755143 tons in 2025. ICES determines this quota to stay within the maximum sustainable yield, which is currently not the case (ICES, 2025). Herring quotas are in line with a long-term strategy agreed upon by several european states which set the 2026

quota at 533914 tons. In 2024 (latest catch data), total catch was below that, but in seven years prior to that, this quota was exceeded (ICES, 2025).

If overfishing increases and stock numbers sink, resident killer whales in the North Atlantic lose their main source of food. Even though they are strong and skilled to adapt to hunting new species, Ford et al. (2009) found that their specialization is actually a limiting factor in how they respond to food availability. Since other fish stocks are also depleted a respecialization in the same geographical area might be altogether impossible. Moreover, it would interfere with the highly complex food web, if large predators change their main prey, since another animal is likely dependant on it (Estes et al., 2009).

A combination of these factors could drive Orcas not only to follow its prey into new regions but also to migrate further north to find more prey abundance. Nevertheless, if stock depletion continues, Orcas could be forced to adapt to new prey species.

4.3 Temperature preferences and climate change

As described by Blanc & Martínez-Rincón (2023), one suitable spot for orcas is in the North-east Atlantic and Arctic area (NEAA) (see section 1.3).
Figure 10 and figures 11 and 12 show a migration in autumn to the highest latitudes compared to the other seasons. Due to the high heat capacity of the Atlantic, it takes all summer to warm up which is why the highest temperatures are usually reached in September (Copernicus, 2024). The distribution to higher latitudes in the warmest months shows that prey species and Orcas respond to warming oceans and avoid too high temperatures further south where they are found in winter for example. Figure 19 shows a negative response of NOrcas/GBT to rising SST, showing again, that orcas have a temperature preference and could be affected by climate change.
At the bottom of the food chain, sits phytoplankton which contains photosynthesizing chlorophyll-a, which is also heavily temperature dependent (fig. 18). Increasing ocean temperatures and loss of sea ice alter the timing (earlier blooming), location and composition of phytoplankton blooms. These changes impact the entire food web and shifts in locations of primary productivity cascade through all trophic levels and affect prey and predator species alike (Ardyna and Arrigo, 2020). This is changing the productivity in the Atlantic ocean and will cause phytoplankton as well as fish and orcas to move into colder, more nutrient-rich waters.

4.4 Impacts of change and other factors

With a higher presence of orcas in polar waters, which can be expected to increase with the continuous decrease in arctic ice (Higdon & Ferguson, 2009), species which are home in the arctic will experience higher predation pressure from boreal species with increasing ocean temperatures (Dupont et al., 2024). This could fundamentally change the arctic food web and derive predators of their usual prey. Moreover, this does not only entail negative consequences for arctic species but also for humans, primarily indegenous peoples who rely on fish as a main food source (Snook et al., 2022).

As was mentioned in section 4.2, human presence in the ocean in the form of boats and submarines and resulting noise pollution are some additional factors that affect orcas (MacGillivray et al., 2025). Since orcas use echolocation and sound to communicate and coordinate themselves during foraging, this could be a great stressor, confusion and could negatively impact foraging success and with that, survival of the species (NOAA Fisheries, 2024).

4.5 Limitations and future research

This study was limited by the data quality much more than the data quantity. The background for data collection was mostly unclear and that made it hard to understand what visible patterns were due to changes in orca behaviour, and which were caused by how and where observers were active. This is especially challenging when exploring environmental changes at higher latitudes, because the number of observing people will go down drastically. Since the tools used for observations, tracking and data collection have changed over time, data from past centuries will ultimately be different than the newest datasets, which again introduces a variable that adds inconsistencies. For example, there seems to have been a step-change in the method of observation from boats before the 2020s and entirely land-based observer methods after that (fig. 3). Due to high seasonal variability and a high seasonal observer bias, it is recommended to monitor these factors more closely.

Moreover, an important distinction to be understood is that OBIS does not track individual animals, so the sightings cannot be simply interpreted as migration patterns but rather as distribution shifts. This can be improved with photo-identification of specific animals.

Both SST and chlorophyll-a were averaged within a year and over the whole study area which does not represent the spatial distribution or differences we see in real life but merely trends over time. These considerations were outside the scope of this study but could be interesting to expand on.

For large-scale monitoring of orcas, a machine-learning model, such as random-forest models, could be used to predict orca density in specific areas depending on factors such as: Season, SST, Chlorophyll-a concentration, prey abundance and thickness or density of sea ice.

5. Conclusion

This study analyzed orca occurrence data in connection with catch sustainability of Atlantic mackerel and herring and environmental indicators SST and chlorophyll-a to assess distribution of killer whales in the North-east Atlantic.

It was found that:

a) There is a spatial migration change of the north-east Atlantic killer whale population and that it is consistent with prey migration which is altered by overfishing and rising sea-surface temperatures.

- The highest densities of NOrcas/GBT were found between 59-69 degrees of latitude.
- There is a strong seasonal variability in migration patterns.

b) Overfishing of Atlantic mackerel and herring was found to have a more immediate impact in orca distribution than changes in SST.

- This will likely cause migration into more productive areas or force a new specialization in prey.
- The connection to Atlantic mackerel stock health was found to be very significant and stronger than that of Atlantic herring. A decrease in mackerel stock health coincides with an increase in “Orca population” (-0.63) and good biological sustainability has a positive impact on the “Orca population” (0.84).
- Changes in SST and phytoplankton distribution which are directly influenced by climate change cause a chain of effects through the entire food web, which could lead to a shift in productive zones into colder waters in the arctic ocean.

c) Finally, while there are uncertainties with data resources like OBIS sea-map, it is a valuable resource which can contribute greatly to research of marine mammals and how they respond to changes in marine ecosystems.

- The observer bias was found to add more uncertainty when related to distance to coast than to latitude distribution which was affected less.

Since only a couple of factors were considered here, the spatial and temporal extent of the consequences is uncertain. This constrains the assessment of impacts on arctic ecosystems and food webs because of a lack of data and inconsistencies in observer bias.

Implications for international policy makers and governments in the North-Atlantic region include the compliance with scientific fishing quotas to ensure a healthy recovery of fish stocks and the ending of overfishing. It is recommended to work towards climate goals in a joint effort to contain and prevent large-scale migrations.

To improve monitoring of orcas, other tools than human observations of animal occurrences would add consistency to get a better understanding of how orcas adapt to overfishing and environmental changes. Technologies like sound signal analysis and tagging could improve data quality for example. Furthermore, especially for arctic ecosystems, combining knowledge with observations and insights from indigenous peoples will not only add value but also help understand the effects ecosystem changes and alterations in the food web have on these groups and how to better support them. Finally, because of their longevity, orcas need to be monitored over larger time spans to better comprehend generational changes.

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Appendix A

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Dataset names and citations for the 5 common marine mammals can be shared upon request.

Appendix B

Table 6: Raw number of Orca sightings for all years

1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
40	15	29	28	43	56	50	52	40	52
1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
21	24	78	81	124	80	111	140	145	150
2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
124	175	193	247	153	195	157	90	133	89
2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
110	86	149	147	114	114	3	7	4	13
2020	2021	2022	2023	2024					
15	22	134	115	222					