Harbour porpoise trends and offshore wind farm effects in the German Bight, North Sea

Analysis of CPOD data

Husum, May 2025

Prepared for BWO e.V.

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Funding partners:

1. BP AEIL
2. Iberdrola
3. Ørsted
4. OWP Gennaker GmbH
5. RWE Offshore Wind GmbH
6. Shell
7. TenneT Offshore GmbH
8. Vattenfall Vindkraft AB

Client:

9. BWO e.V.

Scientific partners:

10. DanTysk Sandbank Offshore Wind GmbH & Co. KG
11. EnBW Hohe See GmbH & Co. KG
12. EnBW Albatros GmbH & Co. KG
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18. Trianel Windkraftwerk Borkum II GmbH & Co. KG
19. UMBO GmbH
20. Veja Mate Offshore Project GmbH
21. WindMW GmbH

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Acknowledgments

We would like to sincerely thank BWO e.V. for providing the data and financing this study.

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AIC:	Akaike Information Criterion (statistical value for comparison of different models)
ARMA:	Auto-Regressive (AR) Moving-Average (MA) process
BHT:	Broad Habitat Types
CPOD:	Cetacean Porpoise Detector
DP10M:	Detection-Positive 10-Minutes
%DP10M/d:	Percentage of Detection-Positive 10-Minutes per day
%DP10M/period:	Percentage of Detection-Positive 10-Minutes per period (year or season)
EEZ:	Exclusive Economic Zone
FFH:	EU Flora Fauna Habitat Directive
GAM:	Generalised Additive Model
GAMM:	Generalised Additive Mixed-effects Model
HDI:	Highest Probability Density Credible Interval
MCMC:	Markov Chain Monte Carlo randomisation
MSFD:	EU Marine Strategy Framework Directive
OHT:	Other Habitat Types
OWF:	Offshore Wind Farm
OWP:	Offshore-Windpark
PAM:	Passive-Acoustic Monitoring
POD:	Porpoise Detector
R:	A statistical software environment
SAC:	EU Special Area of Conservation
UTM:	Universal Transverse Mercator (coordinate system)

1 SUMMARY

The rapidly growing number of offshore wind farms (OWFs) in the German Bight, North Sea, raised questions about long-term effects on the habitat use of the highly mobile harbour porpoise. Previous studies found seemingly contradicting trends for this species in that region. As a consequence, this project was designed to shed more light on the issue by investigating long-term passive-acoustic monitoring (PAM) data obtained by cetacean porpoise detectors (CPODs). This study is based on a 13-year PAM dataset derived from CPOD monitoring between the years of 2010 and 2023 with in total 69 different deployment positions throughout the German EEZ (German Bight, North Sea); with the exception of the northwestern and central part where no acoustic recording devices were deployed.

The study was focussing on the following two main topics:

1) The evaluation of long-term trends of harbour porpoise detection rates in the German Bight and its subareas.

2) A comparison of harbour porpoise detection rates measured within OWFs in operation (positioned in the German Bight) to those in the vicinity of the same wind farms.

For the entire study area and on a whole-year basis, no significant trend or tendency of the harbour porpoise detection rate (*%DP10M/period*) was found in the years 2011 to 2019. On a seasonal basis (*%DP10M/period*), a positive trend was found for winter and a positive tendency for spring, whereas no trend or tendency was registered in summer and autumn.

Our result of no clear overall trend or tendency in the German Bight appears to contradict the findings of another investigation based on aerial observer surveys from 2002 to 2019 by Nachtsheim et al. (2021) which reported an apparently negative trend. When comparing the two studies in more detail, this contradiction can be resolved. One reason was that different periods were investigated. Our overall trend analysis started in 2011, whereas the study by Nachtsheim et al. (2021) began in 2002. That study showed a density increase from 2002 to 2006, then a decrease until 2012, but no clear trend afterwards anymore. Hence, from 2012 onwards, both studies were largely in line in showing no clear trend. A similar issue occurred when comparing our study to Gescha 2. That study reported a positive trend of CPOD detection rates registered in the German Bight from 2010 to 2016, the latter year, however, being a very good year for harbour porpoises. We now could show that the overall yearly detection rate levelled out again after 2016, in the end resulting in no clear trend being found by CPOD data for the period from 2011 to 2019.

Even though the overall trend in the German Bight was largely stable over the study years, the development of detection rates differed among five investigated subareas within the German Bight, for some of which data until 2023 were available (subareas *Northwest* and *Southeast*). Whereas partly negative trends or tendencies were found for the subareas *Northwest* and *Northeast*, the development in the subareas *North* and *Southeast* was more or less positive, while the situation in the subarea *South* remained nearly unchanged. In general, this pointed to a partial shift in porpoise distribution within the German Bight over the years. The subareas *North* and *Southeast* might have become more favourable for porpoises, eventually attracting more animals from subareas *Northwest, Northeast* and possibly elsewhere. Food availability might have played an important role here,

which could also be a major factor regarding a general southward shift of the harbour porpoise distribution within the North Sea registered over the last three decades by four SCANS studies. In this respect, namely sand eels (Ammodytidae) seem to be of great importance for harbour porpoises.

To evaluate the presence of harbour porpoises in relation to OWFs (within OWFs in comparison to the vicinity, i.e., 2.5 km around the OWF border), two generalized additive mixed model (GAMM) approaches were used: a factor model using the spatial OWF reference as a binary factor; and a continuous model using the distance to OWF, allowing to describe nonlinear dependencies of harbour porpoise abundance. Our results show significantly higher detection rates within OWFs than in their vicinity, with an increase of 10.6 % in the factor model. These findings are in line with previous studies looking at single OWFs but apparently contradict other studies showing no or even negative impacts of OWFs on harbour porpoise presence. Regarding models for single OWFs, porpoise detections were found to be higher within the OWFs than in the vicinity of the OWFs for the OWF clusters *Albatros*, *BARD* and *Butendiek*. Only the *DanTysk* and *Borkum West* models show higher porpoise detection rates in the vicinity of the OWFs than within the OWFs, though featuring large confidence intervals due to smaller sample sizes and supposedly great fluctuations in habitat use.

According to our findings, OWFs in operation may attract rather than deter harbour porpoises. Reef effects (offshore foundations and piles serve as a hard substrate and attract fish and other hard substrate-related fauna), as well as refugium effects (within the areas of German OWFs fishing is prohibited) might have been of importance here. Even though service vessels still operate within OWFs, and intrinsic ambient noise is present around the wind turbines, these impacts apparently did not deter harbour porpoises.

As a synopsis of our results, we showed stable harbour porpoise detection rates in the German Bight from 2011 onwards, with differences among five investigated subareas. Increasing detection rates in the subareas *North* and *Southeast* may have been an expression of a changing prey distribution that supposedly was a major driver for a general southward trend of the harbour porpoise distribution within the North Sea observed over the last three decades. As a number of OWFs were built within the German Bight over the last 15 years, on the one hand leading to short-term disturbance during construction, but on the other hand to potential reef and refugium effects on the long-term, the latter may have had its part in altering prey availability for porpoises. Summarising, small-scale (OWFs/OWF clusters) and large-scale (North Sea) shifts in prey distribution are likely to be important for explaining the results of both research topics of the presented study, the stable overall long-term trend in the German Bight, as well as increased detection rates within German OWFs in the North Sea.

2 ZUSAMMENFASSUNG

Die rasch wachsende Zahl von Offshore-Windparks (OWPs) in der Deutschen Bucht, Nordsee, wirft Fragen zu den langfristigen Auswirkungen auf die Lebensraumnutzung des hochmobilen Schweinswals auf. Frühere Studien ergaben scheinbar widersprüchliche Trends für diese Art in dieser Region. Daher sollte dieses Projekt durch die Untersuchung von Langzeitdaten der passiven akustischen Überwachung (PAM), die mit Schweinswal-Detektoren (CPODs) gewonnen wurden, mehr Aufschluss über diese Frage geben. Diese Studie basiert auf einem 13-jährigen PAM-Datensatz, der aus CPOD-Überwachungen zwischen den Jahren 2010 und 2023 mit insgesamt 69 verschiedenen Stationen in der gesamten deutschen AWZ (Deutsche Bucht, Nordsee) gewonnen wurde; mit Ausnahme des nordwestlichen und zentralen Teils, wo keine akustischen Aufzeichnungsgeräte eingesetzt wurden.

Die Studie befasste sich mit den folgenden zwei Forschungsschwerpunkten:

1) Die Ermittlung von Langzeittrends der Schweinswal-Detektionsraten in der Deutschen Bucht und ihren Teilgebieten.

2) Ein Vergleich der Schweinswal-Detektionsraten, die innerhalb der in Betrieb befindlichen OWPs (in der Deutschen Bucht) erfasst wurden, mit denen in der Umgebung der gleichen Windparks.

Für das gesamte Untersuchungsgebiet und auf Ganzjahresbasis wurde in den Jahren 2011 bis 2019 kein signifikanter Trend oder eine Tendenz der Schweinswal-Erkennungsrate (*%DP10M/Periode*) festgestellt. Auf saisonaler Ebene *(%DP10M/Periode*) wurde ein positiver Trend für den Winter und eine positive Tendenz für das Frühjahr festgestellt, während im Sommer und Herbst kein Trend oder keine Tendenz zu verzeichnen war.

Unser Ergebnis, dass es in der Deutschen Bucht keinen eindeutigen Gesamttrend oder eine Tendenz gibt, scheint im Widerspruch zu den Ergebnissen einer anderen Untersuchung zu stehen, die sich auf Luftbeobachtungserhebungen von 2002 bis 2019 von NACHTSHEIM et al. (2021) stützt und einen scheinbar negativen Trend feststellt. Bei einem genaueren Vergleich der beiden Studien kann dieser Widerspruch aufgelöst werden. Ein Grund dafür ist, dass unterschiedliche Zeiträume untersucht wurden. Unsere Gesamttrendanalyse begann im Jahr 2011, während die Studie von NACHTSHEIM et al. (2021) im Jahr 2002 begann. Diese Studie zeigte einen Anstieg der Dichte von 2002 bis 2006, dann einen Rückgang bis 2012, danach aber keinen klaren Trend mehr. Ab 2012 zeigten beide Studien also weitgehend übereinstimmend keinen klaren Trend mehr. Ein ähnliches Problem ergab sich beim Vergleich unserer Studie mit Gescha 2. Diese Studie berichtet über einen positiven Trend der CPOD-Detektionsraten in der Deutschen Bucht von 2010 bis 2016, wobei letzteres Jahr jedoch ein sehr gutes Jahr für Schweinswale war. Wir konnten nun zeigen, dass die jährliche Gesamtdetektionsrate nach 2016 wieder abflachte, sodass für den Zeitraum von 2011 bis 2019 kein eindeutiger Trend bei den CPOD-Daten festgestellt werden konnte.

Auch wenn der Gesamttrend in der Deutschen Bucht über die Untersuchungsjahre weitgehend stabil war, zeigte sich ein unterschiedlicher Trend der Detektionsraten in den fünf untersuchten Teilgebieten innerhalb der Deutschen Bucht, für die teilweise Daten bis 2023 vorlagen (Teilgebiete *Nordwest* und *Südost*). Während für die Teilgebiete *Nordwest* und *Nordost* teilweise negative

Trends bzw. Tendenzen festgestellt wurden, war die Entwicklung in den Teilgebieten *Nord* und *Südost* mehr oder weniger positiv, während die Detektionsraten im Teilgebiet *Süd* nahezu unverändert blieben. Insgesamt deutet dies auf eine teilweise Verschiebung der Schweinswalverteilung innerhalb der Deutschen Bucht im Laufe der Jahre hin. Die Teilgebiete *Nord* und *Südost* könnten für Schweinswale günstiger geworden sein und schließlich mehr Tiere aus den Teilgebieten *Nordwest*, *Nordost* und möglicherweise aus anderen Gebieten angezogen haben. Die Nahrungsverfügbarkeit könnte hier eine wichtige Rolle gespielt haben, was auch ein wichtiger Faktor für eine allgemeine südwärts gerichtete Verschiebung der Schweinswalverbreitung in der Nordsee sein könnte, die in den letzten drei Jahrzehnten in vier SCANS-Studien festgestellt wurde. In dieser Hinsicht scheinen insbesondere Sandaale (Ammodytidae) für Schweinswale von großer Bedeutung zu sein.

Um die Präsenz von Schweinswalen in Bezug auf OWPs zu untersuchen (innerhalb von OWPs im Vergleich zur Umgebung, d.h. 2,5 km um die OWP-Grenze), wurden zwei verallgemeinerte additive gemischte Modellansätze (GAMM) verwendet: ein Faktormodell, dass die räumliche OWP-Referenz als binären Faktor verwendet, und ein kontinuierliches Modell, das die Entfernung zum OWP verwendet und es ermöglicht, nichtlineare Abhängigkeiten der Schweinswalhäufigkeit zu beschreiben. Unsere Ergebnisse zeigen, dass die Detektionsraten innerhalb von OWPs signifikant höher sind als in deren Umgebung. Diese sind innerhalb von OWPs im Faktormodell um 10,6 % höher als in der Umgebung von OWPs. Diese Ergebnisse stehen im Einklang mit früheren Studien, die sich mit einzelnen OWP befassten, widersprechen aber offensichtlich anderen Studien, die keine oder sogar negative Auswirkungen von OWPs auf das Vorkommen von Schweinswalen zeigen. Was die Modelle für einzelne OWPs betrifft, so wurden für die OWP-Cluster Albatros, BARD und Butendiek innerhalb der OWPs mehr Schweinswale nachgewiesen als in der Nähe der OWPs. Nur die Modelle DanTysk und Borkum West zeigen höhere Schweinswal-Nachweisraten in der Nähe der OWPs als innerhalb der OWPs, allerdings mit großen Konfidenzintervallen aufgrund kleinerer Stichprobenumfänge und vermeintlich großer Schwankungen in der Habitatnutzung.

Unseren Erkenntnissen zufolge könnten die in Betrieb befindlichen OWPs Schweinswale eher anziehen als abschrecken. Riffeffekte (Offshore-Fundamente und Pfähle dienen als Hartsubstrat und locken Fische und andere Hartsubstrat-Fauna an) sowie Refugiumseffekte (in den Bereichen deutscher OWPs ist das Fischen verboten) könnten hier von Bedeutung gewesen sein. Auch wenn innerhalb der OWPs noch Wartungsschiffe im Einsatz sind und in der Umgebung der Windenergieanlagen Eigengeräusche vorhanden sind, haben diese Auswirkungen Schweinswale offenbar nicht abgeschreckt.

Als Zusammenfassung unserer Ergebnisse zeigen wir stabile Schweinswal-Detektionsraten in der Deutschen Bucht seit 2011, mit Unterschieden zwischen den fünf untersuchten Teilgebieten. Steigende Nachweisraten in den Teilgebieten *Nord* und *Südost* könnten eine Folge der sich verändernden Beuteverteilung sein, die vermutlich ein Hauptgrund für die in den letzten drei Jahrzehnten beobachtete allgemeine südwärts gerichtete Verschiebung der Schweinswalverbreitung in der Nordsee war. Da in den letzten 15 Jahren eine Reihe von OWPs in der Deutschen Bucht gebaut wurden, was einerseits zu kurzfristigen Störungen während des Baus, andererseits aber auch zu potenziellen Riff- und Refugiumseffekten auf lange Sicht geführt haben könnte, können letztere auch zur Veränderung der Beuteverfügbarkeit für Schweinswale beigetragen haben. Zusammenfassend sind kleinräumige (OWPs/OWP-Cluster) und großräumige (Nordsee) Verschiebungen in der Beuteverteilung wahrscheinlich wichtig, um die Ergebnisse der beiden Forschungsschwerpunkte der vorliegenden Studie – den stabilen langfristigen Gesamttrend in der Deutschen Bucht sowie die erhöhten Detektionsraten innerhalb deutscher OWPs in der Nordsee – zu erklären.

3 INTRODUCTION

The harbour porpoise (*Phocoena phocoena* L., 1758) is the most common cetacean species in the continental shelf waters of north-western Europe (REID ET AL. 2003), being the only cetacean species that breeds in the German Bight of the North Sea. The rapid expansion of offshore wind farms (OWFs) in that region raised questions about long-term effects on the habitat use of highly mobile species such as the harbour porpoise. Recently, negative porpoise trends from 2002 to 2019 in parts of the German exclusive economic zone (EEZ) of the North Sea, assessed by aerial surveys, were reported by NACHTSHEIM et al. (2021). In contrast, the Gescha 2 study reported a positive development from 2010 to 2016 (BIOCONSULT SH ET AL. 2019). Therefore, it was of considerable scientific interest to evaluate porpoise trends in the German Bight over a longer period than investigated by Gescha 2. The main trend analysis of the presented study is based on passive-acoustic monitoring (PAM) using cetacean porpoise detector (CPOD) data from 2011 to 2019, but for some parts of the German Bight even trends until 2023 could be investigated (Figure 4.1). Among others, SIEBERT & RYE (2008), KYHN et al. (2012), JACOBSON et al. (2017), and AMUNDIN et al. (2022) were able to show a positive relationship between PAM detection rates and porpoise densities. Also, a positive correlation between porpoise densities from digital aerial surveys and CPOD detection rates was found in an area of up to 10 km around CPOD stations in the North Sea (SCHUBERT ET AL. 2018). Hence, CPOD detection rates were shown to be a reasonable proxy for relative harbour porpoise densities: on average, higher detection rates correlate with higher densities in up to 10 km around a CPOD measurement position. Following, CPOD monitoring allows for inference on harbour porpoise densities, making trend analyses based on CPOD data feasible, these not only being valid for a few hundred metres around a device but for a range of up to 10 km. Using an arrangement of CPOD stations, even certain inferences on trends in a larger area are possible.

Negative effects of OWFs due to noise emissions during the construction phase have been studied in depth (e.g., TOUGAARD et al. 2009a; BRANDT et al. 2011; HAELTERS et al. 2012; DÄHNE et al. 2013; BIOCONSULT SH et al. 2019; BENHEMMA-LE GALL et al. 2021). However, effects of OWFs in operation are less known. Harbour porpoise reactions to OWFs in operation may be rooted in ambient noise levels, either from maintenance ships or the wind turbines themselves (e.g., KOSCHINSKI et al. 2003a; TOUGAARD et al. 2009b; NORRO et al. 2011), or related to reef (LANGHAMER 2012; BERGSTRÖM ET AL. 2013; MIKKELSEN ET AL. 2013; DEGRAER ET AL. 2020) or refugium effects (BONSU ET AL. 2024). The species is known to react sensibly to ship traffic (HERMANNSEN ET AL. 2014; DYNDO ET AL. 2015; WISNIEWSKA ET AL. 2018; FRANKISH ET AL. 2023) and noise, especially of higher frequencies (LUCKE ET AL. 2008; KASTELEIN ET AL. 2017). However, so far only few studies have investigated the effects of operational OWFs, indicating varying responses of harbour porpoises to OWFs. SCHEIDAT et al. (2012) and POTLOCK et al. (2023) have found a significant increase of harbour porpoise detections with CPODs during the operation of Dutch and British OWFs, compared to the time before the OWF was built. On the contrary, TEILMANN & CARSTENSEN (2012) reported that an operational OWF in Denmark had deteriorating effects on harbour porpoise presence. Finally, VAN POLANEN PETEL et al. (2012) and DÄHNE et al. (2014) found no difference in detections in areas where OWFs where constructed. While showing first evidence of harbour porpoise reactions to operational OWFs, these studies were looking at individual wind farms. To analyse effects on a larger scale, vast datasets are necessary, but direct measures of in-habitat behaviour, as could be acquired by tagging data, are hard to obtain (SCHEIDAT ET AL. 2024; VROOMAN ET AL. 2024). The most extensive data for the German Bight were available in the form of CPOD data, providing continuous information about relative harbour porpoise activity over a long period. Such data were analysed here.

The mentioned aspects which could influence the porpoise presence and distributional development were condensed into two research topics, designed to gain more insight into the long-term trends of harbour porpoise detection rates in the German Bight in general, but also into the effects of OWFs in operation on the animals, an important factor in the light of a growing offshore industry. In detail, the following topics were investigated by this study:

1) The evaluation of long-term trends of harbour porpoise CPOD detection rates in the German Bight and subareas of it.

2) A comparison of harbour porpoise CPOD detection rates measured within offshore wind farms in operation (all positioned in the German Bight) to rates in the vicinity of the same wind farms.

These topics are dealt with in two separate chapters, afterwards being condensed into a synopsis.

4 GENERAL METHODS

4.1 Research area

Data from CPODs deployed in the German EEZ (German Bight, North Sea) were analysed for this study, with the exception of the northwestern and central part of that region where no acoustic recording devices were deployed (Figure 4.1).

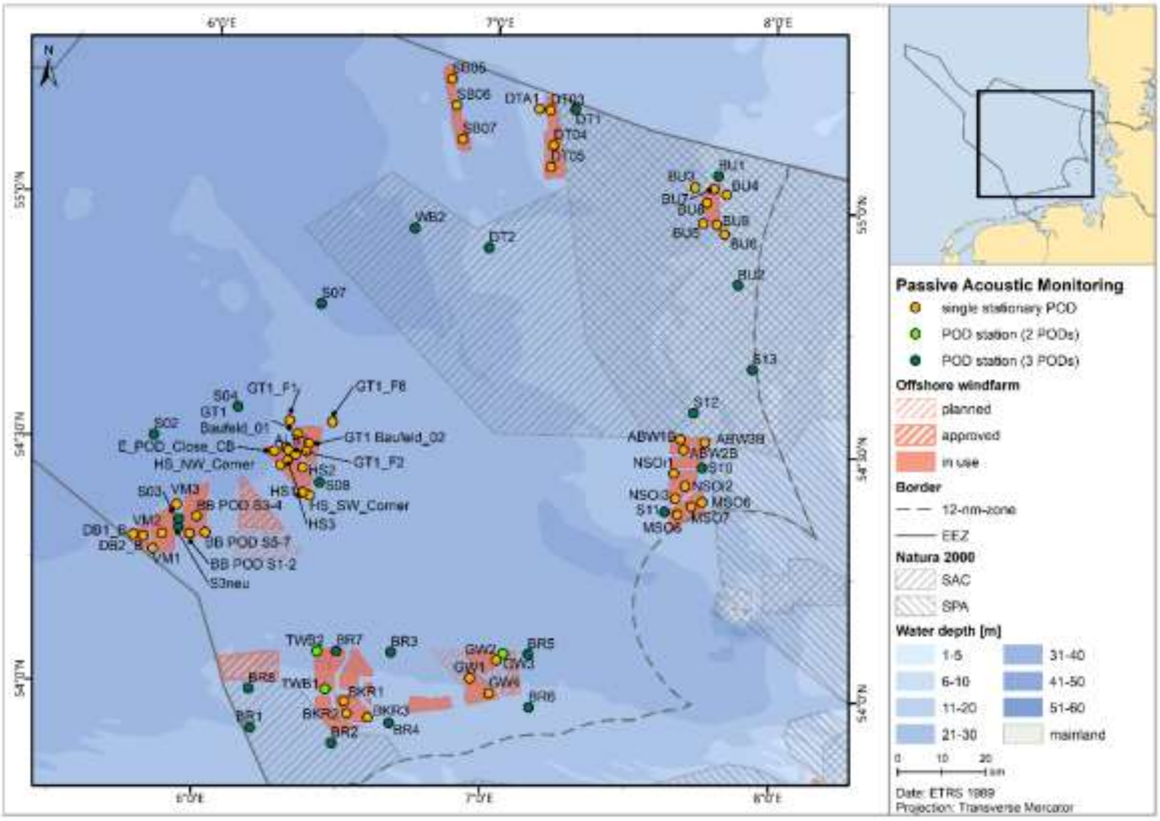

Figure 4.1 Map of the study area with all offshore wind farms planned, approved, or in use until 2023, as well as CPOD positions from which data were available for this study.

4.2 Passive-acoustic monitoring data using CPODs

Harbour porpoises use echo-location through short, high-frequency click sounds to communicate, assess their environment, and locate prey (AKAMATSU ET AL. 2001; WISNIEWSKA ET AL. 2016). PAM is a method using hydrophones to capture the sounds emitted by the animals. In our case specialised devices, so called CPODs (Figure 4.2), were used to detect porpoise clicks. Harbour porpoises emit clicks primarily in a forward direction, with a maximum beam angle of 16.5° (AU ET AL. 1999). As a result, CPODs can only detect porpoises under specific conditions: (1) when the porpoises emit clicks, (2) when they are within approximately 300 m of the hydrophone, and (3) when they are oriented towards the hydrophone. The likelihood of detection thus heavily relies on porpoise behaviour, distance, and the direction in which they emit clicks relative to the CPOD.

Harbour porpoises equipped with a hydrophone have been shown to use their echolocation system almost continuously (AKAMATSU ET AL. 2007; WISNIEWSKA ET AL. 2016). Therefore, echolocation is considered the most crucial sensory perception, allowing a correlation between CPOD detection rates and porpoise density in a marine area due to its constant use. It is a valid assumption that CPOD detection rates roughly indicate true harbour porpoise densities: higher detection rates suggest a greater number of animals present in the area (see Discussion section 5.3.1 for more detail).

CPODs are autonomous data loggers designed to register high-frequency sound events. They consist of an 80 cm long plastic tube with a hydrophone positioned at one end. Attached to the hydrophone are an amplifier and an electronic filter. The hydrophone is omnidirectional, capturing all sound events within the 20 kHz to 160 kHz range. For each click, the device records the main frequency, frequency-response curve, sound duration and intensity (in 8-bit steps), as well as the bandwidth and envelope of the frequency spectrum onto an SD memory card with a maximum capacity of 4 GB. CPODs are powered by ten 1.5 Volt D batteries, which provide energy for at least six weeks. During this period continuous recording takes place.

Figure 4.2 C-PODs: left: ready for deployment; right: opened C-POD.

CPODs provide the following important information on harbour porpoises:

- presence/absence of animals around a station;
- an estimate of relative abundance (the higher the detection rate, the more animals were present at a position);
- assessment of diel and yearly (=phenology) activity cycles.

Assuming that detection rates are not significantly affected by differences between individual CPODs, spatial and temporal variations between stations as well as temporal changes can be assessed at different temporal resolutions. To ensure accuracy, CPODs were calibrated before their initial deployment and regularly throughout the study period, minimising errors due to variations in CPOD sensitivity.

Generally, PAM is suitable for generating continuous long-term datasets, allowing for integration of short-term fluctuations by using detection rates of various temporal resolutions. However, the collected data cover a relatively small area, as the detection range of a CPOD ranges only up to about 300 m. Yet, these data are still a good proxy for relative densities within an area of 10 km around a CPOD (SCHUBERT ET AL. 2018). As another indication, we mostly found a good phenological similarity of the detection rates from the CPOD stations within each subarea. Hence, these rates are apparently representative on a larger spatial scale than the pure detection range of a CPOD. Otherwise, small-scale processes would have led to more considerably differing detection rates among stations within each subarea.

Data collection

In this study, data from two different CPOD deployment schemes are utilised: continuous monitoring positions ("CPOD stations" with three CPODs each) and project-specific stationary CPODs ("project CPODs"). Although deployment specifications vary slightly between locations or companies responsible, the general principle remains consistent across all three schemes: a CPOD is positioned in the water column 5-10 m above the sea floor, secured in place by a mooring system and maintained in the water column by a buoy. Despite differences in design and settings among the two deployment schemes of stationary CPODs, the same technical device, the CPOD (Chelonia Ltd., UK; Figure 4.2), was used. The devices are deployed and maintained by consultant agencies contracted by German authorities and wind farm companies, and calibrated by the manufacturer or the Meeresmuseum Stralsund.

- CPOD stations consist of three CPODs (two exceptions with only two devices) deployed simultaneously. These are positioned within a square formed by four marker buoys, which indicate the location of the CPOD station and prevent ships from accidentally crossing the area and causing equipment loss. Two CPODs are positioned at one buoy within the square, the third CPOD at a second buoy in about 150 m distance from the first one (Figure 4.3). The simultaneous deployment of multiple CPODs at one location accounts for the occasional loss or malfunction of individual CPODs. CPOD stations are serviced approximately every 1 to 2 months, during which memory cards and batteries are exchanged, and lost CPODs are replaced. In noisy environments, the memory cards capacity might be exceeded. To prevent this, a recording limit of 4,096 clicks per minute was set. If this number was reached, the CPOD stopped recording for the remaining seconds of that minute. For analysis, only data from one CPOD at a time were used per CPOD station, and the CPOD with the most complete time series of recordings was always chosen.

- Single CPODs were deployed for specific wind farm projects. They consist of only one CPOD with a similar mooring system and the same CPOD settings as CPOD stations.

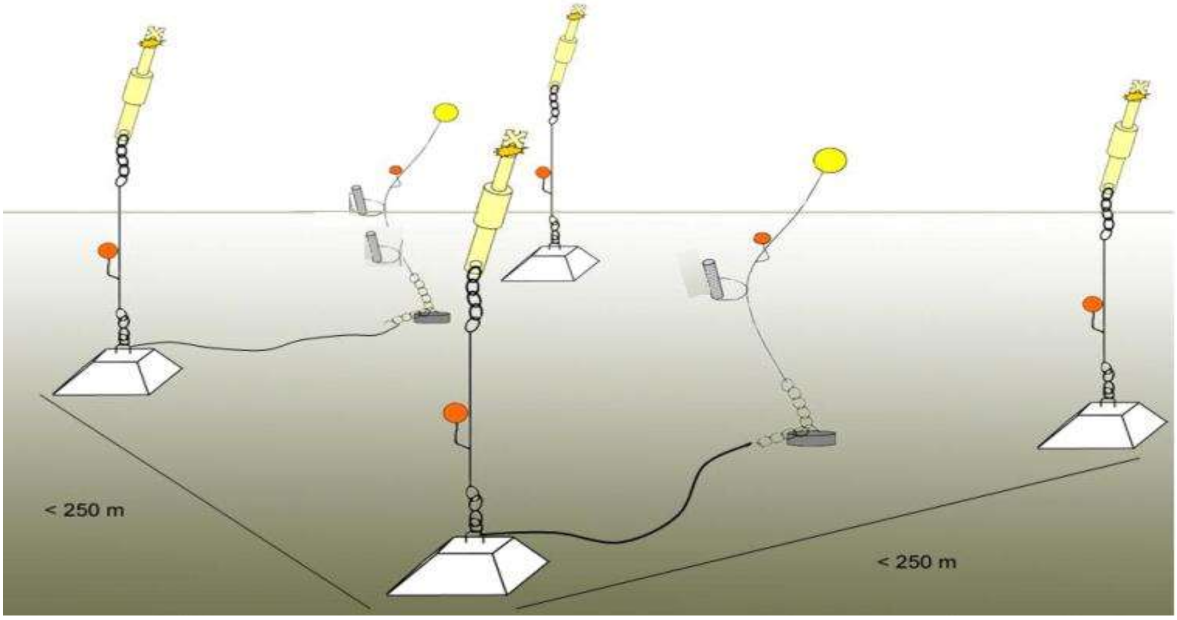

Figure 4.3 *CPOD system used by BioConsult SH for CPOD stations with three devices (drawing: Honnef/Gauger).*

All CPODs were calibrated to equal sensitivity threshold levels (± 3 dB) according to the main frequency of harbour porpoise click sounds (calibration at 125 kHz; best hearing ability of harbour porpoises at 100140 kHz; KASTELEIN et al. 2002, 2015) by the manufacturer Chelonia Ltd or by Deutsches Meeresmuseum Stralsund (DMM).

For this project, data from 24 CPOD stations (22 with three station parts; two with two station parts) and 56 single CPODs were considered for analysis. Figure 4.1 shows the positions of CPOD stations and single CPODs.

For the first research topic (long-term trends), 22 CPOD stations with three redundant devices each were available (Table 9.1), all of these being used for phenology curves. Of these, 14 stations provided sufficient data for trend analyses over the whole intended study period from 2010/11 to 2019/20, in two subareas even from 2009/10 to 2022/23 (*Northwest* and *Southeast*). The remaining eight CPOD stations started later or ended earlier and were discarded from the trend-analysis dataset in order to keep it consistent over time.

For the second research topic, a comparison of detection rates within and in the vicinity of OWFs, 56 single CPODs and 2 CPOD stations with two redundant devices each were available, of which 55 were chosen for analyses (Table 9.2), this in addition to 7 CPOD stations with three devices each (Table 9.2).

Background noise

CPODs register not only porpoise clicks but also all tonal signals with impulse characteristics, meaning signals that exhibit a characteristic peak within the power spectrum of porpoise clicks. As a result, clicks can originate from other sources such as sonars, noise from sediment suspension, surface noise from waves, etc. Therefore, the quality of CPOD recordings must be assessed considering the potential impact of a noisy environment on the probability of accurately recording porpoise clicks. Two main problems arise from high background noise:

1) In a noisy environment, a CPOD's memory card may fill up quickly. To prevent this, CPODs can be programmed with a recording limit per minute, allowing only a certain maximum number of clicks to be registered within one minute. If this limit is reached, the CPOD stops recording for the rest of that minute. This restriction controls the amount of data stored per minute, preventing the memory card from overflowing. If unchecked, this issue could lead to inaccurate porpoise detection rates. For all stationary CPODs used in this study, the click limit was set to 4,096 clicks per minute.

2) Substantial noise also affects the detection of porpoise clicks in the CPOD.exe software. When background noise is significant, it becomes harder to distinguish porpoise clicks from it, a phenomenon known as masking. Consequently, the likelihood that the algorithm correctly identifies porpoise clicks during the recorded time interval decreases as background noise increases. If not accounted for, this would lead to an underestimation of porpoise activity.

We addressed these issues by certain measures given in the Methods chapters of the two research topics.

5 LONG-TERM HARBOUR PORPOISE TRENDS AT CPOD STATIONS

A major objective of this study was to investigate long-term harbour porpoise trends in the German Bight (North Sea). Trends were assessed by data from CPOD stations positioned throughout the area. In this chapter, we address the following research topics:

- Evaluation of the overall long-term trend of harbour porpoises in the German Bight.
- Evaluation of long-term trends in five subareas of the German Bight.

NACHTSHEIM et al. (2021) reported alarming negative trends of harbour porpoise densities in certain parts of the German Bight, based on data from non-digital aerial surveys. These results, if valid, would have significant implications for conservation management. However, as the outcome of that study was highly dependent on weather conditions, the number of surveys and the exact survey dates within a season (dates varied strongly among years), it was a major aim of this study to evaluate if similar results could be found by a different methodology: PAM with CPOD data continuously recorded over many years in different parts of the German Bight.

5.1 Methods

5.1.1 Data preparation and selection

In total, data from 22 long-term CPOD stations positioned throughout the German Bight (North Sea) were available for this study, of which 14 stations provided sufficient data for trend analyses over the whole intended study period from 2010/11 to 2019/20, in two subareas even from 2009/10 to 2022/23 (Table 9.3). The remaining eight CPOD stations started later or ended earlier and were discarded from the trend-analysis dataset in order to keep it consistent over time. Yet, those stations were kept in the dataset for phenology curves.

We addressed the issue of noisy data by taking into account (a) the relationship between porpoise detections and the number of minutes per day when the scan limit was reached, and (b) the relationship between porpoise detections and the number of non-porpoise clicks recorded during that day. To keep comparability with other studies, we accordingly excluded data with more than 3,000,000 clicks per day, and with more than 200 minutes per day exceeding the scan limit. Finally, we excluded days during which the CPODs did not record for the full 24 hours. In overall, this resulted in a 13.4 % exclusion rate for the overall daily CPOD dataset.

Phenology curves and similarity analysis were based on the percentage of detection-positive 10 minutes per day (*%DP10M/d*) as detection rate (i.e., if a porpoise was detected within a 10-minute block of a maximum of 144 per day; 144 was set to 100 %, hence values from 0 to 100 are possible), whereas Bayesian trend analyses were carried out on the percentage of detection-positive 10 minutes per year or season (*%DP10M/period*; similar to the rate above, but here the number of available 10-minute blocks per year or season is set to 100 %). The phenology curves show Loess regressions (wiggliness: *span* chosen as 150/length of time-series in days) on *%DP10M/d*.

5.1.2 Choice of subareas

For the 14 stations chosen for trend analysis, the similarity of harbour porpoise phenology was investigated by means of a t-SNE analysis (VAN DER MAATEN & HINTON 2008) to evaluate if neighbouring stations showed similar phenological patterns (Figure 5.1). This basically led to the designation of five subareas (Figure 5.2). For four subareas (*North, Northwest, Northeast, Southeast*), phenological similarity and geographical proximity matched very well (Figure 5.1 and Figure 5.2). For the fifth subarea (*South*) priority to the geographical proximity was chosen, even though its four stations showed two types of phenology patterns.

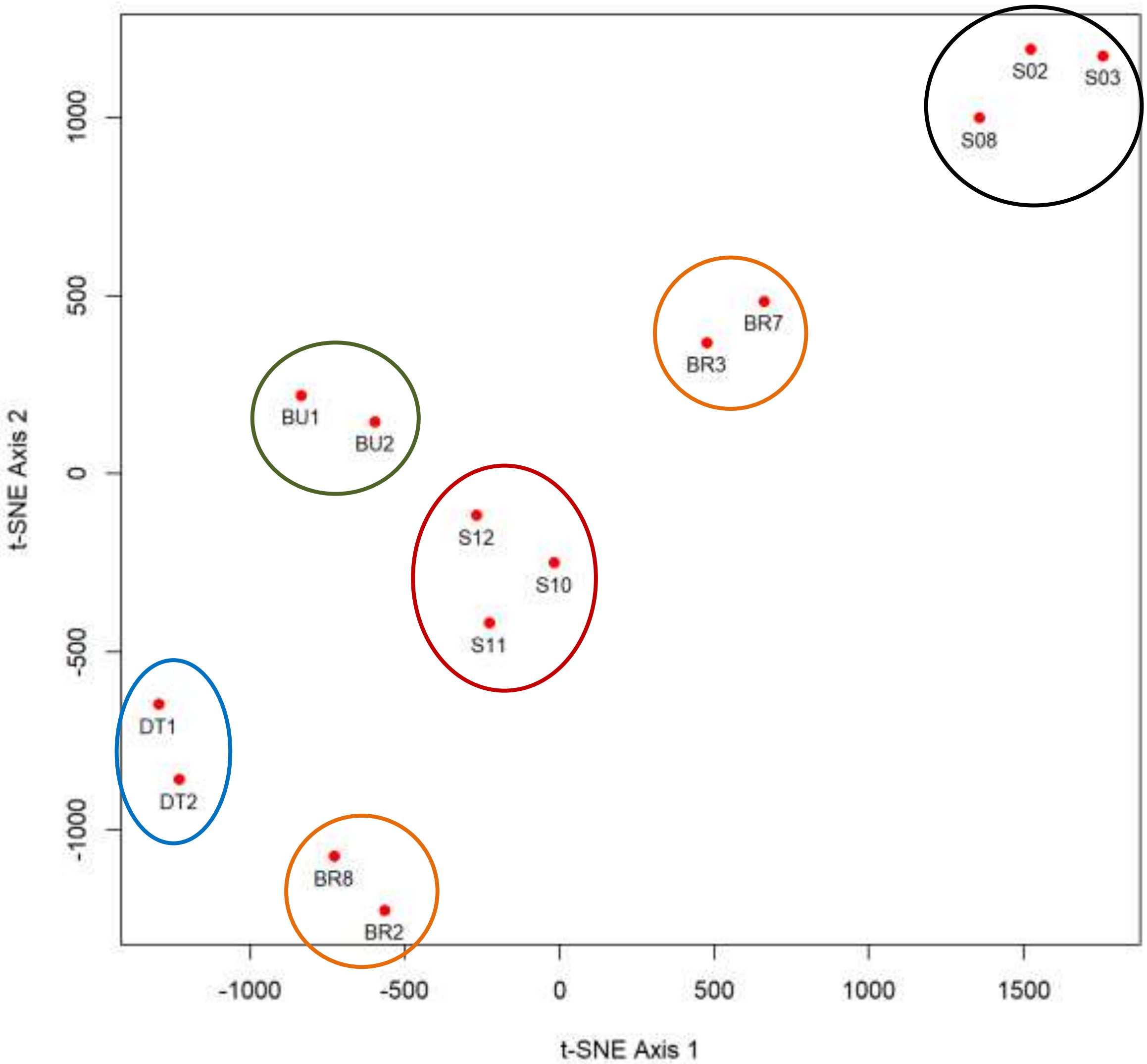

Figure 5.1 Similarity of harbour porpoise phenologies (%DP10M/d: t-SNE analysis; similarity measure: Canberra Metric) among 14 CPOD stations; Northwest: black, North: blue, Northeast: green, Southeast: red, South: orange.

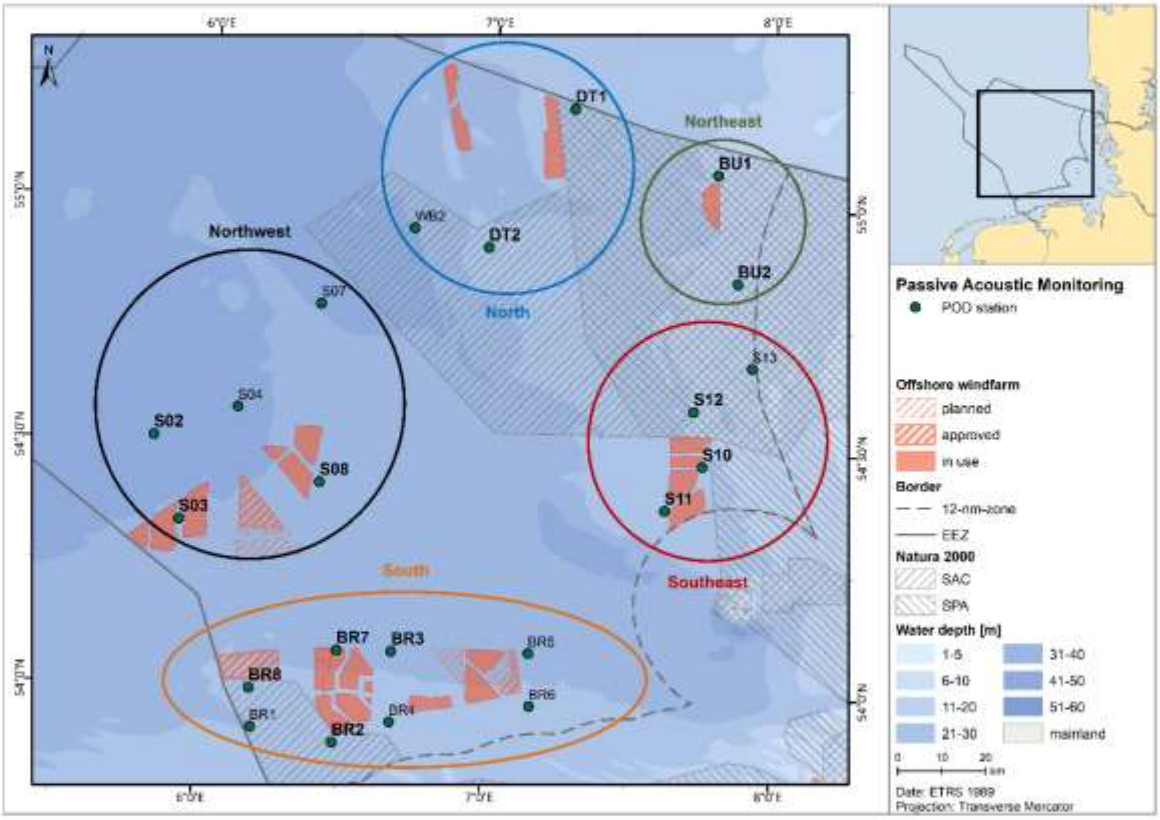

Figure 5.2 *The five chosen subareas of the German Bight, denoted after harbour porpoise phenology and geographical location; furthermore CPOD stations in the region; subarea colours as in Figure 5.1.*

5.1.3 Statistical analyses

Bayesian trend analysis

Bayesian trend analysis was carried out on the percentage of detection-positive 10 minutes per period (%DP10M/period, the latter being year or season, with the following definitions of the four seasons: winter: December to February, spring: March to May, summer: June to August, autumn: September to November) by the R package agTrend version 0.17.7 (JOHNSON 2017) in R version 3.6.3 (R CORE TEAM 2020). The package provided a hierarchical modelling framework for Bayesian trend estimation, capable of accounting for methodological changes and uneven sampling schemes (which was the case only to a minor extent in our study). Using Markov chain Monte Carlo (MCMC) randomisation (GIVENS & HOETING 2005) and a hierarchical model to augment missing site data allowed for direct inference of a trend in regional porpoise detection rates with patchy data by sampling the posterior distribution of all N_{ij} (true detection rate at site i and time j), estimated from n_{ij} (observed detection rate, possibly being subject to survey methodology changes through time and measurement error), and calculate the regional trend, r, for every sample. Hence, this kind of analysis accounted for observation and natural process uncertainty (JOHNSON & FRITZ 2014).

The model was composed of sub-models for the observation process and the true detection-rate process. Principally, the model framework is also capable of accounting for animal availability, which was not used here as we were dealing with detection rates obtained by a standardised method with calibrated CPOD devices.

The (augmented) *%DP10M* values over a certain period (year, season of a year), i.e. n_{ij} (observed detection rate at site i and time j) as an estimate for N_{ij} (true detection rate at site i and time j), was based on the following model representing a log-normal distribution $L\ (\mu, \sigma^2)$ with location parameter µ and scale parameter σ2:

$$\left[n_{ij} \mid N_{ij},\ \mu_{ij},\ \sigma_{ij}\right] = L\left(\mu_{ij},\ \sigma_{ij}^2\right) \qquad [1]$$

The model for the latent and missing true detection rates N_{ij} was defined as follows:

$$\left[N_{ij} \mid \boldsymbol{\beta}_i,\ \omega_{ij}\right] = L\left(\mathbf{d}'_{ij}\boldsymbol{\beta}_i + \omega_{ij},\ \zeta_i^2\right) \qquad [2]$$

where $\mathbf{d}'_{ij}$ is a vector of covariates, $\boldsymbol{\beta}_i$ is a vector of linear coefficients, ω_{ij} = (ω_{i1},. . ., ω_{iJ})’ is a random walk (RW2) process with variance parameter τ_i^2 , and ζ_i^2 is the independent variance parameter. The RW2 component was added to allow flexibility to site-level models, though in our case we chose linear augmentation models for each site as we mostly only had data for about ten years. The model over all sites was nevertheless capable of adding curvature to the trendline by an RW2 process.

For Bayesian inference and augmentation of detection rates, the hierarchical Markov chain Monte Carlo (MCMC) sampler draws realisations from the posterior distribution:

$$[\mathbf{N}, \boldsymbol{\varphi} \mid \mathbf{n}] \propto \prod_{i=1}^{I}\prod_{j=1}^{J}\left\{\left[n_{ij} \mid N_{ij},\ \mu_{ij}, \boldsymbol{\gamma}, \sigma_i\right]^{s(i,j)}\left[N_{ij} \mid \boldsymbol{\beta}_i, \omega_{ij}\right]\right\}[\boldsymbol{\varphi}] \qquad [3]$$

where $\mathbf{N}$ is the vector of all N_{ij}, $\boldsymbol{\varphi}$ is the vector of all parameters, $\mathbf{n}$ is the vector of all n_{ij}, $\boldsymbol{\gamma}$ is a vector of coefficients governing effects of survey methodology changes, [$\boldsymbol{\varphi}$] is the prior distribution of the parameters (we used the default flat prior), and $s(i, j)$ is an indicator function that equals 1 if site i was surveyed at time j. After augmentation, the detection rate at each site was aggregated in each of the MCMC iterations to form a kind of regional cumulative value by the software algorithm (JOHNSON & FRITZ 2014): $\widetilde{N_J} = \sum_i N_{ij}$. This procedure, however, would only have been meaningful when aggregating site abundances to regional abundances, but was not useful with our percentual detection rate. Therefore, we back-calculated the model output to a response scale by dividing the aggregated values by the number of CPOD stations used in the respective model: $\widetilde{N'_J} = \sum_i N_{ij}/i$. We chose an upper limit of 100 here, as this was the maximum possible value of the percentual detection rate. The length of the burn-in sequence after which the MCMC augmentation and aggregation started was set to 1.000 iterations.

Finally, the trend, $r = r\left(\widetilde{\mathbf{N}'}\right)$, was computed as the least-squares slope of log $\widetilde{\mathbf{N}'}$ over the period of interest. After the MCMC algorithm was complete (we chose 5.000 iterations), the trend point estimate was calculated as the median r over all MCMC iterations (shown with range if not all stations were available). The 95 % highest probability density credible interval (HDI) for r was calculated by survey replication and is shown in the trend plots (JOHNSON & FRITZ 2014). Hence, if all stations could be included for a certain point estimate, no iteration over different CPOD station sets was possible and only one value, that for all stations, defined the trend point estimate here. On the other hand, if only a subset of stations had to represent all stations in a certain year, MCMC intervals were plotted for this year.

In the overall dataset, trendlines span from 2011 to 2019 for whole years, from 2010 to 2019 for spring, summer and autumn, and from 2011 to 2020 for winter. This was due to the fact that not all seasons were available for all years, depending on the date when the CPOD series started and ended. Only those years with at least 243 (i.e., two-third) of a maximum of 365 (resp. 366) recording days were considered on the scale of whole years, whereas at least 45 recording days (i.e., half of a three-month period) were considered to be required on the scale of seasons.

The start and end dates also differed among the five subareas. For two of those, Northwest (NW) and Southeast (SE), time series were available until 2022/23; for the others, South (S), Northeast (NE) and North (N), the CPOD series ended in 2019/20, the exact year differing among seasons and stations (see also Table 5.1). The available years for each subarea and season are given on the x-axis of the trend plots.

Bootstrap tests

For assessment of the rate and significance of change, ordinary Bootstrap tests (EFRON & TIBSHIRANI 1993; DAVISON & HINKLEY 1997) were performed by the R package boot version 1.3.24 (CANTY & RIPLEY 2019). Average detection rates in earlier years (period 1: 2011-2014) were compared to those in later years (period 2: always 2016-2019; also 2020-2023 if available for a certain subarea). For comparisons based on whole years reasonably unbiased by seasonal influences, only those years with at least 243 (i.e., two-third) of a maximum of 365 (resp. 366) recording days were considered, whereas for the seasonal tests (e. g., spring of period 1 vs spring of period 2) at least 45 recording days (i.e., half) of a three-month season were required. Hence, seasonal tests were sometimes possible even for years with insufficient data for whole-year comparisons.

A significant increase, or decrease, was identified if more than 97.5 % of the bootstrap statistic values were above, or below zero. An increasing, or decreasing, trend was defined if 85 % to 97.5 % of the bootstrap statistic values fell above, or below zero. Values with less than 85 % of bootstrap statistics above or below zero were considered to indicate only minor or no clear trends.

5.2 Results

5.2.1 Phenology curves

Phenology curves of harbour porpoise detection rates are shown for all 22 available long-term CPOD stations, i.e. also for those with insufficient time range and/or number of days per period for trend analysis. The curves were grouped by subarea for the plots (Figure 5.4 to Figure 5.7).

Detection rates in the subarea *Northwest* were rather low and showed no strong phenological pattern (Figure 5.3). In some years and for some stations, detection rates seem to be higher during winter, in others there are no expressed peaks.

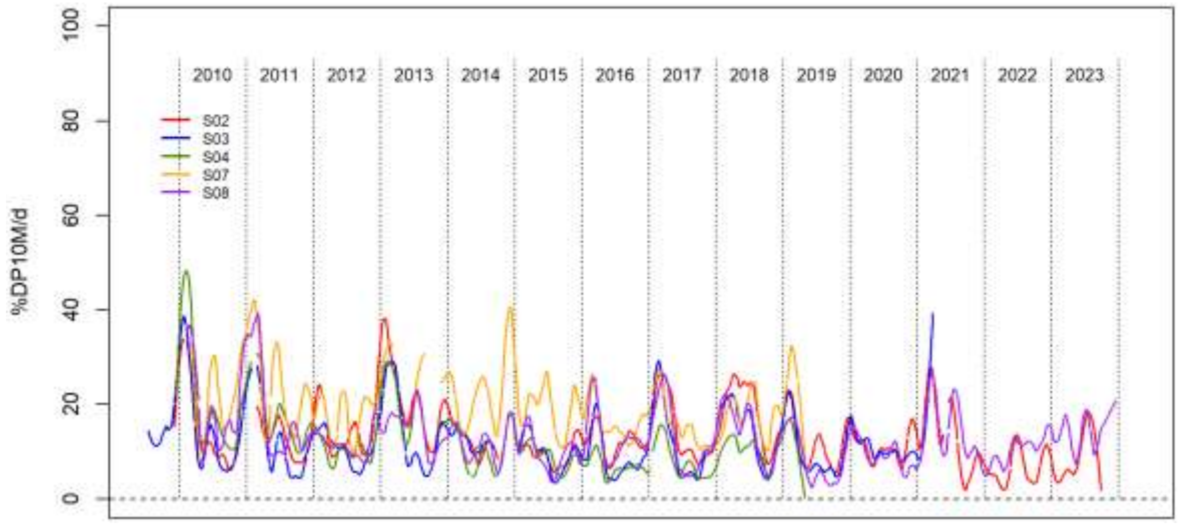

Figure 5.3 Phenology curves of %DP10M/d for all CPOD stations of the subarea Northwest.

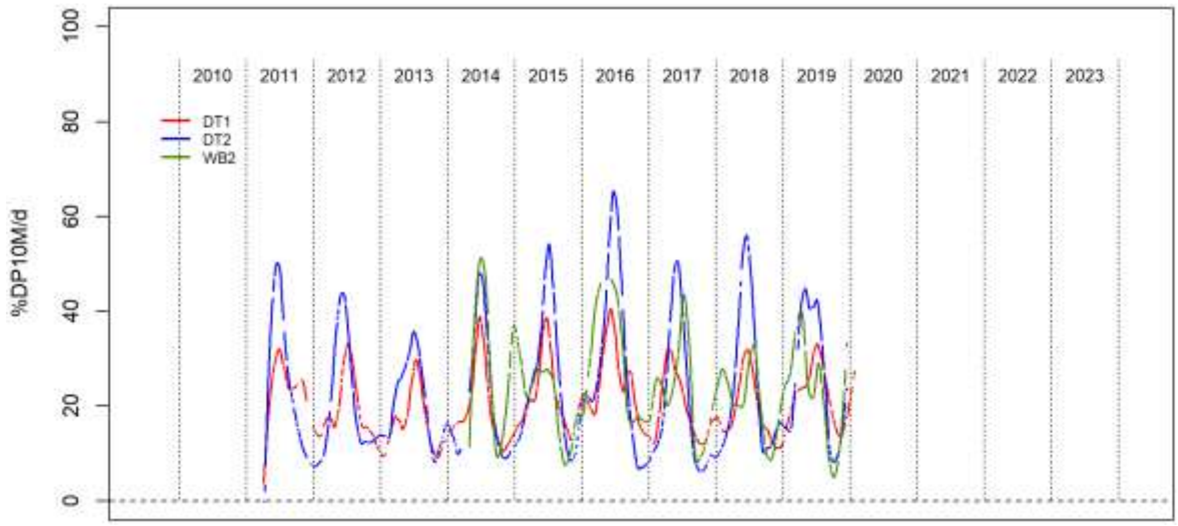

Figure 5.4 Phenology curves of %DP10M/d for all CPOD stations of the subarea North.

CPOD recordings in the subarea *North* were characterised throughout the years by one strong peak in late spring/early summer (Figure 5.4).

The detection rates in the subarea *Northeast* often showed two medium peaks, one in late spring and the other one in autumn (Figure 5.5).

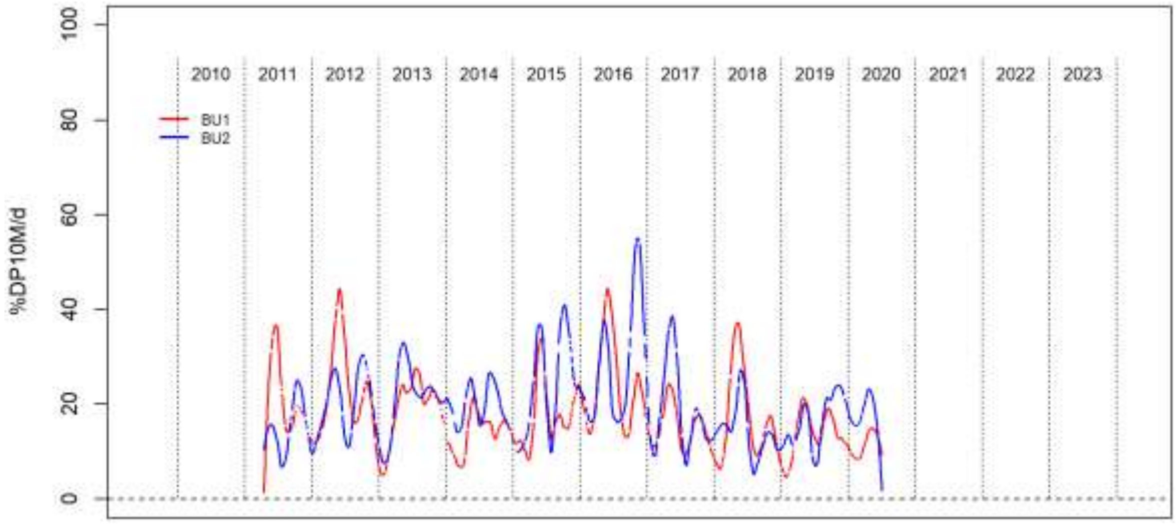

Figure 5.5 Phenology curves of %DP10M/d for all CPOD stations of the subarea Northeast.

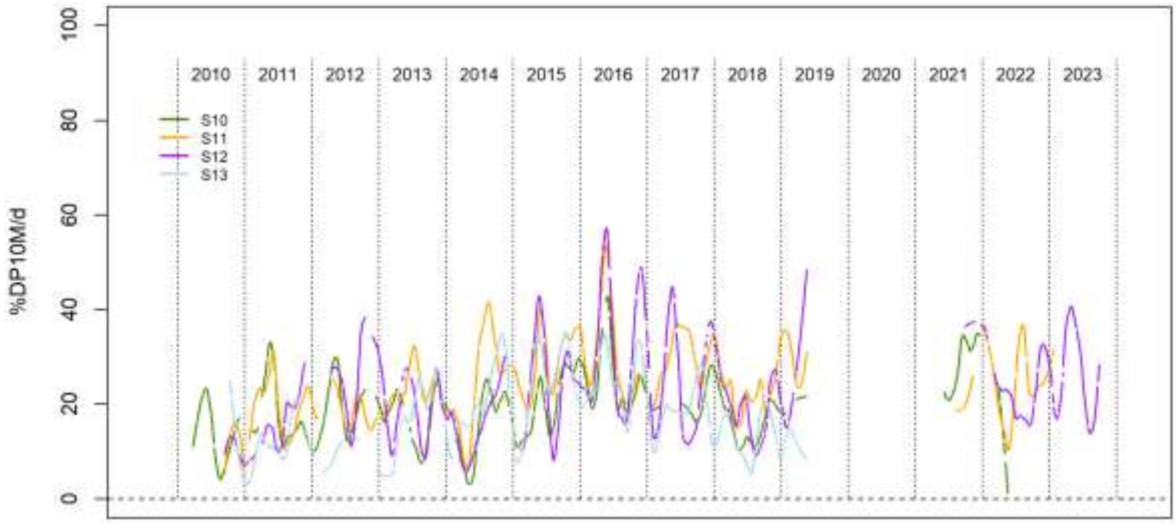

Figure 5.6 Phenology curves of %DP10M/d for all CPOD stations of the subarea Southeast.

Similar to the phenology pattern in the subarea *Northeast* was that in the subarea *Southeast* which also partly showed two peaks (late spring, autumn). The phenological similarity was reflected by proximity of the CPOD stations of those two subareas in the similarity plot (Figure 5.1).

Finally, the phenology patterns at the CPOD stations of subarea *South* were of mixed shapes. Some stations had strong peaks in summer whereas others only showed minor peaks at different times of the year (Figure 5.7). This was also reflected by considerable distances between the points of subarea *South* in the similarity plot (Figure 5.1).

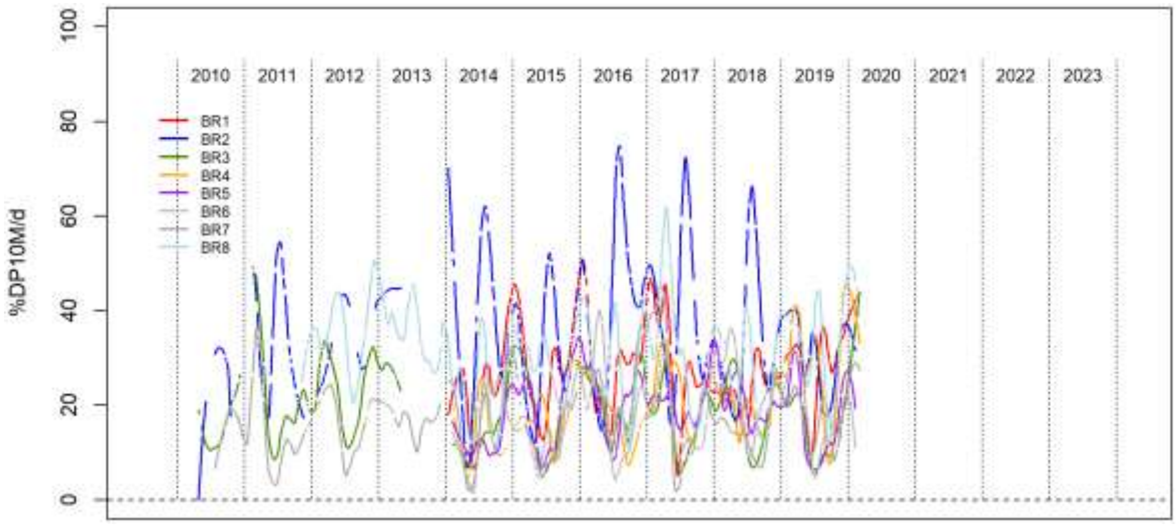

Figure 5.7 Phenology curves of %DP10M/d for all CPOD stations of the subarea South.

5.2.2 Overall trend for the German Bight and trends for five subareas

Bayesian trend analysis with Bootstrap tests indicated no negative or positive trend or tendency (definitions for trend and tendency: see Section 5.1.3) in harbour porpoise detection rates *%DP10M/period* (period being year or season) for the whole study area (German Bight, North Sea) and whole years disregarding season (years available for the overall trend line: 2011 to 2019; Figure 5.8, left panels).

On a seasonal level, no clear trend or tendency was found for summer and autumn, according to the results of Bootstrap tests for pairwise comparisons of the early years 2011 to 2014 to the more recent years 2016 to 2019. However, the tests uncovered a significant increase of the overall porpoise detection rates in winter, as well as an increasing tendency in spring (Table 5.1).

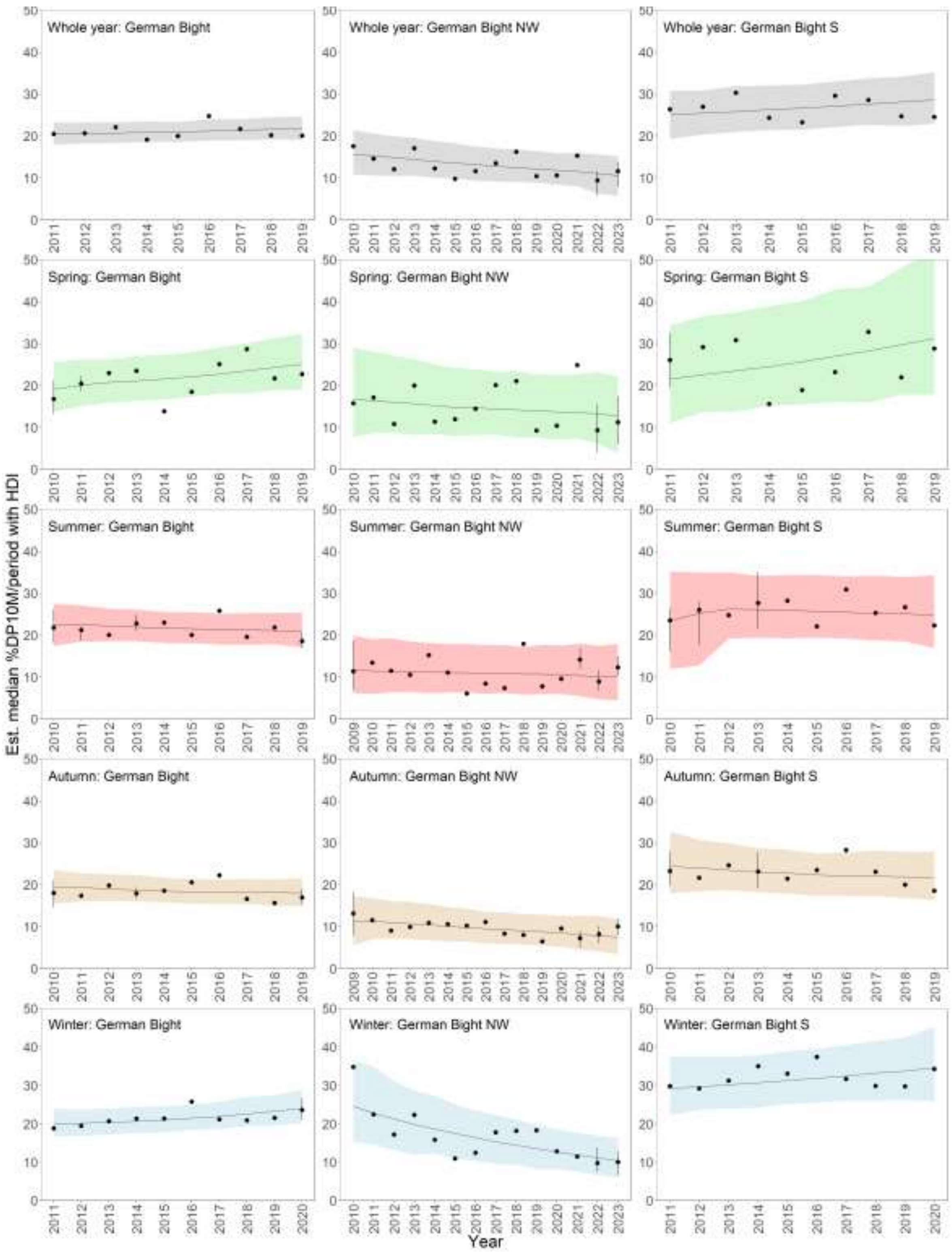

Figure 5.8 *Bayesian trend analysis showing posterior trend lines (with 95 % HDI, shaded area) on trend point estimates (median r over all MCMC iterations, shown with range [vertical bars] if not all stations were available) for whole-year and seasonal data, presented here for all CPOD stations (German Bight), as well as for the two subareas Northwest (NW) and South (S).*

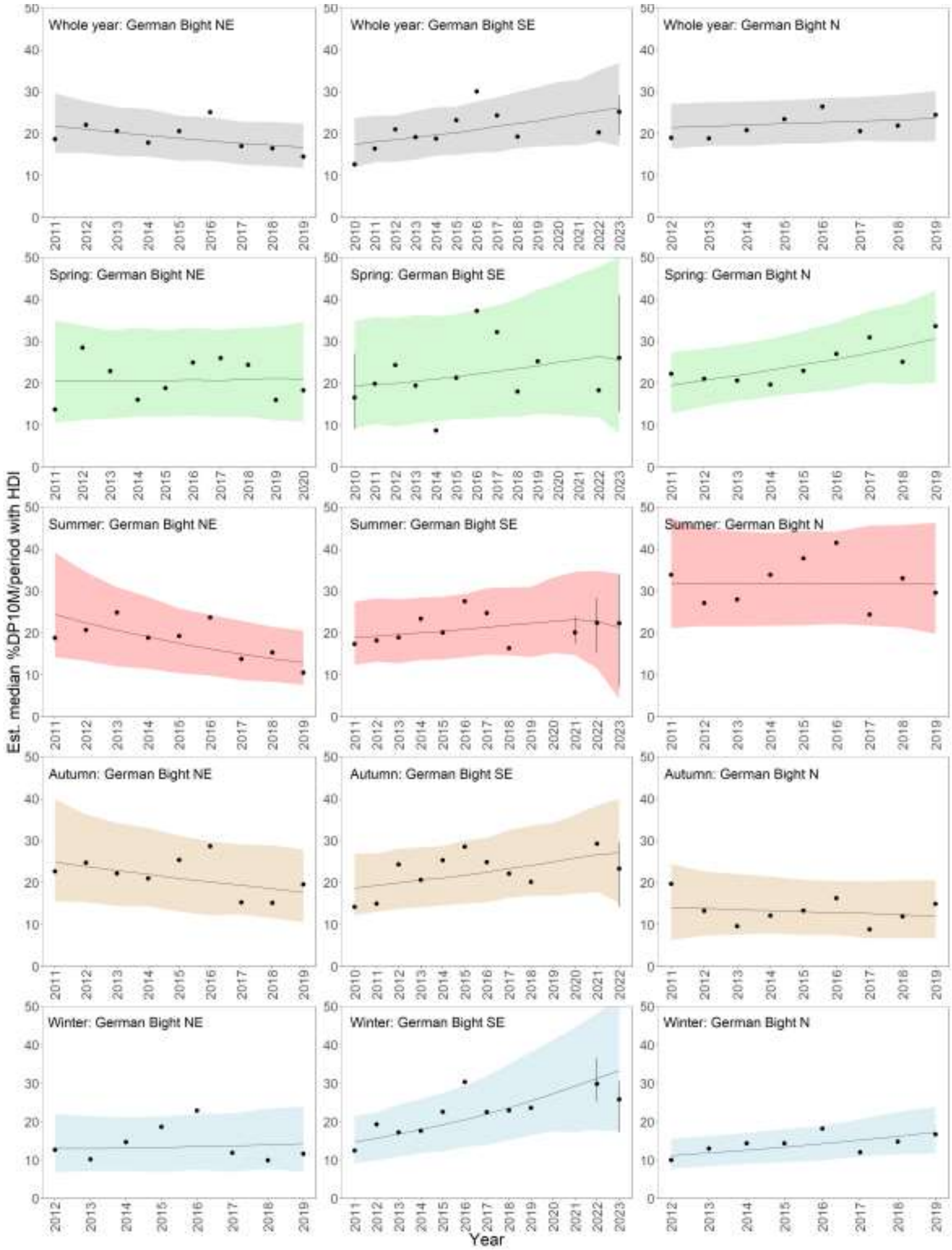

Figure 5.9 Bayesian trend analysis showing posterior trend lines (with 95 % HDI, shaded area) on trend point estimates (median r over all MCMC iterations, shown with range [vertical bars] if not all stations were available) for whole-year and seasonal data, visualised for the subareas North-east (NE), Southeast (SE) and North (N), those three subareas partly overlapping with SAC "Sylt Outer Reef".

Analyses on the scale of subareas yielded the following results. Partly (= at least one of five [one overall and four seasonal] analyses per subarea) positive trends or tendencies of harbour porpoise detection rates were observed for the subareas *Southeast* and *North* (Figure 5.9, middle and right panels; Table 5.1), whereas partly negative trends or tendencies were found for the subareas *North-west* and *Northeast* (Figure 5.8, middle panels; Figure 5.9, left panels; Table 5.1). Detection rates in the subarea *South* showed no clear trend or tendency (Figure 5.8, right panels; Table 5.1).

When looking into more detail, detection rates in the subarea *Southeast* were significantly higher (definition of positive trend according to percentage of Bootstrap test values above zero: ≥97.5 % [signif. level 5 %, two-sided]: Table 5.1) in whole years as well as spring and winter 2016-2018/19, compared to 2011-2014. The same was true for comparisons of winter and whole years 2022-2023 (those most recent years being available for this subarea) to the early years 2011-2014. A positive tendency was found for spring (2022-2023) and summer 2021-2023, compared to 2011-2014 (Table 5.1). For some seasons (spring, winter), the detection rate *%DP10M/period* increased by more than 10 % in this subarea (Table 5.1). These were the strongest increases found across all subareas.

A weak positive development was also found for the subarea *North*. Detection rates in spring and winter of the years 2016-2019 were significantly higher than those in these seasons of the years 2011-2014 (increase of more than 8 % of the detection rate *%DP10M/period* in spring: Table 5.1). At least a positive tendency was found for the whole years 2016-2019, compared to 2011-2014.

On the other hand, the development of detection rates was partly (definition: see above) negative in the subarea *Northwest* (overall, winter). Rates were significantly lower in winter 2020-2023 (those most recent years being available for this subarea), as compared to 2011-2014. A negative tendency was found for the whole years 2020-2023 when compared to 2011-2014, as well as for the seasons autumn and winter 2016-2019 relative to those of the years 2011-2014 (Table 5.1). Generally, porpoise detection rates in this subarea were the lowest of all subareas.

The subarea *Northeast* showed a negative tendency of summer detection rates of the years 2016-2019 relative to those of the years 2011-2014.

Finally, little change of porpoise detection rates (just around or below 1 % of the detection rate *%DP10M/period*) occurred in the subarea *South* from the first (2011-2014) to the second period (2016-2019) (Table 5.1). Also, no clear trend or tendency was found for all comparisons of subareas and seasons not explicitly mentioned above (Table 5.1: uncoloured rows).

*Table 5.1 Results of Bootstrap (BS) tests for pairwise comparisons of %DP10M/period between years of period 1 and 2. Data were analysed for whole years and seasons, overall and for subareas. Absolute change in %DP10M/period and significance level: ns = not significant; * = 5 %; ** = 1 %; *** = 0.1 %. Change: - : decreasing tendency (BS ≤ 15 %); - - : decreasing trend (BS ≤ 2.5 %); + : increasing tendency (BS ≥ 85 %); + + : increasing trend (BS ≥ 97.5 %); 0: no clear tendency.*

Area Stations	Season	Period 1	Period 2	Change of *%DP10M/period*	Change	% BS values over 0 (50 %=equal); *signif.*
Overall	**all-year**	**2011-2014**	**2016-2019**	**+1.06**	**0**	**79.4 *ns***
14 stations	Spring	2011-2014	2016-2019	+4.47	+	97.1 *ns*
(given below)	Summer	2011-2014	2016-2019	-0.03	0	48.2 *ns*
	Autumn	2011-2014	2016-2019	-0.89	0	28.5 *ns*
	Winter	2011-2014	2016-2019	+2.25	+ +	98.9 *
Northwest	**all-year**	**2011-2014**	**2016-2019**	**-1.05**	**0**	**26.9 *ns***
3 stations:	Spring	2011-2014	2016-2019	+1.39	0	66.2 *ns*
S2,S3,S8	Summer	2011-2014	2016-2019	-1.70	0	24.7 *ns*
	Autumn	2011-2014	2016-2019	-1.61	-	6.0 *ns*
	Winter	2011-2014	2016-2019	-2.78	-	9.7 *ns*
later period	**all-year**	**2011-2014**	**2020-2023**	**-2.40**	**-**	**8.8 *ns***
	Spring	2011-2014	2020-2023	-2.29	0	29.5 *ns*
	Summer	2011-2014	2020-2023	+1.19	0	70.6 *ns*
	Autumn	2011-2014	2020-2023	-0.55	0	27.2 *ns*
	Winter	2011-2014	2020-2023	-8.70	- -	0.0 ***
South	**all-year**	**2011-2014**	**2016-2019**	**-0.16**	**0**	**47.2 *ns***
4 stations:	Spring	2011-2014	2016-2019	+1.25	0	59.2 *ns*
BR2,BR3,	Summer	2011-2014	2016-2019	+0.65	0	63.6 *ns*
BR7,BR8	Autumn	2011-2014	2016-2019	-0.20	0	45.1 *ns*
	Winter	2011-2014	2016-2019	+0.85	0	63.3 *ns*
Northeast	**all-year**	**2011-2014**	**2016-2019**	**-1.53**	**0**	**24.9 *ns***
2 stations	Spring	2011-2014	2016-2019	+2.54	0	74.8 *ns*
BU1,BU2	Summer	2011-2014	2016-2019	-4.98	-	5.2 *ns*
	Autumn	2011-2014	2016-2019	-2.97	0	15.3 *ns*
	Winter	2011-2014	2016-2019	+2.11	0	71.5 *ns*
Southeast	**all-year**	**2011-2014**	**2016-2018**	**+5.71**	**+ +**	**97.5 ***
3 stations	Spring	2011-2014	2016-2019	+10.09	+ +	97.6 *
S10,S11,S12	Summer	2011-2014	2016-2018	+3.41	0	84.0 *ns*
	Autumn	2011-2014	2016-2019	+1.07	0	63.9 *ns*
	Winter	2011-2014	2016-2019	+8.19	+ +	100.0 ***
later period	**all-year**	**2011-2014**	**2022-2023**	**+5.96**	**+ +**	**99.1 ***
	Spring	2011-2014	2022-2023	+10.86	+	86.5 *ns*
	Summer	2011-2014	2021-2023	+2.50	+	95.2 *ns*
	Autumn	2011-2014	2021-2022	+3.24	0	83.9 *ns*
	Winter	2011-2014	2022-2023	+12.27	+ +	100.0 ***
North	**all-year**	**2011-2014**	**2016-2019**	**+2.29**	**+**	**87.5 *ns***
2 stations:	Spring	2011-2014	2016-2019	+8.27	+ +	100.0 ***
DT1,DT2	Summer	2011-2014	2016-2019	+1.43	0	64.0 *ns*

	Autumn	2011-2014	2016-2019	-0.69	0	41.3 *ns*
	winter	2011-2014	2016-2019	+3.79	+ +	98.4 *

5.3 Discussion

The harbour porpoise (*Phocoena phocoena* L., 1758) is the most common cetacean species in the continental shelf waters of north-western Europe (Reid et al. 2003), being the only cetacean species that breeds in the German Bight of the North Sea. Recently, negative porpoise trends in parts of the German EEZ of the North Sea, assessed by aerial surveys, were reported by Nachtsheim et al. (2021). Therefore, it was of considerable scientific interest to evaluate porpoise trends in the German Bight over the last years by a different methodology, passive-acoustic monitoring (PAM) by CPODs.

5.3.1 Methodology

All data were collected by a standardised method with CPOD devices calibrated by the manufacturer Chelonia Ltd (UK) and Deutsches Meeresmuseum Stralsund (Germany). CPODs are designed for recording long continuous data series of cetacean signals on a fine-scale temporal resolution. Such continuous recordings are a major advantage of PAM over aerial or ship-based monitoring, which often covers only a few days of a year. Hence, the obtained results of the latter methods are strongly affected by survey conditions and often prone to high stochasticity (the more so if non-digital observer-based aerial surveys are conducted where observer teams might even change over the years). PAM, on the other hand, is restricted to short-range detections of animals within a radius of a few hundred metres. But since a considerable number of CPOD devices was deployed in different parts of the German Bight, we consider our dataset still to be fairly representative and the best at hand for the study area.

Harbour porpoises tagged with a hydrophone were shown to use echolocation almost continuously (Akamatsu et al. 2007; Wisniewska et al. 2016). Hence, echolocation is assumed to be the most important sensory perception, which by its constant use allows for correlation between detection rates of CPODs and porpoise density in marine areas. Among others, Siebert & Rye (2008), Kyhn et al. (2012), Jacobson et al. (2017), and Amundin et al. (2022) were able to show a relationship between PAM detection rates and porpoise densities. A good correlation between porpoise densities from digital aerial surveys and CPOD detection rates was found in an area of up to 10 km around CPOD stations in the North Sea (Schubert et al. 2018). Therefore, CPOD detection rates were shown to be a good proxy for relative harbour porpoise densities: on average, higher detection rates correlate with higher densities in up to 10 km around a CPOD measurement position. As we mostly also found a good phenological similarity of the detection rates from the CPOD stations within a subarea, these rates seem to be representative even on this larger spatial scale. Otherwise, detection rates from stations within any subarea would have differed considerably. Following, CPOD monitoring allows inferences on harbour porpoise densities, making trend analyses based on CPOD data feasible. Detection rates were also used by other authors for monitoring porpoise trends, e.g. for Baltic Proper harbour porpoises by Owen et al. (2021).

By applying a Bayesian framework, this part of the study estimated trends in harbour porpoise detection rates based on data from 14 CPOD stations. Even though not all stations were equipped during the entire study period, the chosen type of Bayesian trend analysis (JOHNSON & FRITZ 2014) was capable of dealing with such gaps and other sources of uncertainty. This method of trend analysis was already shown to adequately estimate harbour porpoise trends in the North Sea and Baltic Sea (NACHTSHEIM et al. 2021; OWEN et al. 2024; based on aerial survey data, the latter reference also on vessel-based surveys).

WHITE (2019) recommended monitoring periods of at least 20 years (10 years for other species) for long-lived species like fishes and marine mammals, since otherwise high uncertainty in population abundance estimates are caused. On the other hand, KESSELRING et al. (2017) stated that the average age at death is 3.67 years in the Baltic Sea and 5.7 years in the North Sea for harbour porpoises, which might thus not be considered a long-lived species. In this light and regarding the fact that some of the CPOD stations used here are not in service anymore, we consider our dataset from a decade of PAM (for two subareas even more) the best available and appropriate to estimate trends for the harbour porpoise in the study area. With regards to the studies of WHITE (2019) and KESSELRING et al. (2017), it would be helpful to prolong CPOD monitoring at certain positions during the next decade to validate our findings and assumptions.

5.3.2 Porpoise trends in the German Bight

This study found no clear overall trend or tendency of harbour porpoise detection rates *%DP10M/period* (year or season) in the German Bight (North Sea) from 2011 to 2019, as those rates only showed a minor increase of around 1 % from the years 2011-2014 to the years 2016-2019. At a first glance, our PAM-based results, which show no indication for a decline, seemingly contradict the reported decline based on observer flight data by NACHTSHEIM et al. (2021). Both studies were carried out in the German North Sea EEZ, however, they covered different periods of time with data from NACHTSHEIM et al. (2021) starting already in 2002. Their data points show no decline from 2012 to 2019 (Figure 5.10), which then is in line with the findings derived from our data.

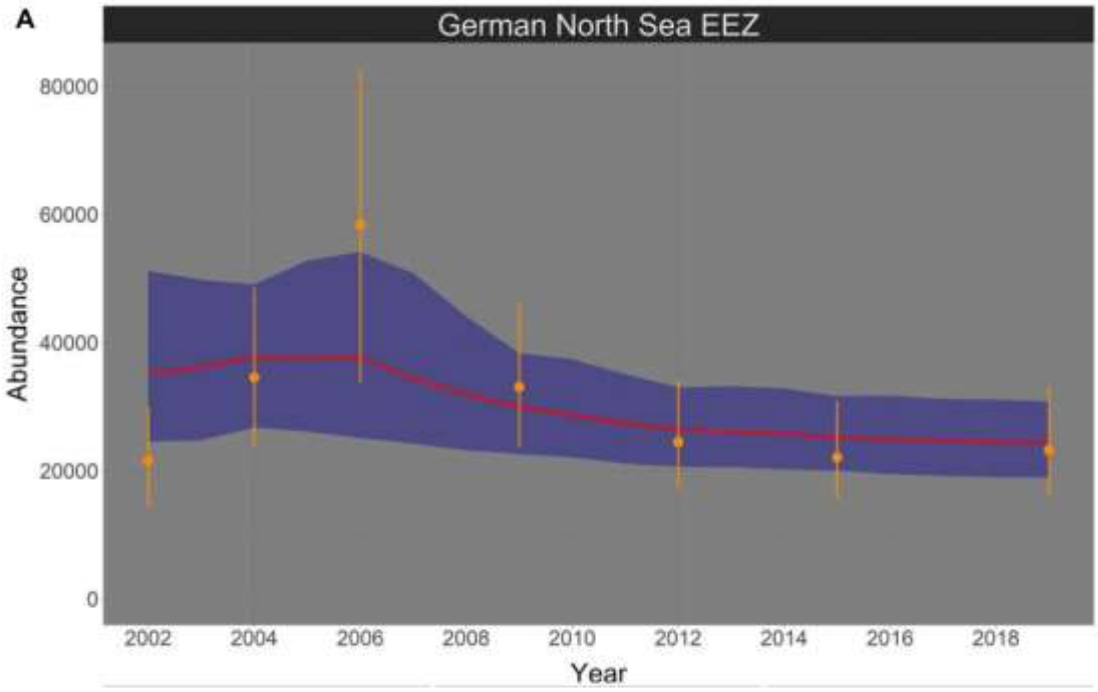

Figure 5.10 Overall trend in harbour porpoise densities, according to NACHTSHEIM et al. (2021).

Therefore, no contradiction was found after taking this into account. It should be noted that NACHTSHEIM et al. (2021) chose a linear model to assess the validity of their proposed negative trend, resulting in a 95.1 % probability of linear decline when there was apparently no linear trend in the data (which was also stated in the text: "After an initial slight increase until 2006, the abundance declined sharply before levelling off toward the end of the study period."). Our results complement findings from the Gescha 2 study (BIOCONSULT SH ET AL. 2019) where until the year 2016, based on a subset of the current data and with a different statistical method (GAMM with covariates), similar patterns have been uncovered. The overall increasing trend found until 2016 by Gescha 2 is consistent with our findings when 2016 was the best year for harbour porpoises. In the years after 2016 not covered by Gescha 2, however, detection rates returned to an intermediate level, resulting in no clear trend until 2019. Summarising, the overall trend of our study, of the Gescha 2 study (BIOCONSULT SH ET AL. 2019) and of NACHTSHEIM et al. (2021) are not contradicting at all, but each of these studies shows only a part of the overall pattern of a supposedly largely stable porpoise presence (though with high year-to-year fluctuations) in the area. Cause for the apparent contradiction of the precedent two studies was on the one hand the inappropriate use of a linear regression by NACHTSHEIM et al. (2021) even after 2010 when no decline was to be seen anymore, and on the other hand the ending of the Gescha 2 study in 2016, a very good year for porpoises, indicating an increase until that year. As a lesson learned for the future, it is important always to be aware of the available temporal scale and strong yearly fluctuation of porpoise data. Furthermore, the trend model has to be selected thoroughly; a linear trend is not adequate if a trend changes its expression over the years. Also, a very good year at the end of a trend should not be overinterpreted as it might just be an outlier within a long-term stable situation.

Even though the overall trend in the German Bight was largely stable over the study years, the development of detection rates differed among the five investigated subareas (Figure 5.2).

Whereas partly negative trends or tendencies were found for the subareas *Northwest* and *North-east*, the development in the subareas *North* and *Southeast* was more or less positive, while the situation in the subarea *South* remained nearly unchanged. Overall, this pointed to a partial shift in porpoise distribution within the German Bight over the years, which has already been stated in Gescha 2 (BioConsult SH et al. 2019) The findings of that study for four subareas in the German Bight (slightly different subdivision: our three subareas *North*, *Northeast* and *Southeast* equal the two subareas 1 and 4 of Gescha 2) are largely reflected by the results of our study when cut at the year 2016. The subareas *North* and *Southeast* might have become more favourable for porpoises, eventually attracting more animals from subareas *Northwest* and *Northeast*. Reasons for this are still to be evaluated, but food availability might have played an important role (e.g., Sveegaard et al. 2012). Starting in 1994, the projects SCANS I, II, III, and IV uncovered that at least over the last three decades the harbour porpoise distribution changed considerably throughout the North Sea, with an overall southward tendency (Hammond et al. 2002, 2013, 2017; Gilles et al. 2023) (Figure 5.11). Going further back in time, a decline of porpoises along with a decline of sandeels (family Ammodytidae), a preferred group of prey species, was already reported from around the Shetland Islands in the 1980s (Evans et al. 1996). A more recent decline of sandeels has since been reported from Scottish waters (The Scottish Government 2023). Changes in porpoise distribution are therefore most probably attributable to a shift in prey distribution over the last decades, as proposed by Ransijn et al. (2019) (Figure 5.12). Namely sandeels seem to be of great importance for the harbour porpoise (Ransijn et al. 2021), especially in spring and summer (Santos et al. 2004).

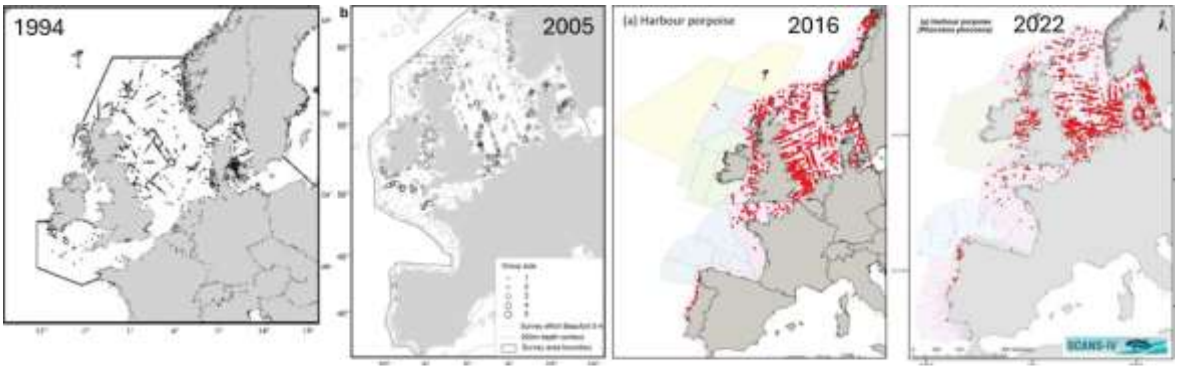

Figure 5.11 Changes in harbour porpoise distribution throughout the North Sea over the last three decades, according to the projects SCANS I-IV (Hammond et al. 2002, 2013, 2017; Gilles et al. 2023).

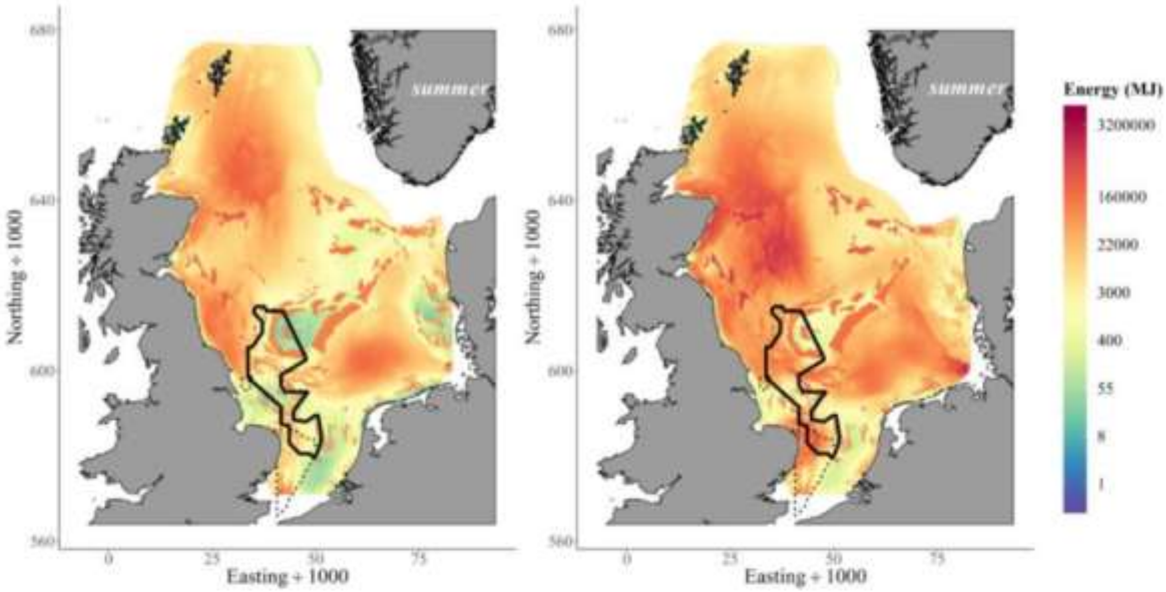

*Figure 5.12 Shift in harbour porpoise prey energy distribution (MJ = Megajoule) throughout the North Sea from 2005 to 2016 (*RANSIJN *et al. 2019; black outline: designated protected areas for the harbour porpoise in the UK).*

Looking into more detail at our different subareas, the development of detection rates differed slightly: detection rate trends were partly negative in *Northwest* (overall and in winter), which was the subarea with generally the lowest detection rates except for winter. *Northwest* turned out to the subarea with the deepest waters and longest distance to the coastline. As the harbour porpoise prefers intermediate water depths for feeding, this subarea is supposed to be of a generally lesser importance for the animals which might use it for opportunistic feeding and/or as a transition zone to more favourable habitats. The decline was strongest in winter, especially when comparing the years 2011-2014 to the here available most recent years 2020-2023 (-8.7 *%DP10M/period*). A decline from 2010 to 2016 in this part of the German Bight was also found by Gescha 2 (BIOCONSULT SH et al. 2019: subarea 3).

At the same time when detection rates decreased in the subarea *Northwest* in winter, a considerable winter increase was found in the subarea *Southeast* (2011-2014 to 2016-2019: +8.2 *%DP10M/period*; 2011-2014 to 2022-2023: +12.3 *%DP10M/period*, being the strongest of all changes). It is regarded an indication for a distributional shift towards shallower waters closer to the southeastern coast. A strong winter increase from 2011 to 2017 was also found by Gescha 2 in the largely overlapping subarea 1 (BIOCONSULT SH ET AL. 2019). Reason might be a more favourable food availability in the latter subarea, at least in winter, but probably also during the other seasons (increase in detection rates over all seasons). A major environmental change in the subarea *Southeast* was the construction and operation of new offshore windfarms (OWFs) in the cluster "Nördlich Helgoland" from 2012 onwards. Despite this fact, a positive development of detection rates was found in that subarea. It is known that monopile structures on rock foundations attract fish (REUBENS ET AL. 2013; VANDENDRIESSCHE ET AL. 2015; WERNER ET AL. 2024), and subsequently sometimes also seals (RUSSELL ET AL. 2014). Since the harbour porpoise is an opportunistic feeder and thus will follow its prey, this behaviour might be a reasonable explanation for the shift in the regional pattern, as the species is known to be attracted by offshore structures in an overfished environment (TODD ET al. 2009). As ship traffic for maintenance of the OWFs is much reduced in winter due to weather conditions, the subarea *Southeast* might have become especially attractive then, compared to summer and autumn (in these, a less expressed but still positive development of detection rates was found). Yet, a strong increase of porpoise detections was also found in spring. Maybe the animals from winter were still present, even though the overall ship traffic in the area will have increased during springtime. The decline of sandeels in Scottish waters might also have been an important factor regarding the distributional shift (The Scottish Government 2023).

The subarea *Northeast* as well as parts of the subareas *North* and *Southeast* are overlapping with the SAC "Sylt Outer Reef" which was reported to show a summer decline in porpoise densities from 2002 to 2019 by Nachtsheim et al. (2021). Our study covers only the later part of that period, with additional years until 2023 in subarea *Southeast*. In contrast to the negative summer trend for the whole German EEZ found by Nachtsheim et al. (2021) which levelled off in later years, there was an apparent decline in their trend for the SAC "Sylt Outer Reef" over the years also investigated by us (2011 to 2019). We could only partly verify this with our CPOD data. Indeed, we also found a tendency of a decrease of detection rates in the subarea *Northeast* (stations BU1 and BU2) in summer 2016 to 2019, when compared to 2011 to 2014. However, the months with highest detection rates in this area were often end of April to June (in some years also September and October), whereas in July and August the porpoise activity was generally lower in subarea *Northeast* (Figure 5.5). Hence, spring might have been the more important season for assessing maximum porpoise densities here, and in that season the detection rates where rather stable. Additionally, in the subareas *Southeast* and *North*, we found no significant change in detection rates from 2011-2014 to 2016-2019 (even a slight increase of +2.5 resp. +1.4 *%DP10M/period*). Furthermore, especially in subarea *North* a strong increasing trend in spring was recorded (+8.3 *%DP10M/period*). No clear trend was found for that region (subarea 4, largely overlapping with our *North*) by Gescha 2, but data were only available until 2016/17. For spring, Nachtsheim et al. (2021) did not have enough aerial data to show an interpretable trend line for the SAC "Sylt Outer Reef", so we cannot present a valid comparison here.

According to Nachtsheim et al. (2021), the years 2016 and 2019 were those with the lowest summer porpoise densities in the SAC "Sylt Outer Reef", considerably pulling down their trend line in the end. Continuous CPOD data, by contrast, showed that especially 2016 was a very good year for the harbour porpoise in nearly all subareas except for *Northwest*, whereas detection rates in 2019 were indeed low in subarea *Northeast* (but not in *North*) (Figure 5.8 and Figure 5.9). What might have been the reason for the partly contradicting results of both studies? Densities in summer 2016 and 2019 were each based on only two flights according to Nachtsheim et al. (2021), these at two days around end of July/beginning of August. Still, the authors consider the flights of those later years of their time series being representative for a whole summer, whereas most of the earlier years' summer densities were further based on flights in June when porpoise activity is generally higher in that area (see last paragraph). Additionally, the authors do not relate to the flight conditions, which would have been essential information for interpretation of flight data. Suboptimal conditions can drop the resulting densities considerably, and Beaufort 0 or 3 (data from this span of conditions were used in that study) make a big difference with regard to the visibility of porpoises, the more so for observer flights when compared to digital aerial surveys (additional bias would have been added if observer teams changed over a long-term survey period). Taking all these factors into account, we postulate that our trends from CPOD data are more reliable in general, since they were based on continuous data mostly recorded over whole seasons or whole years without observer bias. Even though CPOD detection rates are only rough proxies for harbour porpoise densities in a restricted range of up to 10 km around the device, the highly mobile porpoises in a region have still good chances of moving along a certain CPOD over a long continuous recording period (whole season or year). The short detection range is considered only a minor flaw in this respect, compared to the strong heterogeneity introduced to datasets by the shortcomings of observer flights (only daytime data, snapshots of a few days intended to represent whole seasons or years, weather and visibility conditions, changing observer teams). Resulting, we conclude that the differences and apparent contradictions between both studies regarding this area were mainly caused by the heterogeneity of the aerial survey dataset, namely by the insufficient coverage of summer 2016 and 2019, compared to earlier years and to continuous CPOD data. Underlining our assumption, the harbour porpoise density in the southeastern North Sea more than doubled from 0.277 Ind./km^2 in 2016 to 0.616 Ind./km^2 in 2022 (HAMMOND et al. 2017: Block M; GILLES et al. 2023: Block NS-I). When examining the porpoise sighting plots from these publications, it becomes evident that the number of sightings in the area around the SAC “Sylt Outer Reef” is at least stable from 2016 to 2022, if not increasing (Figure 5.11).

The subarea *South* was partly overlapping with the SAC “Borkum Reef Ground”, with – according to NACHTSHEIM et al. (2021; Fig. 7 & Fig. 9) – heterogeneous spring densities from 2002 to 2019 and apparently increasing summer densities from 2008 to 2019 (even though the fewer points here are very much fluctuating, like those of spring). According to our CPOD data, detection rates in spring and summer were rather stable from 2011 to 2019. However, two of the four CPOD stations in this subarea were positioned north of the mentioned SAC; hence, the comparison was skewed here. A very high density in spring 2011 (Fig. 7 in NACHTSHEIM et al. 2021) was surely caused by including only one flight that took place very late in spring (end of May, when densities were generally higher than in March/April in that area; Figure 5.7). We did not find such a peak in spring 2011 in our data which covered the whole season and not just one day. Yet, we would in overall conclude that the trends of both studies are not much contradicting for this part of the North Sea.

The effects of offshore wind farms on marine mammals are much discussed in literature. Though it is known that the construction of OWFs itself leads to short-term displacement of harbour porpoises (TOUGAARD ET AL. 2009a; BRANDT ET AL. 2011; HAELTERS ET AL. 2012; DÄHNE ET AL. 2013; BRANDT ET AL. 2016a; BIOCONSULT SH ET AL. 2019), the effects of windfarms in operation are yet another story. The attraction of seals and porpoises by offshore structures, following the attracted fish, was already mentioned (TODD ET AL. 2009; REUBENS ET AL. 2013; RUSSELL ET AL. 2014; VANDENDRIESSCHE ET AL. 2015; WERNER ET AL. 2024). In accordance to this, harbour porpoise detection rates within and in the proximity of the OWF *alpha ventus* were decreased in the first year after OWF construction, but in the next year rates were higher than in the pre-construction baseline phase (ROSE ET AL. 2014). On the other hand, ship traffic for maintenance of OWFs has the potential for adverse effects on harbour porpoise. Several authors reported short-term negative effects of ships on this species (BARLOW 1988; HERMANNSEN ET AL. 2014; DYNDO ET AL. 2015; WISNIEWSKA ET AL. 2018). Yet, long-term effects are less clear, as studies in the Baltic Sea found no clear change in monthly presence and only little habitat shift of porpoises in the proximity of major shipping lanes and in the presence of ship noise (NEHLS ET AL. 2024; OWEN ET AL. 2024a).

In summary, despite the fact that many offshore wind farms were constructed in the German Bight during the last 15 years, there seems to be an ongoing southward shift in the harbour porpoise distribution within the North Sea, presumably also reflected by the trends in some subareas of the German Bight. The harbour porpoise is an opportunistic species, following its prey to where it is to be found. We assume that the general shift of food resources towards the South, enhanced by positive effects of the many new offshore structures on fish, offsets or even outweighs the adverse effects of OWF construction and shipping noise by OWF maintenance on harbour porpoise in that region (on the other hand, fishing vessels are not allowed to enter the area of offshore wind farms). In the end, this resulted in an overall stable trend of the harbour porpoise in the German Bight, with partly differing but mainly complementary trends in the investigated subareas of that region. The presence of harbour porpoises in the German Bight is of course connected with that in the surrounding seas, hence our findings do not inherently indicate a generally stable population of that species and a good fitness of the animals, but for now a largely stable situation in the German Bight. Nevertheless, also the larger picture in the North Sea is apparently at least stable or even slightly improving, as the four SCANS studies (HAMMOND ET AL. 2002, 2013, 2017; GILLES ET AL. 2023) estimated 335.000 (1994), 345.000 (2005), 361.000 (2013), and 410.000 (2022) harbour porpoises for the North Sea region, indicating a slight increase over the last three decades.

6 HARBOUR PORPOISE DETECTIONS WITHIN AND IN THE VICINITY OF OFFSHORE WIND FARMS

A major aim of this study was to evaluate the differences in detection rates between CPODs deployed within and outside of OWFs. To date, no in-depth analysis comparing passive-acoustic monitoring data from within and in the vicinity of OWFs has been carried out across projects. Our study combines data from long-term monitoring CPOD stations across the German Bight with single CPODs within OWFs to provide a comprehensive insight into the effects of OWFs on harbour porpoise distribution patterns in the German North Sea.

6.1 Methods

6.1.1 CPOD data preparation

The first step consisted of creating one dataset including data from single CPODs and long-term CPOD stations within OWFs and in the vicinity of OWFs. While long-term stations for passive-acoustic monitoring of porpoises have been present in the German Bight since 2010, data from single CPODs lack this level of continuity, hence, a control-impact design has been applied. Although this design can in principle more easily lead to distorted results than a before-after-control-impact (BACI) design, we minimise this probability by analysing many different OWFs simultaneously, thus assuming that local effects 'average out'.

Figure 6.1 shows the locations of the CPODs used in our model approach. While the map includes all OWFs present in 2022, it needs to be kept in mind that these were built successively, so the arrangement of OWFs and unaffected habitats has changed over the course of the study period. For this study, data were used from 10 long-term stations (within 2.5 km distance to closest OWF, Section 6.1.2) and 52 single CPODs (within 2.5 km distance to closest OWF, Section 6.1.2). Long-term CPOD stations are usually comprised of three individual devices to avoid data gaps in case of technical failure. For the models we chose data from only one substation per day (Table 6.1).

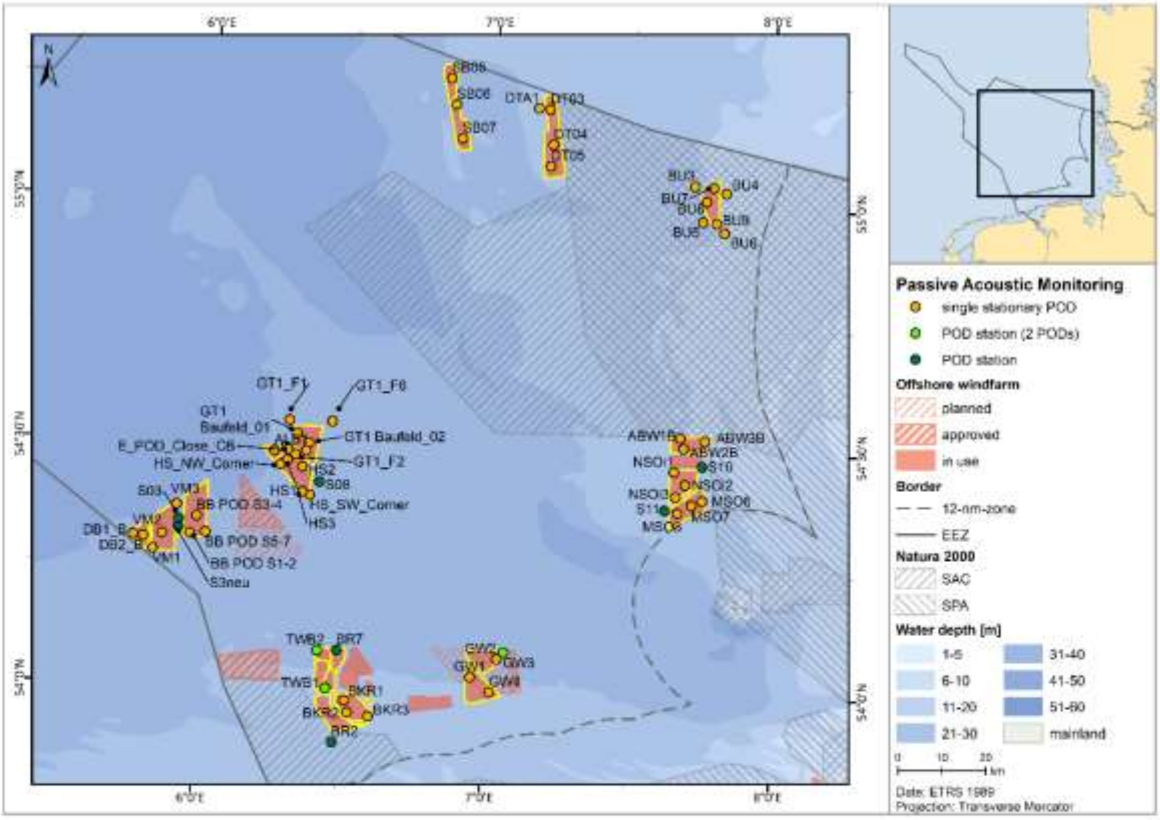

Figure 6.1 Overview of CPOD long-term monitoring stations and single stationary CPODs used in the GAMM models for testing OWF-induced effects on harbour porpoise presence.

Piling noise effects on porpoise activity were not within the scope of this study. Previous investigations estimated an effect radius of up to 20 km during piling and a reduction of harbour porpoise detections 24 hours before and up to 48 hours after piling (Brandt et al. 2016a; BioConsult SH et al. 2019). Therefore, we excluded all days when piling events took place within a radius of 20 km around the respective CPOD, as well as the day before piling and two days after piling. If piling took place just before midnight, a period of at least 48 hours after piling was discarded, and likewise a period of nearly 72 hours after piling was discarded if the piling event occurred just after midnight. This procedure was applied to ensure only full days remained in the final dataset in order to avoid potential biases due to diurnal variability of detection rates, which have been demonstrated in previous studies (e.g. Goodwin 2008; Teilmann et al. 2013).

A CPOD was classified as within an OWF if it was situated within the OWF border, i.e., the circumference line connecting the outer piles. In addition to the characteristic of being a CPOD *within* or *in the vicinity* of an OWF, the shortest distance to the next OWF border was measured and included in the dataset. Distances of CPODs within OWFs were defined to be negative, distances outside of OWFs were positive.

The data analysis aimed to model the general presence of harbour porpoises in terms of vocalisations within and around the OWFs over a long period of time. Noticeably, only few CPODs classified as *within* have a counterpart with exactly the same data period for a CPOD *in the vicinity* and vice versa, since the data regulations for each OWF were determined separately and the aim of CPOD deployment was not exclusively to measure wind farm effects during operation. Rather, for some CPODs, studies focussed on construction effects or long-term effects other than OWFs. Nevertheless, a great dataset was obtained with all CPODs that could be used to analyse effects from operational OWFs on porpoises. In contrast to other studies investigating the effect of an individual OWF on harbour porpoises, the aim of our models was to analyse general patterns of harbour porpoise detections related to OWFs in the German Bight. Therefore, the large dataset is suitable for modelling, even though the data were not overlapping perfectly on a daily basis for within and the vicinity of OWFs. In particular, the applied modern regression approaches can deal with various data inhomogeneities such as an inhomogeneous sampling design, amongst others, by appropriately incorporating various correlation structures in the data. Differences in seasonal harbour porpoise detections (GILLES ET AL. 2016; see SCHAFFELD ET AL. 2016; ZEIN ET AL. 2019) were accounted for by introducing the *dayofyear* variable.

In order to measure harbour porpoise presence over the course of a longer period of time, we started out by using the response variable commonly used in CPOD data handling for expressing the detection rate: detection-positive 10 minutes per day (*DP10M/d*), which describes the number of 10-minute intervals of a day when harbour porpoise clicks were detected. The maximum value of *DP10M/d* is equal to the number of 10-minute blocks in a full day, i.e., 144 *DP10M/d*. To avoid bias caused by diurnal patterns, which are not analysed in this study, only data from complete monitoring days were included in the models.

6.1.2 Definition of OWF clusters and effect range

The first commercial wind farms were finished by 2013 or later (except "alpha ventus", which was a test site finished in 2010 and monitored with the predecessor device, the TPOD; see DÄHNE et al. (2013)). Therefore, we analysed data from 2013 onwards.

Figure 6.2 shows the data availability between March 2013 and September 2022. Coloured bars represent the available intervals after data preparation. The CPODs were assigned to OWFs based on geographical distance for later comparison. In many cases, wind farms were constructed in close proximity to each other, which in terms of effects made it more reasonable to treat those as one entity, hereafter termed *OWF cluster* in contrast to single OWFs.

Based on literature (TOUGAARD ET AL. 2009a; e.g. BRANDT ET AL. 2011; DÄHNE ET AL. 2013) and findings of the "Gescha 2" study (BIOCONSULT SH ET AL. 2019), our first educated guess was that the effect range of OWFs in operation should be 10 km at most. First models were calculated based on this medium-scale dataset, however, when exploring the data and interpreting first results it was found that in distances greater than 2.5 km from OWFs the data availability of CPOD stations became too sparse (19 POD stations between 0 km and 2.5 km distance to the closest wind farm; 10 CPOD stations between 4 km and 6.8 km distance to their closest OWF, and none greater than 6.8 km) and the influence of single positions in that distance was too great for yielding reliable results. Thus, the final models were calculated on a dataset with 2.5 km buffer around OWFs (hereafter: near-scale dataset). However, to get a glimpse of what might be going on further away from OWFs, and for integrity reasons, the results for the 10 km continuous model are shown in the Appendix (Section 9.5).

During the past 15 years, the German Bight underwent constant structural changes due to the construction of new OWFs. Since 2010, several new OWFs have been built. In fact, the number of operational offshore wind turbines in the German Bight has increased 100-fold since 2010 (Deutsche Windguard 2024). Therefore, a crucial step in data preparation was to check the CPOD-to-OWF assignment over the course of the entire study period. For example, prior to the construction of "Hohe See" starting in August 2018 (Figure 6.2, shown in red), the CPOD station S08 was assigned to the OWF "Global Tech 1" (Figure 6.2, first CPOD on y-axis, shown in blue) and the distance to OWF was 4.03 km. After construction of the OWF "Hohe See", the CPOD station was now closer to the newly constructed OWF, so that, from this point in time onwards, it needed to be reassigned to "Hohe See" (Figure 6.2, first CPOD on y-axis, shown in red) with a distance of 1.89 km.

Another special circumstance concerns the CPOD station S3 (Figure 6.2, grey and beige). It is one of the oldest monitoring stations in the German Bight, recording since July 2009. In January 2016, the CPOD station was transferred to another location (around 1,8 km further north) and renamed into S3neu. Hence, the full dataset of S3 and S3neu was included treating them as two different CPOD monitoring-positions. After the construction of the OWF "Veja Mate" in September 2016, S3neu was assigned to the new OWF due to its closer position. Further CPODs that changed their assignment to an OWF were BR2 (first "Borkum Riffgrund1", then "Borkum Riffgrund2") and S10 (first "NordseeOst", then "Kaskasi"). However, their assignments to the defined *OWF clusters* remained unchanged.

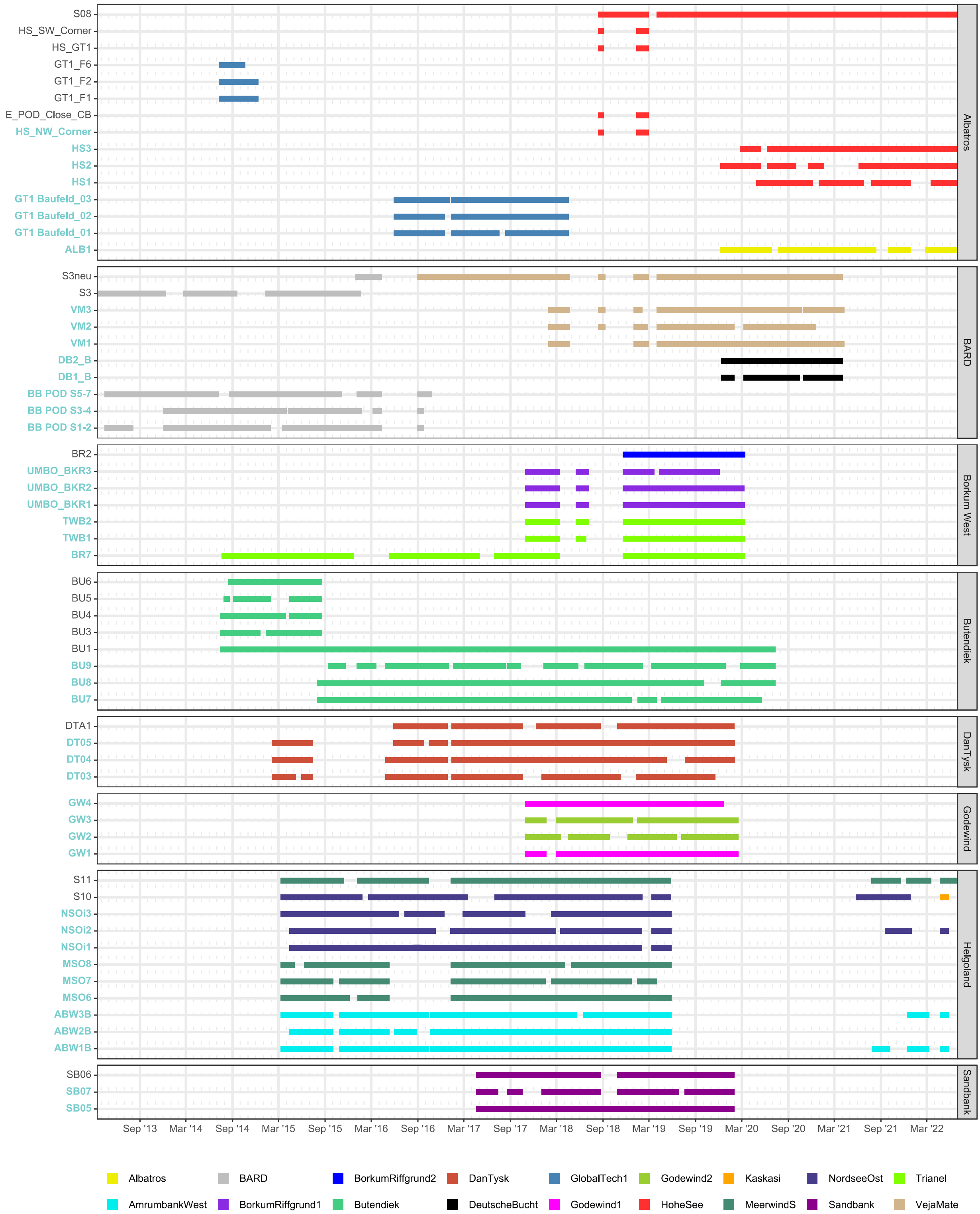

Figure 6.2 *Data availability within OWFs and 2.5 km buffer around OWFs after cropping pile-driving intervals. Labels on the left denominate CPODs used for data collection (black: in vicinity of OWF; blue: within OWF). Labels on the bottom refer to the OWF where the CPOD was located. Note that the data are divided into OWF clusters. Labels on the right show the names of the clusters the CPODs were assigned to. In case of spatially isolated OWFs, cluster and single OWF might be the same.*

6.1.3 Statistical analyses

GAMM model specifications

Analyses were carried out in R, version 4.3.2 (R CORE TEAM 2023). Due to the non-linear relationship of the explanatory variables to the response, a Generalised Additive Mixed Model (GAMM) was applied using the R package *mgcv* (WOOD 2015), supplemented by the corARMA function (nlme package, PINHEIRO & BATES 2024) to handle temporal autocorrelation issues. Previous studies approached the question at hand with GAMM models as well (SCHEIDAT ET AL. 2012; POTLOCK ET AL. 2023), so comparing their findings with a broad model considering the whole German Bight adds valuable insights into the effects of harbour porpoise presence in OWF areas.

Additional packages used for data preparation and modelling were *dplyr* (WICKHAM ET AL. 2023) and *stringr* (WICKHAM 2023) from the *tidyverse* collection (WICKHAM ET AL. 2019), as well as *formula.tools* (BROWN 2018) for preparing model formulas in advance. Date and time data were formatted with *lubridate* (GROLEMUND & WICKHAM 2011). The *oce* package (OCE 2022) was utilised for the management of UTM coordinate data. Model visualisation was carried out with *ggplot2* (WICKHAM 2016). Post-hoc tests were run using the *emmeans* package (LENTH ET AL. 2024).

For the underlying probability distribution of our data, we chose the negative binomial distribution, which is more suitable for overdispersed data than e.g. the Poisson distribution. The final response variable for our models was DP10M/5d, which can be understood as the sum of DP10M over five days grouped by measurement position (single POD/ redundancy reduced POD station). DP10M/5d shows great variability depending on geographical position, temporal factors, and other environmental factors, which renders a simple Poisson distribution unsuitable.

The GAMM output shows the relative change (in percentages) of DP10M/5d to the baseline depicted in the respective plots. In case of a factor variable the change is relative to the first factor level, which is set as reference; in case of a continuous variable the change is relative to the mean estimated by the model and depicted in the plots by the horizontal line with intercept zero.

One model approach was designed using *within OWF / in vicinity of OWF* as a binary factor (variable name: *OWF_reference*), whereas in the second model approach, the main explanatory variable was a continuous variable, *distance to OWF* (negative values: *within OWF;* positive values: *in vicinity of OWF*), allowing to describe nonlinear dependency of harbour porpoise vocalisations concerning this distance-gradient relative to OWF borders. Distances were measured as shortest possible connection between the monitoring position and the OWF border in metres.

Model selection process

To select the models, we used the Akaike information criterion (AIC), which is an estimator of prediction error balanced with model complexity and is calculated for all models and computed on the same dataset. Model AICs can then be compared amongst each other to determine the qualitatively best model within the selection. On the final dataset we thus computed multiple biologically useful models suitable for addressing the difference in harbour porpoise detections with respect to the spatial influence of OWFs in operation – along with different possible covariates. Among each modelling approach, factor or continuous model, we chose the model with the best/lowest AIC and present it here in the report.

Harbour porpoises migrate throughout the course of a year through the German EEZ (SVEEGAARD ET AL. 2012; PESCHKO ET AL. 2016) and thus a) spatially and b) temporally biologically useful independent variables had to be included into the models as well as c) a measure for noise and d) differences among monitoring devices. In previous studies (BIOCONSULT SH ET AL. 2019) we already identified *dayofyear* (b), included as cyclic spline into models, as a suitable variable for phenological differences in porpoise detections. As measure for ambient noise and corresponding overlaying effects of sounds we used the variable *allClx* (c) after ensuring that ambient noise does not correlate with *OWF_reference*. The ident number of CPODs, *podident*, had been proven to be a suitable variable (d) to correct for differences between CPODs by including it as a random factor into the model. Spatial dependency (a) in porpoise detections was accounted for by including a spatial smooth of UTM coordinates latitude and longitude into the models (however, restricted to a larger spatial scale than single OWFs to prevent confounding with the OWF effects). Based on this most basic model we augmented the formula by a measure for OWF reference (*OWF_referene* in factor models or *distance_OWF* in continuous models) and further biologically and ecologically useful variables and compared those amongst each other using the AIC.

Definition of wind farm in the modelling context

Before talking about explanatory variables in detail, the definition of OWF in our context must be clarified. OWFs in the German EEZ cannot merely be seen as a conglomeration of single wind turbines and a platform, they are intrinsically intertwined with OWF-related changes in the environment, such as ship traffic of service vessels, for example. From the harbour porpoises' perspective, an OWF must be considered as an entity of wind turbines and operational ship traffic. We thus refrained from including data on OWF-related shipping activities into our models and thereby avoid an artificial separation of attraction / deterrence effects of OWFs from service shipping.

Variables

For modelling, the data were complemented with independent potential explanatory variables such as: day of year, POD deployment depth, device ID number, station name, geographical location, distance to shipping lane, habitat type, all clicks, OWF cluster, age of OWF / age of OWF cluster (as a proxy for habituation effects), COVID restrictions, and minutes with sonar as a proxy for vessel presence. Since harbour porpoises' habitat use may follow a seasonal phenology and varies on a temporal and spatial scale (GILLES ET AL. 2011; BRANDT ET AL. 2016b; SCHAFFELD ET AL. 2016; ZEIN ET AL. 2019), day of year (*dayofyear*) was integrated as circular nonlinear variable (regression smooth). The meridian distance between coordinates differs depending on the location on Earth, so geographical positions were UTM-transformed from latitude / longitude to easting / northing to standardise distances. A 2D smooth was then included into the models based on *easting* and *northing*.

The age of an OWF was calculated based on the last day of construction. Since previous studies from the study area suggested avoidance of OWFs up to 48 hours after construction activities had ceased (BIOCONSULT SH ET AL. 2019), counting begins two days after OWF finalisation.

Table 6.1 lists the CPOD-related parameters considered for modelling.

Table 6.1 List of all variables considered for statistical model approaches for testing OWF-induced effects on harbour porpoise detections (eventually used variables in the final model are ***bold****).*

Variable	Type	Used in the final model	Description
YY	factor		year
MM	factor		month
DD	factor		day
day	continuous		date
DP10M/5d	**response**	**Yes (response variable in all final models)**	**number of detection-positive 10 minutes per five days**
DP10M/d	response		number of detection-positive 10 minutes per day
positiveMinutes	response		number of detection-positive minutes per day
positiveTrains	response		number of harbour porpoise click trains per day
positiveClx	response		number of harbour porpoise clicks per day
lostSeconds	noise measure; continuous		number of lost seconds (due to reaching the click limit)
minutesOverflow	noise measure; continuous		number of overflow minutes (with lost seconds due to reaching the click limit) per day
podident	**random factor**	**Yes (in all models)**	**CPOD device ID**
minutesSonar	continuous/factor		number of minutes in which sonar was recorded

Variable	Type	Used in the final model	Description
owf_cluster	factor		spatial conglomeration of OWFs which the offshore wind farm in the column OWF is assigned to
owf	factor		OFW in closest proximity to the station (may vary over time depending on com-pleted OWFs)
stationname	factor		unambiguous station name merging a CPOD station and station parts into a spatially and temporally logical entity
OWF_reference	**factor**	**Yes (in factor models)**	**within OWF = 1; in vicinity of OWF = 0**
ht	**factor**	**Yes (except single OWF models and habitat types model)**	**habitat type**
ht_OWF_reference	**factor**	**Yes (habitat types model)**	**habitat type with spatial OWF reference**
northing	**continuous**	**Yes (except single cluster models)**	**UTM transformed latitude of measurement position**
easting	**continuous**	**Yes (except single cluster models)**	**UTM transformed longitude of measurement position**
distance_OWF	**continuous**	**Yes (in continuous mod-els)**	**distance to closest OWF border (negative if within, and positive if in vicinity of OWF)**
distance_shipping	continuous		distance to closest shipping lane
depth_class	factor		category of water depth
COVID	factor		binary: COVID lockdown re-strictions yes / no

Variable	Type	Used in the final model	Description
OWF_reference_COVID	factor		COVID lockdown combined with the binary spatial information relative to the OWF (within and in vicinity)
dayofyear	**continous**	**Yes (in all models)**	**day of year**
POD_depth	factor		deployment depth in water
allClx	**continuous (noise measure)**	**Yes (in all models)**	**allClx variable, number of all clicks detected by CPOD**
age_owf_cluster	continous		age of OWF cluster based on last day of piling, in days
age_owf	continous		age of OWF in days

<u>*Response variable: DP10M/5d*</u>

The final response variable is derived from the variable *DP10M/d* – short for "detection positive ten minutes per day" - which has a daily resolution. *DP10M/d* sports one data point per day measuring the number of ten-minute blocks per day in which at least one porpoise train has been detected. Hence the range of values for *DP10M/d* can be any integer value from 0 to 144.

In our models we had to reduce the temporal resolution of the response variable from daily to five day blocks due to strong temporal autocorrelation in the model residuals (see section Temporal autocorrelation). *DP10M/5d* ("detection positive ten minutes per five days") sports one data point every five days if at least full three days had been recorded. *DP10M/5d* consequently can take values from 0 to 720 (= 5 * 144).

<u>*Random effects: podident*</u>

To consider possible device-specific differences in harbour porpoise detections, the variable *podident* (POD ID; biunique individual device number) was included as random factor into the model. Since each POD was replaced at regular intervals, the POD ID describes the affiliation of the CPOD for the respective measurement period.

<u>*Minutes Sonar*</u>

CPODs not only record porpoise clicks but also ambient noise, temperature (on a relative scale), and a variable called *minutesSonar*. The latter holds information on sonar noise pollution throughout time and is an indirect indicator for ship traffic, since it is mostly ship sonar that is being recorded (Tregenza 2012). In the dataset at hand, this variable indicates the sum of sonar-positive minutes per five days.

Sonar systems and depth finders are built into almost all vessels but are not necessarily used all the time. Hence, the variable *minutesSonar* correlates with ship presence, but to what extent remains unclear. As both in OWFs and in their vicinity ship traffic intrinsically occurs, it is ecologically not worthwhile – and not possible for our dataset – to account for individual ship traffic. For the interpretation of our results, it thus needs to be kept in mind that vessel presence, traffic volume, speed and sonar as well as noise emitted by motors – all vessel-related measures possibly important to porpoises – are still hidden within these data.

Initial raw data exploration indicated more minutes with sonar recordings in the vicinity of OWFs than within (Figure 6.3). More articulate, however, is the opposite relationship between the detection of sonar signals and porpoise detections: A higher number of minutes with sonar recordings correlates with a decreasing number of harbour porpoise *DP10M/5d*. In order to measure the overall effect of OWFs – including ship traffic and its related noise like e.g. sonar – this variable was excluded from the final model.

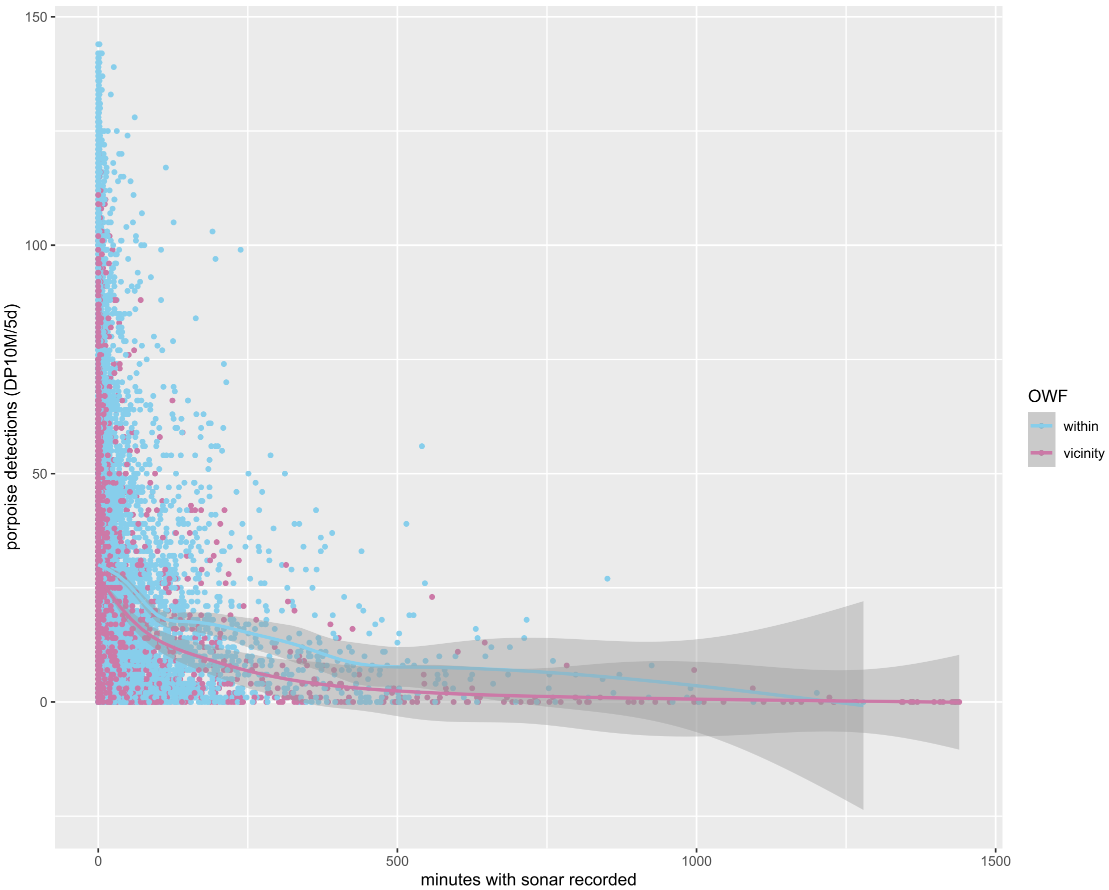

Figure 6.3 Porpoise click detections in relation to minutes with sonar recorded within and in vicinity of OWFs.

allCLx

As stated above, all models included the variable *allClx* ("all clicks") in order to correct for masking effects and detection limits (Section 4.2). We tested whether the noise level in the vicinity of OWFs was generally higher or lower than within OWFs. If so, systematic differences in noise could interfere with differences in porpoise detections in the vicinity of and within OWFs, masking the results of the models. However, detected click numbers in the vicinity of and within OWFs showed no statistically significant difference ($p > 0.05$). In models similar to the final model, where *allClx* was used as response variable, systematic differences in total click detections could not be detected between *within OWF* and *in vicinity* of *OWF*. The most likely reason is that CPODs only record noise with click characteristics and not noise levels in general. Also, detected clicks are known to depend predominantly on noise in relation to weather conditions (sand in suspension, noise from chains of the CPOD-anchoring system, etc.), which are very similar within and in the vicinity of OWFs.

Distance to shipping lane

On the path to find the best models for the data and question at hand, the variable *distance_shipping* (distance to the closest shipping lane) was included in many model formulas, as it was thought to possibly have a great influence on porpoise detections. It was found, however, that the distance to the closest shipping lane was neither strongly correlated to the distance to the closest OWF. As can be seen in Figure 6.4, distance to shipping lane was modelled with great uncertainties. The latter was even the case when this variable was included as the only additional variable in the models (*dayofyear* and *allClx* being always present), and confidence intervals were very large. Models with *distance_shipping* had much larger AICs than those without this variable. Shipping lanes highly differ in general scale and time of traffic volume as well as type of traffic, and other ship traffic such as fishing vessels is not even constrained to shipping lanes. This makes *distance_shipping* a highly artificial variable and a rather ill-suited proxy for ship traffic, especially in the vicinity of OWFs, where most ship traffic is caused by service vessels.

Additionally, including *distance_shipping* as an explanatory variable into models disarrayed the spatial dependency of porpoise detections while simultaneously increasing the statistical uncertainty of the spatial smooth. However, it should be noted that models with *distance_shipping* estimated a more moderate influence of OWFs than models without this variable (Section 6.2.1).

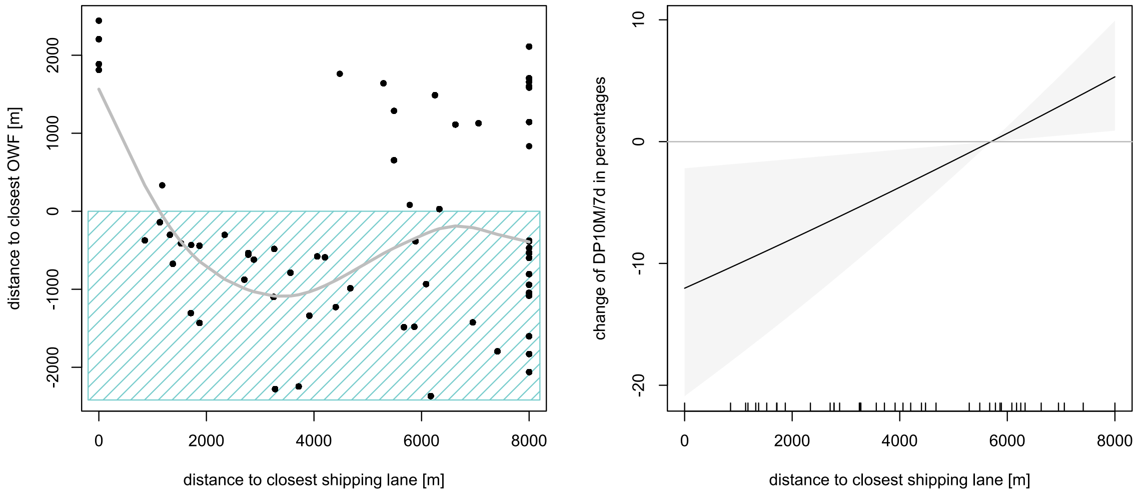

Figure 6.4 *Distance to closest shipping lane in relation to distance to closest OWF (left), and its relation to DPM10/7d when modelled as single explanatory variable (right).*

<u>*Habitat types*</u>

<u>*ht*</u>

Harbour porpoises spend large amounts of time hunting and feeding, rendering prey abundance a key factor for their distribution (GOODWIN 2008; SVEEGAARD ET AL. 2012). To account for various attractive effects of benthic habitats due to differing prey species availability, broad habitat types (BHT) as well as other habitat types (OHT) according to the EU Marine Strategy Framework Directive (EUROPEAN COMMISSION, DIRECTORATE-GENERAL FOR ENVIRONMENT 2017) were included in the habitat types (*ht*) variable (see Appendix Figure 9.4). Habitat types are defined by a combination of water depth (e.g., circalittoral or infralittoral) and sediment type (e.g., fine sand, gravel or rocks). Especially the protected OHT and FFH Directive habitat type “sandbanks which are slightly covered by sea water all the time” plays an important role for harbour porpoises, serving as habitat for one of their main prey fishes, sand eels.

<u>*ht_OWF_reference*</u>

In order to investigate if the detected patterns concerning *OWF_reference* (spatial differences in porpoise detections relative to OWF presence) might be intertwined with habitat type, we created the new factor variable *ht_OWF_reference*. It combines both *ht* and *OWF_reference* into one variable, allowing insights into possible habitat-driven differences in porpoise detection patterns detected with reference to OWF presence.

<u>*COVID*</u>

The variable *COVID* was introduced to highlight and compare the period of the German lockdown restrictions (22nd March 2020 – 04th May 2020) to the respective period of the remaining years in the dataset. Hypothetically, if the increase in *DP10M/5d* within OWFs is an effect of ship evasion rather than attraction by the OWFs, the difference in porpoise detections within OWFs compared to adjacent areas should be diminished when less ships are frequenting the German Bight, as it was the case during COVID restrictions.

During the COVID restrictions from 22nd March 2020 – 04th May 2020 anthropogenic usage of the German EEZ was different compared to prior and post usage. Especially ship traffic had been altered during this period. Based on an article of the Institute for World Economy Kiel (2020), we assumed that ship traffic on shipping lanes, hence commercial traffic concerning the shipping of goods from and to German harbours, was lower during those months where governmental restrictions due to COVID-19 took place (Figure 6.5). Although this approach seemed promising the matter was too complex to address in a mere side note and needs thorough investigation in the future. Especially the extent and effects of anchored cargo ships waiting to enter the harbours during COVID restrictions need to be taken into account along with actual ship traffic data (e.g. AIS data) to enable a more exact comparison with pre-COVID years.

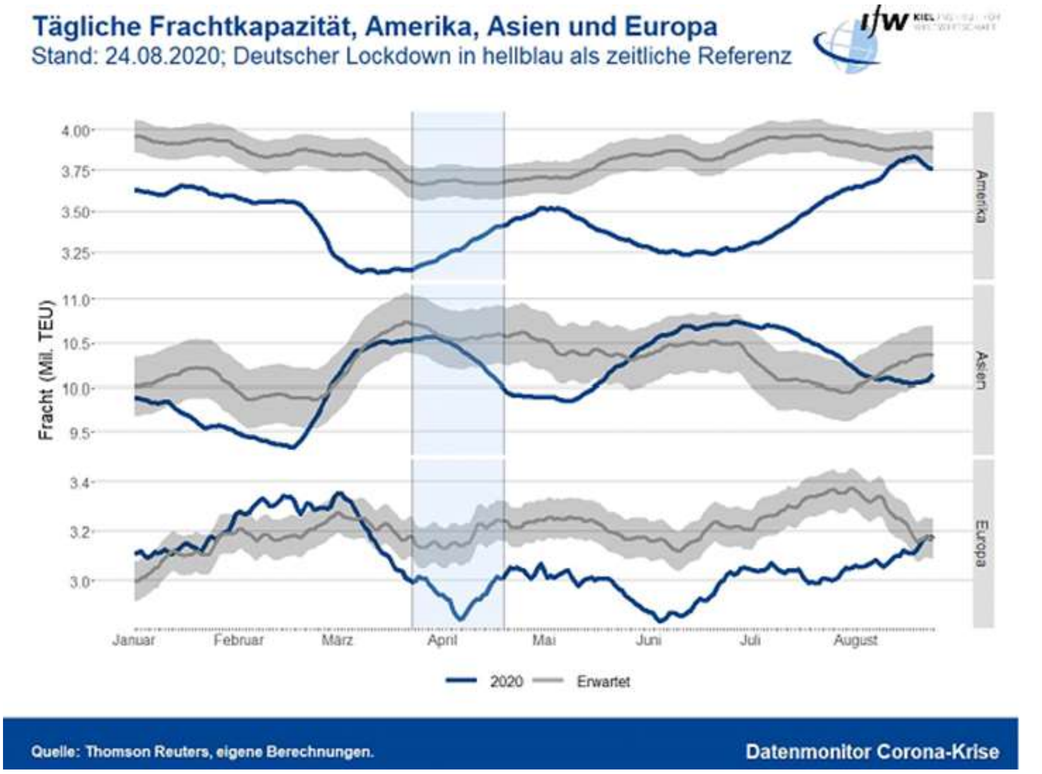

Figure 6.5 Daily freight capacity in America, Asia and Europe, German lockdown restrictions in bright blue (taken from IFW KIEL 2020).

Collinearity

A major challenge in any statistical model is to avoid collinearity, i.e., the inclusion of explanatory variables which derive from the same source and show a high level of linear relationship. Therefore, we thoroughly selected variables based on domain knowledge, raw data plots and, in the case of *allClx*, also models to avoid those problems. In the variable *allClx,* the ratio of positive clicks (porpoise clicks) to ambient noise clicks varies depending on the general sound pressure level to an unknown degree. In the beginning it was unclear, however, if *allClx* was dependent on OWFs and therefore would interfere with our main explanatory variable, *OWF_reference*. Thus, several raw data plots were conducted and separate GAMMs computed with *allClx* being the response and *OWF_reference* the main explanatory variable. All these investigations did not show any sign of dependency of *allClx* to OWF, and thus *allClx* was included in all final models.

The variables *ht* (habitat type) and *water depth* are strongly correlated; the prior is partially generated based on the latter. Habitat type is classified by the Marine Strategy Framework Directive and includes additional information on the nature of seafloor sediments, which in turn have a large impact on which fish species can thrive in certain areas and which cannot. Thus, with fish as the main source of food for harbour porpoises, the sediment affects the attractiveness of an area and possibly the behaviour of harbour porpoises. For this reason, *ht* was considered more meaningful than *water depth*, and therefore used as explanatory variable.

Shipping influence and distance to OWF could have been colinear but their effects would not be originating from the same source, thus just based on this matter it would have been valid to include both type variables into the models. It was, however, not the goal of this study to discern between the influence of OWFs (seen as a conglomeration of wind turbines) and vessel influence. Hence, we refrained from using both variables since it would not be biologically sensible to do otherwise. If, however, one was interested in the effects of wind turbines in contrast to the effect of service vessel presence, vessel data with a high temporal resolution and detailed information on the respective contributions to ambient noise would need to be included into the models.

Temporal autocorrelation

Temporal autocorrelation can be a severe problem with time series datasets like the one at hand. When at a certain time harbour porpoises are detected in one location, the distance they can travel to be detected in another area is limited by the time interval in between measurement points. For this reason, detections at time t are correlated, i.e., more similar to, detections at time t1 than to detections at e.g. time t20. Thus, porpoise detections at time t depend on detections at time t1, which in turn violates the independence assumption for single observations in GAMM models. Those dependent observations can be interpreted as measuring the same event repeatedly.

To deal with the severe temporal autocorrelation in our models, we reduced the temporal resolution of the data from daily *DP10M/d* (the most common measure of harbour porpoise detections) to 5-day blocks (*DP10M/5d*). Choosing the correct time interval is a trade-off between resolution and correlation. A large time window may eliminate temporal autocorrelation completely, but would result in loss of information and resolution, artificially giving time too much explanatory power in the model. To achieve a high resolution while also considerably reducing temporal autocorrelation, we gradually extended the detection-positive 10-minute blocks. Figure 6.6 shows the result of temporal autocorrelation in *DP10M/5d*.

In addition to the reduction of temporal resolution, we included an autocorrelation structure into the model. For this, the parameter *correlation* in the gamm()-function of the mgcv package (WOOD 2015) was handed an autoregressive moving average correlation structure (corARMA function, nlme package, PINHEIRO & BATES 2024) with both the autoregressive order (p) and the moving-average order (q) set to 1.

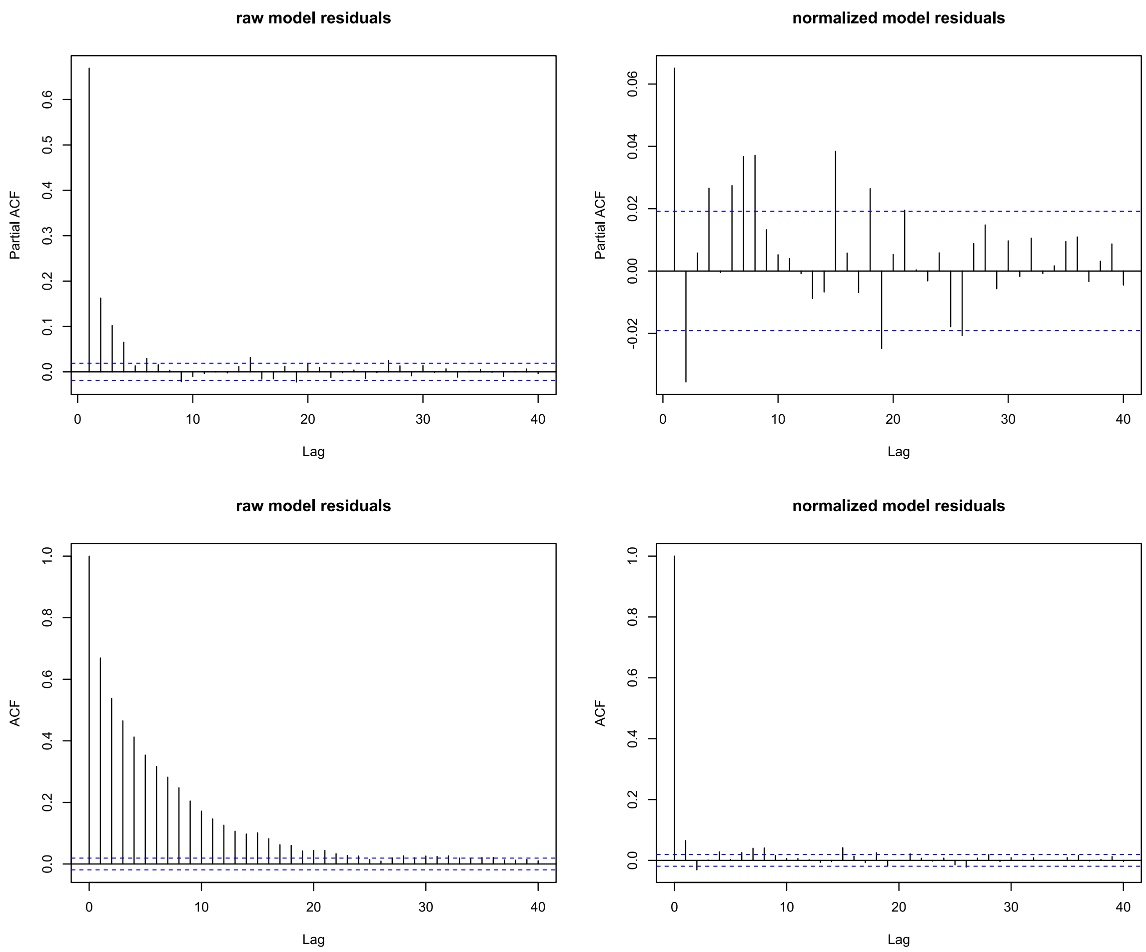

Figure 6.6 Visualisation of the degree of temporal autocorrelation of model residuals with ACF and PACF plots after reducing temporal resolution to 5 days. Right: normalized model residuals with treated autocorrelation. Left: raw model residuals.

Spatial autocorrelation

Spatial autocorrelation occurs if nearby points in space are more similar to each other than more distant points. Our data consist of scattered points throughout the German EEZ, which in themselves are independent of each other, and our tests showed that spatial autocorrelation was not a big issue. By including a 3D smooth over the spatial UTM-transformed coordinates (*easting* and *northing*), the model residuals bubble plot and semivariogram plots (see Appendix Figure 9.5) showed no sign of distinct spatial autocorrelation.

Posthoc Tests

To assess statistical differences in factor levels, we computed posthoc tests on our models. We used the library emmeans (LENTH ET AL. 2024) for this purpose and transformed the estimated mean and standard errors into the response scale afterwards, for better interpretation. *ht* and *COVID* both represent explanatory variables with several levels, and thus the posthoc test needed to be adjusted for multiple pairwise tests by using the Holm-Bonferroni method (HOLM 1979). This ensures that p-values are neither overly confident, nor too conservative if multiple comparisons are applied.

6.2 Results

Harbour porpoise detection rates were found to be significantly higher within OWFs than in their vicinity (*in vicinity*: 2.5 km buffer around OWFs – near-scale dataset) in most models. However, differences in harbour porpoise detections were greater among factor levels for variables like *ht*.

To deduce the patterns and drivers behind these findings in the best way possible, four different models were fitted to the near-scale dataset. Additionally, one continuous model was fitted to the medium-scale dataset (10 km around OWF borders) and model results were then compared to those of the model fitted to the near-scale dataset.

6.2.1 Factor model

To quantitively assess harbour porpoise detections within OWFs and in their vicinity, the factor variable *OWF_reference* with two levels – *within* and *in vicinity of OWFs* – was used. Furthermore, the variables *dayofyear, easting, northing, allClx*, and *ht* were included, as well as *podident* as random factor (see **Model selection process** in section 6.1.3). Harbour porpoise detections, measured in *DP10M/5d* (detection-positive 10 minutes per 5 days), were defined as response variable. All explanatory variables, except for the spatial smooth (*easting*, *northing*), were highly significant in explaining the variance in the model (Table 6.2).

Porpoise detections were higher within OWFs than in their vicinity as could be derived by the model output for the variable OWF_reference (Figure 6.7). The mean increase in porpoise detections within OWFs relative to the porpoise detection mean in the vicinity of OWFs was estimated 10.6 %. For this result, the estimated uncertainty was rather great compared to the estimated mean difference: The confidence interval ranged from -4.3 % to -16.4 %, which gives an absolute difference of 12.1 % between the upper and lower limit of the confidence interval, with 6.3 % from the mean to the upper and 5.8 % from the mean to the lower limit. Posthoc tests (Appendix Table 9.4) on the main explanatory variable, *OWF_reference*, showed, that the difference in factor levels was significant (p-value < 0.001).

Table 6.2 *Variables used in factor model on near-scale dataset. Significance codes: '***' p<0.001, '**' p<0.01, '*' p<0.05, '.' p<0.1, 'n.s' p≥0.1.*

variable	regression technique	purpose	near-scale dataset (2.5 km around OWF)	
			result	significance in model
OWF_reference	factor (two levels)	evaluate OWF influence	significantly more detections within OWFs than in their vicinity	***
dayofyear	cyclic spline	account for yearly differences in detections	seasonal differences	***
easting, northing	3d spline	geographic variation (in UTM coordinates)		.
allClx	spline	account for acoustical masking and technical shortcomings related to ambient noise	negative correlation with *DP10M/5d*	***
ht	factor (five levels)	differences related to habitat types	significant differences between some hts	***
podident	random factor	differences in single PODs	-	-
t	ARIMA	remove temporal autocorrelation	-	-
AIC		goodness of model fit		8,886.931
r-squared adjusted		coefficient of determination		0.220
theta		dispersion parameter		4.015
number of data		sample size		10,476

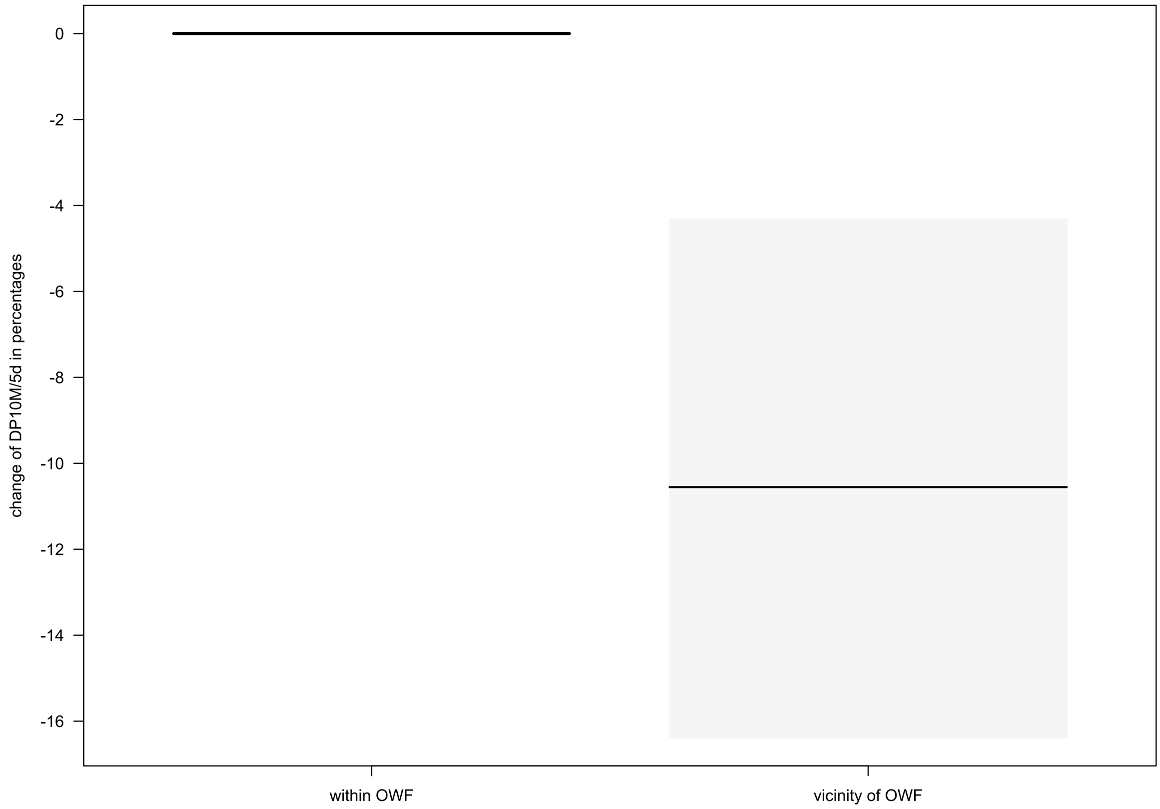

Figure 6.7 *Influence of factor variable OWF_reference on harbour porpoise detections. Black line: averaged values; shaded areas: 95 % confidence interval.*

6.2.2 Continuous model

To qualitatively assess harbour porpoise detections in relation to distance to OWFs, a continuous variable of the distance (in metres) of the measurement position to the closest OWF, *distance_OWF,* was introduced. All other explanatory variables in this approach were the same as in the factor model, hence the variables *dayofyear, easting, northing, allClx,* and *ht* were included as well as *podident* as random factor, and *t* as variable on which the temporal autocorrelation structure was computed. The measure for model fit (AIC) slightly increased compared to the quantitative approach (both fitted to the near-scale dataset; factor model: 8,886.931 (AIC); continuous model: 8,897.882 (AIC)). Nevertheless, the continuous model is suited to investigate how porpoise detections relative to OWFs might be distributed on a spatial scale. All explanatory variables but *distance_OWF* and the spatial smooth, were significant in explaining variance in the model (Table 6.3).

Within OWFs, the confidence intervals of the modelled smooth of the distance related harbour porpoise detections never crosses the baseline and can thus not be considered significantly different from the estimated detection baseline (Figure 6.8). However, the modelled average detection rates (represented by the black line) clearly show a pattern which indicates slightly reduced detections in the vicinity and increased densities within OWFs. Additionally, between 1.4 km and 2.0 km outside of OWFs our model estimates a significant decline in detections. For the whole smooth, uncertainty is minimum 5.8 % (difference in percentage change between upper and lower confidence level) and maximum 40.1 %. The confidence interval was the narrowest around -0.72 km (within OWFs), which is also the distance range where – in our dataset – the highest number of measurement stations are conglomerated. Confidence intervals grow wider in distances which were only represented by few or single measurement stations. From 1.37 km until 1.91 km distance to the closest OWF, harbour porpoise detections were modelled the lowest and the entire confidence interval dropped below the baseline, indicating a significant decline in harbour porpoise detections relative to the overall mean. This decline becomes even more pronounced when looking at the medium-scale dataset (10.0 km around OWFs; see Appendix Table 9.6 and Figure 9.6). Here the drop in modelled detections starts within the OWFs, and in the vicinity of OWFs (between 0 and 2.5 km) modelled detections are significantly lower than the baseline. However, the shape of this curve is dominated by the few measurement stations located between 2.5 km and 6.7 km distance to the OWF border, where highest detection rates are found. Note that measurement stations are distributed unevenly among distance to OWFs between 2.5 km and 6.7 km, and distance coverage is very sparse within the same range.

Table 6.3 *Variables used in the continuous model on near-scale dataset. Note model parameters cannot be compared among models calculated on different datasets. Significance codes: '***' p<0.001, '**' p<0.01, '*' p<0.05, '.' p<0.1, 'n.s.' p≥0.1.*

variable	type in model	purpose	near-scale dataset (2.5 km around OWF)	
			result	**significance**
distance_OWF	spline	evaluate OWF influence	no distinct distance dependent pattern, great uncertainties	n.s.
dayofyear	cyclic spline	account for yearly differences in detections	seasonal differences	***
easting, northing	3d spline	geographic variation (in UTM coordinates)		.
allClx	spline	account for acoustical masking and technical shortcomings related to ambient noise	negative correlation with DP10M/5d	***
ht	factor (five levels)	differences related to hts	significant differences between some hts	***
podident	random factor	differences in single PODs	-	
t	ARIMA	remove temporal autocorrelation	-	
AIC		goodness of model fit		8,897.88
r-squared adjusted		coefficient of determination		0.217
theta		dispersion parameter		4.016
number of data				10,476

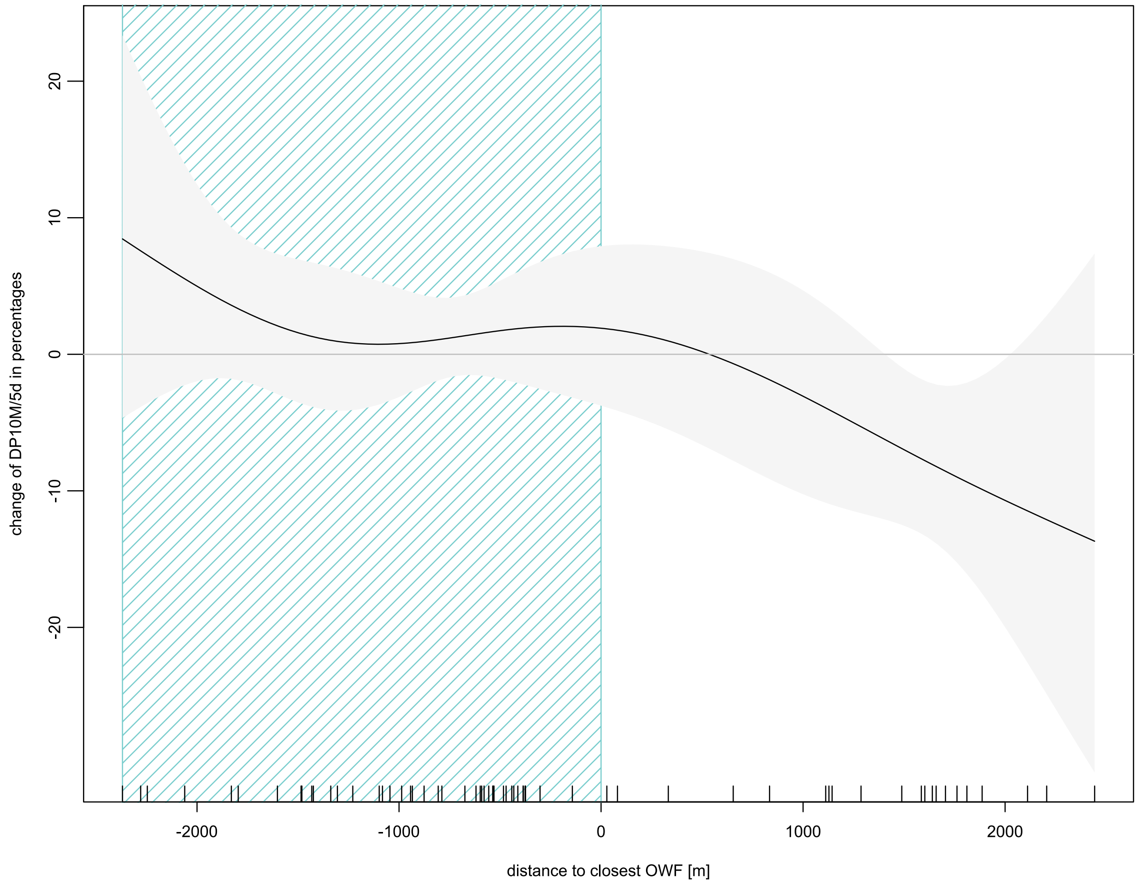

Figure 6.8 Modelled effect of distance to closest OWF on change in porpoise detections; main result of continuous model computed on near-scale dataset (up to 2.5 km around OWFs). Black line: averaged values; shaded areas: 95 % confidence interval. Black bars below: Number of CPODs at a given distance.

6.2.3 Habitat types model

OWFs and their related measurement stations are distributed throughout the German EEZ, which is not a uniform habitat. The variable habitat type (*ht*) estimated great total differences in harbour porpoise detections among different habitats for both the factor model and the continuous model. We thus posed the question whether harbour porpoise detections might be different for OWFs and their adjacent areas depending on the present habitat. We approached this by creating a factor variable *ht_OWF_reference* combining habitat type and the information whether the measurement station in question was located within or in the vicinity of an OWF.

Again, all other explanatory variables were the same as in the models presented above, hence the variables *dayofyear, easting, northing, allClx,* and *ht* were included as well as *podident* as random factor, and *t* as variable on which the temporal autocorrelation structure was computed (Table 6.4). The variable *ht_OWF_reference* was highly significant in explaining variance in the model, and the measure for model fit (ht model: 8,873.94 (AIC)) improved compared to both the continuous model (continuous model: 8,897.88 (AIC)) and the factor model (factor model: 8,886.93 (AIC)).

The overall harbour porpoise detections vary greatly among habitat types. However, the detected difference in the modelled pattern concerning the comparison between within and in the vicinity of OWFs was not as pronounced. Both aspects were investigated with the variable *ht_OWF_reference* which combines *ht* and *OWF_reference* into one factor variable (Figure 6.9). Nevertheless, for the two habitat types *OffshoreCircalitSand* and *Sandbanks*, while being different in their total harbour porpoise detections (*OffshoreCircalitSand*: approx. 40 – 60 % lower detections than the reference level; *Sandbanks*: ca. -10 – 80 % detection difference from the reference level), *within* OWFs higher harbour porpoise detection rates were measured than *in vicinity of* OWFs (Figure 6.9). *CircalitSand* and *Reefs* did not show differences in detection rates *within* and *in vicinity of* OWFs. *CircalitCoarseSed* had no outside measurement positions *in vicinity of* OWFs and thus nothing can be said for this habitat type. Differences between *within* and *in vicinity of* OWF detections were found to be significant for the habitat type *OffshoreCircalitSand* (p-value < 0.001 in posthoc test) and visible but not significant for *Sandbanks* (p-value 0.07 in posthoc test).

*Table 6.4 Variables used in ht model on near-scale dataset. Significance codes: '***' p<0.001, '**' p<0.01, '*' p<0.05, '.' p<0.1, 'n.s.' p≥0.1.*

variable	type in model	purpose	near-scale dataset (2.5 km around OWF)	
			result	significance
ht_OWF_reference	factor (nine levels)	evaluate OWF influence depending on ht	great differences between hts but no distinct differences in the pattern within/in vicinity	***
dayofyear	cyclic spline	account for yearly differences in detections	seasonal differences	***
easting, northing	3d spline	geographic variation (in UTM coordinates)		.
allClx	spline	account for acoustical masking and technical shortcomings related to ambient noise	negative correlation with *DP10M/5d*	***
podident	random factor	differences in single PODs	-	
t	ARIMA	remove temporal autocorrelation	-	
AIC		goodness of model fit		8,873.94
r-squared adjusted		coefficient of determination		0.224
theta		dispersion parameter		4.092
number of data				10,476

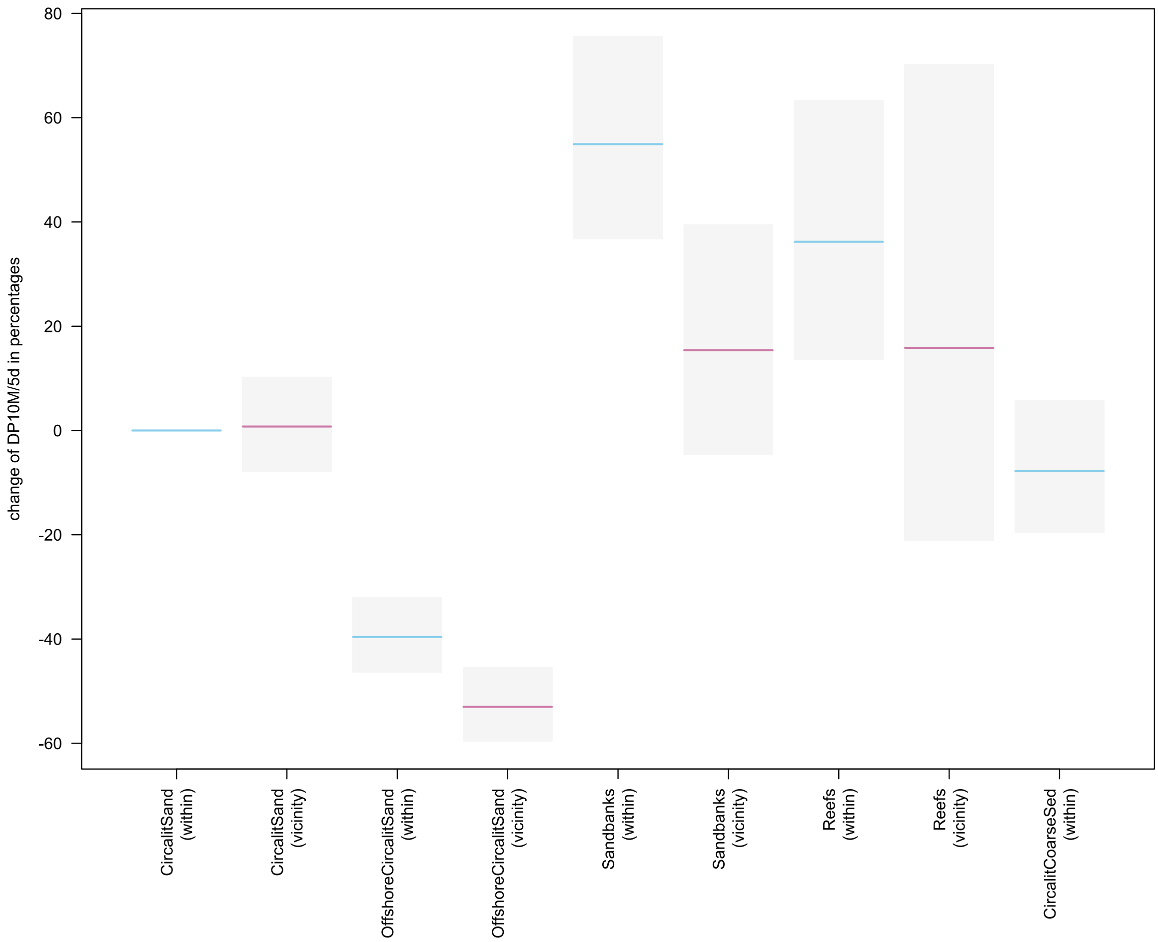

Figure 6.9 Effect of habitat type on harbour porpoise detections within and in the vicinity of OWFs. Coloured line: averaged values; shaded areas: 95 % confidence interval.

6.2.4 Single OWF clusters

Due to limited data for single OWFs, one must treat results for those with even greater care. For *Gode Wind* (consisting of the single OWF “Gode Wind”), not enough data were available to calculate a model for this dataset. For the OWF cluster *BARD* (consisting of: “BARD”, “Veja Mate” and “Deutsche Bucht”) and *Sandbank* (consisting of the single OWF “Sandbank”) significantly fewer harbour porpoise detections were measured *in vicinity of* OWFs than *within* (Figure 9.7). These were the only two models where the variable *OWF_reference* (Table 9.7) was considered as explaining a significant proportion of the model variance. For the OWF clusters *Albatros* (consisting of: “Albatros”, “Hohe See” and “GlobalTech1”), *Butendiek* (consisting of the single OWF “Butendiek”), *BorkumWest* (consisting of: “Borkum Riffgrund1” and “Trianel”), and *Helgoland* (consisting of: “Amrumbank West”, “Nordsee Ost”, “Meerwind Süd/Ost” and “Kaskasi”) no difference between *within* and *in vicinity of* OWFs could be detected. *DanTysk* (consisting of the single OWF “DanTysk”) showed slightly higher detections *in vicinity of* the OWF than *within*.

6.3 Discussion

Our analyses aim to add knowledge to the largely unknown relationship between harbour porpoises and OWFs in operation in the German Bight. The vast amount of CPOD data available for this study enabled us to comprehensively address this question, despite CPODs providing only indirect data about harbour porpoise vocalisations that cannot be translated directly into animal density or behaviour. Two main approaches were used: a factor approach differentiating between detections within and in the vicinity of OWFs, and a continuous approach to analyse detections on a spatial gradient in relation to OWFs.

6.3.1 Underlying data and modelling

POD acoustic recorders have been used to study harbour porpoise presence in the German Bight for more than 15 years (DIEDERICHS ET AL. 2008), being deployed in various locations throughout the North Sea. Studies have verified the correlation of acoustic detections and porpoise densities through visual sightings (KYHN ET AL. 2012; HAELTERS ET AL. 2013), but they cannot be directly translated into abundance. Harbour porpoises are only detected when they emit the click trains they use for echolocation, so the higher the porpoise vocal activity, the more detections will be visible in the CPOD data.

It should be noted that the detectability of harbour porpoise vocalisations using CPODs is limited by background noise (Section 4.2) and thus shows a negative relation to the ambient click soundscape (Section 6.1.2). The variable *allClx*, which represents all sounds recorded by the CPODs, was included into the model to correct for general masking effects. Differences in sensitivity, which occur among CPODs even though they are calibrated regularly, additionally might affect detections slightly. For this reason, we resorted to using the POD ID (*podident*) as a random factor to account for technical discrepancies among devices in our dataset.

6.3.2 Harbour porpoises and OWFs

While negative effects of OWF construction on harbour porpoises are largely recognised, especially during pile driving (TOUGAARD ET AL. 2009a; BRANDT ET AL. 2011; HAELTERS ET AL. 2012; DÄHNE ET AL. 2013; BIOCONSULT SH ET AL. 2019; e.g. BENHEMMA-LE GALL ET AL. 2021), the effects of operational OWFs on harbour porpoises have rarely been studied on a large scale. For that matter, it was unclear whether there is a general attraction to or an avoidance of OWFs, or an indifference.

Avoidance behaviour of harbour porpoises in relation to operational OWFs might be induced by operational ship traffic or by noise emissions of the wind turbines. Several studies have shown that porpoises react sensitively to ship-related noise (HERMANNSEN ET AL. 2014; DYNDO ET AL. 2015; WISNIEWSKA ET AL. 2018; FRANKISH ET AL. 2023). In contrast, wind turbine noise emissions may play a minor role for porpoises compared to the ambient noise of the North Sea, since sound pressure levels only exceed ambient noise at frequencies between 25 Hz and 1 kHz (TOUGAARD ET AL. 2009b; NORRO ET AL. 2011; BELLMANN ET AL. 2023). This frequency range is usually associated with higher threshold tolerances than high frequencies where harbour porpoises are more sensitive (LUCKE ET AL. 2008; KASTELEIN ET AL. 2017). TOUGAARD et al. (2009b) estimated an audibility range for harbour porpoises of max. 70 m from wind turbine foundations. KOSCHINSKI et al. (2003) investigated harbour porpoises' reactions to wind turbine sound, and the results showed no significant behavioural change during noise exposure. While not specifically being attracted to or deterred from areas with wind turbine sound exposure, the animals approached with more care and explored the noise source with more frequent echolocation.

On the other hand, the scientific community has hypothesised that OWFs attract harbour porpoises. For one, the so-called "reef effect" may provide a richer and more diverse feeding ground due to the hard substrate that wind turbines provide in the otherwise sand-dominated North Sea (LANGHAMER 2012; BERGSTRÖM ET AL. 2013; MIKKELSEN ET AL. 2013; DEGRAER ET AL. 2020). Secondly, fisheries are excluded from German OWFs, providing the possibility of growth periods undisrupted by fishing activities. The North Sea is one of the most heavily fished oceans in the world. For example, bottom trawling affects 98 % of the seabed. The area swept by bottom trawling every year exceeds the total seabed area by factor 1.25 (EIGAARD ET AL. 2017). So even though OWF areas are not free from operational ships and other kinds of commercial ship traffic, they may provide a sanctuary from fishing pressure (BONSU ET AL. 2024), and might simultaneously correlate with increased prey abundance.

So far, some studies about harbour porpoise activity within OWFs show contradicting results. In a BACI study, SCHEIDAT et al. (2011, 2012) found a significantly increased harbour porpoise activity in a newly built Dutch OWF, both in comparison to the OWF area prior to construction and to contemporary reference areas. Similarly, POTLOCK et al. (2023) reported a 32 % increase in harbour porpoise activity during operation of a gravity-base OWF in the UK, compared to activity prior to construction. Using alternative foundations may mitigate negative impacts during construction, however, during operation, those OWFs should have comparable effects on harbour porpoises as pile-driven OWFs. In contrast, VAN POLANEN PETEL et al. (2012) and DÄHNE et al. (2014) found no effect of OWFs on harbour porpoise occurrence, and TEILMANN & CARSTENSEN (2012) reported lower porpoise activity within a Danish OWF after construction. However, porpoise activity in this OWF increased over the years, which was interpreted as habituation effect.

The drivers behind these findings are unknown, and different explanations have been given in the studies. As such, the Dutch part of the North Sea is likely a noisier environment than the inner Danish waters. Therefore, what may be perceived as a noisy environment with high operational ship traffic in the calm waters of Denmark may be perceived as a traffic-calmed refuge by harbour porpoises close to the Dutch and British shores, an area dominated by heavily travelled shipping lanes.

6.3.3 German Bight OWF models

Two approaches were followed in this study: The factor model involved differences between detections within an OWF and in its vicinity (outside an OWF in up to 2.5) to test for overall differences between these two areas. A continuous model with distance to OWF (positive distances for outside in up to 2.5 km or 10 km respectively, and negative distances for within an OWF) aimed at identifying effect ranges.

For both models, our results indicate an increase in porpoise detections within OWFs compared to the respective reference areas in the vicinity (Figure 6.7 and Figure 6.8), which was highly significant in the factor model. The mean increase within OWF areas was 10.6 % compared to the reference areas (Figure 6.7). In the continuous model, harbour porpoise detections dropped in the vicinity of OWFs (2.5 km, where the model was cropped due to data deficiencies, see Figure 6.8) in comparison to the overall average. When harbour porpoise presence was modelled beyond 2.5 km distance, this negative trend reversed again (Figure 6.9). However, the confidence intervals were largest between 2.5 km and 10 km as only few CPOD stations provided data within this distance range, so the uncertainty was regarded too high to provide robust results. In addition, areas far off the OWFs might be influenced by other (only partially known) factors than OWFs and can be interpreted in this context only to a very limited extent.

As expected, the variable *allClx*, representing ambient noise levels in general, significantly correlated with the number of harbour porpoise detections in our models (Table 6.2 and Table 6.3). CPODs work best in environments with low noise levels, since the harbour porpoise clicks are less likely to be detected with increasing ambient noise (VERFUß ET AL. 2007). Therefore, the significant effect of *allClx* is at least partly an expression of acoustical masking in our data, and thus it can be considered a correcting variable. KOSCHINSKI et al. (2003) showed that porpoises can hear operational OWF-related sounds and change their behaviour accordingly. It remains unclear if harbour porpoises are attracted to or deterred by the noise emissions themselves, or whether they associate the sounds with certain conditions such as food availability or increased density of barriers, for instance. KOSCHINSKI et al. (2003) highlight the increase of echolocation activity of harbour porpoises around wind turbines. An increase in detection rates within OWFs may not only be the result of higher porpoise densities within the OWFs but also depict higher echolocation rates. Even so, the skewing effect of increased porpoise vocal activity should be considered in the light of the detection algorithm of CPODs and the way the data are being clustered. A high number of click train detections does not directly translate into a higher number of detection-positive 10-minute intervals, because within the same 10-minute block a single click train renders the same result as 10 minutes of continuous detections. Therefore, the effect of increased echolocation is buffered by using the unit *DP10M* in our models.

The variable *dayofyear* also significantly explained differences in harbour porpoise detections (Table 6.2 and Table 6.3). Several studies have shown the seasonality of porpoise distribution in the North Sea (GILLES ET AL. 2011; BRANDT ET AL. 2016b; SCHAFFELD ET AL. 2016; ZEIN ET AL. 2019), so the phenological effect in our models is in line with the scientific literature. Likewise, it has a reasonable ecological background that *easting, northing* and *habitat type* significantly affect harbour porpoise detections. These animals are highly mobile and mainly driven by their search for food in suitable areas (LINNENSCHMIDT ET AL. 2013; WISNIEWSKA ET AL. 2018). Not only do they follow their prey, they also react sensitively to their environment and to disruptions therein such as ship traffic (DYNDO ET AL. 2015; WISNIEWSKA ET AL. 2016).

For this reason, the inclusion of *distance to shipping lane* as an explanatory variable was considered and tested, but ultimately not integrated into the final models. As mentioned in Section 6.1.2, the variable reduced the goodness of fit, likely because shipping traffic is highly variable and cannot be interpreted as a constant ambient factor. AKKAYA BAS et al. (2017) showed that porpoise sightings in the Istanbul Strait were lowest in regions with highest shipping activity, and PIGEAULT et al. (2024)

found that harbour porpoises avoid areas with frequently heavy ship traffic. However, these studies also showed that behavioural patterns and reactions of harbour porpoises cannot simply be explained or predicted by the existence of a shipping lane alone. Rather, numerous factors such as the average number of ships per day within a certain radius, regularity of disturbance, vessel sound levels, individual behavioural reactions, and environmental factors influencing sound propagation play important roles in modelling harbour porpoise reactions to ship traffic. Hence, to investigate shipping noise influence on harbour porpoise detections and maybe entangle it from the influence of operational OWFs, future models should include AIS data rather than distance proxies. Though these data may still be incomplete, they provide a more detailed picture that may be suitable to distinguish between the influence of OWFs and ship traffic.

To take advantage of the fact that CPODs also record sonar, the effect of sonar-positive minutes (*minutesSonar*) on harbour porpoise detections was tested, providing a more specific indicator of ship presence in the vicinity of CPODs than *distance to shipping lane*. As mentioned above, sonar recordings do not translate directly into ship densities, since not all ships may use sonar, and the detections exclude other ship-related noise, which heavily depends on factors such as type of motor, speed and sound propagation. The data indicate more minutes with sonar recordings in the vicinity of OWFs than within (Figure 6.3), which likely reflects the difference in vessel activities and types. More articulate, however, is the opposite relationship between the detection of sonar signals and porpoise detections: A higher number of minutes with sonar recordings correlates with a decreasing number of harbour porpoise *DP10M/5d*, most likely owing to the effect noisier environments have on click detectability (see description of *allClx* in Section *6.1.3*), as well as the fact that harbour porpoises are known to be sensitive to sonar and evading the source of the noise (LINDERHED 2013; KASTELEIN ET AL. 2015b).

Including the variable *minutesSonar* in the final models was found to mask the effects of other factors. It only covers one aspect of shipping activities, and the aim of this study was to analyse differences in porpoise vocalisations among OWFs and adjacent areas, and not to differentiate between ship traffic (sonar) and OWFs. It was therefore not included into the models aiming to assess porpoise vocalisations in relation to OWFs. However, sonar and other ship-related noise play a major role in the habitat use of harbour porpoises, as has been stated by previous studies (LINDERHED 2013; DYNDO ET AL. 2015; KASTELEIN ET AL. 2015b; WISNIEWSKA ET AL. 2018). In the context of fishing restrictions in German OWFs, reduced sonar noise pollution may be intrinsically linked to OWFs in the same way that operational ship traffic, reef and refugium effects are. Thus, distinguishing between the factors that lead to a significant increase in harbour porpoise detections within OWFs in the German Bight is hard to accomplish.

The current state of ship traffic in the whole North Sea provides few opportunities to separate areas that can be used as a baseline reference for unaffected habitats. However, the COVID-19 pandemic yielded a relative respite from human impact when the global economy was dialled down, and with it the shipping operations across the oceans (IFW KIEL 2020). This seemed like a promising opportunity to test the influence of ship traffic on harbour porpoise detections by experiment. Hypothetically, if the increase in *DP10M/5d* within OWFs is an effect of ship evasion rather than attraction by the OWFs, the difference in porpoise detections within OWFs compared to adjacent areas should be diminished when less ships are frequenting the German Bight. Preliminary tests and models did not confirm this hypothesis. Rather, it seemed like harbour porpoise detection rates decreased in general, while remaining higher within OWFs than in their vicinity. This might corroborate the assumption that OWFs attract harbour porpoises by reef effects. However, this approach needs more detailed modelling which would have exceeded the scope and time frame of this project.

If reef effects cause harbour porpoises to seek out OWFs deliberately, one would assume that the attraction to more abundant food sources would increase over the years, during which the artificial habitat is gradually colonised by hard substrate communities. PETERSEN & MALM (2006) state that it takes approximately three years for faunal communities to stabilise after hard substrate has been introduced. We assumed habituation effects such as described by TEILMANN & CARSTENSEN (2012) may become visible when the models take the age of the OWF cluster, i.e., the time interval since the last pile driving event, into account. However, the results were inconclusive when the variable *ageOWF* was introduced. The model did not show that the age of an OWF had a clear effect on harbour porpoise detections within the OWFs. This indicates that age alone might be too simple a proxy for capturing ageing of OWFs. For one, the significant effects of time, location, habitat type, and noise level show that differences in the highly diverse underlying data are best explained on small scales. Analogous to harbour porpoise detections, which are measured in *DP10M/5d*, the *ageOWF* variable is divided into 5-day blocks. While changes in porpoise presence within an OWF may occur over several years, the unit interval may be too small to detect these changes in our model.

Secondly, habituation and reef effects may be different among OWFs, so testing the age against the overall model may smooth variations across the individual wind farm clusters, masking possible effects.

To evaluate if single OWFs show differences in harbour porpoise detections compared to their reference area, as has been carried out for other OWFs in the Netherlands (SCHEIDAT ET AL. 2012; VAN POLANEN PETEL ET AL. 2012), Denmark (TEILMANN & CARSTENSEN 2012), Britain (POTLOCK ET AL. 2023) and the German test wind farm “alpha ventus” (DÄHNE ET AL. 2014), sub-models of the global factor model were run. As mentioned above, these results need to be considered more carefully because the underlying data differ greatly between the OWFs. For example, the dataset of OWF *Sandbank* is comprised of only two CPODs within and two CPODs in the vicinity of the wind farm, spanning a period of nearly three years. However, the *Helgoland* cluster dataset contains information from three CPODs in the vicinity of and nine CPODs within OWFs covering a period of more than four years. Influences of seasonal changes on estimated harbour porpoise detection rates and natural fluctuations such as environmental factors, prey abundance etc. become greater with a smaller dataset, which in turn might overlay the effect of OWFs. This is highlighted by the overall increasing confidence intervals compared to the global model.

From the OWF cluster models, it becomes apparent that harbour porpoises do not spread evenly across the wind farms (Appendix Figure 9.7), as has been shown in the project “Gescha 2” (BIOCONSULT SH ET AL. 2019) and as being indicated by the results in Section 6.2.4. Compared to within the windfarm area, porpoise detections were found to be higher within the OWF cluster *Albatros, BARD* and *Butendiek*, where the largest sample sizes were available. The models for *DanTysk* and *Borkum West*, however, show higher porpoise detection rates in the vicinity of the OWFs, yet featuring large confidence intervals due to smaller sample sizes and most likely, great fluctuations in habitat use. Both OWF clusters border Special Areas of Conservation (SAC), i.e., “Sylt Outer

Reef" and "Borkum Reef Ground", respectively. Both areas are known to be important harbour porpoise habitats and nursing grounds (GILLES ET AL. 2016). It should be noted that *Butendiek* and *Sandbank* are also located within or close to "Sylt Outer Reef", yet these models indicate higher porpoise presence within the respective wind farms. Discrepancies to *DanTysk* may be rooted in prey abundance and habitat types, factors we could not analyse in sufficient detail. An overlap with sand eel habitat as well as a relative tranquillity within the OWF may have led to a higher presence of harbour porpoises during feeding.

The OWF clusters in the south of the German Bight (*Albatros, BARD* and *Borkum West*) are located between two major shipping lanes, "Terschelling" to the south and "German Bight Western Approach" to the north. Habitat use of OWFs by harbour porpoises is most certainly linked to ship traffic in these areas as well. Overall, distinguishing between the interlaced effects of anthropogenic impacts from OWFs and of ecological factors such as prey abundance and habitat suitability remains challenging, especially for individual OWF clusters where the parameters are more nuanced than in the overall dataset.

These findings are in line with previous studies looking at single OWFs (see SCHEIDAT ET AL. 2012; POTLOCK ET AL. 2023), yet seem contradictory to other studies at first, where no or even negative impacts of OWFs on harbour porpoise presence had been found (TEILMANN & CARSTENSEN 2012; VAN POLANEN PETEL ET AL. 2012; DÄHNE ET AL. 2014). However, when we computed the model for individual OWF clusters, the results became more nuanced. Harbour porpoises show great fluctuations in their habitat use throughout the seasons, spending most of the time feeding and following their prey areas (LINNENSCHMIDT ET AL. 2013; WISNIEWSKA ET AL. 2018), but also concentrating in certain areas, e. g. the "Sylt Outer Reef", in spring and summer for breeding (BMUB 2017).

Therefore, the habitat an OWF is located in might play an important role in the distribution of harbour porpoise detections. Yet, little is known about possible drivers behind the varying responses that were reported for harbour porpoises with respect to operational OWFs, as mentioned above. We proceeded by modelling harbour porpoise detections in relation to OWFs, clustered by habitat type. Detection rates varied greatly between habitat types (see Figure 6.9), more so than between OWFs and their vicinity within each model. Although large differences in environmental and anthropogenic impacts as well as smaller sample sizes for each habitat type may play a role in the underlying data, the results suggest that OWF presence does not affect detections as much as the habitat type itself. This is in line with differences in observed harbour porpoise detections between the subareas analysed in Chapter 5.2.2. Specifically, detections were significantly higher (confirmed by posthoc tests, $p < 0.05$) within OWFs than in the vicinity of OWFs for the habitat "offshore circalittoral sand". A trend in the same direction was found for the habitat "sandbanks". For "sandbanks" and "reefs", no significant differences were found with respect to OWF presence. While it is unclear which habitat trait (such as prey availability) might be responsible for the observed pattern, within the German Bight our findings point towards an attraction to OWFs throughout most habitats.

Various studies have highlighted potential reef (LANGHAMER 2012; BERGSTRÖM ET AL. 2013; MIKKELSEN ET AL. 2013; DEGRAER ET AL. 2020) and refugium effects (BONSU ET AL. 2024), as in German OWFs fishing is prohibited. While service vessels still frequently operate in OWFs and intrinsic ambient noise is present around the wind turbines (TOUGAARD ET AL. 2009b; NORRO ET AL. 2011), these circumstances do not seem to deter harbour porpoises according to our results. We refrained from isolating OWF-related ship traffic in form of an additional variable from the overall OWF effect, since it is an intrinsic factor for OWFs. Our approaches containing shipping effects such as testing the distance to the next shipping lane did not yield clear results.

Summarising, we used two GAMM model approaches based on long-term data from CPOD stations and single CPODs in the German Bight to evaluate the presence of harbour porpoises in spatial relation to OWFs. Although CPOD monitoring has been carried out for more than 15 years (DIEDERICHS ET AL. 2008), a before-after control impact study (BACI) was not feasible with our dataset, and a control-impact study has been applied instead. Potential bias was reduced by the high number of different OWFs/POD locations and years. In particular, the analyses compared harbour porpoise detections within OWFs to harbour porpoise detections in their vicinity (buffer zone 2.5 km), using a two-factor model and a continuous model to identify potential effect radii. To minimise temporal autocorrelation, the unit *DP10M/5d* (detection-positive 10 min per 5 days) was chosen for harbour porpoise detection rates. The variable *dayofyear*, a smooth depending on geographical location (as *northing / easting*), general noise recordings (*allClx*), habitat type (*ht*), and CPOD ID (*podident*) were included as supplementary explanatory variables (Section 6.1.2).

Both approaches resulted in significantly higher detection rates within the OWFs compared to in the vicinity of OWFs, with an overall difference of 10.6 % in the factor model.

Our analyses generally point to a clear but minor trend of harbour porpoise attraction to OWFs in the German Bight. We assume reef and refugium effects to be the main reason for this. So, while negative effects of OWFs on harbour porpoises may still persist for a brief period after construction in single areas, the exclusion of fishing activities from OWFs likely renders them suitable refugia for harbour porpoises in the German North Sea.

7 SYNOPSIS

The rapid expansion of offshore wind farms (OWFs) in the German Bight, North Sea, raised questions about long-term effects on the habitat use of the highly mobile harbour porpoise. Recently, negative harbour porpoise trends from 2002 to 2019 in parts of the German EEZ of the North Sea, assessed by aerial surveys, were reported by NACHTSHEIM et al. (2021), whereas the Gescha 2 study found a positive development of harbour porpoise detection rates, assessed by passive-acoustic monitoring (PAM) by cetacean porpoise detectors (CPODs), from 2010 to 2016 (BIOCONSULT SH ET AL. 2019). This study is intended to gain more insight into this issue, also in the light of possible effects of OWFs in operation on harbour porpoise detections in that area. For achieving this goal, longer time-series of PAM data than those investigated by Gescha 2 were analysed here.

Regarding the results of the long-term trend analysis for the entire study area on a cross-seasonal base, neither a significant trend nor tendency of the harbour porpoise detection rate *%DP10M/period* was found from 2011 to 2019. On a seasonal level, a positive trend was found for winter and a positive tendency for spring, whereas no trend or tendency was registered in summer and autumn.

Even though the overall trend in the German Bight was largely stable over the study years, the development of detection rates differed among five investigated subareas within the German Bight. Whereas partly negative trends or tendencies were found for the subareas *Northwest* and *Northeast*, the development in the subareas *North* and *Southeast* was rather positive. The situation in the subarea *South* remained nearly unchanged. In general, this pointed to a partial shift in porpoise distribution within the German Bight over the years. The subareas *North* and *Southeast* supposedly became more favourable for porpoises, possibly attracting more animals from the subareas *Northwest* and *Northeast*. Food availability might have played an important role here, which could also be a major factor regarding a general southward tendency of the harbour porpoise distribution within the North Sea registered over the last three decades by four SCANS studies (HAMMOND ET AL. 2002, 2013, 2017; GILLES ET AL. 2023). In this respect, namely sand eels (Ammodytidae) are supposed to be of great importance for harbour porpoises.

An apparent contradiction of our result of no clear overall trend or tendency in the German Bight to the negative trend reported by NACHTSHEIM et al. (2021) according to aerial observer survey data for the German EEZ could be resolved. One reason was that different periods were investigated. Our overall trend analysis started in 2011, whereas the trend of the NACHTSHEIM study began in 2002. Their overall trend, which was significantly negative according to the used methodology (though porpoise density in the first year 2002 was nearly the same as in the last year 2019, based on a few days of the summer seasons of seven non-subsequent years), showed a density increase from 2002 to 2006, then a decrease until 2012, but no decline afterwards anymore. Hence, from 2012 onwards the NACHTSHEIM and our study were largely in line in showing no negative overall trend.

Similarly, the difference of our steady trend to the increasing trend of the Gescha 2 study was simply based on the partly differing periods available for analysis. The CPOD dataset for Gescha 2 ended in 2016, a very good year for harbour porpoises, which resulted in a picture of a positive development of numbers. We were able to extend the time series by some more years, over which detection rates levelled out again, leading to a steady overall trend.

Summarising trend analyses, the most probable scenario originating from our data and previously published trends is one of a stable development of the harbour porpoise presence from 2011 to 2019, but probably also until 2023. For these additional years data from two subareas were available showing no decline on average but rather indicating a distributional shift from one (*Northwest*) to the other subarea (*Southeast*) over the study years.

To evaluate the presence of harbour porpoises in relation to OWFs (*within* or *in the vicinity*), two main GAMM model approaches were used, showing significantly higher detection rates within OWFs compared to CPOD data from the vicinity of OWFs, with an overall increase of 10.6 % in the factor model. These findings are in line with previous studies looking at single OWFs (see SCHEIDAT ET AL. 2012; POTLOCK ET AL. 2023), but apparently contradict other studies, where no or even negative impacts of OWFs on harbour porpoise presence had been found (TEILMANN & CARSTENSEN 2012; VAN POLANEN PETEL ET AL. 2012; DÄHNE ET AL. 2014). Looking at the models for single OWFs, porpoise detections were found to be higher within the OWFs than in their vicinity (2.5 km around OWF borders) for the OWF clusters *Albatros, BARD* and *Butendiek*, where the largest sample sizes were available. Only the *DanTysk* and *Borkum West* models show higher porpoise detection rates in the vicinity of the OWFs, though featuring large confidence intervals due to smaller sample sizes and supposedly great fluctuations in habitat use.

It seems to be a reasonable assumption that OWFs in operation may rather attract than deter harbour porpoises. Various studies have highlighted potential reef (LANGHAMER 2012; BERGSTRÖM ET AL. 2013; MIKKELSEN ET AL. 2013; DEGRAER ET AL. 2020) and refugium effects (BONSU ET AL. 2024), as within the areas of German OWFs fishing is prohibited. Even though service vessels still operate within the OWFs, and intrinsic ambient noise is present around the wind turbines (TOUGAARD ET AL. 2009b; NORRO ET AL. 2011), these circumstances apparently do not deter harbour porpoises, according to our results.

As a synopsis of all these results, we showed stable harbour porpoise detection rates in the German Bight from 2011 onwards, with subtle differences among five investigated subareas. A proposed distributional shift from subarea *Northwest* to *Southeast* may have been an expression of a shifted prey distribution causing a general southward trend of harbour porpoise distribution within the North Sea over the last three decades. As a number of OWFs were built in the German Bight over the last 15 years, leading to short-term disturbance during construction but to potential reef and refugium effects on the long-term, these may have had its part in altering prey availability for porpoises. In summary, variations in porpoise presence are assumed to be explained by prey distribution for both the large-scale (North Sea) and small-scale (OWFs/OWF clusters) study topics, whereas the latter might additionally have been influenced by ship traffic and resulting refugium effects of OWFs.

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9 APPENDIX

9.1 Tables of CPOD stations and single CPODs

*Table 9.1 22 CPOD stations (each with three CPODs) considered for trend analyses (14 of these were chosen in the end; * indicates CPOD stations that, in addition to the single CPODs in Table 9.2, were also regarded for comparisons of porpoise detections within and in the vicinity of OWFs); in case of a data gap, the second start and end date of deployment are presented; also given is the assigned subarea.*

Station	Start 1	End 1	Start 2	End 2	Subarea (see Figure 5.2)
DT1	03.04.2011	23.01.2020			North
DT2	03.04.2011	17.12.2019			North
WB2	27.04.2014	17.12.2019			North
S02	04.12.2009	25.03.2021			Northwest
S03*	16.07.2009	25.03.2021			Northwest
S04	14.12.2009	28.04.2019	28.07.2022	ongoing	Northwest
S07	07.02.2010	28.04.2019			Northwest
S08*	07.02.2010	ongoing			Northwest
BR1	03.12.2013	04.03.2020			South
BR2*	24.04.2010	02.05.2013	03.12.2013	04.03.2020	South
BR3	24.04.2010	02.05.2013	04.02.2014	03.03.2020	South
BR4	04.02.2014	03.03.2020			South
BR5	03.02.2014	07.02.2020			South
BR6	03.02.2014	07.02.2020			South
BR7*	24.07.2010	04.03.2020			South
BR8	09.11.2011	04.03.2020			South
BU1*	14.04.2011	02.07.2020			Northeast
BU2	14.04.2011	02.07.2020			Northeast
S10*	25.03.2010	18.05.2019	04.06.2021	18.05.2022	Southeast
S11*	12.09.2010	18.05.2019	05.08.2021	22.01.2023	Southeast
S12	12.09.2010	20.05.2019	04.06.2021	ongoing	Southeast
S13	11.10.2010	20.05.2019	28.07.2022	ongoing	Southeast

Table 9.2 *List of 58 available single CPODs and CPOD stations with two redundant devices each (the latter marked with 2PODs); 55 of these plus 7 from the preceding table, all marked with *, were chosen in the end for analyses of porpoise detections within and in the vicinity of those OWFs or OWF clusters mentioned in the last column; also given is the start and end date of CPOD deployment.*

Station	Start	End	OWF or OWF cluster
ALB1*	18.12.2019	09.03.2023	Albatros
E_POD_Close_CB*2PODs	08.05.2018	09.04.2019	Albatros
GT1 Baufeld_01*	10.05.2016	08.04.2018	Albatros
GT1 Baufeld_02*	10.05.2016	08.04.2018	Albatros
GT1 Baufeld_03*	10.05.2016	08.04.2018	Albatros
GT1_F1*	04.08.2012	19.03.2015	Albatros
GT1_F2*	04.08.2012	19.03.2015	Albatros
GT1_F6*	04.08.2012	19.03.2015	Albatros
HS_GT1*	08.05.2018	09.04.2019	Albatros
HS_NW_Corner*	08.05.2018	09.04.2019	Albatros
HS_SW_Corner*	08.05.2018	09.04.2019	Albatros
HS1*	18.12.2019	09.03.2023	Albatros
HS2*	18.12.2019	09.03.2023	Albatros
HS3*	18.12.2019	24.02.2023	Albatros
N_POD_Close_CB2PODs	08.05.2018	09.04.2019	Albatros
BB POD S1-2*	25.04.2013	16.10.2016	BARD
BB POD S3-4*	25.04.2013	16.10.2016	BARD
BB POD S5-7*	25.04.2013	16.10.2016	BARD
DB1_B*	22.12.2019	25.03.2021	BARD
DB2_B*	22.12.2019	25.03.2021	BARD
S3neu*	09.01.2016	25.03.2021	BARD
VM1*	08.02.2018	31.03.2021	BARD
VM2*	08.02.2018	10.12.2020	BARD
VM3*	08.02.2018	31.03.2021	BARD
TWB1*	09.11.2017	04.03.2020	Borkum West
TWB2*	09.11.2017	04.03.2020	Borkum West
UMBO_BKR1*	08.11.2017	03.03.2020	Borkum West
UMBO_BKR2*	08.11.2017	03.03.2020	Borkum West
UMBO_BKR3*	08.11.2017	25.11.2019	Borkum West
BU3*	14.03.2014	10.08.2015	Butendiek
BU4*	14.03.2014	10.08.2015	Butendiek
BU5*	14.03.2014	10.08.2015	Butendiek
BU6*	14.03.2014	10.08.2015	Butendiek
BU7*	10.08.2015	02.07.2020	Butendiek
BU8*	10.08.2015	02.07.2020	Butendiek
BU9*	10.08.2015	02.07.2020	Butendiek
DT03*	13.02.2015	07.11.2019	DanTysk
DT04*	13.02.2015	23.01.2020	DanTysk
DT05*	13.02.2015	23.01.2020	DanTysk

Station	Start	End	OWF or OWF cluster
DTA1*	18.02.2016	22.01.2020	DanTysk
DTA3	18.02.2016	22.01.2020	DanTysk
GW1*	08.11.2017	07.02.2020	Gode Wind
GW2*	08.11.2017	07.02.2020	Gode Wind
GW3*	08.11.2017	07.02.2020	Gode Wind
GW4*	08.11.2017	07.02.2020	Gode Wind
ABW1B*	17.01.2017	17.05.2022	Helgoland
ABW2B*	17.01.2017	19.05.2019	Helgoland
ABW3B*	17.01.2017	17.05.2022	Helgoland
MSO6*	06.12.2016	19.05.2019	Helgoland
MSO7*	06.12.2016	19.05.2019	Helgoland
MSO8*	06.12.2016	19.05.2019	Helgoland
NSOi1*	12.03.2015	19.05.2019	Helgoland
NSOi2*	12.03.2015	17.05.2022	Helgoland
NSOi3*	12.03.2015	19.05.2019	Helgoland
DTA4	18.02.2016	22.01.2020	Sandbank
SB05*	29.04.2017	22.01.2020	Sandbank
SB06*	29.04.2017	22.01.2020	Sandbank
SB07*	29.04.2017	22.01.2020	Sandbank

Table 9.3 *Days per year and season available for trend analysis of 22 CPOD stations from the German Bight, assigned to five subareas. Of these, the 14 stations in bold were selected for further analysis due to sufficient time-series length, overlap, and days with data per year.*

Subarea	**North (N)**			**Northwest (NW)**					**South (S)**								**Northeast (NE)**		**Southeast (SE)**			
CPOD station	**DT1**	**DT2**	WB2	**S02**	**S03**	S04	S07	**S08**	BR1	**BR2**	**BR3**	BR4	BR5	BR6	**BR7**	**BR8**	**BU1**	**BU2**	**S10**	**S11**	**S12**	S13
2009				27	164	17																
autumn					89																	
summer					45																	
winter				27	30	17																
2010				315	353	357	294	323		116	196				155				252	107	109	76
autumn				88	88	88	90	90		39	78				87				89	76	78	46
spring				89	89	92	82	91		37	23								66			
summer				89	89	89	91	90		40	90				38				91			
winter				49	87	88	31	52			5				30				6	31	31	30
2011	190	211		303	328	330	360	360		240	302				332	47	177	235	305	334	268	284
autumn	50	73		91	88	90	89	89		68	87				85	20	40	79	87	90	81	42
spring	56	52		89	89	88	91	91		84	91				82		46	47	68	90	56	81
summer	80	82		89	89	91	91	91		78	90				90		87	87	89	89	89	88
winter	4	4		34	62	61	89	89		10	34				75	27	4	22	61	65	42	73
2012	273	298		329	357	359	362	360		149	350				276	340	323	329	301	294	217	166
autumn	61	67		88	88	88	89	91		28	89				70	87	83	74	48	90	50	9
spring	79	84		75	90	92	91	90		39	90				89	90	88	89	89	48	47	80
summer	83	87		91	89	91	92	91		43	90				90	90	90	90	89	89	89	53
winter	50	60		75	90	88	90	88		39	81				27	73	62	76	75	67	31	24
2013	291	302		356	356	236	205	354		96	106				294	337	325	323	305	341	322	331
autumn	72	64		90	90	17	8	89							88	85	79	76	88	90	88	88
spring	82	87		89	89	89	18	89		53	50				71	90	91	86	64	74	73	73
summer	88	90		89	89	42	89	90							90	83	90	90	67	90	76	92
winter	49	61		88	88	88	90	86		43	56				45	79	65	71	86	87	85	78
2014	315	271	239	266	243	343	358	357	337	308	311	240	324	311	341	345	322	328	330	354	320	329
autumn	86	82	89	30	9	89	90	90	88	85	86	60	89	87	88	86	84	88	86	88	88	88
spring	86	45	34	90	92	78	90	89	88	84	87	75	90	87	88	90	85	88	87	91	88	81
summer	89	87	90	88	83	88	90	90	91	82	91	90	91	85	91	91	88	88	89	88	85	91
winter	54	57	26	58	59	88	88	88	70	57	47	15	54	52	74	78	65	64	68	87	59	69
2015	302	297	331	337	338	358	359	361	336	293	275	282	355	311	298	338	332	320	332	352	297	318
autumn	63	73	80	89	89	90	90	90	82	72	64	77	88	85	81	81	81	81	81	85	82	78
spring	87	83	88	89	89	90	90	91	88	82	81	65	90	72	79	89	89	83	87	92	87	82
summer	87	87	90	89	89	90	90	91	90	82	90	87	90	90	91	90	90	90	88	89	90	89
winter	65	54	73	70	71	88	89	89	76	57	40	53	87	64	47	78	72	66	76	86	38	69
2016	333	314	292	354	353	354	357	357	347	305	348	321	355	350	327	351	343	338	338	325	332	340
autumn	86	81	89	88	87	86	89	89	88	79	89	77	88	88	89	89	89	85	89	89	86	86
spring	90	86	42	89	89	90	90	90	91	84	89	90	90	90	91	91	89	89	77	91	90	90
summer	87	86	83	89	89	89	89	89	89	85	90	89	90	90	89	89	91	90	89	86	89	87

Subarea	North (N)			Northwest (NW)					South (S)								Northeast (NE)		Southeast (SE)			
CPOD station	DT1	DT2	WB2	S02	S03	S04	S07	S08	BR1	BR2	BR3	BR4	BR5	BR6	BR7	BR8	BU1	BU2	S10	S11	S12	S13
winter	70	61	78	88	88	89	89	89	79	57	80	65	87	82	58	82	74	74	83	59	67	77
2017	303	294	319	354	354	341	344	342	333	298	346	305	356	335	351	319	312	327	223	337	325	332
autumn	63	61	68	89	89	89	90	89	75	63	89	61	90	86	88	69	71	73	85	88	72	76
spring	90	85	90	89	89	89	89	89	90	83	90	90	90	76	90	90	84	90	4	88	89	90
summer	89	88	89	89	89	90	90	75	90	87	86	89	90	90	90	89	89	89	51	90	89	89
winter	61	60	72	87	87	73	75	89	78	65	81	65	86	83	83	71	68	75	83	71	75	77
2018	326	320	347	354	354	353	357	358	348	306	336	338	357	358	356	324	336	340	353	354	341	343
autumn	83	78	85	89	89	90	90	90	87	75	75	84	89	90	90	80	81	83	89	88	84	85
spring	89	86	90	89	89	88	90	90	89	81	89	90	90	90	89	78	90	89	90	90	90	90
summer	89	88	90	89	89	89	90	90	90	86	90	90	90	90	90	89	89	91	89	90	90	90
winter	65	68	82	87	87	86	87	88	82	64	82	74	88	88	87	77	76	77	85	86	77	78
2019	307	289	317	353	352	115	115	356	334	315	356	350	358	354	355	311	321	322	79	132	119	118
autumn	75	78	85	88	88			89	89	84	89	89	89	89	89	86	86	84				
spring	78	74	81	89	89	57	57	90	86	76	91	90	91	91	91	74	80	80	56	77	69	72
summer	88	87	90	89	89			89	90	90	90	90	90	90	90	90	88	88				
winter	66	50	61	87	86	58	58	88	69	65	86	81	88	84	85	61	67	70	23	55	50	46
2020	13			355	355			360	55	30	62	62	37	37	60	48	158	151				
autumn				88	88			89														
spring				89	89			90	3	1	2	2			3	1	87	84				
summer				89	89			90									31	31				
winter	13			89	89			91	52	29	60	60	37	37	57	47	40	36				
2021				332	83			358											192	102	49	
autumn				90				90											90	66	40	
spring				77	24			91														
summer				76				90											87	26		
winter				89	59			87											15	10	9	
2022				359				358											47	356	313	
autumn				89				89												90	86	
spring				89				89											47	89	87	
summer				91				91												90	90	
winter				90				89												87	50	
2023				264				342												19	256	
autumn				25				90													25	
spring				90				90													89	
summer				91				91													91	
winter				58				71												19	51	

9.2 Broad habitat types

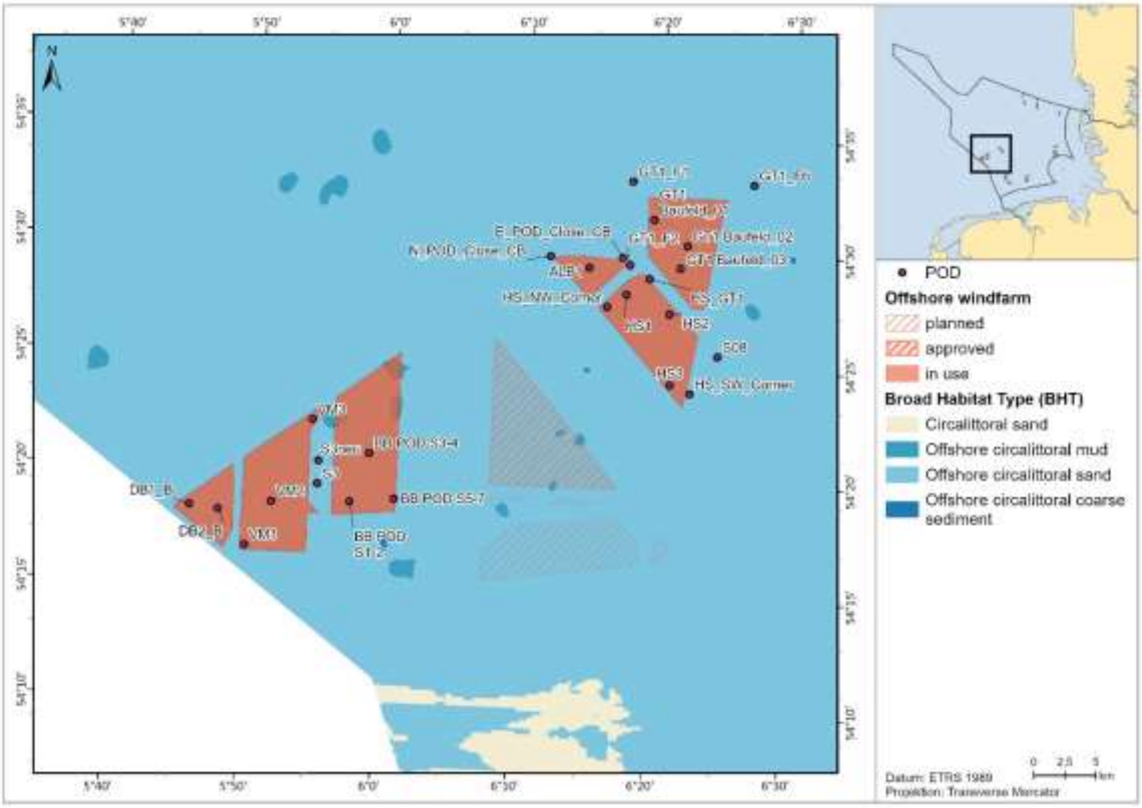

Figure 9.1 OWF clusters (from left to right): BARD ("Deutsche Bucht", "Veja Mate", "BARD") and Albatros ("Albatros", "Global Tech" and "Hohe See").

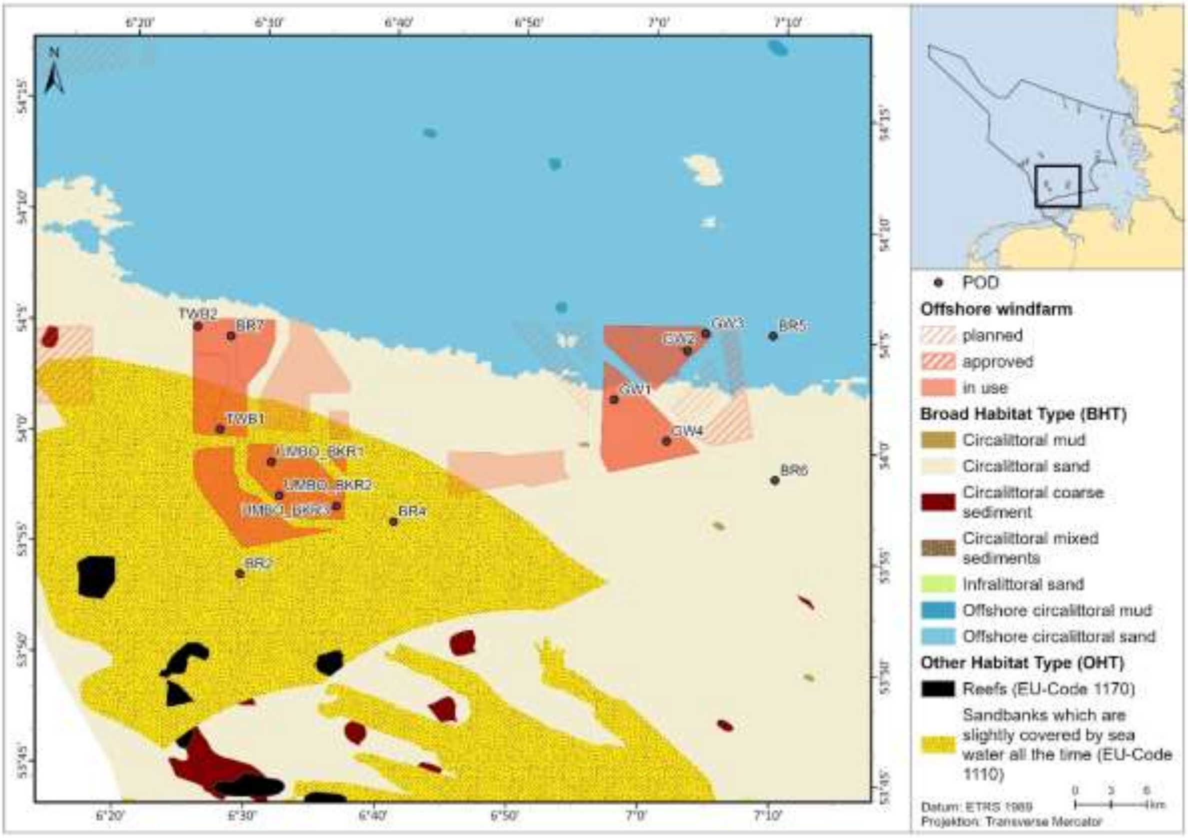

Figure 9.2 *OWF clusters (from west to east): Borkum West ("Borkum Riffgrund1", "Borkum Riffgrund2" and "Trianel") and Gode Wind ("Gode Wind1" and "Gode Wind2").*

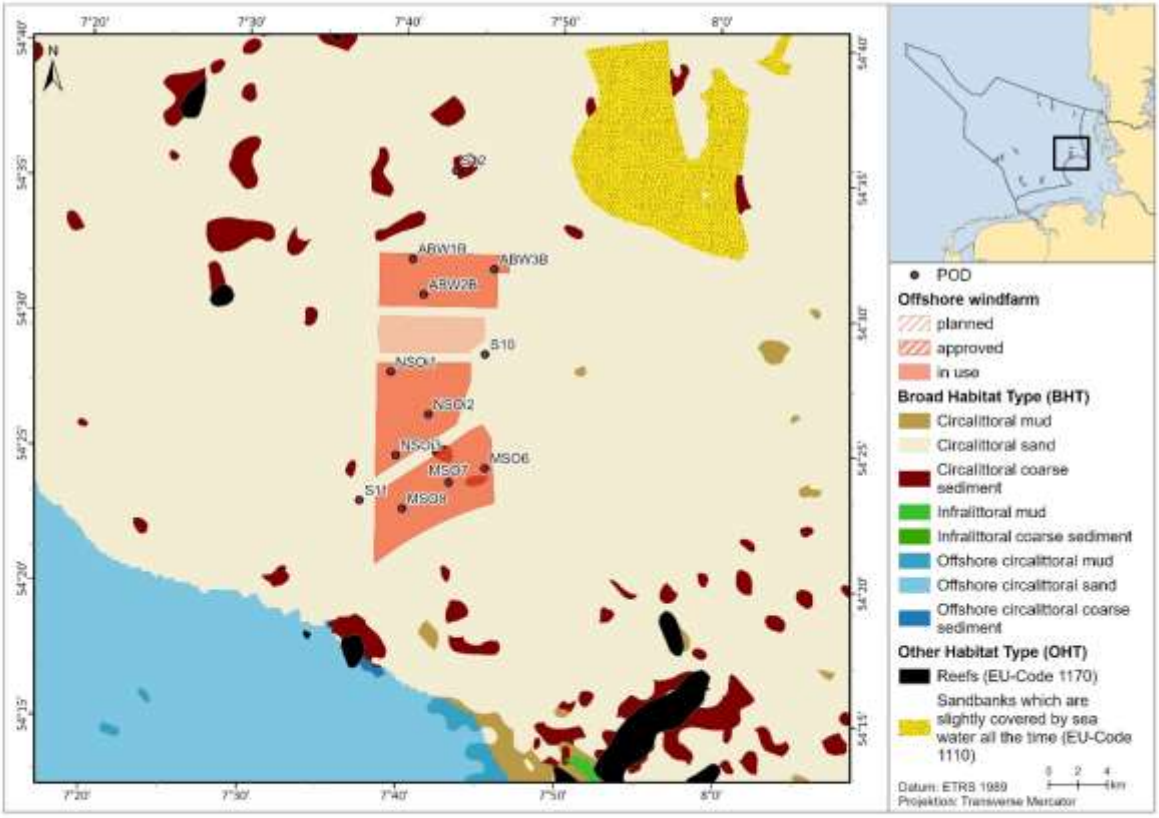

Figure 9.3 OWF cluster Helgoland (from north to south: “Amrumbank West”, “Kaskasi”, “Meerwind Süd”, “Nordsee Ost”).

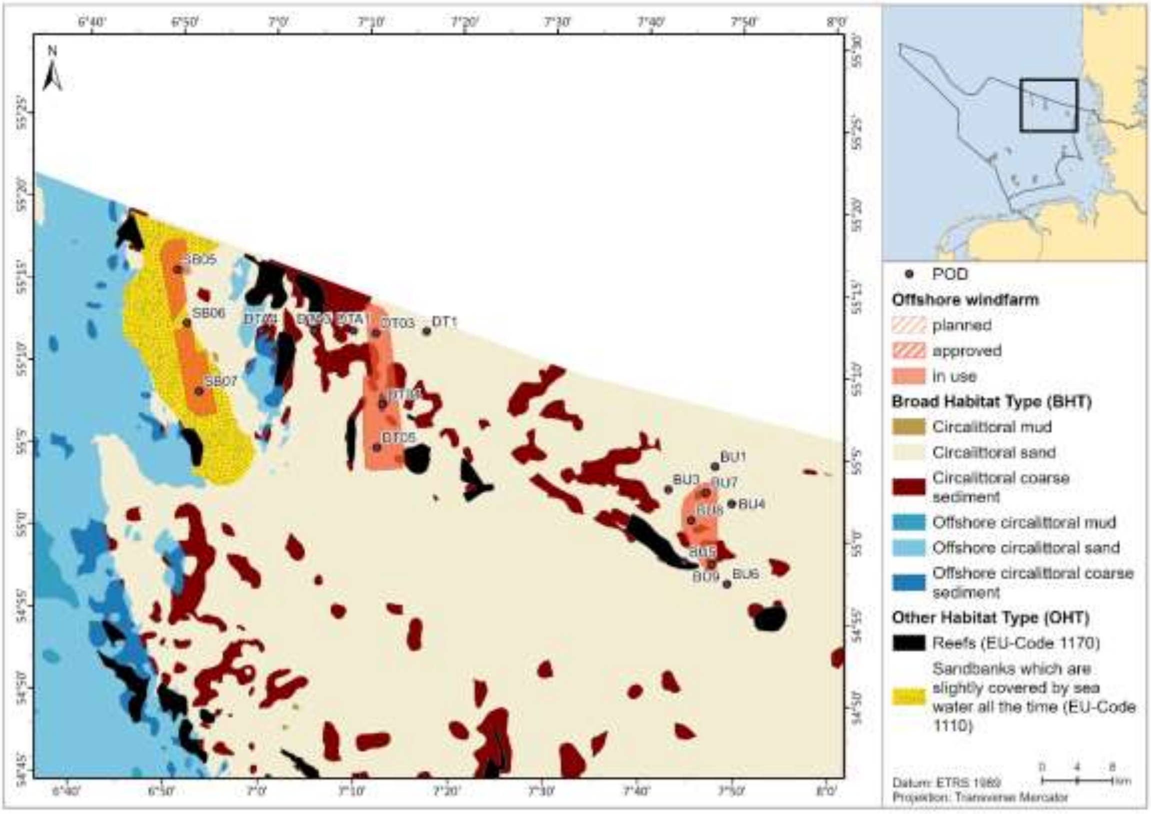

Figure 9.4 Single OWFs (west to east): Sandbank, DanTysk and Butendiek.

9.3 Posthoc tests

Posthoc tests were conducted using the emmeans package (LENTH ET AL. 2024). Estimates and standard errors (SE) have been transformed into the response scale afterwards.

Table 9.4 Pairwise posthoc test for factor model.

contrast	estimate	SE	df	t.ratio	p-value
within - vicinity	11.8	3.43	10456	3.309	0.0009

Table 9.5 Multiple pairwise posthoc test according to Holm-Bonferroni for ht model.

Ht model

contrast	estimate	SE	df	t.ratio	p.value
CircalitSand_in - OffshoreCircalitSand_in	65.606	6.067	10453	8.564	0
CircalitSand_in - Sandbanks_out	-13.341	9.923	10453	-1.513	1
CircalitSand_in - CircalitSand_out	-0.754	4.576	10453	-0.169	1
CircalitSand_in - Reefs_out	-13.693	21.198	10453	-0.766	1

CircalitSand_in - CircalitCoarseSed_in	8.437	7.069	10453	1.186	1
CircalitSand_in - Reefs_in	-26.583	9.472	10453	-3.415	0.012
CircalitSand_in - OffshoreCircalitSand_out	112.808	7.76	10453	10.106	0
CircalitSand_in - Sandbanks_in	-35.455	6.432	10453	-7.024	0
OffshoreCircalitSand_in - Sandbanks_out	-47.671	10.121	10453	-6.718	0
OffshoreCircalitSand_in - CircalitSand_out	-40.071	7.244	10453	-7.321	0
OffshoreCircalitSand_in - Reefs_out	-47.884	22.127	10453	-3.26	0.019
OffshoreCircalitSand_in - CircalitCoarseSed_in	-34.521	9.183	10453	-4.82	0
OffshoreCircalitSand_in - Reefs_in	-55.668	10.523	10453	-8.13	0
OffshoreCircalitSand_in - OffshoreCircalitSand_out	28.503	5.958	10453	4.333	0
OffshoreCircalitSand_in - Sandbanks_in	-61.025	6.57	10453	-14.807	0
Sandbanks_out - CircalitSand_out	14.524	10.508	10453	1.357	1
Sandbanks_out - Reefs_out	-0.406	23.603	10453	-0.019	1
Sandbanks_out - CircalitCoarseSed_in	25.13	11.871	10453	1.999	0.64
Sandbanks_out - Reefs_in	-15.281	12.89	10453	-1.368	1
Sandbanks_out - OffshoreCircalitSand_out	145.569	11.241	10453	8.433	0
Sandbanks_out - Sandbanks_in	-25.519	10.427	10453	-2.971	0.045
CircalitSand_out - Reefs_out	-13.037	21.179	10453	-0.727	1
CircalitSand_out - CircalitCoarseSed_in	9.261	7.277	10453	1.261	1
CircalitSand_out - Reefs_in	-26.025	9.823	10453	-3.217	0.021
CircalitSand_out - OffshoreCircalitSand_out	114.426	8.702	10453	9.142	0
CircalitSand_out - Sandbanks_in	-34.965	7.465	10453	-5.976	0
Reefs_out - CircalitCoarseSed_in	25.64	21.878	10453	1.154	1
Reefs_out - Reefs_in	-14.936	23.2	10453	-0.775	1
Reefs_out - OffshoreCircalitSand_out	146.57	22.737	10453	4.405	0
Reefs_out - Sandbanks_in	-25.215	22.205	10453	-1.449	1
CircalitCoarseSed_in - Reefs_in	-32.295	11.124	10453	-3.697	0.004
CircalitCoarseSed_in - OffshoreCircalitSand_out	96.251	10.361	10453	6.839	0
CircalitCoarseSed_in - Sandbanks_in	-40.477	9.335	10453	-5.813	0
Reefs_in - OffshoreCircalitSand_out	189.863	11.593	10453	9.702	0
Reefs_in - Sandbanks_in	-12.084	10.635	10453	-1.274	1
OffshoreCircalitSand_out - Sandbanks_in	-69.67	8.154	10453	-15.221	0

9.4 Model Diagnostics A

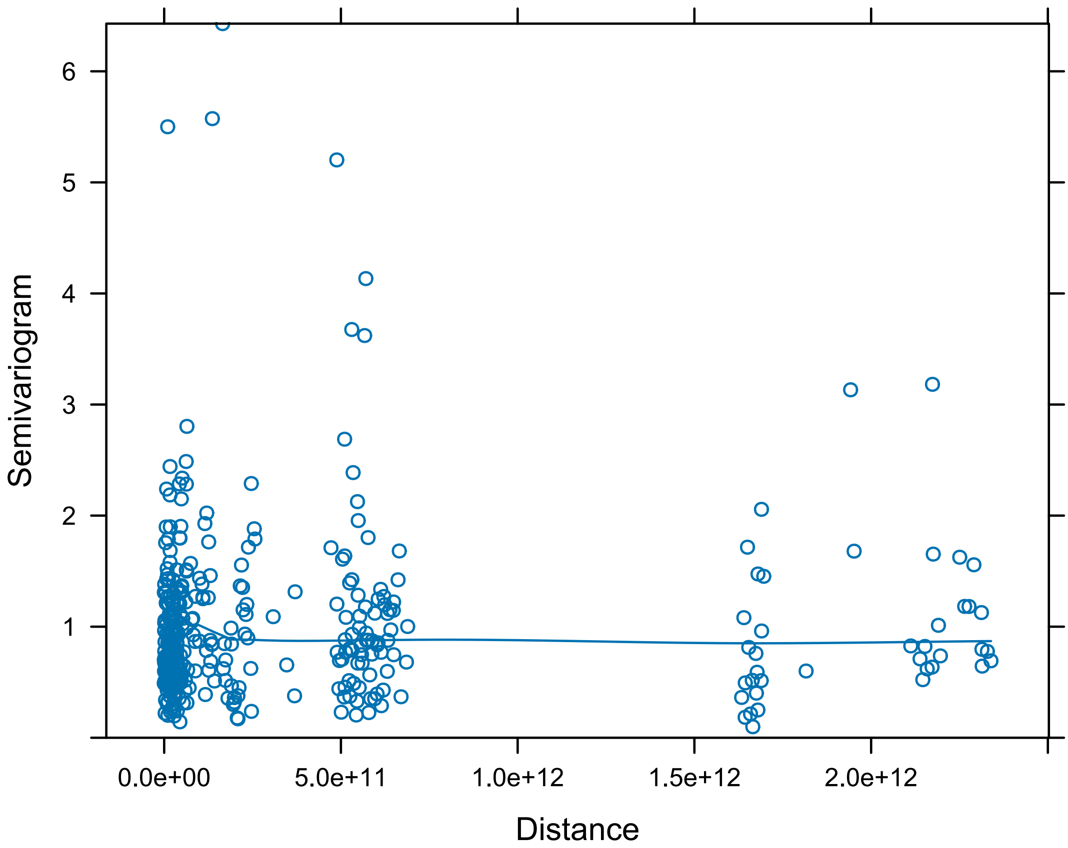

Figure 9.5 Semivariogram of model residuals shows no sign of critical spatial autocorrelation.

9.5 Medium-scale-dataset continuous model

*Table 9.6 Variables used in the continuous model on medium-scale dataset. Note model parameters cannot be compared among models calculated on different datasets. Significance codes: '***' p<0.001, '**' p<0.01, '*' p<0.05, '.' p<0.1, 'n.s.' p≥0.1.*

variable	type in model	purpose	medium-scale dataset (10 km around OWF)	
			result	significance
distance_OWF	spline	evaluate OWF influence	no distinct distance dependent pattern, great uncertainties	*
dayofyear	cyclic spline	account for yearly differences in detections	seasonal differences	***
easting, northing	3d spline	geographic variation (in UTM coordinates)		***
allClx	spline	account for acoustical masking and technical	negative correlation with DP10M/7d	***

		shortcomings related to ambient noise		
ht	factor (five levels)	differences related to hts	significant differences between some hts	***
podident	random factor	differences in single PODs	-	
t	ARIMA	remove temporal auto-correlation	-	
AIC		goodness of model fit		10,597.37
r-squared adjusted		coefficient of determina-tion		0.204
theta		dispersion parameter		3.967
number of data				9,235

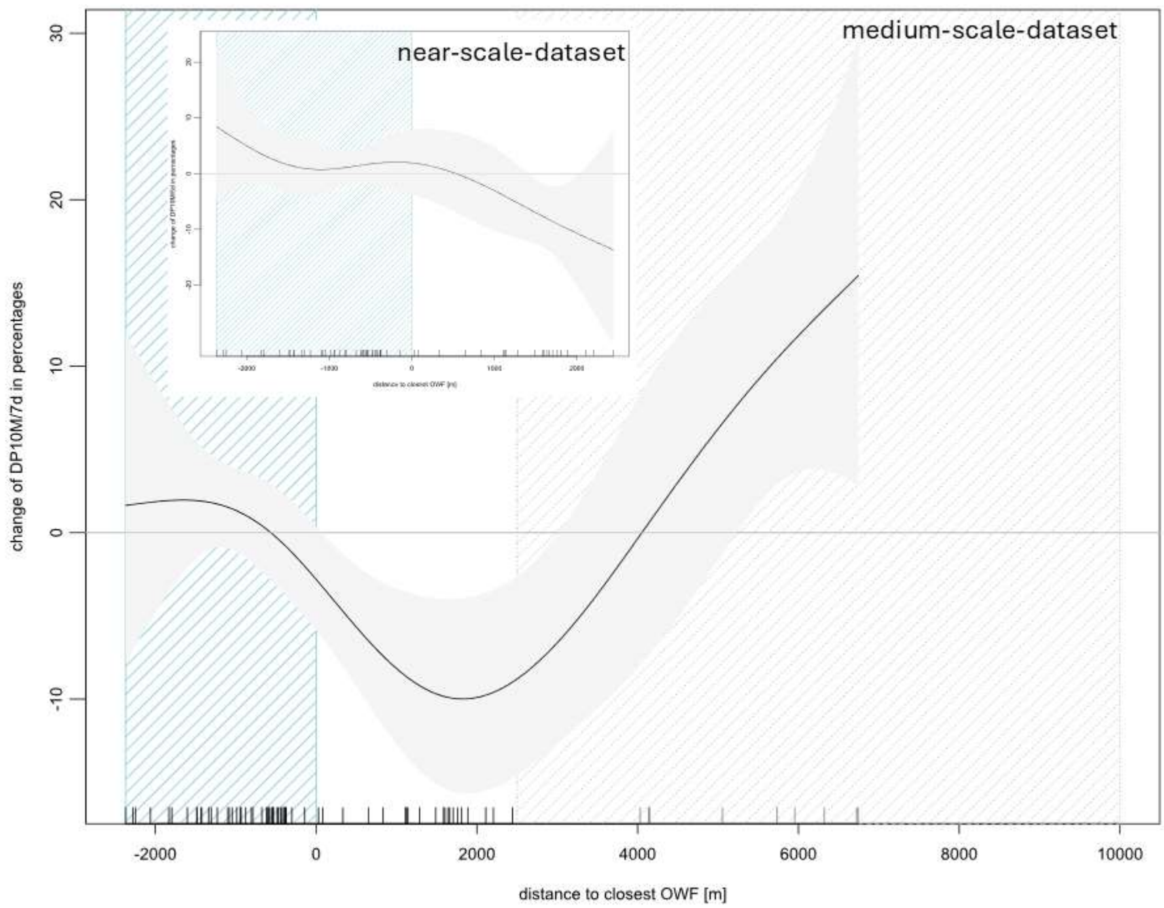

Figure 9.6 *Modelled effect of distance to closest OWF on change in porpoise detections; main result of continuous model computed on medium-scale dataset (up to 10.0 km around OWFs). Notice: no data/monitoring stations available between 7 and 10 km (Section 6.1.2). Black line: averaged values; shaded areas: 95 % confidence interval.*

9.6 Single OWF-models

*Table 9.7 Variables used in single OWF models on near-scale-dataset. Significance codes: '***' p<0.001, '**' p<0.01, '*' p<0.05, '.' p<0.1, 'n.s.' p≥0.1.*

variable	type in model	purpose	near-scale dataset (2.5 km around OWF cluster)						
			Albatross	BARD	Borkum West	Butendiek	DanTysk	Helgoland	Sandbank
within	factor	evaluate wind farm influence	.	***	.	.	.	n.s.	***
dayofyear	cyclic spline	account for yearly differences in detections	***	***	***	***	***	***	***
allClx	spline	account for acoustical masking and technical shortcomings related to ambient noise	***	***	***	***	***	***	***
podident	random factor	differences in single PODs							
t	ARIMA	remove temporal autocorrelation							

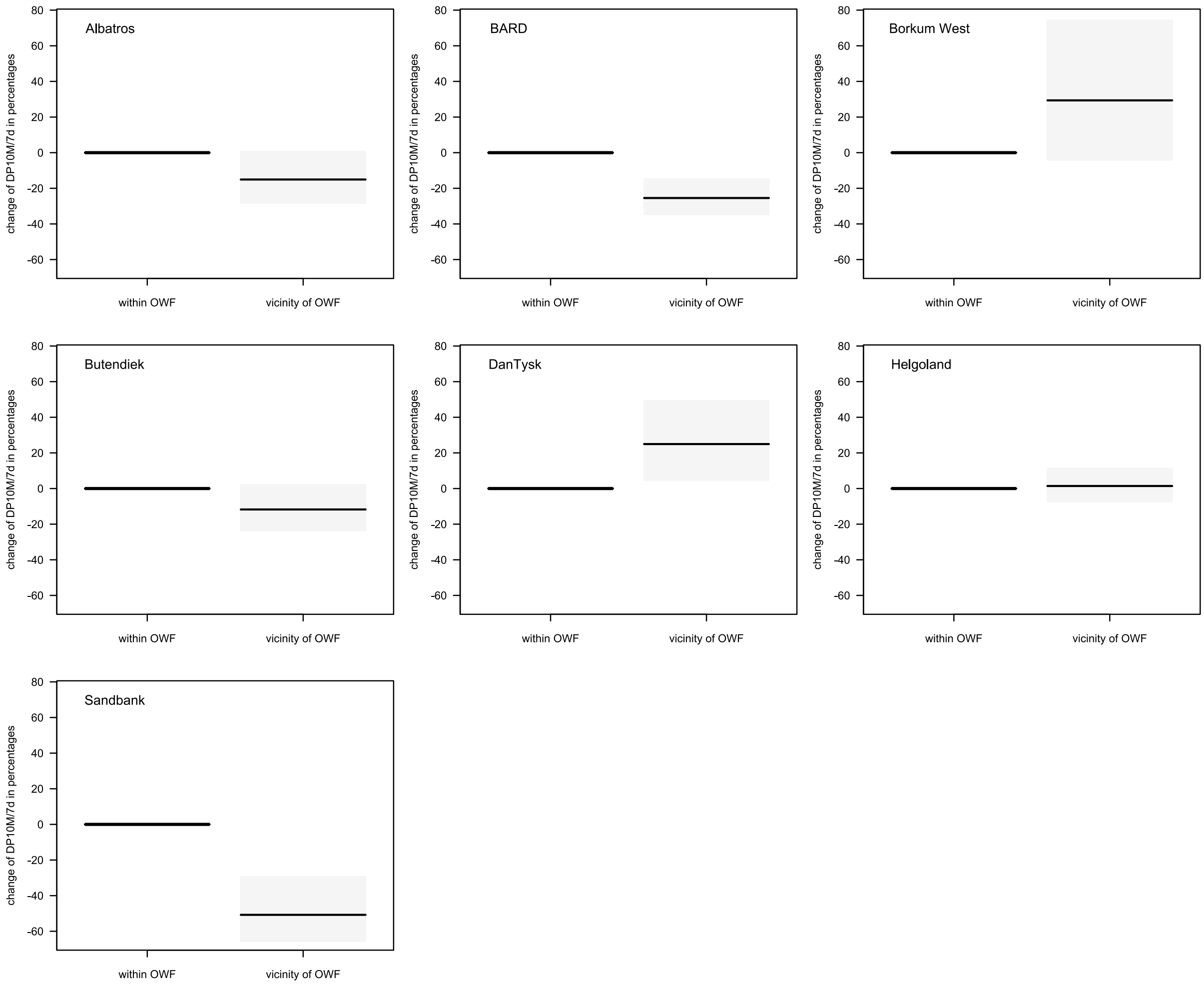

Figure 9.7 Results of single OWF cluster-models (quantitative estimates; factor models). Black lines: averaged values; shaded areas: 95 % confidence interval.

9.7 Model selection

Table 9.8 Model selection factor model

model	***AIC***	***RsqAdj***	***Formula*** (DP10M/5d ~ […] + random = list(podident=~1), family=negbin(theta), method="REML", *correlation = corARMA(form=~t,p=1,q=1))*	***theta***
f11	8886.931	0.220	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + factor(inside) + factor(bht)	4.015

f1e	8893.900	0.226	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF, k = 10) + factor(inside) + factor(bht)	4.090
f1g	8896.598	0.228	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF, k = 10) + factor(inside) + factor(bht) + factor(POD_depth)	4.097
f1a	8903.056	0.222	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + factor(inside) + factor(bht)	4.030
f21	8905.600	0.224	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + factor(inside) + factor(bht) + factor(POD_depth)	4.040
f1h	8908.407	0.239	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF_cluster, k = 10) + factor(inside) + factor(bht) + factor(POD_depth)	4.154
f1f	8909.531	0.236	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF_cluster, k = 10) + factor(inside) + factor(bht)	4.142
f1b	8949.893	0.125	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + factor(inside) + factor(POD_depth)	3.927
f1	8950.258	0.119	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + factor(inside)	3.912
f1k	8950.258	0.119	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + factor(inside)	3.912
f1i	8951.044	0.125	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF, k = 10) + factor(inside) + factor(POD_depth)	3.990
f1c	8952.995	0.119	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF, k = 10) + factor(inside)	3.974
f0	8954.125	0.111	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + factor(inside)	3.868
f3	8958.140	0.111	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(age_OWF, k = 10) + factor(inside)	3.916
f6	8958.140	0.111	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(age_OWF, k = 10) + factor(inside)	3.916
f15	8958.151	0.114	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + factor(inside) + factor(POD_depth)	3.876
f1j	8984.873	0.154	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF_cluster, k = 10) + factor(inside) + factor(POD_depth)	4.028
f1d	8988.491	0.147	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF_cluster, k = 10) + factor(inside)	4.013
f4	8996.414	0.138	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(age_OWF_cluster, k = 10) + factor(inside)	3.979

Table 9.9 Model selection continuous model

model	***AIC***	***RsqAdj***	***Formula*** (DP10M/5d ~ […] + random = list(podident=~1), family=negbin(theta), method="REML", correlation = corARMA(form=~t,p=1,q=1))	***theta***
c11	8897.882	0.217	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + factor(bht)	4.016

c1e	8903.541	0.222	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF, k = 10) + factor(bht)	4.113
c1g	8907.439	0.224	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF, k = 10) + factor(bht) + factor(POD_depth)	4.116
c1a	8914.673	0.218	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + factor(bht)	4.045
c1f	8917.414	0.232	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF_cluster, k = 10) + factor(bht)	4.163
c21	8919.028	0.220	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + factor(bht) + factor(POD_depth)	4.052
c1h	8920.241	0.234	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF_cluster, k = 10) + factor(bht) + factor(POD_depth)	4.169
c1	8934.668	0.120	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3)	3.947
c1k	8934.668	0.120	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3)	3.947
c1b	8938.008	0.126	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + factor(POD_depth)	3.956
c1c	8939.250	0.123	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF, k = 10)	4.012
c1i	8940.405	0.125	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF, k = 10) + factor(POD_depth)	4.021
c3	8945.106	0.113	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(age_OWF, k = 10)	3.934
c15	8945.483	0.117	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + factor(POD_depth)	3.886
c1d	8977.446	0.147	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF_cluster, k = 10)	4.050
c1j	8977.571	0.154	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF_cluster, k = 10) + factor(POD_depth)	4.057
c4	8985.985	0.141	s(distance_OWF, k = 5, fx = TRUE) + s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(age_OWF_cluster, k = 10)	3.996

Table 9.10 Model selection habitat types model

model	***AIC***	***RsqAdj***	***Formula*** (DP10M/5d ~ […] + random = list(podident=~1), family=negbin(theta), method="REML", *correlation = corARMA(form=~t,p=1,q=1))*	***theta***
f11a	8873.944	0.224	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + factor(ht_OWF_reference)	4.092
f1ea	8881.855	0.225	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(age_OWF, k = 10) + factor(ht_OWF_reference)	4.161
f1e	8886.794	0.227	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + s(age_OWF, k = 10) + factor(ht_OWF_reference)	4.205
f11	8886.919	0.225	s(dayofyear, bs = "cc", k = 8) + s(easting, northing, k = 3) + s(allClx, k = 7) + s(distance_shipping, k = 3) + factor(ht_OWF_reference)	4.127