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Abstract

Acoustic data collection trials on pelagic freezer-trawlers were realised in 2012 during several fishing trips targeting blue whiting west of the British Isles in spring, North Sea herring in summer, and horse mackerel in the English Channel and Celtic Sea in autumn. Echosounders were calibrated and time- and position-stamped data logged along the path covered by the vessels. The acoustic detections recorded during different types of trawler activity within a fishing trip ('searching', 'stationary', and 'fishing') were compared between target species. The highest proportion of time spent for activity 'fishing' was observed in the blue whiting fishery (82%), while that value was lower in the horse mackerel and herring fishery (68% and 54%). In all fisheries the quantified mean fish densities recorded were significantly higher during 'fishing' than during 'searching'. Changes in recorded fish density magnitudes over time before and after trawling also showed different patterns between fisheries. The quantified peculiarities exhibited by the specific fishing trip data is discussed in light of incorporating them in monitoring programs and analysis methods that can advance ecosystem understanding. Potential future approaches for analysis methods of opportunistically recorded acoustic fishing vessel data are discussed.

Keywords

acoustic data; blue whiting; echosounder; fishing vessel; freezer-trawler; herring; horse mackerel

1. Introduction

Sustainable management of marine resources and services is increasingly being based on an ecosystem approach (Bianchi and Skjoldal, 2008; Levin *et al*. 2009; McLeod and Leslie, 2009; Link, 2010; Katsanevakis *et al*. 2011; Kruse *et al*., 2012). Apart from a holistic understanding about how human activities impact on the system, such an approach requires quantitative knowledge about fundamental ecosystem processes (Curtin and Prellezo, 2010). To develop this knowledge, information on the distribution, abundance and productivity of different biological ecosystem components are required (Demer *et al.* 2009; Handegard *et al*. 2013). However, the specific monitoring and sampling programmes currently in place are largely designed to assess individual ecosystem components. Available data therefore often do not satisfy the requirements of advanced ecosystem models (Fulton, 2010; Rose *et al*. 2010). The latter are designed to enhance our ecosystem process understanding and to make predictions based on biological and physical characteristics of the ecosystem over extended spatio-temporal scales.

Scientific acoustic surveys are an essential source of information for current stock assessments of widely distributed pelagic fish populations, which show distinct migration patterns throughout their life cycles (e.g. Iversen, 2002). Echosounders are used to continuously collect fish density data along systematic survey transects. The acoustic intensity reflected by the fish can subsequently be converted into average fish density-per-area values inside the covered area. A survey age-structured biomass index for the targeted stock can then be derived from the acoustic data in combination with collected biological samples. However, scientific surveys are limited by practical and financial constraints and the resulting coverage often provides only a snapshot view of the stock abundance at a very particular point in time. Furthermore, many commercial stocks cannot be sufficiently covered by a directed acoustic survey due to resource limitations or survey practicalities. The resulting lack of spatially resolved abundance information for many species severely constrains the parameterisation and prediction capabilities of advanced ecosystem models needed to serve as a foundation for ecosystem-based management.

One possible solution to the increased data requirements for the ecosystem approach was discussed by Koslow (2009), Trenkel *et al*. (2011), and Handegard *et al*. (2012), who specifically suggested the combination of different acoustic sampling platforms in a framework to simultaneously collect information on species distributions at previously inaccessible spatio-temporal scales. Godø *et al.* (2014) have thoroughly discussed and termed this integrated monitoring concept ‘Marine Ecosystem Acoustics’ (MEA). They highlighted adequate temporal and spatial coverage as one of the main challenges that poses to be unsurmountable with traditional sampling methods. To extend the temporal scales of data collection , Godø *et al*. 2014 proposed the possibility of enhanced and increased collection of acoustic data from ships of opportunity (e.g. ferries or fishing vessels), which are already becoming advanced and increasingly important acoustic platforms (Karp, 2007).

Acoustic equipment available on pelagic fishing vessels is nowadays of comparable design and performance as those used on scientific research vessels. On many occasions, fishing vessels have in fact been chartered to carry out dedicated acoustic surveys following a standardised design (Honkalehto *et al*. 2011; Hordyk *et al*. 2011; Karp 2007; Ressler *et al*. 2009). Providing that a list of protocols are defined to insure quality standards (Karp, 2007), these vessels can therefore serve as acoustic data collection platforms and provide useful information complementing or in some cases compensating for the lack of scientific survey data. The Dutch pelagic fleet is composed of a small number of large (80 - 145m length) freezer-trawlers which are operational all year round on different fishing grounds in the northeast Atlantic, off western Africa and in the south Pacific. A considerable amount of quantitative information on fish distribution and biomass could potentially be made available at negligible costs by simply recording acoustic data from these vessels during regular fishing trips. In order to make scientific use of these data, they would need to be collected routinely and at the required quality (Karp, 2007). Furthermore, it is evident that the behaviour of commercial vessels exhibited during fishing activities does not follow a systematic sampling design. Therefore, to allow for these data to be used as a source of useful information, it is essential to understand the mechanisms affecting the way they are collected.

This paper describes the potential of regular acoustic data collected by freezer-trawlers to deliver: complementing information to monitoring surveys, relative biomass indices for target species, or population behaviour over wider temporal scales. Echosounders were calibrated and data collected during several fishing trips throughout an annual cycle targeting different commercially important species. The data were analysed to investigate differences caused by the behaviour of the different target species and the resulting fishing activity. Understanding such peculiarities will be vital for developing analysis methods to interpret and make use of these data in the process of ecosystem understanding. Eventually, potential future developments in analysis methods are discussed.

2. Materials and Methods

2.1. *Data collection*

Acoustic data were collected and recorded on pelagic freezer-trawlers during fishing trips between February and September 2012 targeting Northeast Atlantic blue whiting (*Micromesistius poutassou*), North Sea herring (*Clupea harengus*), and horse mackerel (*Trachurus trachurus*) in the English Channel (Table 1). All vessels included in the present study, were equipped with either the commercial Simrad ES70 or the scientific Simrad EK60 echosounders operated at 38 kHz. Time- and GPS position-stamped raw acoustic data from the echosounders were recorded to external hard disks. The hard disks were directly connected to the computers operating the echosounders prior to each individual fishing trip and collected after the trawlers returned to port. For operational reasons, echosounders were set to log data from the very beginning of the trip when leaving the home port until arrival back in port to prevent accidental data loss and to monitor the proper functioning of the echosounder during the whole recording period. During data collection, echosounder settings such as pulse duration, input power and transceiver gain remained fixed.

2.2. Calibration of acoustic equipment

Calibration of acoustic equipment used for scientific purposes is vital to ensure the correct functioning of the system, get an estimate of the stability of the recorded data, adjust the uncompensated received signal amplitude relative to that of a reference target, and to gain insights into potential error sources in the resulting dataset. A total of four calibrations of the 38 kHz Simrad ES70/EK60 systems installed onboard three different pelagic freezer-trawlers were successfully performed either directly before, during or adjacent to respective fishing trips. For each calibration, the vessels steamed into a sheltered bay close to the fishing grounds (either SW Ireland or Scapa Flow, Scotland, UK) and followed common recommendations for standard sphere calibrations of scientific split-beam echosounders (Foote *et al*. 1987; Simmonds and MacLennan, 2005). Each calibration was performed with two spheres attached at least 4 m apart to enable verification of the measurements as well as adding additional weight to the setup to enhance the stability of the top sphere used for calibration measurements. The raw data recorded during the calibration procedure of the ES70 systems were replayed and visualised in the calibration tool of the Simrad ER60 software (Andersen, 2001) to assure a sufficient amount and satisfying spread of data points throughout the beam had been collected. For the vessel where the EK60 system was available, the calibration was conducted completely using the ER60 software.

2.3. Data processing

The calibration settings were used to update the transceiver gains and acoustic beam patterns on the trawler equipped with the Simrad EK60 echosounder before the start of the effective fishing trip. For the other vessels that used Simrad ES70 systems, the calibration values were applied *a posteriori* during post-processing. Data collected by the Simrad ES70 echosounders contain an embedded systematic error component (Ryan and Kloser 2004). The error has the shape of a periodic triangular wave of approximately 1dB peak-to-peak amplitude with a period of exactly 2721 data points. Inspection of the wave showed that data points remain stable for 16 pings, after which there is a step over to the next level where the next stable group of 16 data points resides. The structure of the error wave can be identified from the transmit pulse section in the raw data header information and used as a basis for adjusting the entire echogram accordingly. A java applet ('ES60adjust') developed by scientists from the Australian Commonwealth Scientific and Industrial Research Organisation (CSIRO) was used to remove the triangular wave error (Keith et al., 2005). The wave-corrected acoustic raw data from the Simrad ES70, or the original raw data provided by the Simrad EK60 system, were post-processed and analysed using LSSS v1.6 (Large Scale Survey System, marec, NO, www.marec.no). Implementation of the calibration results were applied through the KORONA module within LSSS. The resulting error-corrected and calibrated datasets were then used for scrutinising procedures, i.e. the data post-processing where acoustic volume backscatter values (s_V) of fish schools are allocated to species. The scrutinising process was based on a combination of expert judgement by scientists having covered the same areas and species with acoustic surveys, and the catch information available from trawl lists provided by the skippers.

Scrutinising was done for data collected during four individual fishing trips with a total of 73 days. Individual fishing trips lasting approximately 3 weeks could be scrutinised within a total effort of 24 hours using LSSS. To improve data quality before the scrutinising process, the following pre-processing steps were performed in LSSS (c.f. Korneliussen *et al*., 2009): (i) remove spike noise from other, non-synchronised acoustic instruments; (ii) replace any missing pings by interpolation; (iii) quantify the background noise, using the data in each ping; (iv) remove the noise from the dataset. After echogram scrutiny, LSSS was used to produce output reports containing mean date, time, position and acoustic area density values (Nautical Area Scattering Coefficient (NASC), s_A; m^2 nm^{-2}; MacLennan *et al*., 2002) of the respective fish species per 1 nm intervals along the track covered by the trawlers.

2.4. Data analysis

Using the information provided by the skippers' logbooks, the acoustic intervals corresponding to the start and end times of a trawl haul were identified for each fishing trip. For further analyses, only intervals between the start of the first and end of the last trawl were used in every fishing trip. Acoustic data also contained the recorded speed of the vessels, and for every 1 nm interval the average vessel speed was available. During the data scrutiny process, intervals corresponding to stationary periods (e.g. after hauling or during catch processing) were identified based on low observed speed (below typical speeds observed during trawling: <~3 kts). Eventually, all intervals were allocated to three different activity periods: (1) 'stationary', corresponding to all intervals having low observed speed (<~3 kts); (2) 'fishing', corresponding to intervals within logbook recorded haul start and end times; and (3) 'searching', corresponding to intervals falling between 'fishing' and 'stationary'.

Start and end times of the 1 nm intervals were used to allocate a duration and mid-time to different intervals. The interval mid-time was equal to the time of the middle ping in each interval. As the trawl information was time referenced, the mean times of the 1 nm fishing trip intervals were allocated to the nearest 15 minute time bin relative to the trawl start, i.e. the shooting of the trawl. Thereby, all intervals with a positive 15 minute time bin value (after trawl start) were only used if they also coincided with the activity 'fishing' of that respective trawl. By definition, negative time bins corresponded to activity 'searching' and started soonest after the end of the 'fishing' activity of the previous trawl or any subsequent 'stationary' activity. In that way, fish detection information of the recorded intervals could be related to trawling time and compared between the different trips.

3. Results

Data collected on blue whiting (WHB) trips covered areas along the continental shelf slope west of the British Isles and Ireland. The analysed herring (HER) fishing trip generally covered the northern North Sea around the Orkney and Shetland Islands, while data collected during a trip targeted at horse mackerel (HOM) covered the English Channel (Figure 1). The duration of different activity periods of the acoustic fish density interval data were compared by target species in the fishery. The highest proportion of time spent for activity 'fishing' was observed for the analysed WHB fishing trips (82%). The time proportion allocated to 'fishing' activity was less for both the HOM (68%) and HER (54%) trips, where proportionally more time for 'searching' was used (Figure 2). Mean duration (±s.d.) of 1 nm trip intervals allocated to 'fishing' were 13.8 (±6.6; HOM), 15.5 (±6.4; HER), and 16.9 (±5.8; WHB) minutes. The observed mean speeds (±s.d.) for the 'fishing' & 'searching' activities were 4.5 (±1.5) & 11.8 (±1.9) for the HOM, 3.8 (±1.1) & 10.5 (±2.5) for the HER, and 3.5 (±0.9) & 8.8 (±2.2) knots for the WHB trip, respectively. s_A measured per interval on each fishing trip were bootstrapped to give means and s.d. per trip activity (Figure 3). All trips showed significant differences between mean s_A recorded during 'fishing' and 'searching' (Student's t-test; HER: $t = 64.6$, $p < 0.001$; WHB: $t = 224.4$, $p < 0.001$; HOM: $t = 239.2$, $p < 0.001$). The mean s_A recorded during 'fishing' were higher on all trips, with the HER showing a 1.5x, the WHB a 2.1x, and the HOM trip a 3.3x difference between 'fishing' and 'searching'. There were distinct differences in the magnitudes of observed absolute s_A values between the fisheries: mean s_A values observed during WHB had magnitudes of $x10^3$, those for HER had magnitudes of $x10^2$, and those for HOM had magnitudes of $x10^1$. For the HER fishing trip, the mean s_A per individual 15 minute time bins around the time at which the net of the closest trawl was shot showed an approximately Gaussian distribution pattern. A LOESS curve fitted through the values showed a gradual increase in observed mean s_A per time bin from about three hours before the trawling process towards a peak around the shooting time, and a coherent decrease thereafter (Figure 4a). To get an indication of expected density levels when detections are at a low level in areas away from the peak spots, the 5^{th} percentile of all observed acoustic fish detections throughout the 'fishing' and 'searching' activity was taken. For HER, the 5^{th} percentile of observed densities was low at just 18.3 m^2nm^{-2}. For WHB trips, a higher low-level fish detection was observed (5^{th} percentile: 1595 m^2nm^{-2}). The LOESS curve fitted through the detections of blue whiting increased from 3.5 hours before trawling towards a peak around one hour before the shooting of the net and declined steadily thereafter (Figure 4b). As for WHB, the HOM fishery was characterised by a relatively high value of low-level fish detections (5^{th} percentile: 22.4 m^2nm^{-2}) during the 'fishing' and 'searching' activity when compared to peak detection values. Detections increased during the 'searching' period throughout the 3.5 hour period before the start of the trawling process and peaked at the time when the net was shot. Thereafter, detections of horse mackerel decreased, however, the degree of decrease was less pronounced when compared to the other two fisheries (Figure 4c). The relative mean cumulative frequencies of acoustic fish detections per trawl event during the 'searching' activity up to the point in time when trawling begun showed different rates of increase between fisheries. A logistic regression fitted to the mean cumulative acoustic detections per 15 minute bin for all trawls in the HER trip showed an increase at about two hours before the start of the fishing process. For the WHB trips, that increase was already evident at about three hours before the start of the trawls and the subsequent rate of increase was correspondingly smaller. For the HOM trip, the cumulative detections per 15 minute time bin exhibited a marked increase at about one hour before the start of the fishing activity. The values were generally more variable when compared to both the HER and WHB trips, resulting in a poorer (higher χ^2 ratio) albeit still significant fit of the logistic regression model to the HOM data (HER: χ^2=0.60, p<0.001; WHB: χ^2=0.81, p<0.001, HOM: χ^2=1.43, p<0.001).

4. Discussion

In the process of incorporating the wider ecosystem in conservation and management decisions, such as for the ecosystem approach to fisheries management (EAFM), a sound understanding of the processes governing ecosystem mechanisms is required (Botsford *et al*., 1997; Duda and Sherman 2002; Pikitch *et al*., 2004; Cury *et al*., 2008; Bellido *et al.*, 2011). This knowledge will have to be based on complex trophic ecosystem models relying on data collected at relevant spatial and temporal scales for validation and parameterisation (Handegard *et al*. 2013). Assessment methods used for management of fisheries resources have so far largely been focussing on individual species stocks and their life cycle characteristics without great consideration for interactions between species or environmental parameters, however, there are exceptions (Witherell *et al.*, 2000; Kaufman, *et al*., 2005; Constable, 2011). Most fisheries independent monitoring programmes currently in place have developed into accurate tools to assess trends in the state (biomass or abundance at age/length) of a stock life cycle stage. Consequently, they follow a rigid methodology to maintain time series integrity and concentrate at times and locations that provide optimal sampling conditions. In that way, the widespread distributions of pelagic fish stocks for example have led to the development of specific acoustic surveys that capture the adult stock components at times when they are most receptive to that survey technique (Simmonds and MacLennan, 2005). Often the time during or just before the spawning period is suitable because the fish aggregate in schools in distinct areas of their distributional range that can be covered by a survey vessel within a short time period (i.e. a few weeks) to minimise bias due to migration. Data required for the EAFM may however need to span a longer time period and wider space in order to capture relevant biological and physical interactions of fish stocks with their environment.

The standardised and established setup of many dedicated pelagic fish monitoring surveys prevent collection of additional environmental and biological data over wider temporal and spatial scales as required for the EAFM (Handegard *et al.*, 2013). Monitoring approaches that can deliver such data should ideally consist of a network of connected sensor platforms that can span many trophic biological scales and physical dynamics at high spatio-temporal resolution. The proposed network of sensor systems consist of stationary observations (buoys, landers), autonomous and controlled platforms, but also platforms of opportunity. The latter, albeit being hampered by a lack of controllable sampling design, have the advantage that they are relatively cheap and operate over a wide area and time. One example of an opportunistic platform to monitor the pelagic ecosystem are fishing vessels. These are nowadays advanced acoustic platforms and have been used by scientists for example as survey vessels (Honkalehto et al. 2011; Hordyk et al. 2011; Karp 2007; Ressler et al. 2009) or to deliver high resolution small scale information on fish schooling characteristics (Shen *et al*., 2008; Shen *et al*., 2009). In Eastern Canada for instance, near real-time management decisions about the herring fishery are taken on the basis of such industry based surveys (Melvin *et al*. 2001). Based on this idea, Canadian scientists have developed an automatic acoustic logging system and collected data on Atlantic herring during fishing operations in early 2000 (Melvin *et al*. 2002). The data were used to monitor the aggregation of herring and decide on the timing of the scientific survey (performed on the same fishing vessels). However, this approach comes with its own drawbacks as the availability of fishing vessels for performing such surveys is limited and the related costs and loss of income still have to be covered. Attempts have been made to combine data collection and fishing activity, for example by using spare time during regular fishing trips to perform mini-surveys (O'Driscoll and Macaulay 2005). But unfortunately that is only practicable when such time is available (e.g. during processing of the catch on a factory vessels) and if the fish resource is distributed over a restricted area (e.g. deep sea fish over sea mounts). Another way to utilise fishing vessels as acoustic sampling platforms is to collect data on them opportunistically. However, the application and utilisation of such data is problematic and has so far not been widely addressed. The primary reasons for this are: the large volume of data collected (requiring increased resources for analysis), the lack of system calibrations, and the absence of a predetermined sampling design, which therefore calls for novel and innovative statistical and/or modelling approaches. Barbeaux (2012) and Barbeaux *et al*. (2013) described analyses of opportunistically collected but non-calibrated fishing vessel data to inform on fish aggregation and distribution. In this paper we demonstrated the potential of routine acoustic data collection on freezer-trawlers, the calibration of their echosounder systems, and initial interpretation of results from different fisheries as a first step in developing further data utilisation methods.

Processing of large acoustic data sets is a real concern. While time required for analysis of scientific survey data can be considerable, the data amount resulting from weeks’ worth of acoustic recordings from several fishing vessels is yet an order of magnitude bigger. A potential solution to this is automated data processing which may especially become applicable in cases where data were collected at more than one acoustic frequency or even over a wide bandwidth. Fishing vessels are continuously upgrading their acoustic systems and some already collect data at several frequencies. Such techniques have already been used successfully for many years in scientific surveys to discriminate between groups of fish, micronekton and zooplankton and also for discrimination between biological targets and physical phenomena such as bubbles (Horne, 2000). Korneliussen and Ona (2002) used multifrequency processing techniques to distinguish various targets such as mackerel, swimbladdered fish, and zooplankton. With further advances in acoustic technology such as broadband systems (Lavery *et al.*, 2010; Stanton *et al.*, 2010; Stanton *et al.*, 2011), identification of scattering groups or even individual species will likely be much improved and allow for more objective and automated, therefore efficient data processing approaches.

In the data presented here, different acoustic detection patterns could be observed between the three target fisheries covered. Vessels involved in the blue whiting fishery were strongly confined to geographical features (shelf slope), as the resource is typically assumed to be aggregating there in high densities. As a result, more constant acoustic detections could be observed when blue whiting was targeted, with less time spent for searching once the fishing grounds were reached. Clupeids such as herring on the other hand are typically more characterised by localised schooling behaviour with larger shoals or schools and aggregations occurring more sporadically (Blaxter and Hunter, 1982; Blaxter, 1985; Beare *et al.*, 2002), hence increasing the relative time spent searching for the trawlers. The observed magnitudes of fish densities in situations of low detection levels, typically away from fishing hotspots, where therefore relatively low for herring. A similar but even more heterogeneous distribution situation was observed for the horse mackerel fishery where differences in acoustic densities between 'fishing' and 'searching' seemed to be even higher. Based on such differences in aggregation and distribution patterns of the fish resource, cumulative detection patterns were also better predictable for species such as blue whiting and herring. An aspect that was not considered here but could have affected the nature of the observed data was the simultaneous use of acoustic equipment other than the echosounder. To detect and pursuit schools especially during herring and horse mackerel fisheries the skippers make extensive use of omnidirectional sonars (Brehmer *et al*., 2006). With that additional aid, covering a larger volume of water, echosounder detections were not the only source of information available to influence fishing decisions. Recorded fish densities from the echosounder were therefore not solely affecting the duration of the 'searching' period, which may have otherwise been extended had there been less acoustic tools available. Such interactions will have to be considered when analysing acoustic fish detections in combination with the behaviour of the fishers and fish distribution patterns to potentially derive for example abundance estimates from the data. Apart from the simple extraction of acoustic fish density values in 2D space, quantification of acoustic detection patterns in relation to fishing behaviour will indeed be an important step in the process of deriving useful characteristics from acoustic fishing vessel data.

Based on the data collection exercise described here, a few conclusions can be drawn in light of developing further steps to utilise acoustic fishing vessel data for ecosystem understanding. Measured acoustic densities represent an important proxy for fish abundance. These recorded densities may thus easily be translated to fairly accurate biomass levels representative for the locations of the different fish hotspot areas within the time window covered by the fishing vessels. More importantly, however, for these data to be useful for ecosystem management they need to be representative of the wider stock distribution and abundance over the wider temporal scales covered. The results showed that information on distribution patterns could indeed be derived from the data and that these differed between species. Given that some important species like herring show no population size-dependent effect on observed acoustic densities per fish school (Beare *et al*., 2002), it may be valid to link observations from hotspot areas to stock abundance. However, due to the effect of vessel behaviour the validity and sensitivity of such an approach still has to be verified. The fishing behaviour-governed acoustic detection characteristics together with knowledge about distribution patterns of different target species may for instance be used in developing individual based models (IBM) to verify analysis methods and derive robust and representative relative abundance indices (e.g. Shin and Cury, 2004; Bastardie *et al*., 2010). Similarly, irrespective of the specific aggregation behaviour of different species, fish searching time may also be affected by both stock biomass and/or stock area extension, and these factors including their interactions would have to be quantified in order to draw any useful conclusions. The linking of fishing patterns with acoustic observations could be facilitated by applying methods or approaches that are currently used to analyse vessel monitoring system (VMS) data (Deng *et al*., 2005; Mills *et al*., 2007; Lee *et al*., 2010; Gerritsen and Lordan, 2011). Finally, geostatistics (Matheron, 1971) could make a promising contribution to modelling the spatiotemporal fish distribution patterns given the preferential sampling of acoustic data from fishing vessels (Petitgas, 2001; Diggle *et al.*, 2010). These different potential analysis approaches are further elaborated in the following paragraphs.

The primary motivation of the vessel owners that participated in the collection and sharing of the data presented here was the wish to partake in the fisheries data collection and monitoring process for stock assessment. There is little doubt that increased stakeholder involvement in the stock assessment process has several benefits and may lead to more acceptable and therefore successful integrated ecosystem based fisheries management (Grimble and Wellard, 1997; Reed, 2008; Levin *et al.*, 2009). One way to achieve this is by using the acoustic data collected on fishing vessels to derive abundance indices, which can then be incorporate to stock assessment models. The data collected during fishing operations however follows by definition a selective sampling pattern and departs from the usual requirement for scientific surveys of performing a synoptic coverage of the stock. Data collected during fishing trips spans several weeks and the fishing seasons for stocks considered here typically extend over a one or two month period. This implies that the spatial distribution of the resource, especially for species actively migrating during the fishing season such as blue whiting, may change substantially over the period covered. There is thus a real risk of double counting the fish if the whole data set would be considered. In addition, sampling (i.e. fishing) effort is concentrated on areas of high fish density where catches are likely to be maximised, while areas of minor interest for the fishery, albeit still containing significant portions of for example younger fish, are not covered. In that respect, the fishing vessel acoustic data are more similar to the common catch per unit effort (CPUE) data derived in bottom trawl fisheries. 'Acoustic detections per unit effort' could therefore be a useful CPUE proxy in pelagic fisheries, where the direct measure of CPUE solely based on trawl catches is not valid (Hilborn and Walters, 1992). Nonetheless, the methods commonly implemented to derive abundance estimates from scientific acoustic surveys, i.e. averaging detected fish densities over the surveyed area, will not be applicable to the acoustic data collected by fishing vessels due to the lack of a non-biased sampling design. Alternative types of indices, such as surface occupation indices (Castillo and Robotham, 2004) could also be investigated for these data. The accuracy and robustness of different types of abundance indices derived from fishing vessel acoustic data may be investigated with an IBM fisheries simulator. Such a tool could be developed to model the behaviour of a fleet of vessels fishing on a spatially distributed resource and collecting "virtual" acoustic data along their track. Abundance indices can then be computed from these virtual data using different methods and compared to the "true" abundance which is known in the simulator. Realistic resource distributions can be based on the observed spatial distribution and variability of available scientific survey data. Calibration of the simulator to give the vessels a more realistic behaviour could be done using the combined information from the observed fishing behaviour characterised by the linked fishing activity and fish abundance. That information can be obtained from the collected acoustic fishing vessel data, as shown in the present study, e.g. the models and/or observed data described here in Figures 2-4. Preliminary results from that type of exercise indicate that abundance indices derived from fishing vessel acoustic data may be of a limited accuracy for species that are densely aggregated, such as blue whiting. However, abundance indices derived for more heterogeneously distributed species such as herring yielded a higher accuracy (Brunel *et al*., 2013). This can be explained by the fact that for the latter species, searching time represents a larger proportion of the fishing trips, which may therefore result in a more representative sampling of the stock.

A fruitful approach may be the combination of VMS data analysis tools, which are typically used to classify the different fishing trip activities (Lee *et al*., 2010), with acoustic fish density recordings collected on the same trips. VMS data are typically used to estimate spatial and temporal distributions of trawling impacts on species, habitats, and ecosystem processes (Collie *et al*., 2000; Kaiser *et al*., 2002), or to monitor fleet responses to management actions (Rijnsdoorp *et al*., 2001; Dinmore *et al*., 2003; Mills *et al*., 2005). Since 2005, high resolution position data at intervals of 2h or less have been collected in EU waters from all fishing vessels >15m long (EC, 2003). Recorded acoustic data provide a spatial history record of the fishing trip, however at a much higher resolution, since data points are typically collected at an interval of one second. A whole suite of existing VMS data analysis tools could therefore be applied to the very high resolution time-space acoustic data to supply a more accurate picture of fishing effort in addition to the synoptic collection of pelagic fish densities. A possible approach may then be to investigate if 'trained' VMS methods could be used to replicate the acoustic observations of a fishing trip, i.e. to infer fish densities solely from speed and time-space position patterns of vessels. Gerritsen and Lordan (2011) presented an example where VMS data were combined with catch data in a bottom trawl fishery to derive spatially resolved catch and effort data at much higher resolution than previously possible. Following this, the same principle could therefore be applied to acoustic and VMS data in the case of pelagic fisheries.

Arguably the most promising approach to analyse and model fish densities from fishing vessel acoustic data, due to the ability to take into account the spatial and temporal sampling peculiarities, are geostatistical methods. Essentially, geostatistics is used to model spatial variability of variables such as fish densities and then utilise that model to make predictions of variable values at given locations (Matheron, 1971). The methods have been established and widely used for fisheries applications, especially fish survey analyses (Petitgas, 2001; Rivoirard *et al*., 2008), survey design (Barange and Hampton, 1997; Fletcher and Summer, 1999), or ecological studies (Cianelli *et al*., 2008). Possible ways to use the potential of geostatistics with the type of acoustic data described here may include using co-kriging to combine different spatial datasets like fishing vessel, scientific survey or environmental parameter data (Petitgas, 2001). Georgakarakos and Kitsiou (2008) used that approach to model the spatial distribution of small pelagic fish. The method produced the best results when sea surface temperature and depth variables were included in the model, which indicated the enhanced modelling potential when combining different data sources. They especially highlighted the significant reduction of the overall estimation error and its effect on subsequent stock assessment and management. There may also be potential in adding the acoustic information from fishing vessels usually collected in high density areas with those collected by survey vessels that follow a systematic design. These data would have to be from areas that were covered synoptically by both survey and fishing vessel platforms in order to avoid bias due to fish movement and variations in their aggregative behaviour (Petitgas, 2001). A further step may then be the incorporation of a model that takes into account the temporal change of the fish population, especially since the fishing vessel data covers an extensive time range (e.g. Zhou, 1998). Denham and Mueller (2010) used time varying spatial models to consider the underlying movement of fish populations over extended spatiotemporal dimensions to successfully estimate changes in prawn catch rates. In any case, ignoring the particular preferential sampling pattern of these data can lead to serious misleading geostatistical inferences (Diggle *et al*., 2010).

Based on the freezer-trawler acoustic data collection exercise and results presented here, continuation and further development of such initiatives seem feasible. Opportunistically collected acoustic data from fishing vessels can provide an additional puzzle piece in the process to create a more holistic picture of the ecosystem. Their potential will be enhanced by the introduction of structured, more widespread data collection programmes and further development of automated data processing. Thereafter, there is a clear need for sophisticated data analysis methods in order to make these data operationally useful for ecosystem management.

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References

Andersen, L.N., 2001. The new Simrad EK60 scientific echosounder system. J. Acoust.Soc. Am. 109, 2336.

Barange, M., Hampton, I. (1997) Spatial structure of co-occuring anchovy and sardine populations from acoustic data: implications for survey design. Fish. Oceanogr. 6: 94-108.

Barbeaux, S.J. 2012. Scientific Acoustic Data from Commercial Fishing Vessels: Eastern Bering Sea Walleye Pollock (*Theragra chalcogramma*). PhD Thesis. University of Washington, WA, USA, 245 pp.

Barbeaux, S.J., Horne, J.K., and Dorn, M.W. 2013. Characterizing walleye pollock (*Theragra chalcogramma*) winter distribution from opportunistic acoustic data. ICES J. Mar. Sci. 70, 1162-1173.

Bastardie, F., Nielsen, J.R. Andersen, B.S., Eigaard, O.R. 2010. Effects of fishing effort allocation scenarios on energy efficiency and profitability: An individual based model applied to Danish fisheries. Fish. Res. 106, 501-516.

Beare, D.J., Reid, D.G., Petitgas, P. (2002). Spatio-temporal patterns in herring (Clupea harengus L.) school abundance and size in the northwest North Sea: modelling space–time dependencies to allow examination of the impact of local school abundance on school size. ICES J. Mar. Sci. 59, 469-479.

Bellido, J., Santos, M., Pennino, M., Valeiras, X., Pierce, G.J. 2011. Fishery discards and bycatch: solutions for an ecosystem approach to fisheries management? Hydrobiologia 670, 317-333

Blaxter, J.H.S. 1985. The herring: a successful species? Can. J. Fish. Aq. Sci. 42, 21-30.

Blaxter, J.H.S., Hunter, J.R. 1982. The biology of the clupeoid fishes. Adv. Mar. Biol. 20, 1-223.

Botsford, L.W., Castilla, J.C., Peterson, C.H. 1997. The management of fisheries and marine ecosystems. Science 277(5325): 509.

Brehmer, P., Lafont, T., Georgakerakos, S., Josse, E., Gerlotto, F., Collet, C. 2006. Omnidirectional multibeam sonar monitoring: applications in fisheries science. Fish. Fish. 7, 165-179.

Brunel, T., Fässler, S.M.M., de Haan, D., Hintzen, N., van der Kamp, P., Ybema, S. 2010. Towards abundance estimates for jack mackerel in the South Pacific based on acoustic data collected by the commercial vessels. IMARES Report C149/10. 21 pp.

Brunel, T., Gastauer, S., Fässler, S.M.M., Burggraaf, D. 2013. Using acoustic data from pelagic fishing vessels to monitor fish stocks. IMARES report C021/03. 40pp.

Castillo, J., Robotham, H. 2004. Spatial structure and geometry of schools of sardine (Sardinops sagax) in relation to abundance, fishing effort, and catch in northern Chile. ICES J. Mar. Sci. 61, 1113-1119.

Ciannelli, L., Fauchald, P., Chan, K.S., Agostini, V.N., Dingsør, G.E. 2008. Spatial fisheries ecology: recent progress and future prospects. J. Mar. Syst. 71, 223-236.

Cury P.M., Shin Y.J., Planque B., Durant J.M., Fromentin J.M., Kramer-Schadt S., Stenseth N.C., Travers M., Grimm, V. 2008. Ecosystem oceanography for global change in fisheries. Trends Ecol Evol 23(6):338–346

Denham, A, Mueller, U. 2010 Incorporating Survey Data to Improve Space–Time Geostatistical Analysis of King Prawn Catch Rate, in: geoENV VII – Geostatistics for Environmental Applications Quantitative Geology and Geostatistics Volume 16, pp. 13-25.

Deng, R., Dichmont, C., Milton, D., Haywood, M., Vance, D., Hall, N., Die, D. 2005. Can vessel monitoring system data also be used to study trawling intensity and population depletion? The example of Australia's northern prawn fishery. Can. J. Fish. Aq. Sci. 62, 611-622.

Diggle, P.J., Menezes, R., Su, T.-l. (2010). Geostatistical inference under preferential sampling. J. R. Stat. Soc. Ser. C. Appl. Stat. 59, 191-232.

Duda, A.M., Sherman, K. 2002. A new imperative for improving management of large marine ecosystems. Ocean. Coast. Manag. 45, 797–833.

Fässler, S.M.M., Teal, L.R., Lusseau, S.M., Ruardij, P. 2012. Determining herring habitat quality from acoustically derived zooplankton abundance in the northern North Sea. ICES CM 2012/B:04.

Fletcher, W. J., Sumner, N. R. 1999. Spatial distribution of sardine (Sardinops sagax) eggs and larvae: an application of geostatistics and resampling to survey data. Can. J. Fish. Aq. Sci. 56, 907-914.

Gerritsen, H., Lordan, C. 2011. Integrating vessel monitoring systems (VMS) data with 634 daily catch data from logbooks to explore the spatial distribution of catch and 635 effort at high resolution. ICES J. Mar. Sci. 68, 245-252.

Georgakarakos, S., Kitsiou, D. 2008. Mapping abundance distribution of small pelagic species applying hydroacoustics and Co-kriging techniques. Hydrobiologia. 612, 155-169.

Grimble, R., Wellard, K., 1997. Stakeholder methodologies in natural resource management: a review of concepts, contexts, experiences and opportunities. Agric. Syst. 55, 173-193.

Gulland, J.A. 1969. Manual of methods for fish stock assessment. Part 1. Fish population analysis. FAO Manuals in Fisheries Science No. 4, Rome.

Hilborn, R., Walters, C.J., 1992. Quantitative fisheries stock assessment. Choice, dynamics and uncertainty. Chapman & Hall, New York 570 pp.

Honkalehto, T., Ressler, P.H., Towler, R.H., Wilson, C.D. 2011. Using acoustic data from fishing vessels to estimate walleye pollock (Theragra chalcogramma) abundance in the eastern Bering Sea. Can. J. Fish. Aq. Sci. 68, 1231-1242.

Hordyk, A.R., Loneragan, N.R., Diver, G., Prince, J.D. 2011. A cost-effective alternative for assessing the size of deep-water fish aggregations. Mar. Fresh. Res. 62, 480-490

Horne, J.K. 2000. Acoustic approaches to remote species identification: a review. Fish. Oceanogr. 9, 356-371.

Iversen, S.A. 2002. Changes in the perception of the migration pattern of Northeast Atlantic mackerel during the last 100 years. ICES Mar. Sci. Symp. 215, 382–390.

Karp, W. 2007. Collection of acoustic data from fishing vessels. ICES Coop. Res. Rep. 287, 1–90.

Keith, G.J., Ryan, T.E., Kloser, R.J. 2005. ES60adjust.jar. Java software utility to remove a systematic error in Simrad ES60 data. CSIRO Marine and Atmospheric Research, Castray Esplanade, Hobart, Tasmania, Australia. (https://bitbucket.org/gjm/calibration-code/src/a06a5e33af67/es60adjust).

Korneliussen, R.J., Ona, E. 2002. An operational system for processing and visualizing multi-frequency acoustic data. ICES J. Mar. Sci. 59, 293-313.

Lavery, A.C., Chu, D., Moum, J.N. 2010. Measurements of acoustic scattering from zooplankton and oceanic microstructure using a broadband echosounder. ICES J. Mar. Sci. 67, 379-394.

Lee, J., South, A.B., Jennings, S., 2010. Developing reliable, repeatable, and accessible methods to provide high-resolution estimates of fishing-effort distributions from vessel monitoring system (VMS) data. ICES J. Mar. Sci. 67, 1260-1271.

Levin, P.S., Fogarty, M.J., Murawski, S.A. Fluharty, D. 2009. Integrated ecosystem assessments: developing the scientific basis for ecosystem-based management of the ocean. PLoS Biology 7, e1000014. doi: 10.1371/ journal.pbio.1000014.

Matheron, G. 1971. The theory of regionalized variables and its applications, Technical Report 5, Cahiers du Centre de Morphologie Mathematique.

Melvin, G., Li, Y.C., Mayer, L., Clay, A. 2002. Commercial fishing vessels, automatic acoustic logging systems and 3D data visualization. ICES J. Mar. Sci. 59, 179-189.

Melvin, G.D., Stephenson, R.L., Power, M.J., Fife, F.J., Clark, K.J. 2001. Industry acoustic surveys as the basis for in-season decisions in a co-management regime, in: Funk F *et al*. (eds) Herring Expectations for a new millennium. University of Alaska Sea Grant, AK-SG-01-04, Fairbanks, Alaska, pp 675-688.

Mills, C.M., Townsend, S.E., Jennings, S., Eastwood, P.D., Houghton, C.A. 2007. Estimating high resolution trawl fishing effort from satellite-based vessel monitoring system data. ICES J. Mar. Sci. 64, 248-55.

O'Driscoll, R.L., Macaulay, G.J. 2005. Using fish-processing time to carry out acoustic surveys from commercial vessels. ICES J. Mar. Sci. 62, 295-305.

Petitgas, P., 2001. Geostatistics in fisheries survey design and stock assessment: models, variances and applications. Fish. Fish. 1, 231–249.

Pikitch, E.K.; Santora, C., Babcock, E.A., Bakun, A., Bonfil, R., Conover, D.O., Dayton, P., Doukakis, P., Fluharty, D., Heneman, B., Houde, E.D., Link, J., Livingston, P.A., Mangel, M., McAllister, M.K., Pope, J., Sainsbury, K.J. 2004: Ecosystem-based fishery management. Science 305, 346–347.

Reed, M. 2008. Stakeholder participation for environmental management: a literature review. Biol. Cons. 141, 2417-2431.

Ressler, P.H., Fleischer, G.W., Wespestad, V.G., Harms, J. 2009. Developing a commercial-vessel-based stock assessment survey methodology for monitoring the US west coast widow rockfish (Sebastes entomelas) stock. Fish. Res. 99, 63-73.

Ryan, T.E., Kloser, R.J. 2004. Improving the precision of ES60 and EK60 echosounder applications. Report of the Working Group on Fisheries Acoustic Science and Technology (WGFAST), 20-23 April 2004, Gydnia, Poland. ICES CM2004/B:06.

Shen, H., Quinn, T.J., Wespestad, V., Dorn, M.W., Kookesh, M. 2008. Using acoustics to evaluate the effect of fishing on school characteristics of walleye pollock, in: Resiliency of gadid stocks to fishing and climate change. Alaska Sea Grant, University of Alaska Fairbanks. 125-140pp.

Shen, H., Dorn, M.W., Wespestad, V., Quinn, T.J. 2009. Schooling pattern of eastern Bering Sea walleye pollock and its effect on fishing behavior. ICES J. Mar. Sci. 66, 1284–1288. doi:10.1093/icesjms/fsp071.

Shin, Y.J., Cury, P. 2004. Using an individual-based model of fish assemblages to study the response of size spectra to changes in fishing. Can. J. Fish. Aquat. Sci. 61, 414-431.

Stanton, T.K., Chu, D., Lavery, A.C. 2011. Broadband active acoustic sensing of fish and zooplankton in the kilohertz to megahertz range: Pursuing Van Holliday's vision. J. Acoust. Soc. Am. 130, 2324.

Stanton, T.K., Chu, D., Jech, J.M., Irish, J.D. 2010. New broadband methods for resonance classification and high-resolution imagery of fish with swimbladders using a modified commercial broadband echosounder. ICES J. Mar. Sci. 67, 365-378.

Kaufman, L., Heneman, B., Barnes, J.T. Fujita, R. 2004. Transition from low to high data richness: an experiment in ecosystem-based fishery management from California. Bul. Mar. Sci. 74, 693-708.

Witherell, D., Pautzke, C., Fluharty, D., 2000. An ecosystembased approach for Alaska groundfish fisheries. ICES J. Mar. Sci. 57, 771-777.

Figure 1. Map of freezer-trawler fishing track from which acoustic data were collected in 2012.

Figure 2. Relative proportion of time spent fishing (grey) and searching (white) after the vessels have reached the fishing grounds (HER: North Sea herring; WHB: Northeast Atlantic blue whiting; HOM: Channel horse mackerel), between starting the first and finishing the last trawl.

Figure 3. Bootstrapped mean acoustic densities (n=1000) recorded on different fishing trips (HER: North Sea herring; WHB: Northeast Atlantic blue whiting; HOM: Channel horse mackerel) during fishing (grey) and searching (white) activities.

Figure 4. Mean (+S.E.) fish densities (NASC: nautical area scattering coefficient) per 15 minute time bins before (negative values; 'searching' period) and after (positive values; 'fishing' period) shooting the net (zero) during: a) the herring, b) blue whiting, and c) horse mackerel fisheries. LOESS curves (solid lines) were fitted to the mean values and 5^{th} percentiles of fish densities observed during the 'fishing' and 'searching' periods are given (dashed lines).

Figure 1
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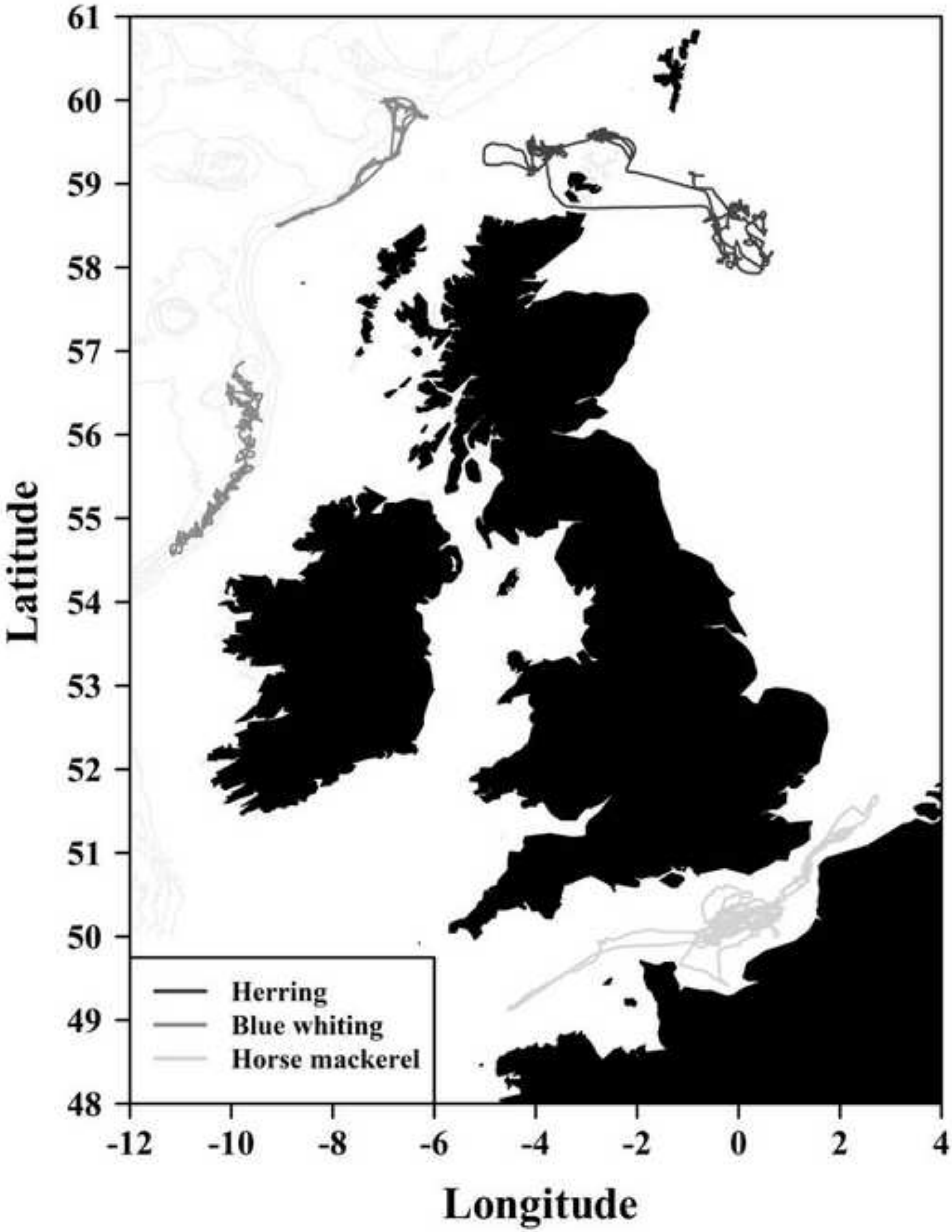

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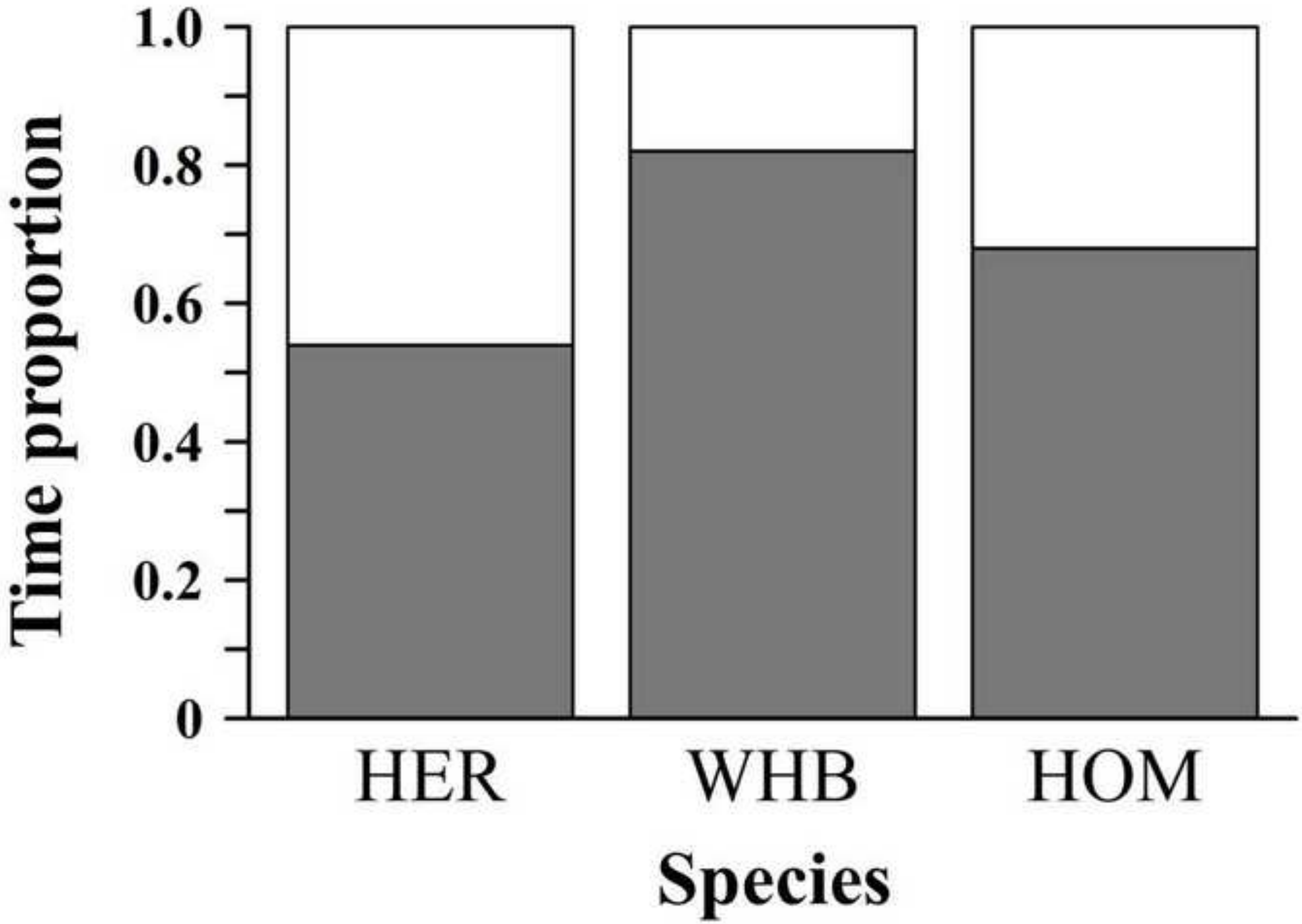

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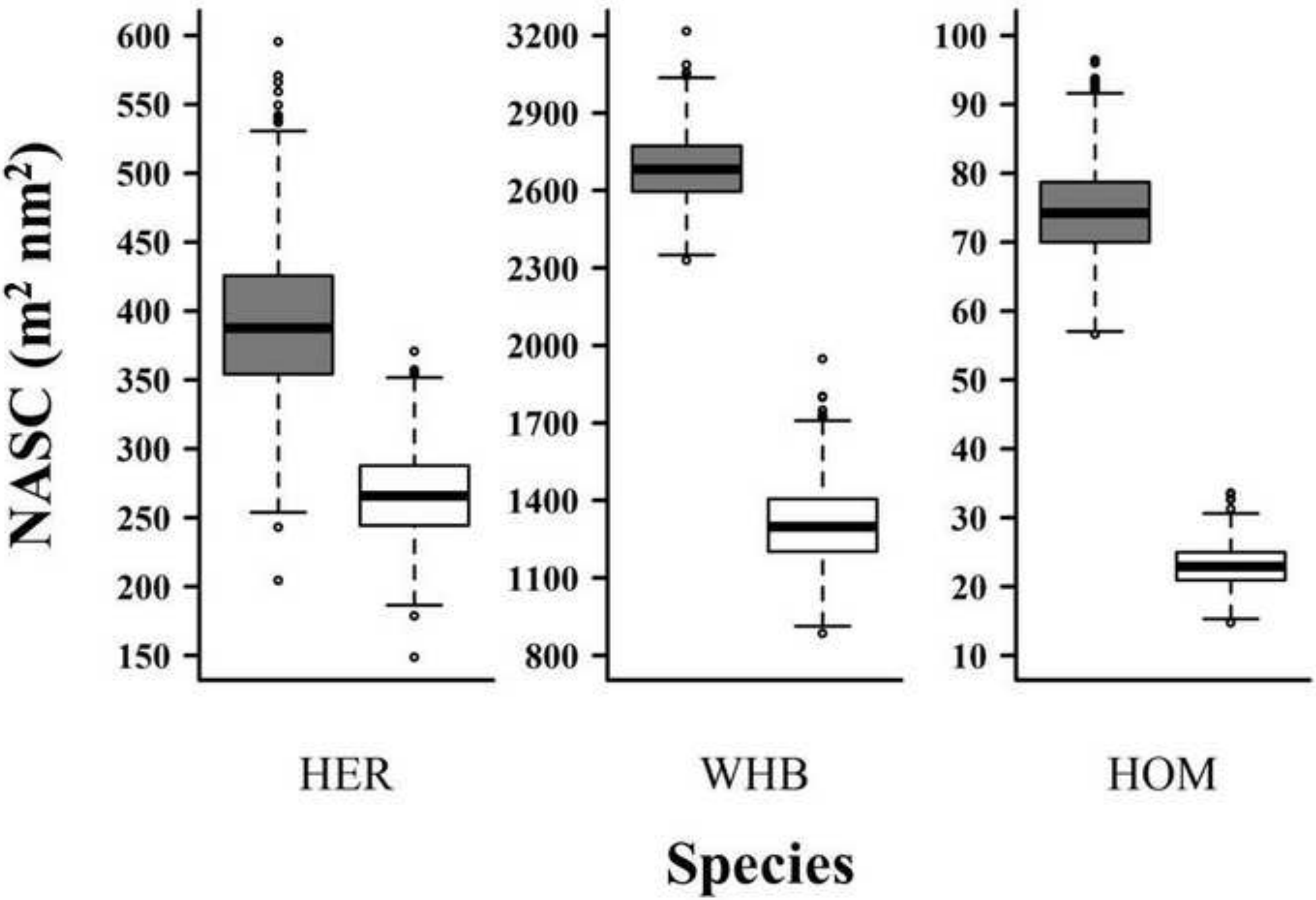

Figure 4
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