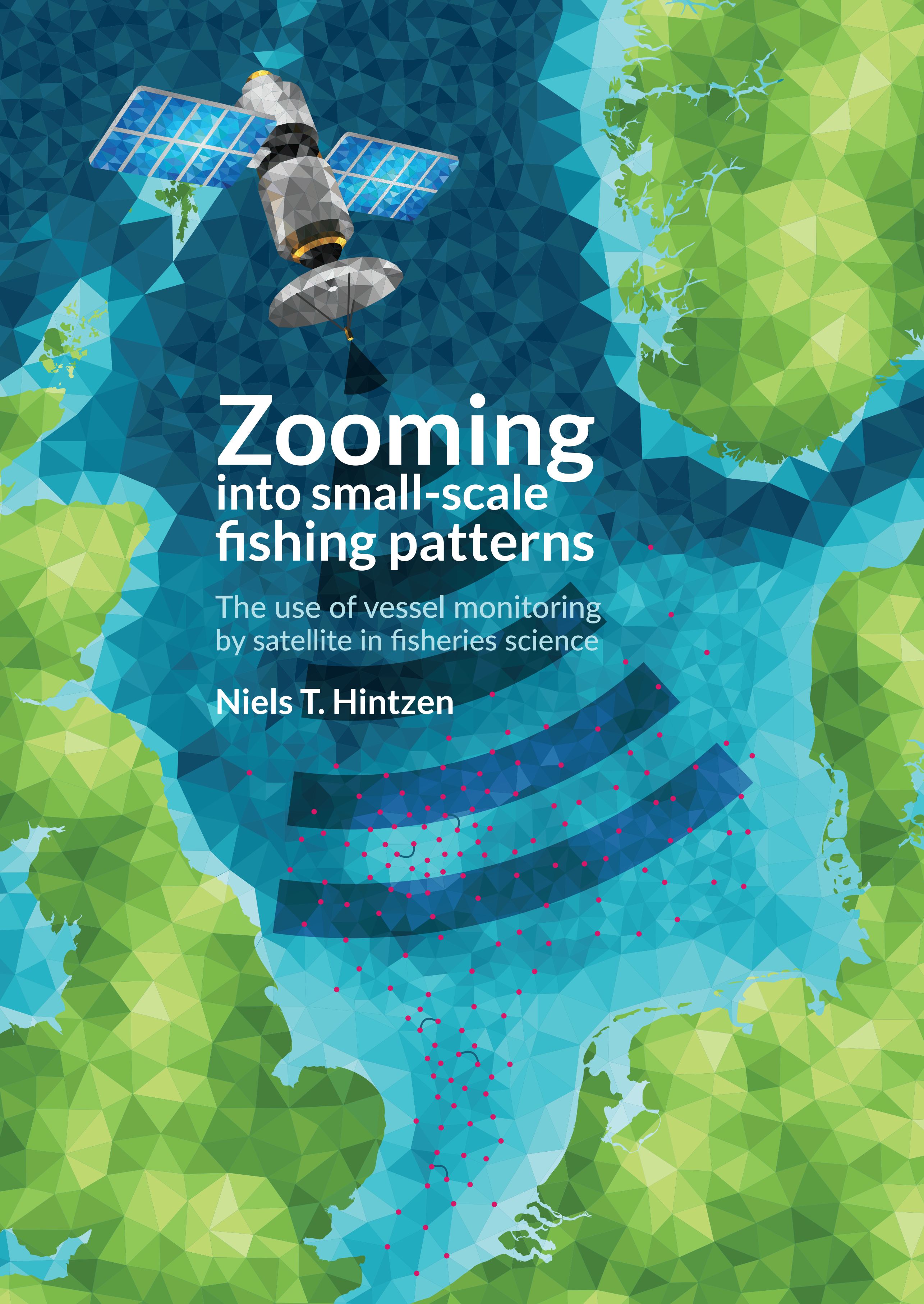

Zooming into small-scale fishing patterns

The use of vessel monitoring by satellite in fisheries science

Niels T. Hintzen

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Niels T. Hintzen

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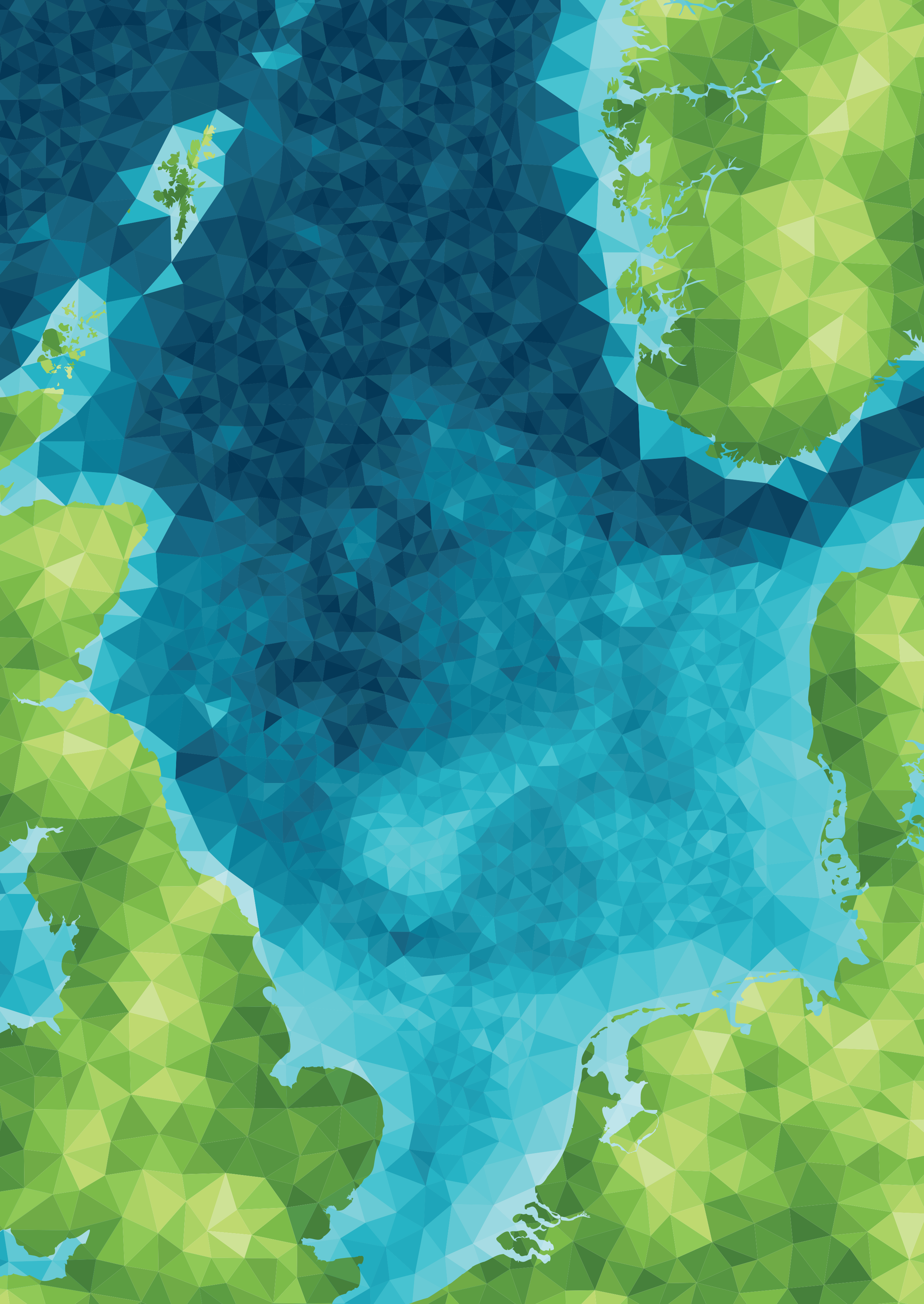

1

Introduction

Fisheries management

Fishing activities have been documented since the late medieval period (Barrett *et al.*, 2004), with information on flatfish fisheries being documented since the 16th century (Bennema and Rijnsdorp, 2015). In Europe, regular documenting of fisheries statistics on a broad scale started in the early 1900s (Thurstan *et al.* 2010, Lassen *et al.* 2012). With Beverton & Holt (Beverton and Holt, 1957) and Ricker (Ricker, 1954) describing the essentials for understanding the effects of fisheries exploitation on populations, fisheries management based on this understanding started to develop. The need for fisheries management is clear given the worldwide increase in stocks being fished above biologically sustainable levels (FAO, 2018). With a rough estimate of 4.6 million fishing vessels, landings of around 90 million tonnes of marine captures in 2016 (FAO, 2018), fisheries management is not a simple task at hand. Given that around 40% of the global population depends for more than 20% on the marine environment for their main source of animal protein (FAO, 2018), effective fisheries management is key to delivering worldwide food security.

The ultimate goal of fisheries management is to take consideration of all ecosystem links that are present in the marine environment (Garcia, 2003) and to ensure that the ecosystem as a whole is resilient (Holling, 1973) to stressors such as climate change (Doney *et al.*, 2012; Miller *et al.*, 2010). To date, only a few cases have demonstrated how ecosystem drivers could be incorporated in fisheries management (Skern-Mauritzen *et al.*, 2016). Incorporating these ecosystem drivers is key, however, to be able to appropriately study the trade-offs between exploitation and ecosystem conservation and to allow setting sustainable targets for the future (Blanchard *et al.*, 2014; Jennings *et al.*, 2012). Part of the difficulty in studying the trade-offs is one of scale, where fishing can have very localized impacts (van der Reijden *et al.* 2019) at the scale of tens of meters while our understanding of ecosystem functioning and data availability often spans several kilometres.

Meanwhile, the impact of fisheries is clearly different across fleet segments. Marine captures come in different forms such as shellfish, crustaceans, flatfish, round fish or pelagic fish. Each of these is targeted by a different fleet segment with fishing practice and gear design specifically tailored to their operation. As a result, the impact fishing has on the environment is different for each segment. Hence effective fisheries management requires accounting for many elements of an ecosystem and has been embedded within EU regulations such as the EU the Bird (EC 2009) and Habitat Directive (EC 1992), the Marine Strategy Framework Directive (EC 2008) and the Common Fisheries Policy (EC 2002). For example, certain bird species rely on fish as food and hence fisheries management needs to ensure that a sufficiently large fraction of the resource is protected from human exploitation.

Around a quarter of the fisheries catches are demersal fish and shellfish assemblages landed by bottom trawlers (Amoroso *et al.*, 2018). These bottom trawlers drag fishing gears over the seafloor. Hence, these trawlers leave a substantial footprint (Amoroso *et al.*, 2018; Pitcher *et al.*, 2017; Eigaard *et al.*, 2017), impacting benthic species (Sciberras *et al.*, 2018; van der Reijden *et al.*, 2018; van Denderen *et al.*, 2014) and influencing nutrient cycles in the seafloor sediment (Tiano *et al.*, 2019). As such, marine habitats are impacted, often at very local scales, and requires fisheries management to account for these small-scale pressures to ensure ecosystem functioning and biodiversity protection throughout a sea basin. Alterations in food web composition due to fishing furthermore affects ecosystem functioning and hence fishers are required to limit their impact on larger individuals or those species occupying a specific tropic level such as pelagic species do (Shephard *et al.*, 2014; Shephard *et al.*, 2011).

These policies have been developed with best available science and much of the data currently needed to evaluate the effectiveness of these policies is collected under the Data Collection Framework (DCF). It is clear that collection of fisheries data such as commercial landing statistics, bycatch information and fleet size indicators reported annually at sea basin scales are crucial for fisheries management while the demand for information on fishing activity at even smaller spatial and temporal scales is increasing owing to an increased competition for space in marine shelf areas (Ramos *et al.*, 2014; Bastardie *et al.*, 2015). These shelf areas have to accommodate aquaculture (Dempster and Sanchez-Jerez, 2008), nature reserves (Edgar *et al.*, 2014), wind energy (Stelzenmüller *et al.*, 2016), shipping, oil and gas industry, and military use. Clear rules to define who has right to use which areas to prevent cross-sector collisions (UNCLOS, 1982) are needed as well as detailed information on the spatial and temporal behaviour of fishers for fisheries management to deliver on safeguarding ecosystem functioning.

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Fisheries regulation

To manage fisheries, rules are required along with means to ensure that these rules are followed. In 1983, the European Union adopted such rules by means of the Common Fisheries Policy, that brought together fisheries management within the 200 mile limits of each of the EU Member States (Symes, 1997; Daan, 1997). Fisheries managers from all Member States annually agree on quotas for fish stocks in different management areas and allocate shares to specific member states (EC, 2020). At the member state level, fishers can be assigned individual quotas (Arnason, 1998; Salz, 1996; Smit, 2001) and thus know exactly how much fish they can annually land per species. Initially, the CFP had a primary focus on Total Allowable Catches (TACs), which were based on scientific advice from international organisations such as the International Council for Exploration of the Seas (ICES) and the Scientific, Technical and Economic Committee for Fisheries (STECF). Within these organisations, stock assessment models and mixed fisheries models are used to provide TAC advice for over 200 species (ICES, 2018b; 2018c; ICES, 2019), each relying on the administration of catches by fishing fleets in logbooks, and scientific monitoring of the fish stocks of interest.

Additionally, there are specific rules in place, fitted under the umbrella of 'technical measures' (EC, 2019), that regulate the use of fishing gear. The technical measures aim to minimize the impact of fishing on the marine environment (Catchpole *et al.*, 2005). The measures include rules to limit bycatches in general, and more specific bycatches of undersized fish through mesh size restrictions. The technical measures also include a recently introduced landing obligation (Batsleer *et al.*, 2016) and limitations to fishing with gears that could have a detrimental effect on the seafloor and the benthic community (Hiddink *et al.*, 2017; Rijnsdorp *et al.*, 2018; Polet *et al.*, 2017).

In a further attempt to regulate fisheries, specific areas can be closed to fisheries, either permanently (Ostermann, 1998) or temporarily (van Overzee and Rijnsdorp, 2015; Needle and Catarino, 2011) to protect benthic communities, birds, mammals, and fish stocks (EC, 1979; EC, 1992/1995). For example, the North Sea cod stock that was in a poor state in the early 2000s was protected from fisheries through spatial closures (Poos and Rijnsdorp, 2007). In so called Marine Protected Areas (MPAs), managers expect that without disturbance by fishing, recovery of ecosystems takes place, that the area has a refuge function, and in some cases acts as a source of inflow of individuals and biomass to adjacent areas (Beare *et al.*, 2013; Christensen *et al.*, 2009; Dinmore, 2003).

For all fisheries regulations mentioned above, reliable data is required to verify if the rules are obeyed to. Both Vessel Monitoring by Satellite (VMS) and log-book data have demonstrated to be crucial in this sense.

VMS and logbook data in fisheries control

In 1993 the European Commission agreed to introduce a satellite system that would permanently determine the position of fishing vessels (EC, 1993: Article 3), that became known as the VMS system (EC, 1997). Operationalizing this system took almost a decade in most European Member States. In the Netherlands, it was fully in place for large fishing vessels in 2002. Prior to 2002, trials with logging of GPS positions were already commissioned and these demonstrated to be of great use for describing fishing effort in greater detail than had previously been possible (Rijnsdorp *et al.*, 1998). VMS was introduced incrementally for the fleets: All vessels larger than 24m were equipped at the start (usually large trawlers and pelagic vessels) while in 2005 vessels larger than 15m were added to this group (smaller vessels that generally fish closer to the coastline such as euro cutters). In 2012 vessels with sizes over 12m had to carry VMS. Vessels smaller than 12m such as fishers operating gillnets are exempted from carrying VMS.

In the VMS system, a 'ping', consists of a signal from the fishing vessel to the satellite containing its GPS position, timestamp, vessel ID, speed and heading. Prior to 2014, such pings were sent roughly every two hours, while currently the interval time is between 30 minutes and one hour for most fleet segments. With the VMS information, authorities can verify in real time if vessels are active only in areas open to fishing in support of fisheries control. In post-processing, reported management area of landings are cross-checked against GPS information from vessels. Given the precise information on fishing grounds that could be obtained from this dataset, there are numerous confidentiality concerns that limit the exchange of VMS data for non-enforcement purposes.

Logbook data has been around much longer than VMS data with records being stored by Statistics Netherlands (Centraal Bureau voor de Statistiek, CBS) since the early 1960s, it was only in 1987 that regulations were put in place to officially report daily catches by filling out daily logbook records (EC, 1987; Berg, 1999). The initiative was taken after a governmental crisis about poor control of compliance to fisheries regulations and illegal fishing practice in the

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1980s. Logbook data includes information on vessel ID, a date stamp, several vessel characteristics, such as departure and landing harbour, departure and landing time, gear information, and fishing location at ICES rectangle resolution. An ICES rectangle measures one longitudinal degree by ½ a latitudinal degree, resulting in a surface area of approx. 3600km2 in the North Sea. Registrations in the logbooks also have to include the estimated catch composition by species, per day and ICES rectangle combination. Logbook data is used to cross-check quota uptake and adherence to technical measures such as mesh size restrictions. In the Netherlands, the Netherlands Food and Consumer Product Safety Authority (NVWA, previously the AID) is tasked with collecting and storing VMS and logbook information for enforcement purposes.

Beyond the use of these data sources for fisheries management and control, they are of great value in science as the vast amount of data being routinely collected is difficult to match with scientific research cruises.

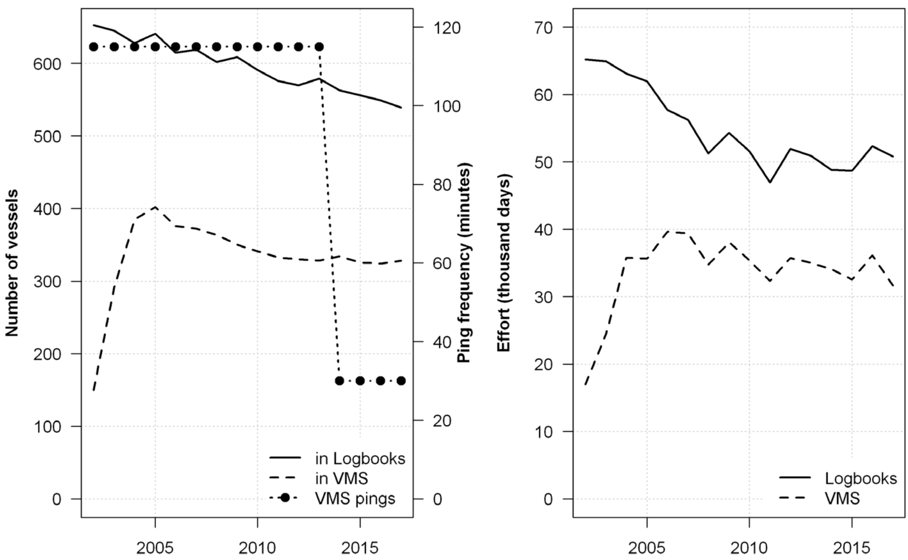

Figure 1.1 Left: Number of vessels in the Dutch fleet as reported in logbooks and VMS over the years. Overlaid the average ping frequency of VMS registered vessels (right-hand axis). Right: Days at sea as reported by all vessels that are mandatory to fill out logbooks and fishing effort (time spend fishing) as estimated from VMS.

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VMS and logbook data in fisheries science

The precise spatial distribution of fishers has long been a fisherman's secret, simply because accurate positioning data only became available with the introduction of GPS and its use in non-military and commercial products in the mid-1990s (El-Rabbany, 2002; Rijnsdorp *et al.*, 1998). As such, only anecdotal information was available from fishers themselves that described what environmental features they used when searching for fish. With the introduction of VMS, scientists in Northern Europe no longer had to rely on logbook data with a resolution of approximately 60x60km, the ICES rectangle, but had routinely access to position data with an accuracy of around 100m. The introduction of VMS boosted the ability to explore the location of fishing (Murawski *et al.*, 2005; Stelzenmuller *et al.*, 2008; Fock, 2008), its relation to the habitat (Hiddink *et al.*, 2006; Kaiser *et al.*, 2006) and interaction with other fishing vessels (Poos and Rijnsdorp, 2007) or users (Bastardie *et al.*, 2015).

The value of VMS and logbook data for science became especially apparent when VMS records were matched with logbooks on date and vessel ID to isolate fleet segments and map fishing effort at a much higher spatial resolution (e.g. km scale) than was previously possible with logbook data alone (Murawski *et al.*, 2005; Mills *et al.*, 2007; Witt, 2007; Stelzenmuller *et al.*, 2008; Pedersen *et al.*, 2009; Bastardie *et al.*, 2010; Gerritsen and Lordan, 2011). The availability of both datasets not only triggered mapping exercises but also opened doors to study fleet and fishers behaviour in greater detail (Vermard *et al.*, 2010; Walker and Bez, 2010; Russo *et al.*, 2011; Poos *et al.*, 2013; Maina *et al.*, 2016).

Tracks of individual fishers were analysed using Lévy trajectories (Bertrand *et al.*, 2005), Bayesian Hidden Markov Models (Vermard *et al.*, 2010), state-space models (Walker and Bez, 2010; Jonsen, 2005) and Spatial Agent Based Models (Sys *et al.*, 2015). These studies provided insights into the concepts of fishers as foragers where their distribution reflects resource density (Bertrand *et al.*, 2005) and where behavioural states could be classified such as fishing (foraging) and steaming (searching) (Vermard *et al.*, 2010) and describing the reasons for changes between these states (Walker and Bez, 2010).

Other studies focussed on the use of space where their distribution was compared to the Ideal Free Distribution (IDF) (Gillis *et al.*, 1993; Poos *et al.*, 2010) and Poisson and Negative binomial distributions to study their aggregation behaviour (Ellis *et al.*, 2014; Hintzen *et al.*, 2018). The study by Poos *et al.* (2010)

showed that either interference competition or differences in catch efficiency could lead to spatial segregation of fleet segments. Ellis *et al.* (2014) showed that when trawling tracks of fishing were projected onto a small spatial grid (at a microspatial scale, with grid cells the size of the gear), and one would count the number of times each grid cell was fished, hereby creating a frequency distribution, this distribution could be approximated by a negative binomial or Poisson distribution providing an estimate of clustering (i.e. aggregation of fishing effort). A Poisson distribution would point to random distribution in space while an overdispersed Negative Binomial distribution would point to a degree of aggregation. Describing fisheries behaviour with theoretical distributions like the IDF or Negative Binomial help to predict fisheries distribution under changes in fleet composition or in areas for which VMS data is lacking (Amoroso *et al.*, 2018; Hintzen *et al.*, 2018).

Explaining fishers behaviour also played an import role in studies focussing on competition (Poos and Rijnsdorp, 2007; Rijnsdorp *et al.*, 2000; Sys *et al.*, 2017; Poos *et al.*, 2020) and displacement (Bastardie *et al.*, 2015; Stelzenmüller *et al.*, 2016), that investigate how catch rates change when more fishers compete for the same resource or if due to legislation fishers are forced to move to other fishing grounds. These studies are highly topical given the current debates on offshore wind, Brexit (Turenhout *et al.*, 2017) and room for nature conservation at sea that may all limit the available space for fishers.

In addition to the conceptual models developed to study fishers behaviour, statistical methods have been developed to link distributions of fishers to environmental characteristics such as depth and substrate (Hiddink *et al.*, 2006; Jennings *et al.*, 2012; van Denderen *et al.*, 2014; Rijnsdorp *et al.*, 2018) and showed that similar fishing intensities can have different impacts on benthic communities under different environmental conditions. Van der Reijden *et al.*, (2018) showed specific hotspots in the spatial distribution of Dutch bottom trawl fishers that were located in uncommon habitat types. The development of statistical software like INLA (Rue *et al.*, 2017) made it possible to account for spatio-temporal correlation present in VMS and logbook data and study the linkage of fishing vessels and habitats in more detail (Hintzen *et al.*, 2021).

Finally, VMS and logbook data have been used to study other behavioural aspects such as the adaptation of fishing speed to save fuel consumption in response to increasing fuel price (Beare and Machiels, 2012; Poos *et al.*, 2013) or the recurring nature of fishing a specific fishing ground (van Denderen *et al.*, 2015).

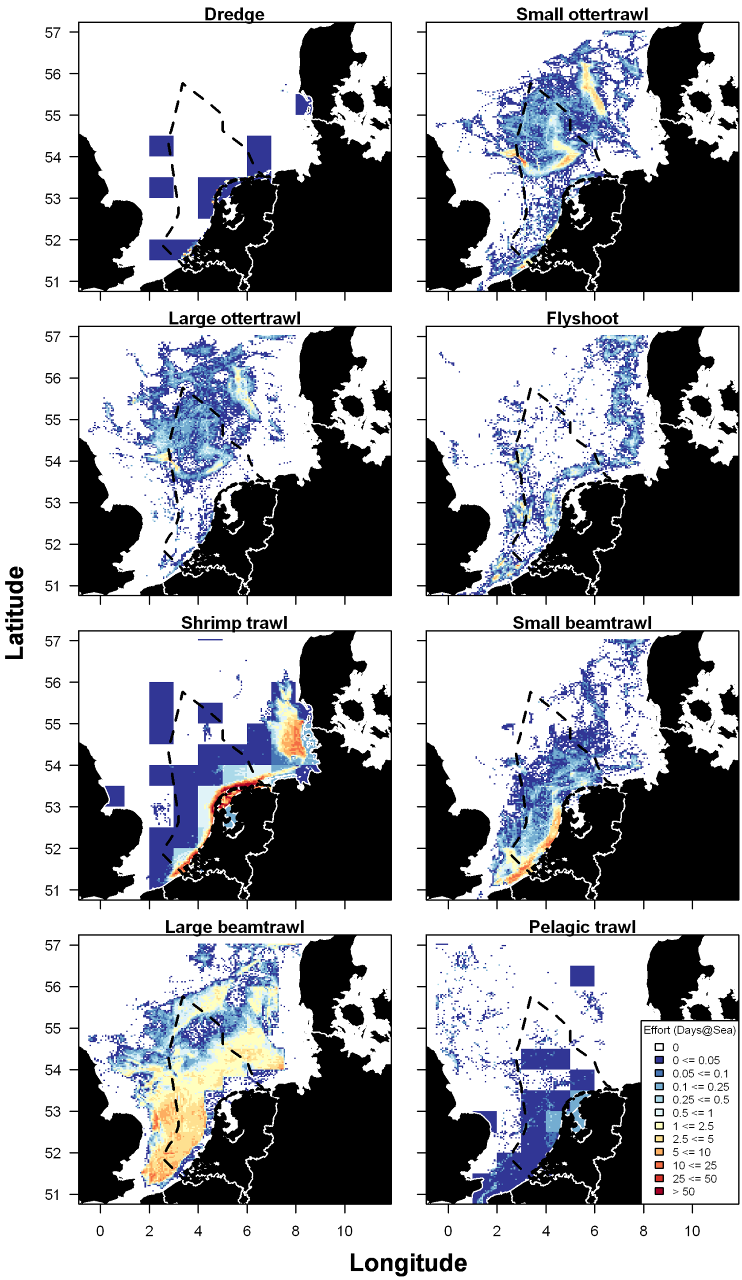

Figure 1.2 Distribution maps of fishing effort (expressed in days at sea) based on VMS and logbooks of the main active fishing gear segments in the Netherlands averaged over the years 2008 – 2017 at a resolution of approximately 15km^2 per grid cell. For fleet segments for which there is no VMS data available, the coarser resolution of ICES rectangles is shown at approximately 3600 km^2 blocks. Dashed line represents the border of the Dutch Exclusive Economic Zone.

Uncertainty in VMS and logbook data

The temporal resolution, at roughly 2 hours, is a problem for reconstructing fishing effort of individual vessels (Piet and Hintzen, 2012; Piet and Quirijns, 2009). For that reason, interpolation routines were developed (Fock, 2008; Hintzen *et al.*, 2010) based on straight lines or splines (Hermite, 1863) between consecutive points to artificially increase the spatio-temporal resolution. The increased detail allowed analyses of fishing impact to be studied at micro-scales, such as 10s of meters to one kilometre scale (Hintzen *et al.*, 2018; Eigaard *et al.*, 2017; Amoroso *et al.*, 2018). Because tracks are based on interpolation, the estimates of fishing impact are uncertain and although these could be reflected in quantitative manners (van Denderen *et al.*, 2014), the introduction of high-resolution observation data such as Automatic Identification System data (AIS, a radio signal transmitted similar in design as VMS but at polling frequencies of several seconds) (Natale *et al.*, 2015; Kroodsma *et al.*, 2018) in the 2010s was welcomed by the scientific community. It was soon pointed out that studies based on AIS should be interpreted carefully because of missing observations for almost every vessel present in the datasets (Shepperson *et al.*, 2018).

With the vast amount of data available in VMS, AIS, and logbooks, being able to efficiently, reliably, and repeatably produce consistent results is a challenge. Individual researchers tend to make slightly different assumptions in their workflow to process these datasets, each with slightly different results as an outcome. This is especially important in studies where across countries fisheries data needs to be combined to produce a combined overview of fishing impact (ICES, 2018a; Amoroso *et al.*, 2018; Eigaard *et al.*, 2017). In those instances, working from a common language, e.g. a standardized workflow or software tool (Hintzen *et al.*, 2012; Russo *et al.*, 2014) minimizes the chance on misinterpretations of the results.

Outline of the thesis

The increased competition for marine space between nature conservation, energy exploitation, transportation and fisheries highlight the need to address marine resource management at small spatial scales. This coincides with the aim to move towards ecosystem-based fisheries management where small-scale impacts are as important to ensure ecosystem functioning at sea basin scales. There is hence an intrinsic drive to increase our understanding of fishing impact in local patches. Key to this development is the availability of a suitable data source depicting fishing patterns at local scales which became available with the introduction of VMS in the early 2000s. It's usefulness for science in support of fisheries management was soon proven but allowing interpretations of fishing impact to be made at small spatial scales required technical development of tools to handle the data and new statistical techniques to analyse it appropriately. Hence, the objective of this PhD project was to expand the use of VMS data to study the impact of fishing at small spatial scales (tens of meters).

The vast amount of VMS and logbook data that became available required a standardized approach for its analyses to tailor the interpretation of the results (Lee *et al.*, 2010). Primarily because the confidential nature of both VMS and logbook datasets, and reluctance to share raw VMS and logbook data across countries (Hinz *et al.*, 2013), required the development of a standardized approach for pan-European (Eigaard *et al.*, 2017) and worldwide (Amoroso *et al.*, 2018) investigations of the impact of fishing. **Chapter 2** describes the development of an open-source software package VMStools (Hintzen *et al.*, 2012) that allows for scripted analyses of VMS and logbook data. The software package makes use of a suite of pre-defined functions that enables users to perform identical analyses on country-specific datasets. The development of standardized analyses in Europe benefitted from already routinely available standardized formats for VMS and logbook data (ICES, 2009).

In the first decade of the existence of VMS, a location 'ping' was emitted roughly every two hours. With an approximate average speed of 7 knots for beam trawlers (Lee *et al.*, 2010; Poos *et al.*, 2013; Beare and Machiels, 2012), i.e. 13 km/h, the spatial detail provided through VMS was still limited to several kilometres. It was therefore that we developed an interpolation routine (Hintzen *et al.*, 2010) in **chapter 3** that outperformed previously assumed straight-line interpolation of trawling tracks. With the artificial increase in the spatial resolution of the data, we are able to assess the impact of fishing at the spatio-temporal scale at which fishing occurs (van Denderen *et al.*, 2015; Piet and Hintzen, 2012; Piet and Quirijns, 2009; van der Reijden *et al.*, 2019).

The increase in data availability and resolution allowed developing hypothesis on the mechanism underlying aggregation of fishing activity (Ellis *et al.*, 2014; van der Reijden *et al.*, 2018), a feature that was already observed from maps of VMS pings. With VMS data available for a long enough period to perform time-series analyses, I studied in **chapter 4** the persistence of fine-scale patches of aggregated fishing effort, i.e. fishing grounds. The chapter concludes that the fine-scale distribution of fishing effort was highly persistent in time and likely well explained by habitat characteristics such as depth profile and type of substrate.

Chapter 5 describes a statistical framework to test if environmental conditions were a good predictor of fishing effort, and quantify the habitat preference of specific bottom trawling gears. The results suggest that especially relative depth and substrate type are important explanatory variables of bottom trawling activity. This approach contributes to our understanding of the distribution of target species, and our ability to predict fishing activity under changes in available space, relevant in light of increased spatial claims for nature and offshore wind energy in the North Sea. This analyses relied substantially on the availability of highly detailed environmental dataset (Consortium, 2018; Wilson *et al.*, 2018) that only became available on high spatial resolution in recent years.

In **chapter 6** an overview of the findings of the thesis is presented including a discussion on the main assumptions of studies. Furthermore, I discuss how our understanding of small-scale fishing patterns can contribute to the ecosystem approach to fisheries management.

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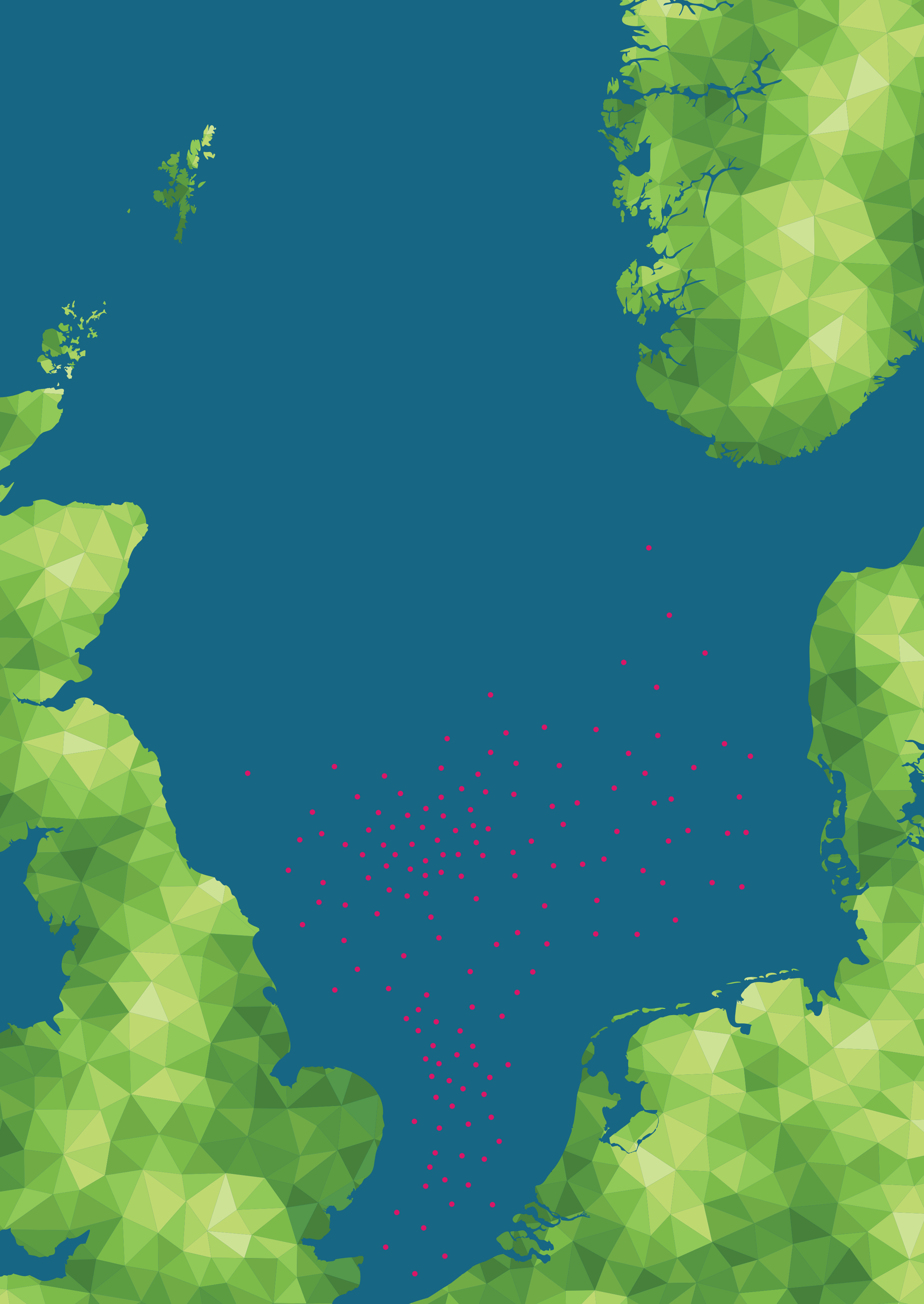

2

VMStools: Open-source software for the processing, analysis and visualisation of fisheries logbook and VMS data

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Abstract

VMStools is a package of open-source software, build using the freeware environment R, specifically developed for the processing, analysis and visualisation of landings (logbooks) and vessel location data (VMS) from commercial fisheries. Analyses start with standardized data formats for logbook (EFLALO) and VMS (TACSAT), enabling users to conduct a variety of analyses using generic algorithms. Embedded functionality handles erroneous data point detection and removal, métier identification through the use of clustering techniques, linking logbook and VMS data together in order to distinguish fishing from other activities, provide high-resolution maps of both fishing effort and -landings, interpolate vessel tracks, calculate indicators of fishing impact as listed under the Data Collection Framework at different spatio-temporal scales. Finally data can be transformed into other existing formats, for example to populate regional databases like FishFrame. This paper describes workflow examples of these features while online material allows a head start to perform these analyses. This software incorporates state-of-the art VMS and logbook analysing methods standardizing the process towards obtaining pan-European, or even worldwide indicators of fishing distribution and impact as required for spatial planning.

Keywords

Area based management
Fishing impact
Indicators
Marine spatial planning
Métier analyses

2

Introduction

Growing pressures by various human activities on the marine environment and international commitments to the conservation of biodiversity or seafloor integrity (CEC, 2007) have led to increased interest in marine spatial planning and in the tools required for an assessment of the impact of pressures (Douvere and Ehler, 2009). Fishing is considered, given its widespread occurrence, to be probably the main human activity impacting the seafloor (Eastwood *et al.*, 2007; Kaiser *et al.*, 2006). Vessel Monitoring by Satellite (VMS) system data on the spatial distribution of fisheries have in the European Union been collected from 2000 onwards (EC, 2002; Piet *et al.*, 2007), originally introduced for control purposes. However, no regional assessments on the spatial impact of international fishing activities on the seafloor have yet been conducted. An important reason relates to concerns over confidentiality and commercial sensitivity over the use of raw VMS data, as exact vessel positions are identified. However, aggregating VMS into métiers, following strict protocols, should overcome this, thereby facilitating the wider exchange of data in Europe (Lee *et al.*,2010). However, defining métiers is in itself a difficult issue, as identifying distinct and well-defined types of fishing activities can be executed using a variety of criteria and methods, often including an element of subjectivity (ICES, 2003). In spite of intense scientific activity in this field over the last two decades, no standardized approach for defining métiers across regions and countries has yet emerged (Ulrich *et al.*, 2009).

Time is pressing to deal with the technical issues, of among others, métier identification and confidentiality, as the implementation of an ecosystem approach to fisheries management and part of the revised Common Fisheries Policy, require a move towards fleet and area-based management (EC, 2008). These advances may be used to direct marine spatial planning and to reduce the pressure by human activities on the marine environment.

In European Union (EU) member states, information on the spatial distribution of fishing activity can be obtained from two main sources: the logbooks and the VMS data (EC, 2002). (i) Logbooks are the responsibility of the skipper of each vessel and have been mandatory on all commercial fishing vessels larger than 10 m cruising in EU waters since 1985 or when landings exceed 50 kg (EC, 1993; Long and Curran, 2000). Logbook data, here referred to as the combined dataset of the fleet register, logbook data filled out by skippers and sale slips, provide information on aspects of the fishing operations (gear types used, mesh size, landings) and the physical characteristics of each vessel (e.g., vessel size, engine power). In their logbooks the fishermen must also declare the location (usually at the ICES statistical rectangle level, grid cells of 1° longitude, 0.5° latitude) and the date where each landing was taken. (ii) The VMS regulations (mandatory on vessels >24 m in length from 2000 to 2004; and >15 m from 2005 to 2011), first introduced in January 2000, require the regular submission (via satellite) of the exact locations (longitude, latitude, speed and heading) of each vessel to a centralized database. Typically the intervals between positions or pings are 1 or 2 h.

In the past decade, VMS analyses have mainly focused on mapping fishing effort distribution (see a review in Lee *et al.*, 2010) and on refining the methodology for describing fishing tracks or activity (Mills *et al.*, 2007; Hintzen *et al.*, 2010; Vermard *et al.*, 2010). Some recent studies have explored methods for allocating logbook catches to VMS positions (Bastardie *et al.*, 2010a; Gerritsen and Lordan, 2011). Hence, logbook and VMS data are complementary and the coupling of logbook and VMS data has already proven powerful, also for describing the spatial distribution of impact on the marine biota habitat at a much finer spatial or temporal resolution (Bastardie *et al.*, 2010a; Eastwood *et al.*, 2007; Fock, 2008; Gerritsen and Lordan, 2011; Hintzen *et al.*, 2010; Lee *et al.*, 2010; Mills *et al.*, 2007; Pedersen *et al.*, 2009; Stelzenmuller *et al.*, 2008; Vermard *et al.*, 2010; Walker and Bez, 2010).

In most of the studies listed above, however, the data have been processed with *ad hoc* tools, making the analyses difficult to repeat even if the methodology is well described. The use of predefined (standardized) data formats in combination with standard scripts would allow various operators to perform identical analyses on similar data sources (Cagnacci and Urbano, 2008), and would therefore provide opportunities to accelerate our understanding of the marine habitat and its use (Reichman *et al.*, 2011; Kranstauber *et al.*, 2011). Ecopath with Ecosim (Christensen and Walters, 2004), as a standardized framework for example, has accelerated the use of ecosystem models, and its applications are found all over the world. Likewise, *FLR* (Kell *et al.*, 2007) which is also an R 'add-on' package (R Development Core Team, 2008) has proved to be extremely useful for standardizing stock assessments and management strategy evaluations (Kraak *et al.*, 2008; Pastoors *et al.*, 2007; Sainsbury *et al.*, 2000). In this paper we demonstrate how the use of the *VMStools* package to jointly analyse VMS and logbook data improves our understanding of the marine habitat and its usage by fisheries.

VMStools uses two standardized data formats, EFLALO (EU logbook data) and TACSAT (the VMS positions). These formats build on work done and agreements made during previous EU funded scientific projects such as TECTAC, CAFÉ and AFRAME (see Supplementary Appendix A) and are well known within the International Council for the Exploration of the Sea (ICES) community. Once the data have been imported into R, a series of functions linked by scripts enable a range of tasks to be completed in a single software environment. Métiers, for example, can be identified objectively from logbook landings species compositions using multivariate and clustering techniques; fishing activity can be distinguished from other activities (i.e. vessels in harbour or steaming); logbook and VMS data can be linked (Bastardie *et al.*, 2010a) and individual vessel tracks can be interpolated both linearly and non-linearly using Hermite spline functions (Hintzen *et al.*, 2010). The package can furthermore be used to explore the effect of different spatial (grid size) and temporal aggregations (monthly, quarterly, annually) which can be extremely important when determining fishing impact and its indicators (Piet and Quirijns, 2009), of which three of those listed under the Data Collection Framework are embedded within the package too.

Materials and methods

This software was developed during the EU funded project 'Development of tools for logbook and VMS data analysis (MARE/2008/10 lot 2)'. The open-source statistical computing environment, R, was selected because it is free, is used widely in the fisheries scientific community, and already incorporates a range of useful add-on packages capable of dealing with spatial data. A public repository has been created for hosting the development of the package, from which the latest version of *VMStools* can also be downloaded (http://code.google.com/p/VMStools/). Each program submitted to the repository must have a manual describing its use and, furthermore, must be designed to use TACSAT and EFLALO formats. (Note: from here on 'tacsat' will be used as a reference to the formatted VMS dataset while 'eflalo' is used as a reference to the formatted logbook data.) Anyone with an interest in analysing such data can get involved by contacting the authors. Illustrations of the use of the tools (for example scripts, see also Supplementary Appendix B) are also available on the repository. These scripts describe possible ways the R functions can be combined when analysing and coupling VMS and logbook data. The most salient points are described below (references to R functions currently incorporated within the package are given in *italics*).

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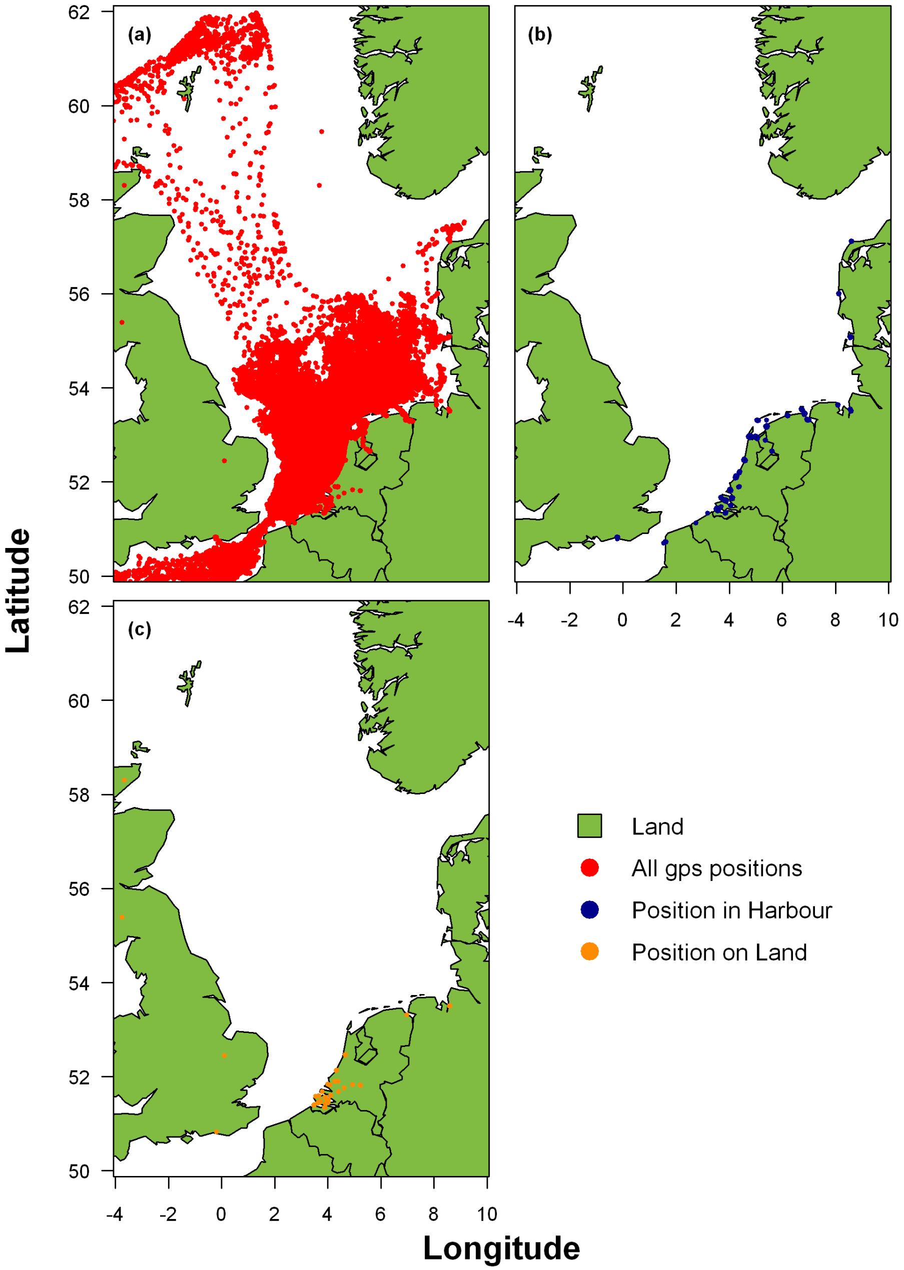

Figure 2.1 Panels show part of the North Sea where in panel (a) red dots represent all vessel positions as listed in the tacsat file. In panel (b), dark blue dots represent all points that are flagged 'in harbour' which have been selected based on a 3 km radius from a chosen central point in each European harbour. In panel (c) all vessel locations that are located on land are represented by dark orange dots. The analyses are based on the example tacsat and eflalo datasets available in the *VMStools* package.

Data

VMS and logbook processing using *VMStools* first requires eflalo and tacsat data to be created in the correct format. Each of these datasets has a pre-defined structure (see Supplementary Appendix A) with certain mandatory columns. Data are imported into R from csv files (comma separated values) using *readEflalo* and *readTacsat*, which ensures that each column of data is in the correct format (internal check by *formatEflalo* and *formatTacsat*), e.g. date, character or number. To illustrate these datasets the Dutch fishing industry and Ministry kindly gave the authors the permission to incorporate subsets of raw logbook and VMS data directly into the *VMStools* package. For confidentiality purposes, these data have been disguised, and noise has been added to the recorded vessel positions. These data are now thus an embedded component of the package, allowing potential users to test and demonstrate the software. These example datasets are also used to illustrate the software functioning within this paper.

Cleaning the data

In many instances, both VMS and EU logbook data contain erroneous entries. It is common to find vessel positions on land, implausibly high speeds, headings outside a compass range, and duplicate records. As advised by ICES (2010), these errors should be removed or flagged. In addition, vessel positions lying either in harbours, or very close to harbours should be identified. The *VMStools* package distinguishes such records using standard GIS-type point-in-polygon calculations. Functions such as, *sortTacsat*, *pointOnLand* and *pointInHarbour* are examples of how this process is facilitated, supported by command line access to extensive harbour position lists and European coastline shapefiles.

Within this exercise, positions in the tacsat file which were outside longitudinal or latitudinal ranges (latitude >90 or latitude <-90, longitude <-180 or longitude >180), or had speed records of more than 20 knots were removed. After filtering out duplicate records, points in harbour were removed (*pointInHarbour*), as were points on land (*pointOnLand*, see Figure 2.1, Table 2.1). In addition to 'true' duplicates, the tacsat file was also filtered for pseudo-duplicate positions where records with intervals of less than 5 min were removed (likely due to errors in VMS data transponder on-board a vessel). Spurious mesh sizes (>150 mm in the example dataset) in the eflalo dataset were also removed, while landings that were larger than approximately 30x any other landing recorded of that species were flagged. In addition, non-unique trip IDs were removed where a trip ID consisted of the combination of vessel ID, trip number, haul and ICES statistical rectangle of the landing.

Table 2.1 Overview of processing and filtering results of the example tacsat and eflalo data files. Original number of rows in each dataset is given, while percentages removed/flagged are calculated based on the original number of entry rows.

	Processing description	% removed/flagged
Tacsat	-	97,015 rows
Tacsat	Longitude, latitude and speed outside range	0.00%
Tacsat	Duplicate records removed	0%
Tacsat	Points in harbour	15.22%
Tacsat	Points on land	0.16%
Eflalo	-	4539 rows
Eflalo	Mesh size out of range	0.57%
Eflalo	Duplicate records removed	2.05%
Eflalo	Arrival date before departure date	0%

Métier identification

Fishing operations and fishing trips showing similar patterns need to be grouped by métiers according to the Data Collection Framework for the European Union (DCF, EC, 2008). The DCF has defined métiers according to a hierarchical structure using six nested levels (see also https://datacollection.jrc.ec.europa.eu/web/dcf/wordef/fishing-activity-metier): Level 1 – Activity (fishing/non fishing), Level 2 – Gear class (e.g. trawls, dredges), Level 3 – Gear group (e.g. bottom trawls, pelagic trawls), Level 4 – Gear type (e.g. Bottom otter trawl (OTB), Bottom pair trawl (PTB)), Level 5 – Target assemblage based on main species type (e.g., Demersal fish, Crustaceans), Level 6 – Mesh size and other selective devices. Because logbooks do not contain the information on the assemblage of targeted species as required by the definition of the métier at the level 5, a number of methods have been used in the past to identify these, typically using a variety of statistical analyses on landings profiles from logbook data (see also the reviews by Marchal, 2008; Ulrich *et al.*, 2009). In order to implement and compare some of the most commonly used of these methods in a generic and objective framework, a workflow has been set up to apply multivariate and clustering analyses to the logbook landings composition, in order to deduce it for each fishing operation (logbook event). The details of the methodology included in the present *VMStools* library are the subject of another paper (Deporte *et al.*, in press, including a flow diagram of the steps described below) and only the salient points need to be recapitulated here. The steps undertaken can be summarized as follows:

(i) First it is necessary to identify the most valuable species in the logbooks so the size of the dataset can be rendered manageable (*selectMainSpecies* and *extractTableMainSpecies*). (ii) Secondly the total inertia of the dataset must be reduced by applying the routines *getTableAfterPCA* which runs principal component analysis (PCA) followed by a selection of clustering methods: Hierarchical Agglomerative Classification (HAC, Hartigan, 1975), K-Means (Hartigan and Wong, 1979) or Clustering LARge Applications (CLARA) algorithm (Kaufman and Rousseeuw, 1990), *getMetierClusters*. The PCA aims to make the clustering process easier by reducing the amount of information comprised in the dataset to its substantial part only. Clusters group similar logbook events and are characterized by specific assemblages of different species (which are conveniently referred to as Level 7, by opposition to the predefined Level 5 assemblages based on species type). (iii) Thirdly, a conversion of métier at this Level 7 to métier DCF Level 5 categories is executed using *compareToOrdination*. This latter function also permits the comparison of these results with those obtained using alternative simple ordination methods. (iv) Finally any newly derived logbook data can be allocated into the pre-defined categories or métiers using a discriminant analysis embedded in the *predictMetier* function. To ease the whole workflow, all these sequential steps (except for the last one) have also been pooled into one single routine (*getEflaloMetierLevel7)*, which reads an eflalo dataset in and returns it together with a métier definition both at Level 5 and at Level 7.

The first step of the métier identification on the example eflalo dataset consists of determining the main species, realized using the *selectMainSpecies* function.

This function encompasses three methods: (i) species selection by HAC clustering, (ii) species selection by their proportion of the total catch, and (iii) species selection by their proportion of the catch of at least one logbook event. Each method gives a set of species and returns a set of main species to be included in the métier identification. After defining the main species, the original input dataset is subset to only these species (*extractTableMainSpecies*). PCAs are executed to reduce the dimension of the data with the function *getTableAfterPCA*. The "70% of the initial inertia" criterion was used to determine the number of axis to retain. The CLARA clustering algorithm was finally used to define the clusters.

Linking tacsat and eflalo data

By linking tacsat and eflalo data investigators can potentially explore the spatial distribution of fishing effort and landings in much greater detail than was hitherto possible (Fock, 2008; Bastardie *et al.*, 2010a; Gerritsen and Lordan, 2011; Hintzen *et al.*, 2010; Lee *et al.*, 2010; Piet *et al.*, 2007). Linking tacsat and eflalo data implies that individual tacsat pings can be assigned to a particular trip as given in the eflalo dataset. This step is particularly important, as all subsequent analyses depend on the success of the linking. Linking both sources of information requires identifying common vessels identifiers (ID), and date and time limits that define the start and end of a trip or logbook event. The simplest approach is to select the VMS positions that occurred between the departure and arrival dates for each trip described in the logbook data, and to assign unique trip identifiers to them. Sometimes, however, it is not possible to match tacsat records with every trip identified in the eflalo data, and in these cases the non-matching observations can be flagged with a '0' (*mergeEflalo2Tacsat*). Another, more sophisticated method available in the *VMStools* package (see Bastardie *et al.*, 2010a), links trips by their midpoint (*mergeEflalo2Pings*).

Fishing activity

When investigating the behaviour of fishers or analysing, e.g. the impact of fishing on the seabed, it is necessary to distinguish different activities. In most instances, a distinction is made between drifting, fishing and steaming based on speed thresholds (Bastardie *et al.*, 2010a; Fock, 2008; Rijnsdorp *et al.*, 1998), although it has also been shown that better estimates can result if the information represented by vessel heading is utilized (Mills *et al.*, 2007; Vermard *et al.*, 2010). Although none of these methods will result in perfect identification of fishing behaviour, application does result in a marked improvement of our perception of spatial and temporal fishing activity and its effects on the ecosystem (Eastwood *et al.*, 2007). Methods to identify, and therefore quantify fishing activity have been incorporated into the *segmentTacsatSpeed* (Bastardie *et al.*, 2010a) or the *filterTacsat* functions in *VMStools*. There are many possible ways that fishing activity can be summarized. One can simply sum tacsat pings (where a ping represents the transmitted hourly or two hourly record of a vessels ID, position, speed, heading and date/time stamp), fishing time or fishing distance over any spatial compartment. Once fishing activity has been established the *VMStools* package then allows the analyst to explore the spatial and temporal complexity within VMS data.

Based on the established link between the example tacsat and eflalo datasets, reported landings and values from the eflalo dataset were assigned to the exact positions in the tacsat dataset. Eflalo cash values were only assigned to fishing tacsat positions for which the *segmentTacsatSpeed* function was used. This function returns fishing thresholds for each vessel given the gears used (see Figure 2.2). Tacsat records with speeds between these thresholds were assumed to be fishing.

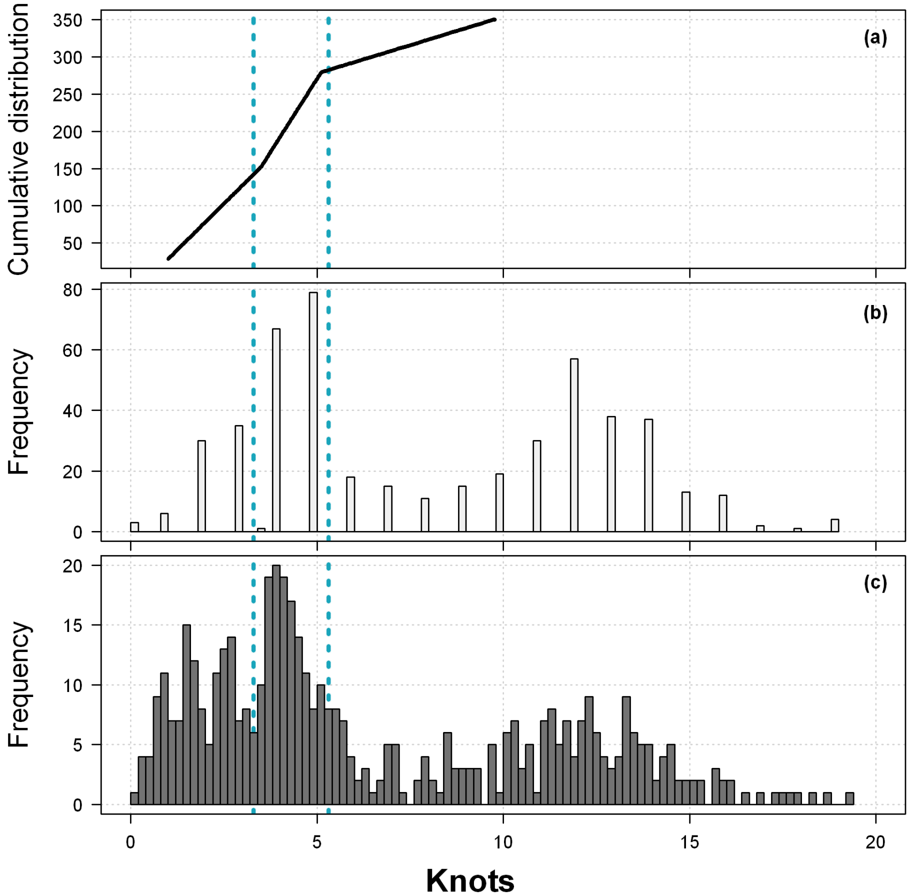

Figure 2.2 Vessel-speed profile analysis of vessel (ID = "298138", gear = OTM) by segmented regression where panel (a) represents the cumulative distribution of calculated speeds. The blue vertical dotted lines represent the speed thresholds (at 3.29 and 5.31 knots) as identified by the segmented regression in which the vessel is assumed to be fishing. Panel (b) shows the instantaneous speed distribution as provided by the VMS data while panel (c) shows the speed distribution calculated given the Euclidian distance and time interval between successive VMS pings. The analyses are based on the example tacsat and eflalo datasets available in the *VMStools* package.

Spatial distribution of landings and cash value

Logbook declarations are made at the coarse spatial scale of the ICES statistical rectangle (1° longitude x 0.5° latitude resulting in squares of approximately ~30nm x 30nm). Furthermore, the locations reported in the logbook are sometimes incorrect for a range of possible reasons (Gerritsen and Lordan, 2011). A sensible solution, then, is to exploit the connection between eflalo and tacsat to distribute landings and cash values from the logbooks at the much higher spatial (and probably more accurate) and temporal resolutions in VMS. There are, however, different aggregation levels at which these landings and cash values might be distributed among the tacsat fishing points (Bastardie *et al.*, 2010a; Gerritsen and Lordan, 2011; Poos and Rijnsdorp, 2007). One method incorporated in the *VMStools* package (*mergeEflalo2Pings*, *splitAmongPings*) distinguishes three different orders, each with two or three levels, and for which a quality flag of the matching is issued. The first order is that of a full match between eflalo and tacsat using vessel IDs and trip numbers. The second order implies a match only on vessel ID, while third order means that no matching on vessel ID or trip number was possible. For first order matches, landings and cash values can be distributed among the tacsat positions that were identified fishing, at all the various levels. These can be: landing day, landing ICES rectangle or trip number only; or a combination of these three. For second order situations, it is clear that only matches based on landing day and landing rectangle are possible. In the case of third order matches, however, distribution of landings and/or cash values can take place only between matches by landing day or landing rectangle. If no match can be found at any of the orders described, landings and/or cash values are, perforce, uniformly distributed among all tacsat pings within a year. In most occasions, however, only tacsat pings are used in which a fishing activity is assumed (see Supplementary Appendix C for an overview scheme).

The allocation of cash values and landings to the example tacsat and eflalo dataset was carried out according to the following hierarchy: (i) a full match on date, ICES rectangle and vessel IDs; (ii) a partial match between ICES rectangle and vessel IDs; and (iii) a weak match using only vessel IDs. Those eflalo records that could not be linked to any tacsat record at all are assigned first to tacsat records with similar vessel ID, following identical hierarchical levels, while those records without even similar vessel IDs are only assigned to records with matching landing date and ICES rectangle. Using this protocol we ensure that no cash-values or landings from the eflalo data are lost (see Figure 2.3).

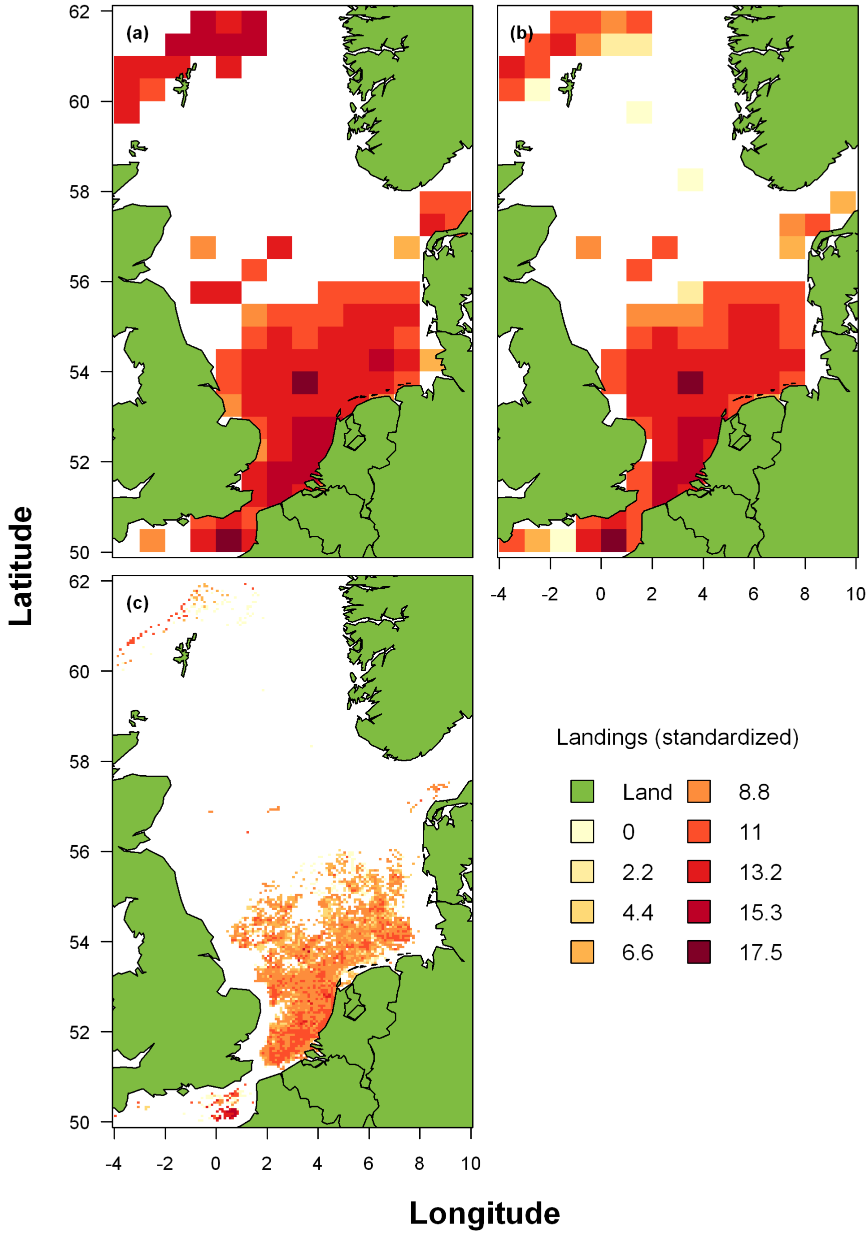

Figure 2.3 Panels show aggregated and standardized (for confidentiality purposes) landings of herring, plaice and sole in (part of) the North Sea where in panel (a) landings from eflalo by ICES statistical rectangle (the highest spatial detail possible, 1 × 0.5 grid cell in respectively longitudinal and latitudinal degrees) are shown; Panel (b) shows landings after linking tacsat and eflalo by ICES statistical and distributing landings from eflalo according to tacsat positions. Panel (c) shows landings after linking tacsat and eflalo by 0.1 × 0.05 grid cell in respectively longitudinal and latitudinal degrees. The analyses are based on the example tacsat and eflalo datasets available in the *VMStools* package.

2

Interpolation and uncertainty

It can be informative to interpolate between the 1 or 2 h interval tacsat positions to e.g. calculate area swept by mobile bottom gears or identify the origin of catches. Different interpolation techniques have been developed (Hintzen *et al.*, 2010) of which straight line interpolation and the cubic Hermite spline method are embedded within the *VMStools* package (*interpolateTacsat*, *interpolation2Tacsat*). These methods can be used either in combination with an uncertainty estimator of possible trawling activity (*calculateCI*), or with methods for representing trawling tracks at their actual gear widths (*addWidth*).

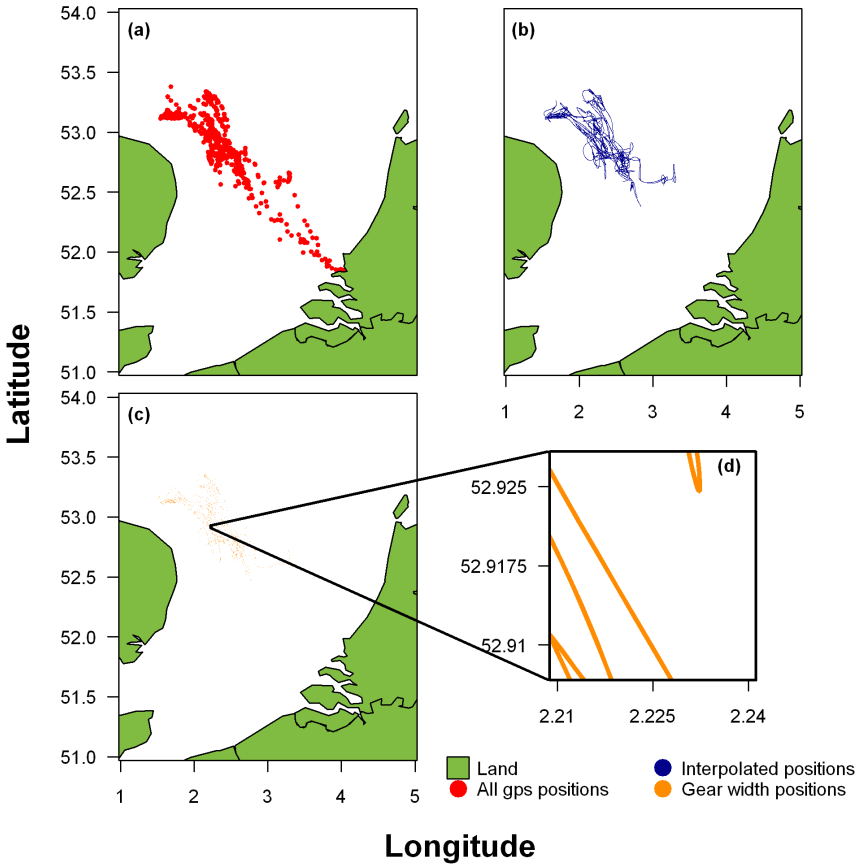

Figure 2.4 Panels show the distribution of a single fishing vessel in the southern North Sea (ID = "157", gear = TBB) where panel (a) represents all the VMS pings available in the test tacsat dataset in *VMStools* after filtering erroneous records. Panel (b) shows the interpolated fishing tracks where non-fishing behaviour has been filtered out. Panel (c) shows a similar interpolation, however, added with a representative gear width. As this gear width only stretches 24 m, it is hardly visible on the large North Sea scale, hence, panel (d) represents an enlargement of a smaller area where the width of the gear is spatially shown. The analyses are based on the example tacsat and eflalo datasets available in the *VMStools* package.

From the example tacsat dataset, fishing tracks were reconstructed using the interpolation routines available in the *VMStools* package. This routine has, as yet, only been parameterized for large beam trawl fisheries. For the purpose of this example, however, we applied it here to all métiers in our test data. The interpolated track can be represented as a curved line segment (via cubic Hermite spline interpolation) or as a polygon reflecting the actual width of the gear. This enables scientists, in combination with GIS applications (e.g. *Grid-2KML* can output data to Google Earth), to view the scale of trawling impact by interactively zooming in and out (see Figure 2.4 for a static representation). Hereafter, landings values were attributed to evenly spaced interpolated positions (*interpolation2Tacsat*).

Spatial resolution

The analyses described above are all executed without the need for any pre-defined spatial resolution, as they are conducted at the scale of the individual VMS pings. For the purpose of visualising results on maps (e.g. fishing effort per spatial unit) any size spatial grid can be defined (*vmsGridCreate*, *createGrid*) using the package. *VMStools* allows the definition of spatial grids, given any step in either the longitudinal or latitudinal directions. Alternatively, a more restricted spatial grid definition is available where each grid cell is given a unique name following the C-square notation as developed by Rees (Rees, 2006). It should also be noted here that the spatial analyses included in *VMStools* rely heavily on class structure of the *sp* (Bivand *et al.*, 2008) and *PBSMapping* (Schnute *et al.*, 2008) R add-on packages and their functionality regarding polygon and shapefile calculations.

The aggregated tacsat and eflalo results, as presented in Figure 2.3c is defined on approximately square spatial grid cells with longitudinal steps of 0.1° and latitudinal steps of 0.05°. A ten times more detailed spatial grid is defined for the results in Figure 2.5b,c.

Indicators

Under the Ecosystem Approach to Fisheries Management, the use of indicators to describe ecosystem status or health has gained importance over the past years and several of those suggested can only be calculated by combining information from logbook and VMS data. The EU Data Collection Framework (EC, 2008) has identified three indicators that describe the spatial extent and impact of fishing activity: “Distribution of fishing activities”, “Aggregation of fishing activities”, and “Areas not impacted by mobile bottom gears” all of

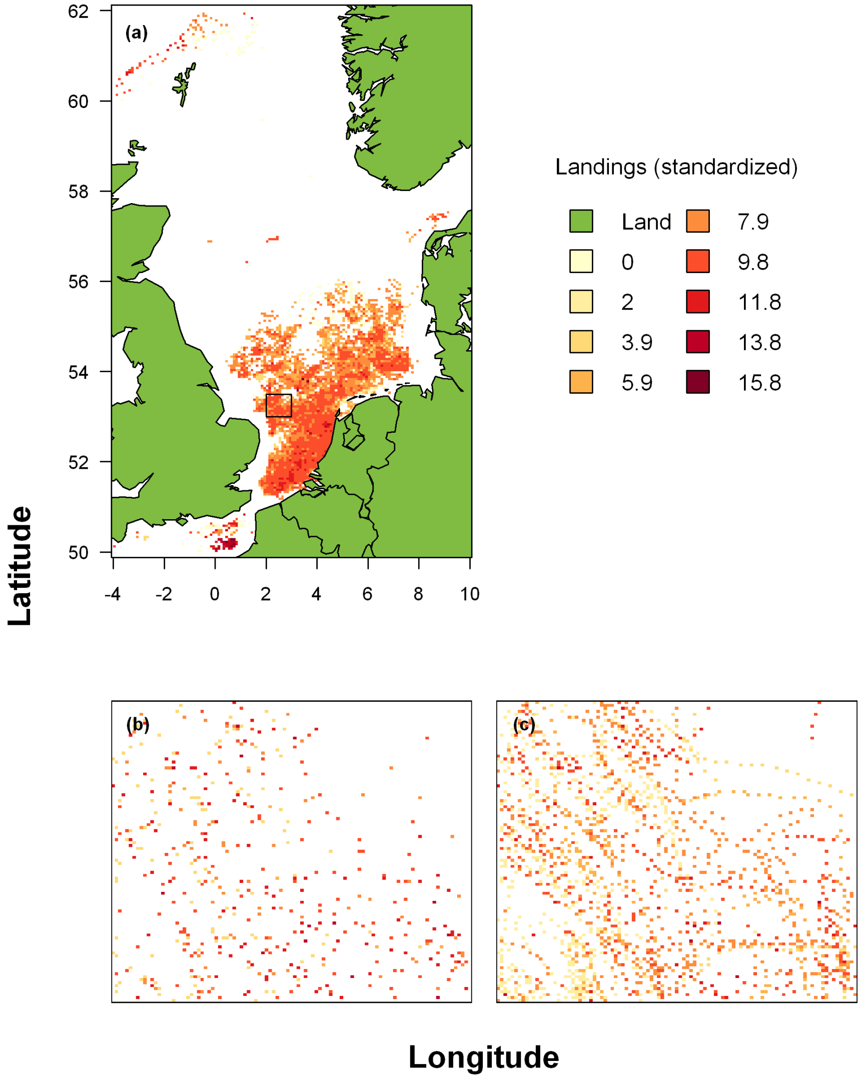

Figure 2.5 Panels show aggregated and standardized (for confidentiality purposes) landings of herring, plaice and sole in (part of) the North Sea where in panel (a) the standardized landings as obtained from the tacsat dataset are shown at a scale of 0.1 × 0.05 in respectively longitudinal and latitudinal degrees. Panel (b) shows an enlargement, and finer spatial scale, of the black squared area from panel (a) at a scale of 0.01 × 0.005 in respectively longitudinal and latitudinal degrees. Panel (c), also shows an enlargement at a finer spatial scale of this area, but is based on a tacsat dataset complemented with reconstructed fishing tracks where each successful track is assigned eight intermediate points. The analyses are based on the example tacsat and eflalo datasets available in the *VMStools* package.

which can be estimated using the function *indicator* in the *VMStools* package. It should be remembered that the choice of the spatial and temporal resolution (month, quarter, year) is of great importance when calculating these indicators.

The DCF indicator 5, distribution of fishing activities, is calculated based on the interval rate between pings in the example tacsat dataset. The minimal number of hours of fishing activity to be included in the calculation was set to 0, while the spatial grid defined had cell dimensions of 0.1° longitude to 0.05° latitude. To calculate the surface, the 'Trapezoid' option was used over a more accurate but slower UTM (Universal Transverse Mercator) projection option.

Visualisation

"A picture is worth a thousand words" is a particularly apt expression in the case of combined VMS and logbook analyses. The presentation of these data on maps which include geographic features such as coastlines and depth contours is extremely useful, and the *VMStools* package contains a rich suite of programs for facilitating such visualisation. Mapping routines have been developed to simplify the visualisation of tacsat and eflalo datasets, supported by existing routines from the *sp* package (e.g. *mapGrid*, *vmsGridCreate*, *plotTools*). These maps can be examined with the standard R plotting functions, while exports to other common spatial data formats are also possible. *Grid2KML*, for example, enables data to be examined in Google Earth, allowing users to interactively zoom in/out. Functionality is also available for creating animated GIFs (Graphics Interchange Format) directly from within R, via sequences of plots (*landingsMaps2GIFanim* using the *animation* R add-on package).

Regional databases

In many situations it is important to be able to assess the impact of fisheries at pan-European scales, i.e. by combining data from many EU member states. The confidentiality of these commercial data (both VMS and logbook), however, means that raw data will not be distributed freely among EU member states in the short term, making integrated analyses impossible. The only realistic solution, therefore, is to combine data from different countries in an aggregated format. In this context, the data warehouse for regional databases FishFrame (ICES, 2009) can now accommodate aggregated tacsat and eflalo data (see Supplementary Appendix D for details). The program *pings2Fishframe* converts combined eflalo and tacsat data into the format used by FishFrame. Within FishFrame, reporting tools then allow users to display and extract any subset or combination of data required. As a proof of concept, FishFrame has been populated with subsets of Dutch and Danish data using tacsat, eflalo and the *VMStools* package.

FishFrame can be accessed over the web (http://www.fishframe.org). An extraction has been made using the 'Data Output' option, while selecting only Danish landing weights for the first quarter of the year 2010 from the available landings VMS report. A C-square spatial grid was used to plot the total weight matching the VMS data. The final figure was exported from the FishFrame web-interface and included in this paper which is shown in Figure 2.6.

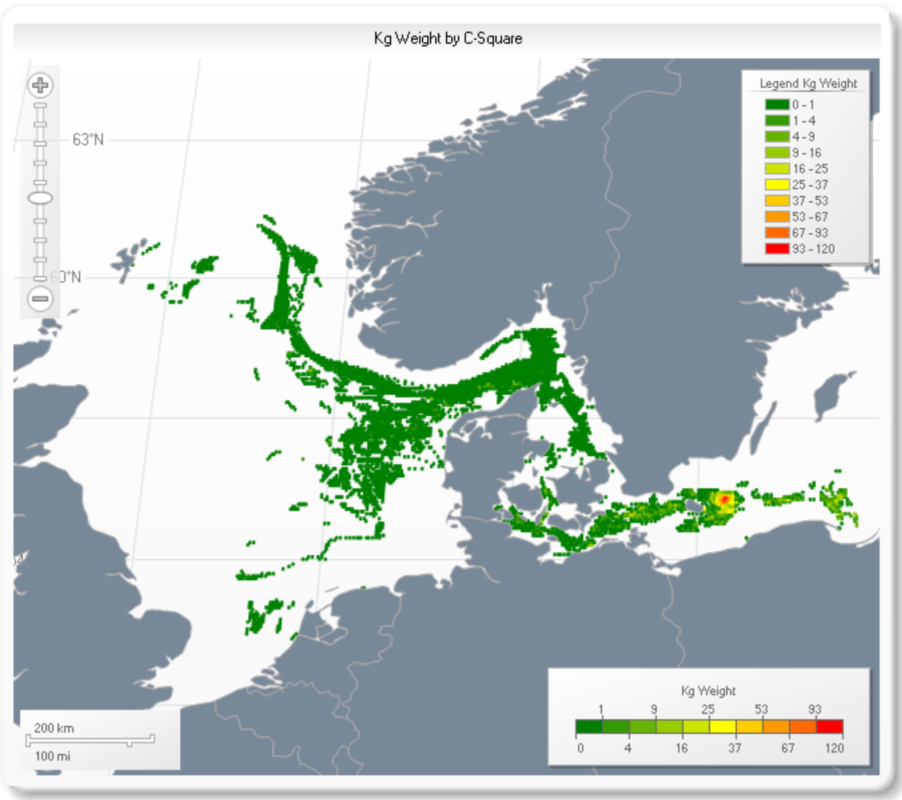

Figure 2.6 Landings (in kg) of Atlantic cod by the Danish fleet in the first quarter of 2010 as extracted from the online FishFrame data warehouse. Landings are aggregated at a scale of 0.05 × 0.05 in longitudinal and latitudinal degrees (smallest C-square resolution).

Table 2.2 Overview of software availability and system requirements.

Name of software	VMStools
Developers	IMARES, DTU-Aqua, IFREMER, CEFAS
Contact	Niels.Hintzen@wur.nl
Year first available	2011
Hardware recommended	2 GB RAM, 2 GHz CPU
Software required	≥R2.11.1, compiled for Unix or Windows OS
Program Language	R
Program size	~4 MB
Availability	http://code.google.com/p/vmstools/downloads/list
Cost	Free, available as package under R

VMStools availability and testing

In Table 2.2, a short overview of software availability and system requirements is given. To ensure the quality of the *VMStools* software, different methods have already been extensively tested and published in peer-reviewed journals (i.e. Bastardie *et al.*, 2010b; Gerritsen and Lordan, 2011; Hintzen *et al.*, 2010). Further testing is promoted through the use of the embedded example tacsat and eflalo which enables reliable and repeatable testing. Thereby, a manual page is written for each function available, which can be accessed at the command line in R or as a printable digital document (also available at http://code.google.com/p/VMStools/downloads/list), which includes an example of the function tested to operate properly when 'compiling' the R package. At the time of writing 78 functions are available in *VMStools*.

Results

The general methods as described above have been applied to the example tacsat and eflalo dataset. As the datasets only comprise a subset of total activity of Dutch vessels over a two year period, no conclusions or remarks are drawn on the basis of actual patterns observed. The tables and figures are for illustration purposes only to present the capabilities of the software.

Cleaning the data

Table 2.1 lists the number of records in the tacsat and eflalo datasets that were removed or flagged as they were regarded to be incorrect. In total 15% of the total tacsat records and 3% of the eflalo records were flagged or removed. Contrary to our findings in the example, in general tacsat datasets contain many duplicate records where either the GPS transponder malfunctioned or the storage of records was processed incorrectly. Due to pre-analyses to construct the example tacsat dataset, most of these have been removed.

Métier identification

For the example eflalo data, the HAC method (i) selects 30, the second method (ii) nine, and the third (iii) 31 species out of the 78 initial species. The combination of these sets defines the species retained. Within this exercise, 32 species which represent 98.9% of the total catch are retained for further analyses (*extractTableMainSpecies*). The PCAs of the "70% of the initial inertia" criteria indicates that 21 axes are needed to retain this threshold. Clusters of similar logbook events characterized by species assemblage are processed using the *getMetierClusters*, where the clustering method CLARA has been used to identify the métiers of the example eflalo dataset. This method proposes a classification in four clusters characterized by one or more species. The clusters count respectively 4040, 69, 244 and 186 logbook events. Cluster one corresponds to a flatfish métier, listing sole and plaice as main target species. Cluster two lists eel and lobster while cluster three is characterized by mackerel and Horse mackerel. The fourth cluster is characterized by sea bass and mullets (see Figure 2.7). Hereafter, the eflalo dataset is complemented with a column indicating the métier identification per logbook event.

Linking eflalo to tacsat data

In total 96% of all tacsat records could be linked to an eflalo record. The results of this process are shown in Figure 2.3a which represents landings from eflalo data by ICES statistical rectangle. Landings are then assigned to tacsat positions and the output summed over the same grid (ICES statistical rectangles, Figure 2.3b); while in the last map (Figure 2.3c) the same data is aggregated over a finer grid. Clearly, while the first two plots are rather similar a totally different understanding of landings by this fleet is gained when examining the data at the finer scales.

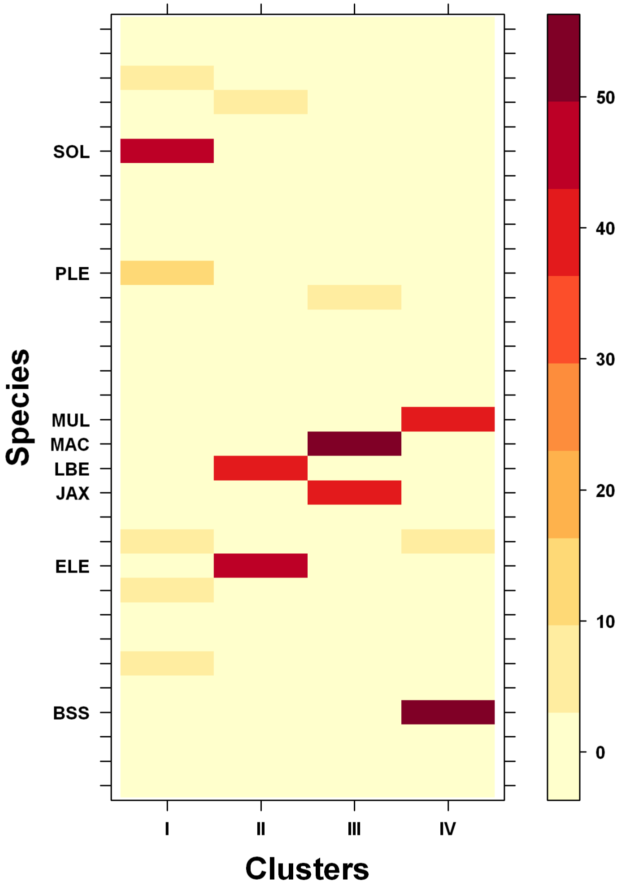

Figure 2.7 Percentage of cash value per species (FAO code) per cluster (I–IV) applying the procedure PCA & CLARA algorithm on the example eflalo data set available in the *VMStools* package. Only species labels with cash value greater than 10% within at least one cluster are displayed for clarity. *Abbreviations*: SOL: sole, PLE: plaice, MUL: Mullets, MAC: mackerel, LBE: European lobster, JAX: Horse mackerel, ELE: Eel, BSS: sea bass.

Fishing activity

Fishing activity has been determined for all vessels, however, Figure 2.2 only shows the results for vessel ID 298138. The analyses, based on speeds, computed from the Euclidian distance and time difference between VMS pings, rather than instantaneous speed, results in a fishing speed upper and lower boundary of respectively 3.29 and 5.31 knots. Figure 2.2a represents the cumulative and pre-smoothed distribution of speeds employed by the vessel, while Figure 2.2b represents the instantaneous speed distribution where Figure 2.2c represents the calculated speed distribution.

Reconstruction of fishing trips with higher ping-rates

In total 11,668 fishing tracks (interpolation between two consecutive VMS pings) were reconstructed from the tacsat dataset, noting that reconstruction is set to take place only when fishing positions are at most 2 h apart. In our test data this amounts to 46% of all tacsat records classified as fishing.

Figure 2.5a presents the fine scale distribution of landings of herring, plaice and sole in the North Sea, identical to Figure 2.3c. The difference between panels (Figure 2.5b) and (Figure 2.5c) shows how the information-density and perception of spatial impact can differ when using different track reconstruction techniques. Figure 2.4a shows the tacsat positions of vessel 157 employing a beam trawl gear. Figure 2.4b shows the same vessel, however, now after reconstruction of fishing trips. Adding a width to the same interpolation (*addWidth*) results in Figure 2.4c and d representing the actual width of the gear.

Indicators

A graphical representation of distribution of fishing activity, calculated based on the example tacsat and eflalo dataset, by month, as follows from Table 2.3, is given in Figure 2.8. The activity is defined as the number of hours of fishing activity in each grid cell.

Table 2.3 Results by month of DCF indicator 5 calculation on three different spatial scales. Spatial scales are given in degrees longitude and degrees latitude respectively. Values denote the total surface (in km^2) with fishing activity by month as calculated as the sum of the grid cells surface with fishing activity.

Month	Spatial scale 1–0.5	Spatial scale 0.1–0.05	Spatial scale 0.01–0.005
1	107,535	6649	100
2	88,238	6866	131
3	74,442	8776	301
4	127,857	9201	150
5	182,241	48,894	1734
6	150,221	17,245	391
7	95,719	4300	69
8	124,076	9769	208
9	182,898	75,217	3337
10	130,768	10,010	136
11	112,094	6355	84
12	49,307	4723	86

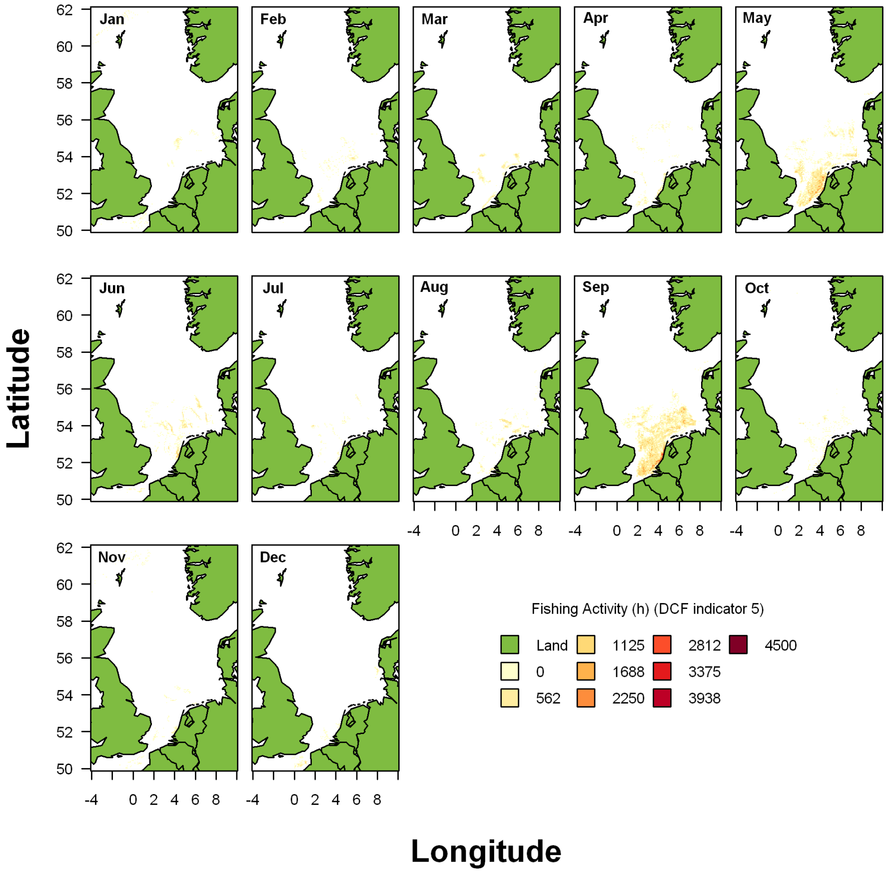

Figure 2.8 Panels show the activity of fishing by month, based on the DCF indicator 5, represented at a scale of 0.1 × 0.05 in respectively longitudinal and latitudinal degrees. The aggregated indicator values can be obtained from Table 2.3. The analyses are based on the example tacsat and eflalo datasets available in the *VMStools* package.

Fishframe

FishFrame is only populated with real data. Hence, the example given in Figure 2.6 represents Danish landings data in (part of) 2010 of species cod. The pre-processing to populate FishFrame with these data was executed using the *VMStools* package.

Discussion

Vessel Monitoring by Satellite system data are valuable for quantifying the fishing activity and impact of fishing on the marine environment. They can be used to inform spatial planning, to address conservation and biodiversity management and to monitor the pressure on the seafloor and bottom impact of fishing (CEC, 2007). This study demonstrates how VMS data and logbook analyses can be performed in an efficient and standardized manner using the *VMStools* package in conjunction with R. Although the literature provides examples of similar procedures, analyses and visualisations of VMS and logbook data (Bastardie *et al.*, 2010a; Fock, 2008; Gerritsen and Lordan, 2011; Hintzen *et al.*, 2010; ICES, 2010; Lee *et al.*, 2010; Pedersen *et al.*, 2009), no framework had yet been presented that enables such analyses to take place in a consistent manner via transparent open-access tools. Similarly, while many previous studies have applied clustering methods to define métiers at the national level (Marchal, 2008; Ulrich *et al.*, 2009), no generic framework for comparing these methods and suggesting a complete, objective and operational workflow for the analyses of landings profiles at the supra-national (regional) level had yet been implemented. The strength of the *VMStools* package is that it has built upon the existing, but isolated tools, to provide such a unified framework. Hence, the *VMStools* library is qualified to respond to the demand for standard and transparent procedures that can be done by different analysts, and is already recommended as the basis for future work on VMS and logbook analyses by ICES (2011).

Here, R was chosen as the development environment for a variety of reasons. In Europe, many fisheries institutes are familiar with its operation, secondly it is freely available, and thirdly it has an ever-growing list of additional libraries (Thyer *et al.*, 2011) which can be utilized within the VMS and logbook analyses. It is often criticised for being computationally slow in comparison with other systems especially when dealing with large datasets such as VMS data. In constructing generic routines, however, we ensured that the algorithms are as efficient as possible and indeed most jobs can be achieved quickly and hence we believe that the advantages of R outweigh its disadvantages. For example, there is no need to switch between different programs to complete a back-to-back analyses, or use complicated interfaces that allow different software programs to communicate with each other, in contrast to other geospatial tools where a suite of programs is used to improve speed performance of the analyses (Roberts *et al.*, 2010; Cagnacci and Urbano, 2008). Further these are often prone to failures when updates are released (Roberts *et al.*, 2010). Moreover, documentation of the generic functions is straightforward, as is the creation of help files and the provision of example scripts. The mapping facilities in R are also very powerful. However, although many of the generic functions take the spherical shape of the earth into account (utilizing additional libraries), it is to be noted that no true GIS environment is mimicked, and this may, in some situations result in small differences, as in most calculations the earth is assumed to be described by a perfect sphere. Especially when decreasing the spatial resolution, the differences become significantly different.

Key to the start of *VMStools* was an agreement on common data formats. The data formats (eflalo, tacsat) were chosen on the basis that many European fisheries institutes had previous expertise in using them for exchanging scientific programs and data. Hence, it was viewed as a practical solution to implement these formats as standard and on which all functions developed rely. The use of these standardized data formats can and has facilitated the development of the software greatly (Kranstauber *et al.*, 2011) and also ensures users of a degree of quality assurance marked as important by ICES (2010). Moreover, the standardized input files can be processed with *VMStools* and then output files can be created which can be uploaded into FishFrame. Once the data are in FishFrame, data from different countries all over the world can then be integrated to produce regional maps. The advantage of this approach is that each country always keeps its raw VMS and logbook data locally, while also being able to exploit the more comprehensive coverage available in the regional database of aggregated data. These aggregated VMS and logbook data can then be linked to other fishery-related data types, e.g. survey information, biological sampling or discard information.

Providing software with built-in functionality to efficiently process and analyse VMS and logbook data also has its downside. Scientists, who are not aware of the implications of the raw VMS and logbook data, can potentially misinterpret the results provided via one of the algorithms. The ability, for example, to distribute landings and the associated cash-values from logbooks among VMS positions is still controversial; although such analyses are already appearing in the literature (Gerritsen and Lordan, 2011). The procedure can give the impression that landings were indeed taken from these very localised positions, and this may be misleading since it is merely an interpretation of independent sources, and thus it depends much on our ability to merge the VMS data successfully with the logbooks and to estimate real fishing activity.

Developing software in science should facilitate the scientific process to either standardize certain processes or make them more efficient. The framework described here enables scientists to easily combine detailed information from, e.g. companies laying cables, oil and gas exploration, or wind farms with fishing activity information which can be used to inform, at fine spatial scale, models that study spatially explicit fisheries behaviour and their impact on marine ecosystems (Bastardie *et al.*, 2010b). The spatial detail comprised by the combined information might be used to link environmental drivers to fisheries behaviour, or even to relate sea mammal tracking data with fishing data for, e.g. spatial overlap studies to determine human-mammal competition (Matthiopoulos *et al.*, 2008) or sea bird movement to fishing activity (Copello and Quintana, 2009) in and outside closed areas (Trebilco *et al.*, 2008).

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Especially when dealing with spatial management, the information obtained from linked VMS and logbook data plays an important role (Dinmore, 2003; Fock, 2008; Murawski *et al.*, 2005; Pedersen *et al.*, 2009; Stelzenmuller *et al.*, 2008) where spatial activity information is used to facilitate the process in designing marine protected areas or inform stakeholders on fishing impact. Similarly, grouping fishing activities into limited numbers of métiers at the regional scale is the first necessary step towards integrated fleet-based fisheries management, allowing moving beyond the current single-stock management schemes when fisheries are mixed (Ulrich *et al.*, 2009; Deporte *et al.*, in press). New insights in these fields, supported by technical advances could easily be incorporated exposing scientific breakthroughs to a much larger public and provide a transition from output to outcome oriented science where applications may change how spatial management is organized (Matthews *et al.*, 2011). Hence, the authors hope that the *VMStools* framework will allow the user to focus on (a better understanding of) the impact of human activities on the marine ecosystem where the knowledge gained, not necessarily the software, plays a central role (Matthews *et al.*, 2011).

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.fishres.2011.11.007.

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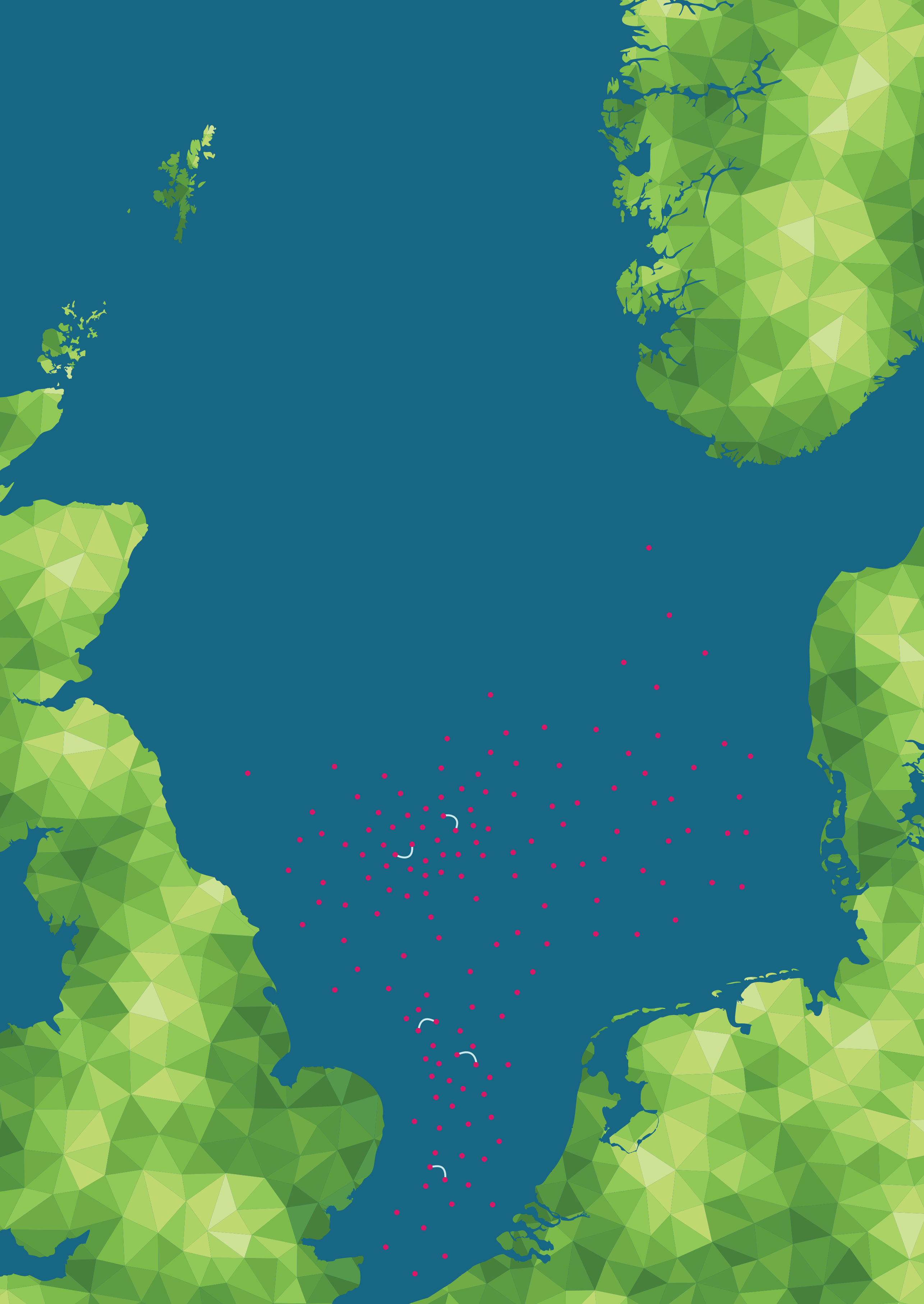

3

Improved estimation of trawling tracks using cubic Hermite spline interpolation of position registration data

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Abstract

For control and enforcement purposes, all fishing vessels operating in European waters are equipped with satellite-based Vessel Monitoring by Satellite systems (VMS) recording their position at regular time intervals. VMS data are increasingly used by scientists to study spatial and temporal patterns of fishing activity and thus fishing impact (e.g. surface of sea bed trawled during a fishing trip). However, due to their low resolution (2 h basis), these data may provide a biased perception of fishing impact. We present here a method aiming at interpolating vessel trajectories from VMS data points to obtain higher-resolution data on vessel trajectories which in turn should provide improved estimates of the spatial and temporal patterns of fishing activity and hence fishing impact. This method is based on a spline interpolation technique, the cubic Hermite spline (cHs), using position, heading and speed to interpolate the trawl track of a vessel between two succeeding VMS data points. To take uncertainty of the interpolated track into account, the method also determines a confidence interval, which represents the spatial distribution of vessel presence probability between two successive VMS positions. The cHs method was compared to the straight line interpolation technique using a reference data set with intervals of 6 min which was assumed to represent the real trawl tracks. The results showed that the cHs method approximates the real trawl track markedly better than a straight line interpolation. The cHs method should therefore be preferred to the conventional straight line approach to interpolate vessel tracks in studies aiming at estimating fishing impact from VMS data.

Keywords

VMS
Interpolation
Fishing impact
High resolution
Hermite spline

Introduction

Originally, the Vessel Monitoring by Satellite system (VMS) was introduced by the European Union in 2002 (EC, 2002) for control purposes to check, among others, whether fishing vessels are operating in areas where fishing activity is not allowed or to check the fishing activity of vessels that hold quotas and licences to fish in specific areas. VMS data is a valuable source of information for fisheries scientists and have manifold potential applications: analyzing the dynamics of fisheries (Kourti *et al.*, 2005), providing high resolution information on fishing effort (Mills *et al.*, 2007) or describing fish distribution (Bertrand *et al.*, 2005). However, most often VMS data is only provided at intervals of one or two hours (Bertrand *et al.*, 2005; Kourti *et al.*, 2005; Mills *et al.*, 2007). This may not be precise enough for some applications, e.g. estimating vessel trawl track (Deng, 2005) or study the impact of fishing gear on the benthic fauna (Piet *et al.*, 2000; Hiddink *et al.*, 2006a,b). Information on a higher resolution is especially needed to accurately account for the effects of trawling on more sedentary ecosystem components such as benthic organisms (Piet and Quirijns, 2009) and to measure fleet responses to management actions (Mills *et al.*, 2007). A possible solution for this problem is to interpolate between the position registrations, resulting in improved high resolution estimates of spatial fishing patterns.

Most research on interpolating trajectories is carried out in the field of animal tracking experiments (Jonsen, 2003; Ryan, 2004; Jonsen, 2005; Tremblay, 2006; Hedger *et al.*, 2008) where several different types of techniques, such as state-space modeling, random walk approaches and spline interpolations, have been used to either capture animal behavior or to reconstruct their movement patterns. Most of these studies use GPS positioning data as their main source of information. However, in fisheries, only few have attempted to capture fishing vessel behavior based on tracking data like VMS. In these attempts fishing impact was mostly represented by the VMS data points themselves (Rijnsdorp *et al.*, 1998; Dinmore, 2003; Hiddink *et al.*, 2006a,b; Piet *et al.*, 2007). But some recent studies have focused on interpolating trawl tracks from GPS positioning data. In this area of research, linear interpolation (connecting succeeding data points with a straight line) is commonly applied and only the width of the gear is accounted for in reconstructing a trawled surface (Eastwood, 2007; Stelzenmuller *et al.*, 2008). However, Deng (2005) stated that straight line interpolation is still likely to underestimate the length of the trawl track, especially when the interval between position registrations is large. Two different

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models, formulated by Fock (2008) and Mills *et al.* (2007), aim to account for this underestimation of track length and, at the same time, consider uncertainty of the trawling track. The model formulated by Fock (2008) reallocates effort based on the behavior of the fishery. Effort is allocated to four new points, each differing one quartile from each other, starting along the line to the succeeding position record. Mills *et al.* (2007) approach is in principle similar to that of Fock (2008) as he also redistributes estimated trawling effort based on a straight line interpolation between successive VMS records. However, Mills uses a 'best estimate' between minimum and maximum deviation from the straight line as the determinant for the uncertainty estimate. These methods are one of the few to consider uncertainty on the trawl track. None of the fisheries related attempts however, have considered using an interpolation method other than based on a linear interpolation between two succeeding points.

The method described here interpolates the trajectories of fishing vessels between succeeding VMS data points using a technique based on a cubic Hermite spline interpolation. The emerging curved trajectories have been applied to reconstruct animal tracks (Tremblay, 2006). In addition to the position information provided within VMS data, the method can also incorporate speed and heading at VMS data points, thereby ensuring more accurate estimations of the real vessel trawl track.

Two types of use of trawl tracks based on VMS data can be distinguished: one uses the tracks to determine the impact on an area in terms of the proportions of the surface of that area trawled with a specific frequency (Piet *et al.*, 2000). The other involves the analysis of samples in fished and unfished areas, or along gradients of fishing intensity (Frid *et al.*, 1999; Blyth *et al.*, 2004; Tillin *et al.*, 2006). In the first case the main requirement of a reconstructed trawl track is that its length needs to be accurately estimated while in the second case it is the position of the trawl track. Hence, there is a need for an interpolation technique that can cover both these purposes.

The aim of this paper is to show how the cHs method can be applied to estimate trawl tracks from position registration data. In addition, the method provides a confidence interval around the interpolated track, reflecting uncertainty in the estimation of the interpolated track. In order to accommodate both uses of estimating trawl tracks we used two approaches to optimize the performance of this new method against the commonly used straight line (SL) interpolation technique.

Materials and methods

Data description

To evaluate the performance of the cHs method in interpolating between position registrations, we used Automatic Position Registration (APR) data with a much shorter time interval (6 min) than the regular VMS data (with 1–2 h intervals on average). We assume that these APR data describes the real trawling track and is used as a reference.

The APR data were obtained as part of a study to investigate the micro-scale distribution of beam trawl effort in the Dutch flatfish fishery (Rijnsdorp *et al.*, 1998). Within this study, positions of vessels were recorded every 6 min with an Automated Position Recording system that was connected to the navigator (Decca, GPS, DGPS). Position information was recorded on a removable memory card with an accuracy of 0.1 min (±180 m). The accuracy of the recorded position is less than that of the navigator (±12–100 m). At each position, the speed of the vessel (S) was calculated from the distance covered to the subsequent position multiplied with the time interval between these data position points. The average speed during fishing (FS), was 6 knots, with some variation between vessels related to the engine power, and differed from the speed during steaming (about 12 knots). Position recordings were classified in one of three classes (fishing, steaming, floating) based on the speed of the vessel. Hence fishing positions were defined as: FS-2≤Speed≤FS + 2; steaming positions: Speed > (FS + 2); floating positions: Speed < (FS-2) (Rijnsdorp *et al.*, 1998). In this study, only fishing records have been used. Heading of the vessels at each recorded position is not given in the 6 min data set. These headings had to be calculated separately, taking into account the spherical shape of the earth. At each position, heading was calculated based on the direction towards the subsequent position. Computed speed and headings were added to the dataset. This however implies that vessels were always heading straight towards the next interval, 6 min later. The following information obtained from this dataset was used within this study: ship name, year, month, day, hour and minute of the registration, position in degrees longitude and latitude with resolution of 0.1 min, speed of the vessel and heading. These sources of information are currently present in all European VMS data. The interpolation method developed is applied to VMS like data (with a 2 h interval), generated from the APR data, while the original 6 min interval data is used to test the accuracy of the method.

Selecting the interpolation technique

Several interpolation techniques could potentially be used to estimate fishing trajectories from VMS data points. However, the size of most VMS data sets is very large thereby requiring many interpolations. Hence, the choice for an interpolation method depends on the ease of construction and quickness of computation. In addition, the method should ideally incorporate as much of the information available in the VMS data, be able to deal with discontinuous data (as VMS pings might be missing, or non-fishing pings are removed) and should pass through the given position registration points.

A linear interpolation, connecting succeeding position registration points, is one of the easiest and quickest interpolation techniques that can deal with discontinuous data. However, additional information that is available on heading and speed that might indicate a trajectory deviating from the shortest route between two points is not incorporated thereby compromising its ability to reconstruct a fishing trajectory. Another technique, referred to as spline interpolations are often used in interpolation studies (Tremblay, 2006; Hedger *et al.*, 2008; Hijmans *et al.*, 2005; Hedin *et al.*, 1996; Jeffrey *et al.*, 2001). These splines can be considered to minimize the measure of roughness in an interpolation and are defined by piecewise polynomials which make them easy to implement. The family of splines however is big, each member having its own advantages and disadvantages. Many interpolation splines need four position data points to interpolate the trajectory between two points. However, since the VMS data used is discontinuous at times (i.e. only two or three sequential points are available), the use of these types of splines will interpolate less trajectories in comparison to e.g. a linear interpolation which only needs two points. Other splines, like Bézier splines, do not pass through all position registration points available, and hence cannot be used within this study. The cubic Hermite spline (Hermite, 1863; de Boor, 1978) needs four points too. However, the combination of heading and speed at both registration points are treated as two points. Together with the VMS data points, the interpolation can be constructed. This latter method is easy to construct as it is based on four polynomials, passes through all position registration points, can be applied on discontinuous data because of the need of only 2 registration points and can also incorporate the data on heading and speed that is available in the VMS dataset.

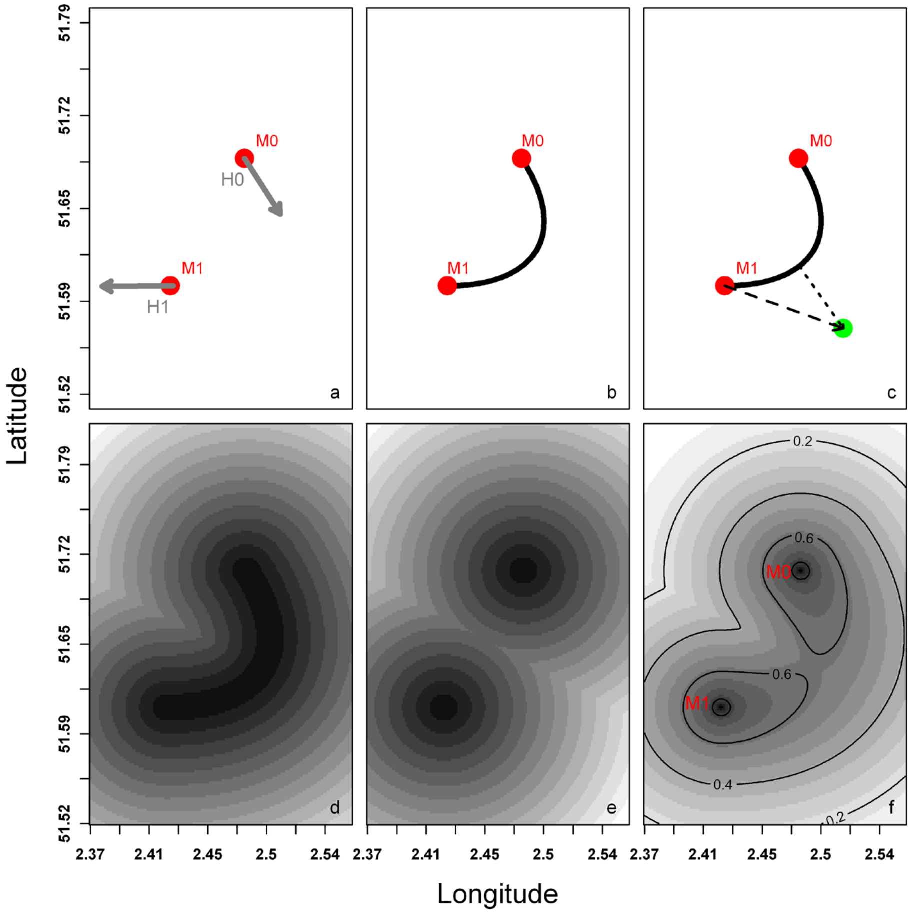

Figure 3.1 Schematic representation of the process starting with two succeeding VMS position registrations towards an estimated track surrounded by a confidence interval. (a) The start- and end-point of the vessel are represented by M_0 and M_1 respectively, the heading of the vessel at start- and end-point are represented by the small arrows H_0 and H_1 . Based on the value of *fm* these arrows become longer/shorter influencing the curvature of the interpolation (see panel b). For small values of *fm* the interpolation will approximate a straight line between M_0 and M_1 . (b) Interpolated track based on cubic Hermite spline (black solid line). (c) The parameter D_{SD} for a random point on a grid (green dot) depends on the distance marked by the dashed arrow (black dashed arrow) from M_1 to the green dot. The parameter D_{scale} for a random point on a grid (green dot) depends on the shortest distance from the green dot to the interpolated trajectory. This distance is represented by the dotted arrow (black dotted arrow). (d) Shortest distance from each point on a grid to the interpolated track. Lighter grey represents more distant grid cells. This distance is used to define the value of parameter D_{scale} for each point on a grid. (e) Shortest distance from each point on a grid to either M_0 or M_1. Lighter grey represents more distant grid cells. This distance is used to define the value of parameter D_{SD} for each point on a grid. (f) Interpolation between two succeeding VMS data points surrounded by a confidence interval. At positions M_0 and M_1, values equal one.

cHs method

The cubic Hermite spline is a third-degree spline where each polynomial is in the Hermite form. The cHs method uses two of these polynomials to describe separately the interpolation in the longitudinal and latitudinal direction in relation to time. A polynomial in the Hermite form consists of two control parameters, here each represents a combination of speed and heading (see Equation (3.1)), named H_0 and H_1 originating at the two control points M_0 and M_1. Vectors representing speed and direction (H_0 and H_1) are obtained by combining components in the longitudinal and latitudinal directions ($H_{k,i}$ and $H_{k,j}$). The control points are represented by the GPS positions at M_0 and M_1. The equation describing the cubic Hermite spline in both longitudinal and latitudinal direction (resp. f_{lon} and f_{lat}) over the normalized time interval t is given in Equation (3.1).

3

$$
\begin{aligned}
&H_{k,i} = speed \cdot \sin(heading)\\
&H_{k,j} = speed \cdot \cos(heading)\\
&\quad \text{With } k\{0, 1\}\\
&\quad k = 0 \text{ denotes the start position, } k = 1 \text{ denotes the end position}\\
&f_{\text{lon}}(t) = (2t^3 - 3t^2 + 1) \cdot M_{0,i} + (t^3 - 2t^2 + t) \cdot H_{0,i}\\
&\qquad\quad + (-2t^3 + 3t^2) \cdot M_{1,i} + (t^3 - t^2) \cdot H_{1,i}\\
&f_{\text{lat}}(t) = (2t^3 - 3t^2 + 1) \cdot M_{0,j} + (t^3 - 2t^2 + t) \cdot H_{0,j}\\
&\qquad\quad + (-2t^3 + 3t^2) \cdot M_{1,j} + (t^3 - t^2) \cdot H_{1,j}\\
&\quad \text{With } t \text{ element of } [0, 1]
\end{aligned}
\tag{3.1}
$$

The interpolated track is projected onto a large grid, which represents the sea surface. This grid consists of grid cells with sizes depending on the chosen resolution (here a resolution of 0.3 nm x 0.3 nm per grid cell is chosen). Hence, each grid cell has a position on the grid and is referred to by one longitude and latitude value.

The calculation of the confidence interval depends on two variables: $D_{int,G_{i,j}}$ and $D_{M,G_{i,j}}$. $D_{int,G_{i,j}}$ is defined as the shortest distance of a point $G_{i,j}$ on a grid (i and j denoting longitude and latitude respectively) (see Equation (3.2)) while $D_{M,G_{i,j}}$ is defined as the shortest distance from point $G_{i,j}$ to either M_0 or M_1 (see Equation (3.3)).

$$
\begin{aligned}
&D_{int,G_{i,j}} = \min\left([G_i - f_{\text{lon}}(t)]^2 + [G_j - f_{\text{lat}}(t)]^2\right)^{1/2}\\
&\qquad\qquad \text{With } t \text{ element of } [0, 1]
\end{aligned}
\tag{3.2}
$$

$$D_{M,G_{i,j}} = \min\left([(G_i - M_{0,i})^2 + (G_j - M_{0,j})^2]^{1/2}, \; [(G_i - M_{1,i})^2 + (G_j - M_{1,j})^2]^{1/2}\right) \tag{3.3}$$

The probability of a specific position on a grid, $P_{G_{i,j}}$ being trawled during the vessel movement is given by Equation (3.4). The spatial probability assumes a Gaussian distribution where distance to the interpolated track relates to the difference from the mean of the distribution (i.e. mean = 0), and distance to either start- or end-point is used as a measure for the standard deviation of the probability distribution. Note that the probability is at its maximum at both the start- and end-point and these are scaled to 1. All other positions are scaled accordingly.

$$P_{G_{i,j}} = \frac{1}{\sqrt{2\pi D_{M,G_{i,j}}}} \exp\left(-\frac{1}{2}\left(\frac{D^2_{int,G_{i,j}}}{D^2_{M,G_{i,j}}}\right)\right) \tag{3.4}$$

3

Several parameters have been used to optimize and scale the outcome of the algorithm to the spatial scale it is applied on. The vectors at point H_0 and H_1, representing both speed and heading, can be multiplied with a variable *fm* to either increase or reduce the vector length and hence the effect of the heading and speed on the interpolation. The parameters D_{scale} and D_{SD} are defined to scale respectively D_{int} and D_M. D_{scale} scales the distances from each position on a grid by multiplying D_{int} with D_{scale}, while D_{SD} scales D_M according to; D_M raised to the power D_{SD}. Hence,

Equation (3.1) can be rewritten as:

$$\begin{aligned} f_{\text{lon}}(t) &= (2t^3 - 3t^2 + 1) \cdot M_{0,i} + (t^3 - 2t^2 + t) \cdot fm \cdot H_{0,i} \\ &\quad + (-2t^3 + 3t^2) \cdot M_{1,i} + (t^3 - t^2) \cdot fm \cdot H_{1,i} \\ f_{\text{lat}}(t) &= (2t^3 - 3t^2 + 1) \cdot M_{0,j} + (t^3 - 2t^2 + t) \cdot fm \cdot H_{0,j} \\ &\quad + (-2t^3 + 3t^2) \cdot M_{1,j} + (t^3 - t^2) \cdot fm \cdot H_{1,j} \end{aligned} \tag{3.5}$$

With t element of [0, 1]

And Equation (3.4) can be rewritten as:

$$P_{G_{i,j}} = \frac{1}{\sqrt{2\pi D^{D_{\text{SD}}}_{M,G_{i,j}}}} \exp\left(-\frac{1}{2}\left(\frac{[D_{int,G_{i,j}} \cdot D_{\text{scale}}]^2}{[D^{D_{\text{SD}}}_{M,G_{i,j}}]^2}\right)\right) \tag{3.6}$$

The process of interpolating between two succeeding VMS position registrations towards a spatial impact estimate of a fishing trip is schematically represented in Figure 3.1. Two succeeding VMS data points, M_0 and M_1, are connected by the cHs while velocity vectors at both these points (H_0 and H_1) determine the curvature of the interpolation. Higher speeds result in more convex interpolated trajectories. The spatial confidence interval added to the interpolation depends on both the distance from a specific point in space to the interpolated track and the distance from this specific point to either the start- or end-point. The probability that a vessel has trawled an area is reflected by the confidence interval.

Optimization

Optimization processes were designed to find a parameter space that provides the best approximation of the real track by the algorithm. This was carried out for two different scenarios, starting by only varying the parameter *fm*. In the first scenario the average distance between the interpolated track and the real track was minimized. In the second scenario, the difference in total length of the interpolated track and the real track was minimized. Hereafter, the results for *fm* were subsequently used to find a parameter space for D_{SD} and D_{scale}. In between two successive registration points, each vessel has a maximum travel range. This is defined as an ellipse by Mills *et al.* (2007) having the two data points as focal points. The width of the confidence interval is optimized to equal a 5% chance that a vessel went outside this maximum travel range. The probability at both start- and end-point (M_0 and M_1) are optimized to equal one. For the optimization, 10 weekly fishing trips, each from a different Dutch beam trawler, were randomly selected from the APR dataset (period 1993–1996). The fishing trips comprised between 26 and 48 interpolations (mean = 40), where one interpolation is the estimate of the trawl track between two position registrations deemed to be fishing, and 2 h apart. A two-tailed sensitivity analyses of the parameters was executed by optimizing the objective function to be 10% higher than the result of the scenario optimization run.

Comparison

The fit of both optimization processes for the cHs interpolation were compared to the fit of an interpolation by a straight line (SL). The accuracy of the fit of the first optimization was described by the distance between the real track and the interpolated track, higher distances indicated a poorer fit. This distance was estimated by dividing the cHs, SL and real track of a particular interpolation, over the same time interval, into 99 equal time increments, ob-

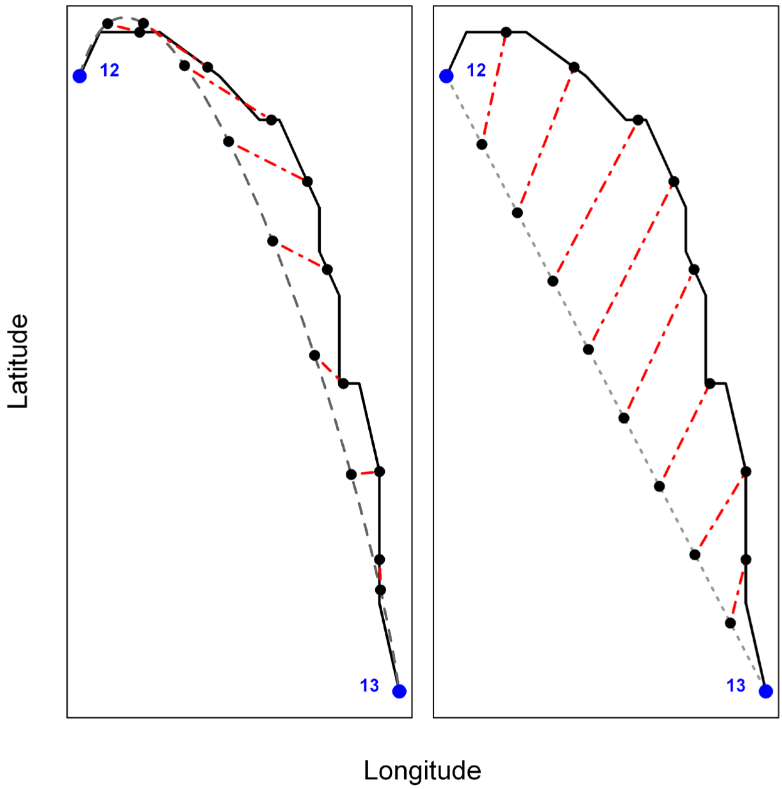

Figure 3.2 Graphical example of the computation of the average distance between an interpolation and the real track which is based upon the average length of the red dash-dotted lines (in total 100, only 8 displayed in the figure for clarity). Left: representation of the true track (black solid line) between two succeeding VMS data points (blue points) and the cHs interpolation (dark grey dashed line). Red dash-dotted lines indicate the distance between the real and the interpolated track at equally spaced points. Right: as left but for a straight line interpolation compared to the real track.

taining 100 positions on the track. Distances between the interpolations at each point x and the real track were summed (see Equation (3.7), see Figure 3.2 for a graphical example) and divided by 100 to determine the average distance, $\overline{Dist}$, from the cHs and SL interpolations to the real track:

$$\overline{Dist} = \frac{1}{100} \cdot \sum_{x=1}^{100} \left([R_{\text{lon}}(x) - F_{\text{lon}}(x)]^2 + [R_{\text{lat}}(x) - F_{\text{lat}}(x)]^2 \right)^{1/2} \tag{3.7}$$

where $R_{lon,lat}$ represents the real track while $F_{lon,lat}$ represents either the cHs or the SL interpolation.

The length of the cHs interpolation can be calculated analytically while the length of the real track can be computed by adding up the distances between each 6 min data point (as they are assumed to be connected by a straight line). The length of the SL interpolation ($Length_{SL}$) can be computed using the coordinates of the start- (0) and end-point (1) (see Equation (3.8)).

$$Length_{SL} = 2 \cdot \text{atan2}\left(\sqrt{b}, \sqrt{1-b}\right) \cdot R \tag{3.8}$$

$$b = \sin^2\left(\frac{M_{1,j} - M_{0,j}}{2}\right) + \cos(M_{0,j}) \cdot \cos(M_{1,j}) \cdot \sin^2\left(\frac{M_{1,i} - M_{0,i}}{2}\right)$$

3

where R represents the earth's radius in km.

The differences of both the interpolations in length with the real track indicate to what extend the methods can approximate the real track length.

Results

By tuning the parameters to the two different scenarios described in Section 2.4, optimal parameter values were obtained representing the multiplication factor of the length of the vectors in Figure 3.1a (*fm*), scaling of distance to the interpolated track (D_{scale}) (Figure 3.1c and d) and scaling of distance to either the start- or endpoint (D_{SD}) (Figure 3.1c and e). Table 3.1 lists the parameter settings for the two scenarios, including the results of the sensitivity analyses. As an example, Figure 3.3 shows a trawl track consisting of 12 succeeding interpolations between position registrations with a 2-h interval, based on the parameter setting for scenario 1. Each interpolation between these points is presented separately in Figure 3.3 as well, clarifying the differences in track estimation for the cHs interpolation and a straight line interpolation in comparison to the real track. In 9 out of 12 of the examples, the cHs interpolation approximates the real track better than the SL interpolation,i.e. $\overline{Dist_{cHs}} < \overline{Dist_{SL}}$. In three cases however, i.e. between succeeding points 3–4, 4–5 and 7–8, the SL performs better than the cHs interpolation.

Table 3.1 Parameter setting obtained from the optimization process for the two different scenarios. 1: minimum average deviation of cHs from real track. 2: minimum difference between total length of cHs and real track. Sensitivity analyses results are given between parentheses.

Scenario	*fm*	D_{scale}	D_{SD}
1	0.20(±0.08)	19.74(±4.06)	0.20(±0.04)
2	0.47(±0.03)	16.92(±3.10)	0.19(±0.05)

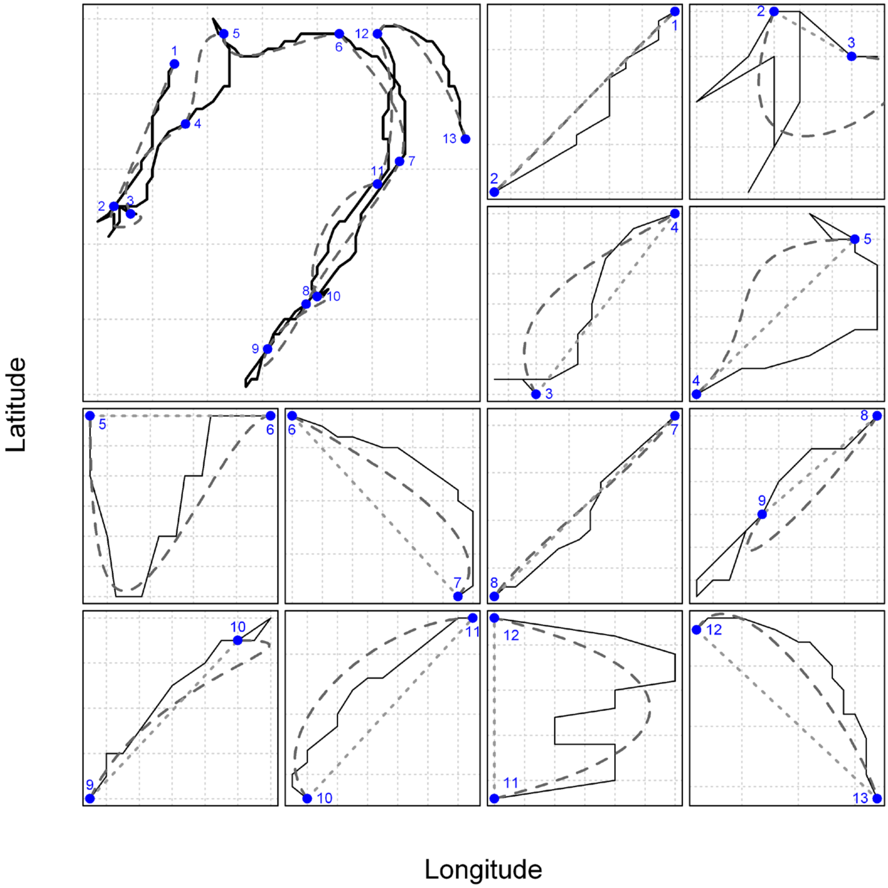

Figure 3.3 Estimation of the real trawl track (top left, solid black line) consisting of 13 succeeding 2-hourly position registrations (blue points) obtained from APR dataset 1 (see Figure 3.4). The cHs interpolation is represented by the dashed dark grey line. (Smaller panels) Estimations of the real trawl track between two succeeding position registrations (blue points) (corresponding to the tracks shown in the top-left panel), the cHs interpolation (dark grey dashed line) and straight line interpolation (light grey dotted line).

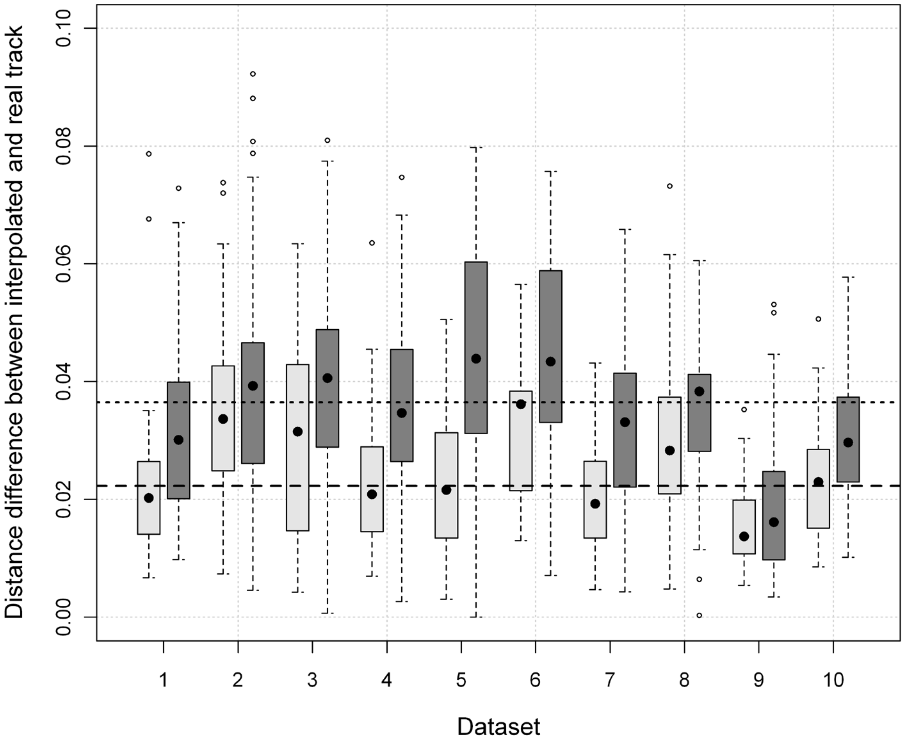

Figure 3.4 Comparison of the average distance between the real track and the estimated track based on the cubic Hermite spline (cHs) (light grey) using optimization scenario 1 and the straight line (SL) method (dark grey) presented in a boxplot. The first and third quantile of each dataset are represented by the shaded boxes, while minimum and maximum observations, not being outliers, are represented by the dotted vertical lines. Outlying results (more than 1.5 times the interquantile distance away from the 1st or 3rd quantile) are represented by open circles. Smaller distances represent a closer fit of the interpolation to the real track, where a distance of 0 indicates a perfect fit. cHs median across the datasets is indicated by the black dashed line, while median for the SL interpolation is represented by the light grey dotted line.

The difference between $\overline{Dist}_{SL}$ and $\overline{Dist}_{cHs}$ varies per data set (see Figure 3.4) but is on average 39% (sensitivity ranges: +:30%,−:27%) less when based on the cHs method with optimization scenario 1 in comparison to the SL interpolation. This indicates that the estimation by the cHs method of the real track is markedly better than the approximation of the SL method. Using the parameter settings optimized for scenario 2 however result in a larger difference compared to the SL approach (−12%, +:−20%,−:4%).

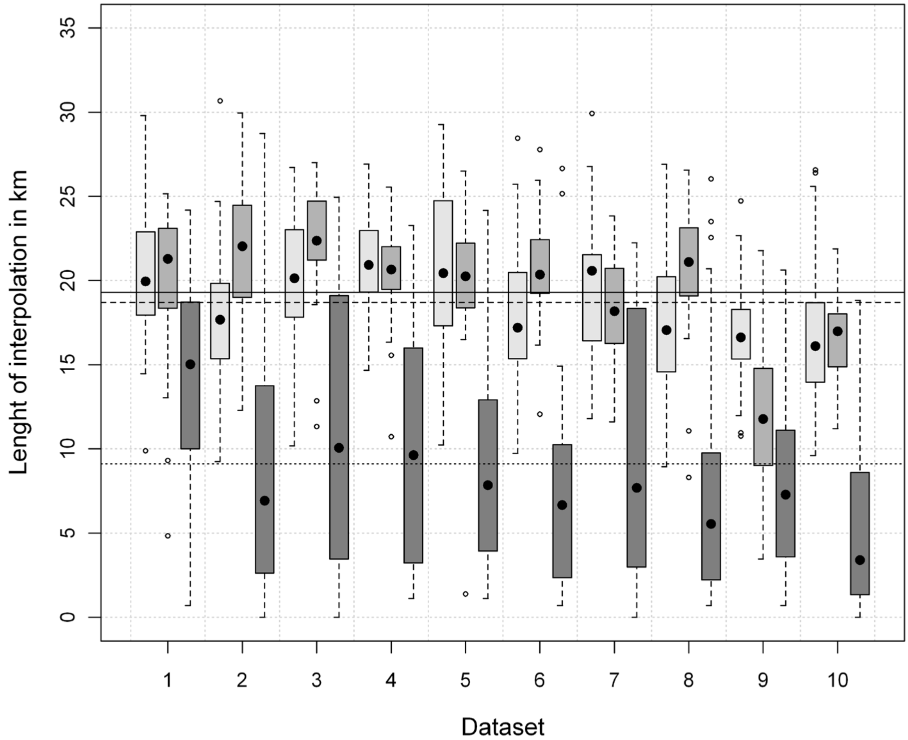

Figure 3.5 Comparison of the length of the interpolations with the length of the real track. cHs (optimization scenario 2) is presented by the light grey boxplot at the left hand side, real track by the grey boxplot in the middle and SL by the dark grey boxplot on the right hand side of each dataset. cHs median across the datasets is indicated by the dark grey dashed line, while median for the SL interpolation is represented by the light grey dotted line and median for the real track is presented by the black solid line.

Figure 3.5 shows the total length of the estimated fishing tracks, under the parameter settings of optimization scenario 2, for both the cHs and SL interpolation and the real track. The estimate of the total distance trawled by the cHs approximates the real track distance to a high level. The SL method however, considerably underestimates the real track length. The deviation of the real track length by the cHs method is on average less than 3% (+:−6%,−:3.2%), while this deviation of the SL method is on average 53%. When parameter settings of scenario 1 are used, the deviation is on average 36% (+:25%,−:45%), which is still better than the estimation by the SL method

3

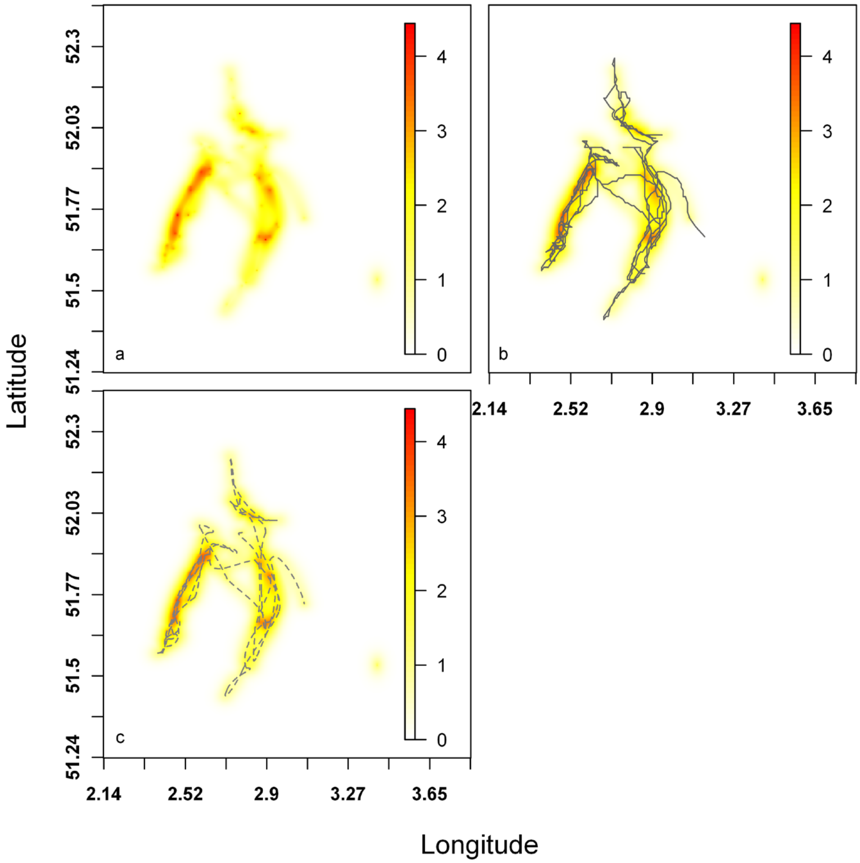

Figure 3.6 (a) Estimation of average number of times an area is probably trawled based on the application of the cubic Hermite spline interpolation on the VMS position registrations of one fishing trip of one vessel during approximately 1 week of fishing. (b) Same as (a), including real trawl tracks (dark grey solid line). (c) Same as (a), including cHs interpolated trawl tracks (grey dashed line).

Interpolated tracks from many different VMS data points, each including a confidence interval, can be combined in order to provide a detailed overview of total fishing impact. This may be the total fishing impact of one vessel over an entire trip but can also be the combination of several trips of the same vessel or of many vessels belonging to the same fishery. Figure 3.6a represents the estimation of average number of times the area is probably trawled by one vessel during one fishing trip. Figure 3.6b and c respectively represent the same average number of times the area is probably trawled including the real vessel track (b) and the cHs interpolated track (c). The chance of a specific area to be trawled cannot exceed the value 1 in a single interpolation. However, when fishing vessels cross already trawled areas, chances can be summed, resulting in a decreased chance the area has not been fished, or interpreted in another way: an increase in the average number of times it has probably been trawled. Note that this should be considered an estimate of trawling intensity and does not represent the number of times it is actually trawled.

Discussion

This study has shown that the cHs function can estimate the fishing track between VMS position registrations better than the commonly used linear interpolation. This follows Deng's (2005) statement that fishing tracks are rarely straight and it is therefore very likely that linear interpolations underestimate the true length of trawl tracks. The cHs method introduced in this study provides a much better approximation of the true trawl length by only underestimating the true trawl length by less than 3% on average. Estimates of the fishing impact based on a calculated area trawled which, in turn, is based on the estimated trawl length (Hiddink *et al.*, 2006a,b; Piet *et al.*, 2007) would therefore be more accurate when based on tracks interpolated with the cHs method.

The increased accuracy in using the cHs method in comparison to straight line interpolations is also reflected by the average distance between the estimated and real track which is 39% smaller. Hence, the cHs method has the ability to supply more accurate information at higher spatial resolution, while it should be noted however that not all sources of uncertainty are taken into account, e.g. accounting for uncertainty in VMS position registration. The combination of the accurate interpolation and the possibility to determine a confidence interval is useful in studies aiming at determining the impact of fishing on a specific ecosystem component comparing samples from fished and unfished areas, or following a gradient of fishing intensity as in Frid *et al.* (1999), Blyth *et al.* (2004), Tillin *et al.* (2006) and Craeymeersch *et al.* (2000).

For both applications, the first one using the tracks to determine the impact on an area in terms of the proportions of the surface of that area trawled with a specific frequency and the second involves the analysis of samples in fished and unfished areas, or along gradients of fishing intensity, different parameter optimization methods were developed. Using the optimization method corresponding to one application affected negatively the outcome for the other application which is shown by the sensitivity analyses. This shows that the cHs method does not estimate one perfect path, and in our case still underestimates track length. Better under standing of the behavior of the fisheries, combined with accounting for spatial distribution of the target species might result in an even better approximation of the real track as the parameter settings or confidence interval might be adjusted for these new insights. However, even when parameter settings for scenario 2 were switched with scenario 1 to test the applications, the performance of the cHs method remained an improvement compared to the SL method.

This method cannot perfectly estimate the trawl path as the cHs can only produce smoothed trajectories and is unable to reproduce the erratic behavior of fishing vessels, such as sudden changes in direction (cf. Figure 3.3, between points 2 and 3). However, such sudden changes in direction do not necessarily represent the true behavior of the fishing vessels, since the assumption of a straight line track between two succeeding data points may not always be true. Note that this pre-smoothing of the APR data might have influenced the interpolation fitting and hence is a source of uncertainty of the method's success. Despite this shortcoming, the cHs method, performs markedly better than the commonly used straight line methods developed and applied by Eastwood (2007) and Stelzenmuller *et al.* (2008).

The cHs method functioning also depends on the fisheries it is applied to. As this method has been tuned here for the specific case of the Dutch beam trawl fishery, showing variability on a vessel level in the success of trawling track estimation, the parameter estimates are probably not suitable for applying the method to other fisheries. However, the method is designed to be generic as it uses VMS data containing information on; direction, speed and registration points, which are available in all European VMS data. As the method is specifically using speed recordings to distinguish activities, and assumes a speed >0 while fishing, it is very likely that the cHs method can be applied to other towed gear fisheries, provided that high resolution data are available for the tuning procedure, and provide better track interpolations than the SL method. It should be noted however that in this specific case, the interval of VMS records is approximately the same as the duration of a haul. Interpolating VMS records for fisheries with a shorter haul duration would most likely require a higher VMS record interval to successfully apply this method.

Finally, this method can inform the choice of the time interval required for the control and enforcement purposes for which VMS was initially intended. An improved interpolation algorithm, like the cHs method, can allow longer time intervals for the same precision, thereby increasing the cost-efficiency of VMS.

Acknowledgements

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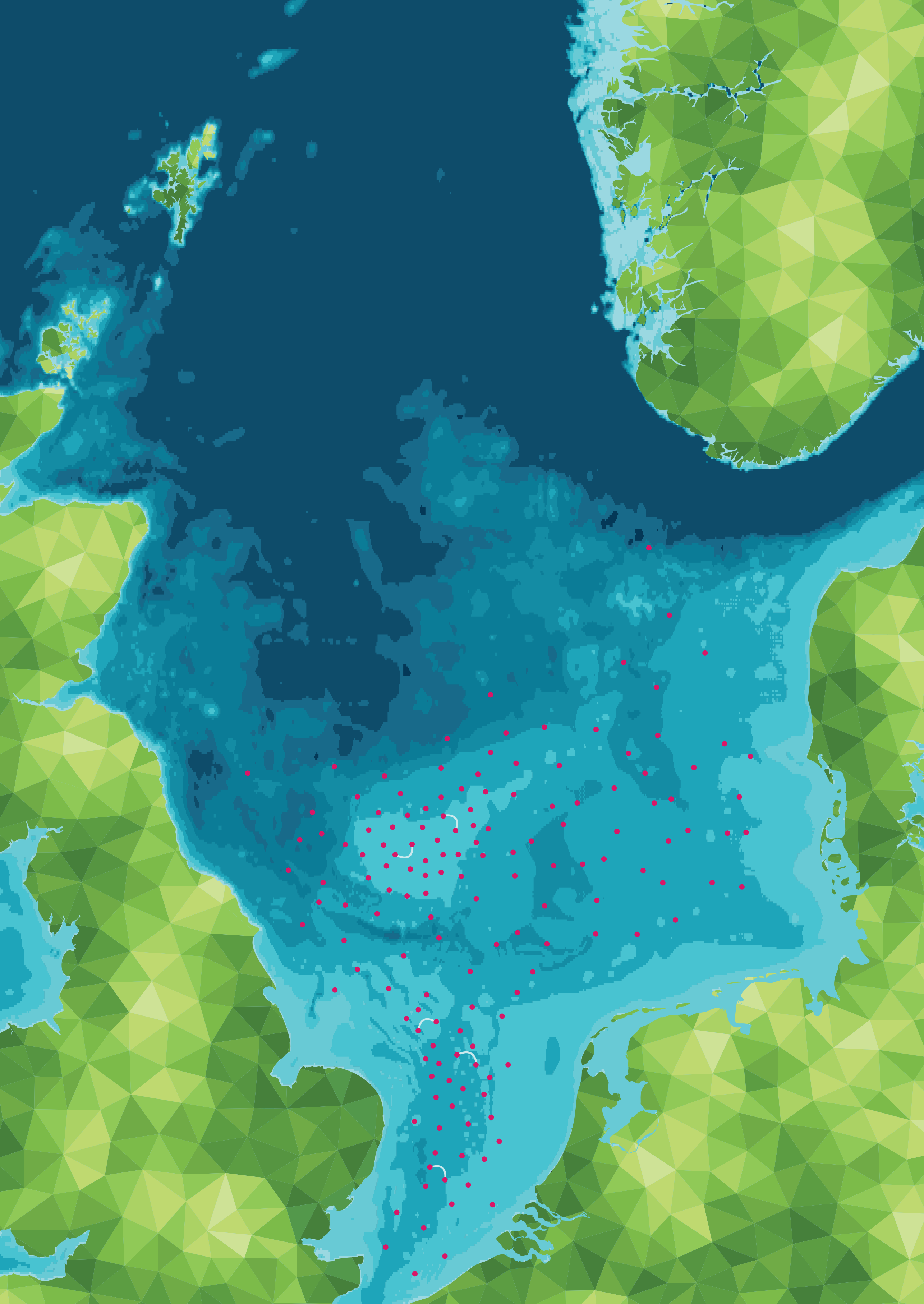

4

Persistence in the fine-scale distribution and spatial aggregation of fishing

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Abstract

High-resolution vessel monitoring (VMS) data have led to detailed estimates of the distribution of fishing in both time and space. While several studies have documented large-scale changes in fishing distribution, fine-scale patterns are still poorly documented, despite VMS data allowing for such analyses. We apply a methodology that can explain and predict effort allocation at fine spatial scales; a scale relevant to assess impact on the benthic ecosystem. This study uses VMS data to quantify the stability of fishing grounds (i.e. aggregated fishing effort) at a microscale (tens of meters). The model links effort registered at a large scale (ICES rectangle; 1° longitude x 0.5° latitude, ~3600 km^2) to fine spatial trawling intensities at a local scale (i.e. scale matching gear width, here 24 m). For the first time in the literature, the method estimates the part of an ICES rectangle that is unfavourable or inaccessible for fisheries, which is shown to be highly stable over time and suggests higher proportions of inaccessible grounds for either extremely muddy or courser substrates. The study furthermore shows high stability in aggregation of fishing, where aggregation shows a positive relationship with depth heterogeneity and a negative relationship with year-on-year variability in fishing intensity.

Keywords

Beam trawling
Benthic impact
Effects of trawling
Inaccessible habitat
North Sea
Unfavourable habitat
VMS

Introduction

In the 2000s, a wealth of high-resolution data became available on the locations of bottom fishing through the introduction of the vessel monitoring by satellite system (EC, 2002; Piet *et al.*, 2007). The data, which were collected for enforcement purposes, became available for science and was used to study the distribution and dynamics of fisheries and their impact on benthic ecosystems (Witt and Godley, 2007; Poos and Rijnsdorp, 2007a; Hintzen *et al.*, 2010; Poos *et al.*, 2013; van Denderen *et al.*, 2015). Most studies focussed on describing the spatial and temporal extend of historic fishing activity (Stelzenmuller *et al.*, 2008; Pedersen *et al.*, 2009; Bastardie *et al.*, 2010a; Gerritsen and Lordan, 2011) by presenting maps of fishing pressure or effort based on vessel monitoring system (VMS) and logbook data.

Such large-scale maps showed that fishing was heterogeneous in space (Murawski *et al.*, 2005; Chang and Yuan, 2014; Eigaard *et al.*, 2016a; Kroodsma *et al.*, 2018). While this heterogeneous distribution of fishing was apparent and well-studied at large spatial scales (>10 km), aggregation at small spatial scales (<100 m) has received surprisingly little attention. Understanding the mechanism of aggregation behaviour at such small spatial scales could lead to an understanding of how the patterns on large spatial-scale fisheries maps arise.

The large-scale heterogeneous distribution (>10 km) of fishers in space and time results from a number of factors, including density and distribution of target species which vary by year and season (Piet and Hintzen, 2012; van Denderen *et al.*, 2015; Maina *et al.*, 2016) due to fish migration (Hunter *et al.*, 2003; Teal *et al.*, 2012), distance to harbour (Sampson, 1991), fuel price (Poos *et al.*, 2013), technical capabilities to fish in different habitat types, and/ or quota/effort limitations (Batsleer *et al.*, 2013). The ability to trawl in a specific location is furthermore limited by the state of the seabed where areas with boulders will be avoided to prevent gear loss during fishing operations. Fleet dynamics studies (Gillis *et al.*, 1995a, b; Bastardie *et al.*, 2010b, 2015; Poos *et al.*, 2010; Batsleer *et al.*, 2016) and suitable fisheries habitat modelling studies (Nilsson and Ziegler, 2007; Maina *et al.*, 2016) have been used to study the mechanisms that underlie fishers' behaviour and explain how heterogeneous patterns in distribution arise. The spatial scale of most of these studies equals or is somewhat smaller than the management scale unit applicable in the study area (e.g. an ICES rectangle, ~ 60 x 60 km). To complement the fleet dynamic studies, we therefore focus on describing the mechanism by which fishers aggregate fishing effort at small spatial scales.

At small spatial scales (~1 km), fishing is shown to be patchy (Rijnsdorp *et al.*, 1998; Ellis *et al.*, 2014; Natale *et al.*, 2015; Eigaard *et al.*, 2016a) and seems to be related to the (patchy) distribution of the target species (Poos and Rijnsdorp, 2007b; Sys *et al.*, 2017). However, patchiness can also arise from a heterogeneous seabed which limits, for example heavy gear to be operated on hard substrates. This patchy behaviour can be described by a count process where each count represents a certain fishing intensity on a small surface area (e.g. gridcells) of the seabed. Ellis *et al.* (2014) showed that when fishing tracks were projected onto such a small spatial grid (at a microspatial scale, with gridcells the size of the gear), the frequency distribution of the number of times each gridcell was fished would inform us on the degree of clustering of fishing effort in space (i.e. aggregation of fishing effort). When computed over a number of years, it would also reveal how this degree of clustering changed over time. The clustering also allows us to define three types of areas: (i) those gridcells where fishing is impossible (always a zero count on fishing intensity), (ii) areas where fishing is less profitable or difficult to operate (most of the times a zero count on fishing intensity), and (iii) areas where fishing is profitable with good access conditions (most of the times a non-zero count on fishing intensity). In this study, we develop an approach to differentiate between these areas and subsequently study the stability of these three types of areas in time and space.

The Dutch demersal fishing fleet mainly operating in the southern North Sea is taken as a case study for our analyses (Figure 4.1). Since the 1960s, this fleet has predominantly focussed on two flatfish species: sole (*Solea solea*) and plaice (*Pleuronectes platessa*) (Rijnsdorp *et al.*, 2008), with sole being the more profitable but less abundant of the two. Until 2010, both species were targeted by a traditional beam trawl (see Eigaard *et al.*, 2016b for gear characteristics) that use tickler chains or chain mats to disturb the fish out of the seabed. From 2010 onward, gear innovation increased substantially to reduce fuel costs, leading to the use of electric pulse gear (van Marlen *et al.*, 2014). This electric pulse gear allowed the fishery to move to different areas previously not accessible by the heavy beam trawl; hence, this study focusses only on the period until 2009.

In this study, we estimate the aggregation of fishing intensity of the Dutch beam trawl fleet within ICES rectangles and investigate how stable aggregation is over time. We test how much inter-annual variation in the location of fishing exists and how well-defined unfavourable and inaccessible areas are for the

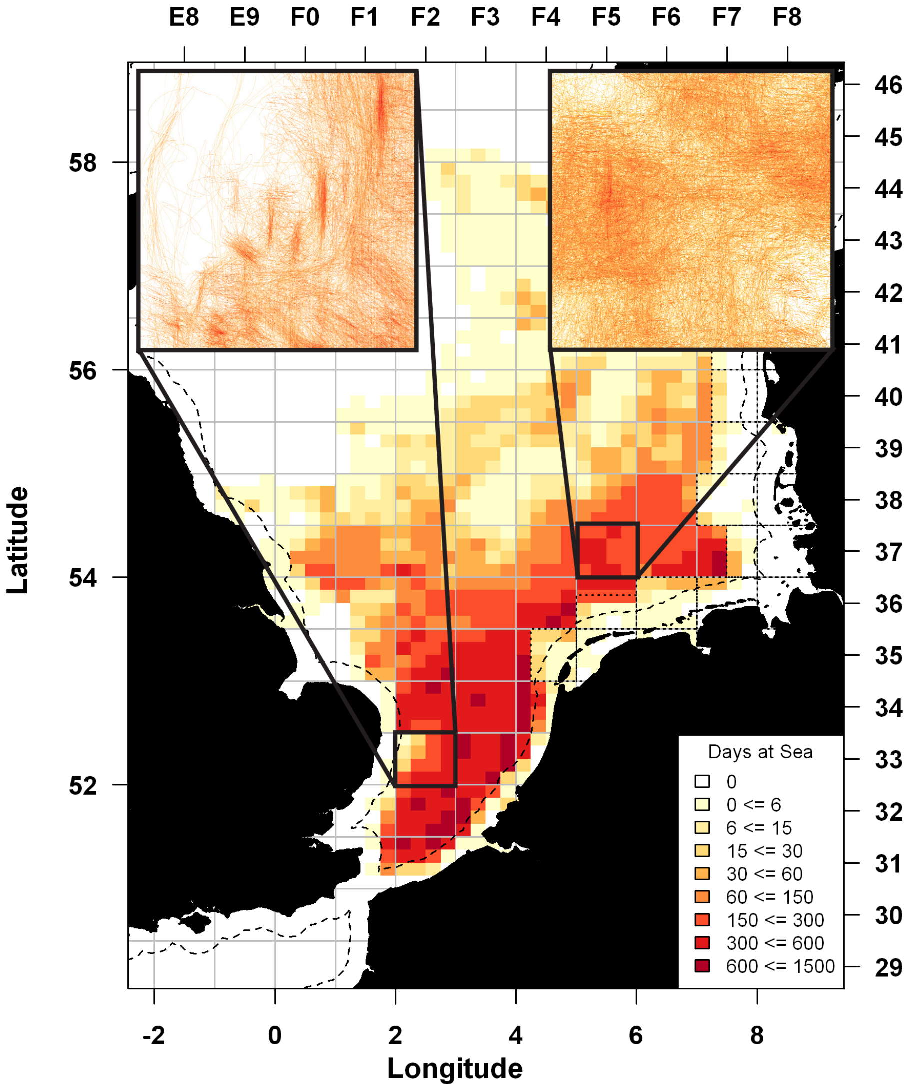

Figure 4.1 Spatial distribution of fishing effort by the beam trawl fleet during 2002–2009 at a scale of 0.25 x 0.125 decimal degrees longitude and latitude, respectively. The dashed line indicates the 12 nautical mile zone. The dotted line indicates the plaice box. Top left insert represents a zoom to 24 x 24 m gridcells of ICES rectangle 33F2 (See top and right-hand axis for ICES rectangle navigation) and top right insert represents a zoom to 24 x 24 m gridcells of ICES rectangle 37F5.

4

fishing fleet in space and time. For these analyses, we link the ICES rectangle management unit, the scale at which target species distribution is predictable, to fishers' effort and their small spatial-scale distribution observed using VMS. This approach allows us to predict small-scale fishing distribution patterns for historic time-periods when only effort data are available at larger spatial scales, such as the ICES rectangle, or to scale down the fishing effort predictions from fleet dynamic models to the fine-grained spatial units required to assess trawling impact. This will allow us to estimate at small spatial scale, for instance, the net benefit to seabed integrity and benthic communities in cases where fishers are expected to displace effort owing to marine protected areas.

Material and methods

Data

VMS and logbook data from all Dutch-flagged vessels fishing with beam trawl gear (TBB) in the North Sea were used for this analysis. The data series span the years 2002–2009. The year 2002 is the first in which VMS data are representative for the entire TBB fleet, and 2009 is the last year in which >90% of the beam trawl fleet fished with the traditional tickler chains rather than the new electric pulse gear (van Marlen *et al.*, 2014). Fishing effort decreased over the study period from 25 000 to 15 000 fishing days per year.

The VMS data contain information on vessel ID, speed, and heading over ground, GPS position, and date-time stamp, and the data are emitted roughly every 2 h. The logbook data contain information on: vessel length and horse power, trip information such as gear and mesh size used, and the daily catch by species, referenced by the ICES rectangle in which fishing took place. An ICES rectangle is a rectangular square measuring one longitudinal degree by 1/2 a latitudinal degree of approx. 3600km^2. Each square is given a name starting with two digits, referring to the latitude, followed by a letter and number combination referring to longitude. Logbooks are completed at the end of a fishing trip, which usually spans a working week. Combining the two datasets allowed us to select the VMS positions from large beam trawlers (>300 hp). The traditional and pulse beam trawl are both registered in the logbooks using the same naming convention "TBB". A database maintained at Wageningen Marine Research containing specific details on gear specifications and their introduction date was used to differentiate between pulse and traditional beam trawling. Only traditional beam trawling data were used.

Creating count data

VMS and logbook data were carefully scrutinized for erroneous entries (Hintzen *et al.*, 2012). Fishing activity was defined based on speed profiles (Poos *et al.*, 2013). Vessel tracks were interpolated following Hintzen *et al.* (2010), and position of the gear behind the vessel was estimated following van Denderen *et al.* (2015). All interpolated GPS positions were projected onto a grid measuring ~24 x 24 m (at 53° latitude), i.e. 0.00036 decimal degrees longitude x 0.000215 decimal degrees latitude, matching the width of the gear (2 x 12 m beam width). Each position inside a gridcell counted as trawling the total gridcell once. On a yearly basis, the number of trawls in each gridcell was counted, and a frequency distribution per ICES rectangle was calculated.

Estimating the level of aggregation of fishing

The analyses to assess aggregation of fishing are based on methods developed by Ellis *et al.* (2014). When fishing is aggregated, certain gridcells are trawled more often (and others less often) than would be expected based on random behaviour. Furthermore, the number of times a certain gridcell is trawled depends not only on the degree of aggregation, but also on the total effort the fishing fleet expends within an ICES rectangle. The count of fishing intensities of all gridcells combined can be described by a frequency distribution that can follow a negative binomial (*NB*, fishing effort is aggregated in space), Poisson (*P*, fishing effort is random in space), or binomial distribution (*B*, fishing effort is a hit-or-miss process [did not occur in our dataset]). Gridcells with a zero fishing intensity are given extra attention in this study. Zero fishing intensities are caused by either (i) low overall effort in the ICES rectangle, (ii) unfavourable gridcells (e.g. low availability of resource or low catchability), or (iii) inaccessible gridcells (due to the nature of the seabed such as boulders). All three statistical distributions can account for gridcells with zero fishing intensity. In some cases, however, there are ICES rectangles with excessive amounts of gridcells with zero fishing intensity (for our analyses, the gridcells inside the 12-mile zone and the plaice box were excluded so as to not artificially inflate the number of zero observations). When an ICES rectangle contains large inaccessible areas, this will result in an excessive number of gridcells with zero fishing intensity, independent of the total fishing effort in that ICES rectangle. We, therefore, fitted a zero-truncated Negative Binomial (TNB) to the non-zero counts (Y) of fishing intensities in the ith gridcell in each kth ICES rectangle. The *NB* is expressed in terms of size n and mean effort μ. Size is defined as $\frac{\mu}{\beta}$ where β is the aggregation (more commonly known as overdispersion) parameter (being larger than 0), and μ is the average trawling frequency over all gridcells in the ICES rectangle. The μ values were estimated for each ICES rectangle separately using the truncated *NB*. The *β* parameter was treated as a random effect to reduce the effective number of parameters to estimate [see Equation (4.1)]. Log-likelihood methods were used in the TMB framework (Fournier *et al.*, 2012; Kristensen, 2014; Kristensen *et al.*, 2015) to estimate these parameters.

$$\begin{aligned} Y_{i,k} &\sim \mathrm{TNB}(\mu_k, B_k); \quad Y_{i,k} > 0 \\ B_k &\sim \mathrm{Gaussian}\ (\beta_k,\ \sigma_k) \end{aligned} \tag{4.1}$$

To assess the stability in the aggregation parameter, a linear model was fitted to the estimated aggregation (*β*) parameters. Furthermore, the aggregation parameters estimated were contrasted with variability in the bathymetric position index (BPI) which is a measure of the depth at a specific location relative to the depth in the surrounding grid cells within 5km, and the proportion of sand within the ICES rectangle, as a proxy for substrate variability.

4

Estimating unfavourable and inaccessible areas

A high number of unfavourable and inaccessible grid cells in an ICES rectangle causes excessive zero counts in the frequency distributions that cannot be explained by the negative binomial (NB) distribution. In ICES rectangles where this fraction of excessive zeros (P_{false}) is negligible, all observed gridcells with zero fishing intensity belong to the NB distribution and are considered accessible, but were simply not visited during that specific year. One characteristic of these rectangles is that the number of gridcells with zero counts decreases if fishing effort increases. For this scenario, under extreme high fishing effort, all gridcells with zero fishing effort will ultimately disappear. In contrast, in ICES rectangles with a large number of inaccessible gridcells, the proportion of excessive zeros will be high (i.e. $P_{false} >> 0$), the frequency distribution of counts does not follow a NB, and the amount of fishing effort has no effect on the estimation of excessive zeros.

Even under extreme high fishing effort, the number of gridcells with a zero count fishing intensity will remain the same. For unfavourable areas, gridcells with zero fishing intensity will decline under an increase in fishing effort, and gridcells with zero fishing intensity will still be present in years with higher fishing effort (which is not the case when all areas are favourable), but will ultimately disappear under extreme high fishing effort.

The relationship between fishing effort and the fraction of excessive number of zeros ($P_{\text{false},i}$) was modelled as the inverse logit of a linear relationship with μ, intercept *a*, and slope *b* [see Equation (4.2)]. Subscript *i* refers to the years 2002–2009. Contrary to the method applied, described by Equation (4.1), grid-cells with zero counts are included in the estimation procedure. Part of these zero counts are labelled as excessive if P_{false} >0. Estimated aggregation (β) parameters, as obtained from the analyses applying Equation (4.1), were assumed known for the estimation of P_{false}:

$$P_{\text{false},i,k} = 1 - P(Y_{i,k} = 0) = 1 - \frac{\exp\left(a_k + \mu_{i,k} b_k\right)}{1 + \exp\left(a_k + \mu_{i,k} b_k\right)} \tag{4.2}$$

The estimated intercept of Equation (4.2) (i.e. the number of excessive zeros when no fishing takes place and μ is zero) provided us with a combined estimate of the total proportion of inaccessible and unfavourable areas within a rectangle. The inaccessible proportion was taken as the minimum fraction in the time-series, and the remaining zeros were attributed to the unfavourable grounds. As such, each ICES rectangle is associated with one time-invariant estimate of inaccessible and unfavourable fractions of the surface area. See Figure 4.6 for a graphical representation.

Estimated proportion of inaccessible and unfavourable areas were contrasted with substrate proportions in each of the rectangles to provide a mechanistic link between gear accessibility and fishing activity. Substrate proportion was obtained from the dbSeabed data base (Jenkins, 1997).

Estimating between-year variability in the location of fishing

The amount of fishing effort each 24 x 24 m gridcell receives can vary temporally due to overall changes in fishing effort or changes in distribution of fishing effort within the ICES rectangle. To assess whether the fishing grounds were stable in space over time, we estimated the between-year variability in fishing effort in each gridcell of an ICES rectangle and compared it with the variability under random fishing. A linear model assuming a negative binomial distribution was fitted to the time-series of fishing intensity of each individual gridcell, taking the log of total fishing effort in the ICES rectangle as an offset, providing an estimate of θ that described the between-year variability. The θ parameter can be converted to variance following $\mu + \mu^2/\theta$. To obtain an estimate of between-year variability in an ICES rectangle, the distribution of θ estimates of all the gridcells in an ICES rectangle was approximated by a log-normal distribution, with corresponding mean $\bar{\theta}$ and variance. The observations from the gridcells were subsequently shuffled 100 times, and the same procedure was applied on each repetition. This resulted in 100 $\bar{\theta}$ estimates. Finally, we calculated the probability that the observed θ could be part of the distribution of θ values from the random iterations. In cases where this probability was low, the variance in the observed data is substantially lower than the variance in the random iterations, and we may conclude that the ICES rectangle is stable over time.

Results

Study area and general statistics

After erroneous positions and positions in harbour were removed, the VMS contained positions of 153 vessels. These vessels transmitted 1.7 million records, of which 1.5 million were associated with fishing. The number of fishing positions recorded decreased during the study period by 40%, coinciding with a reduction in fleet capacity.

Estimated level of aggregation of fishing

Of the 95 ICES rectangles in the study area, 61 had fishing activity during the study period, of which 39 had a sufficient number of trawling recordings to estimate aggregation parameters. These 39 rectangles represented 95% of the total fishing effort by the Dutch beam trawl fishery. Figure 4.2 shows the estimated aggregation (β) parameters for each specific year–rectangle combination. Clear changes in aggregation are visible in only two rectangles (encircled with a dashed line, five rectangles with significant linear trends, but without clear step changes, are encircled with a black line), while all other rectangles show stable or varying aggregation from year to year without a clear trend. The median aggregation parameter across all rectangles is 0.22, with a minimum of 0.05 (close to random behaviour) in rectangle 39F3 and a maximum of 0.43 in rectangle 34F2.

Figure 4.3 shows how the aggregated trawling distribution differs from a random distribution. Aggregation by the fishing fleet leaves more gridcells untrawled, while other gridcells are trawled more frequently, with intensities of 3 or larger. For example, gridcells that were trawled 7 times were 20-fold more frequent in the observed aggregated distribution, compared to a random dis-

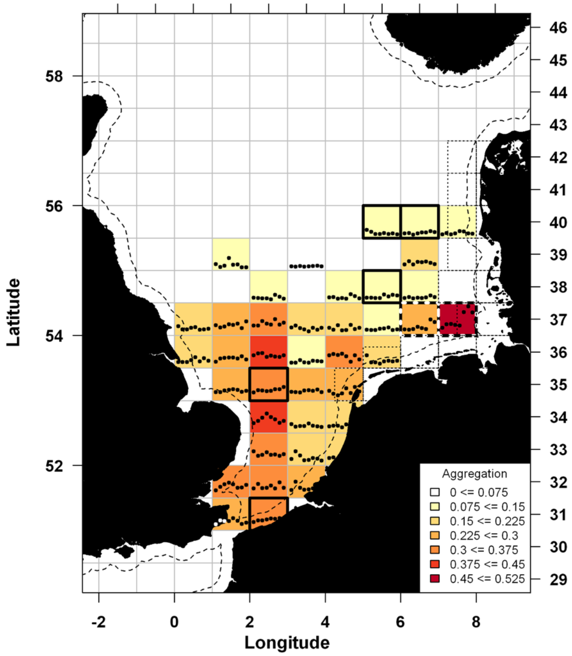

Figure 4.2 Time-series of the aggregation parameter β estimated for each year (2002–2009) per ICES rectangle. Each black dot (or white dot near Dover, UK) represents an estimate of β for each year, each rectangle being an *x*–*y* plot, with year on the *x*-axis and the parameter value β on the *y*-axis. The dashed line indicates the 12 nautical mile zone. The dotted line indicates the plaice box. The background colour of each rectangle represents the time-series average amount of aggregation, and dashed-encircled rectangles show clear trends in aggregation. Solid Black-encircled rectangles have significant linear trends, but without clear change in aggregation.

tribution. Aggregation seems to increase with higher variability in depth profile (more hills and troughs) (Figure 4.4) levelling off at around a bathymetric position index (BPI) of 15 m, which suggests aggregation to be driven by a heterogeneous depth landscape.

Inaccessible and unfavourable areas vs. fishing grounds

Based on the number of untrawled gridcells within each year and rectangle, we estimated the proportion of these untrawled gridcells that exceeded the proportion of zeros as predicted by the fitted NB distribution. These gridcells were classified as inaccessible and unfavourable areas. Of these, the proportion of gridcells that were untrawled in all years were classified as inaccessible. Unfavourable areas exist in rectangles with low fishing effort and low fisheries aggregation, but are not associated with zero trawls in all years (see Figure 4.6

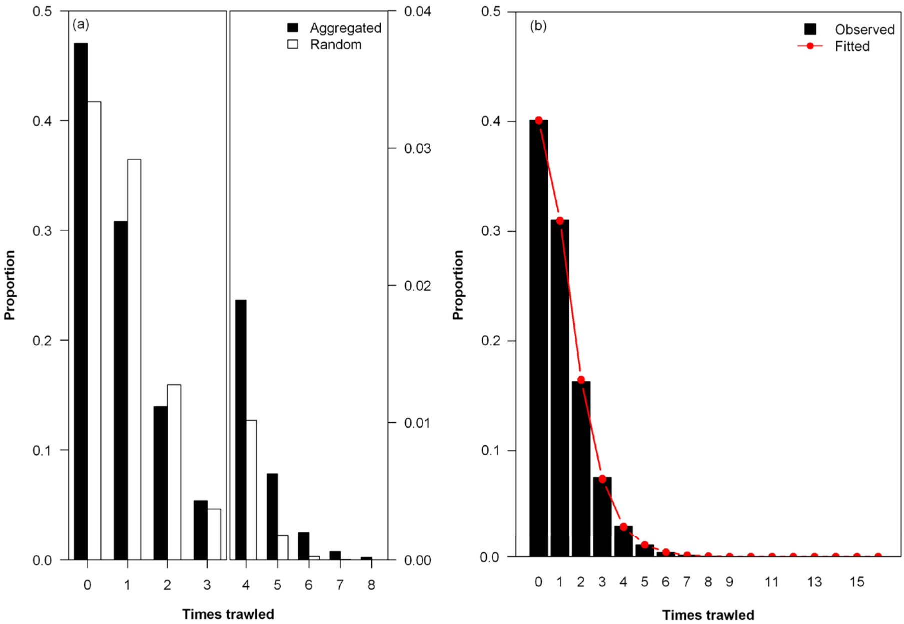

Figure 4.3 (a) Representation of average trawling frequency under the aggregation parameter β (β = 0.33) for ICES rectangle 33F2 (right inset rectangle of Figure 4.1), contrasted with a random process. The same surface area (of the year 2005) is trawled in both. Note the axis break between 3–4 times trawled. (b) Fitted vs. observed counts of trawling intensities at individual gridcells in ICES rectangle 33F2 in 2005 (left inset rectangle of Figure 4.1).

for a graphical presentation of the procedure used to estimate unfavourable and inaccessible areas). The results are shown in Figure 4.5. Some rectangles show high proportions of inaccessible or unfavourable areas (especially along the east coast of the UK and around 3° longitude and 55° latitude), while all areas in the southern North Sea and along the Dutch coast seem accessible and favourable. No significant time trend in the fraction of inaccessible and unfavourable areas was observed in any of the rectangles, although effort did vary between years. There is substantial difference in the proportion of inaccessible and unfavourable areas among rectangles. Figure 4.7 shows that there are indications that such inaccessible areas are associated with higher contents of coarse substrate. In contrast, substrate does not seem to play a role defining unfavourable grounds.

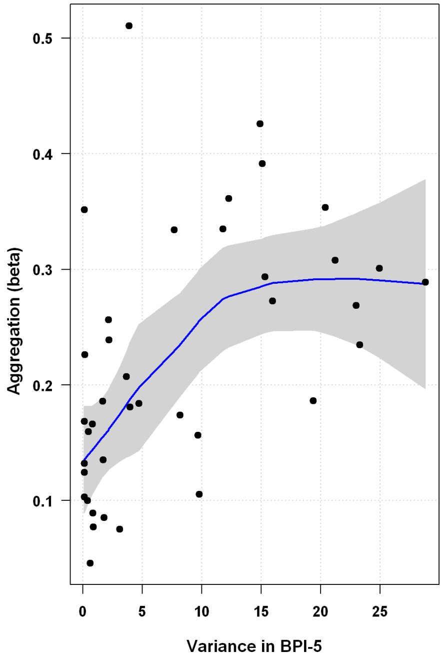

Figure 4.4 Estimated aggregation β for each of the ICES rectangles studied. Each dot represents an ICES rectangle. For each rectangle, the variance in BPI (bathymetric position index, higher BPI values indicate higher variability in depth profile, i.e. more hills and troughs) is given on the *x*-axis, and a smoother has been added as a solid line (and its confidence interval – shaded area).

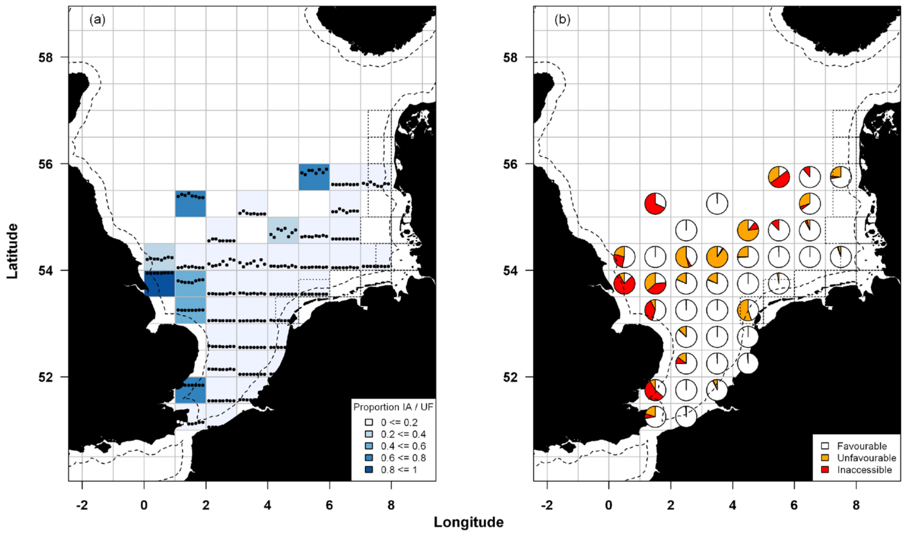

Figure 4.5 (a) Time-series of the proportion of untrawled gridcells representing either inaccessible (IA) or unfavourable (UF) areas. Each black dot (or white dot near Dover, UK) represents the fraction of IA|UF in a year, each rectangle being an *x*–*y* plot, with year on the *x*-axis and the parameter value on the y-axis. Background of rectangles is colour coded and represents the average fraction IA|UF. (b) Estimated proportion of inaccessible (red), unfavourable (orange), and favourable (white) areas per rectangle. The dashed line in both maps indicates the 12-mile zone. The dotted line indicates the plaice box.

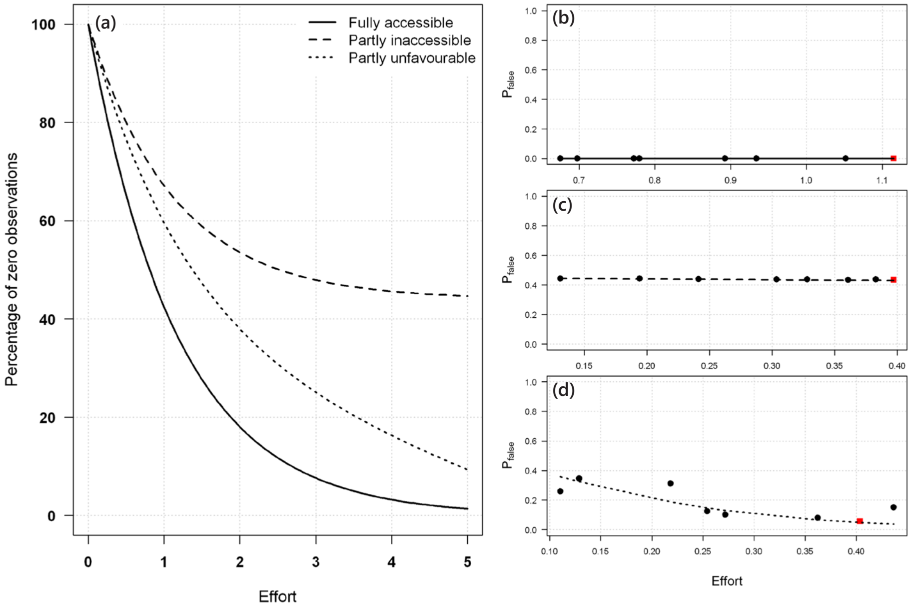

Figure 4.6 (a) Change in expected percentage of gridcells with a zero count in ICES rectangles that are either fully accessible, partly inaccessible, or partly unfavourable under increasing effort. (b–d) Fitted relationship between P_{false} and effort. Panel (b) refers to an ICES rectangle that is fully accessible, panel (c) refers to an ICES rectangle that is partly inaccessible, and panel (d) refers to an ICES rectangle that is partly unfavourable. Dots/squares refer to individual years, and the square indicates the lowest observed value in the time-series denoting the proportion of inaccessible areas. Lines represent the fitted relationships. In all panels, effort is expressed as swept area ratios.

Estimated between-year variability in the location of fishing

Figure 4.8a shows that areas close to the Dutch coastline are more stable in the location of fishing from year to year than areas farther away. Generally speaking, areas with higher effort also show less variability in between-year change in fishing location. A large area in the northern part of the distribution area has a between-year variability that is not significantly different from a random choice in fishing location, while those areas in the south are significantly more stable than a random choice. Figure 4.8b shows the relation of the between-year variability (θ) and the estimated average aggregation by ICES rectangle, indicating that rectangles with high estimated aggregation (β) are also associated with low between-year variability. Overall, 67% of the effort over the study period is allocated to rectangles with low between-year variability.

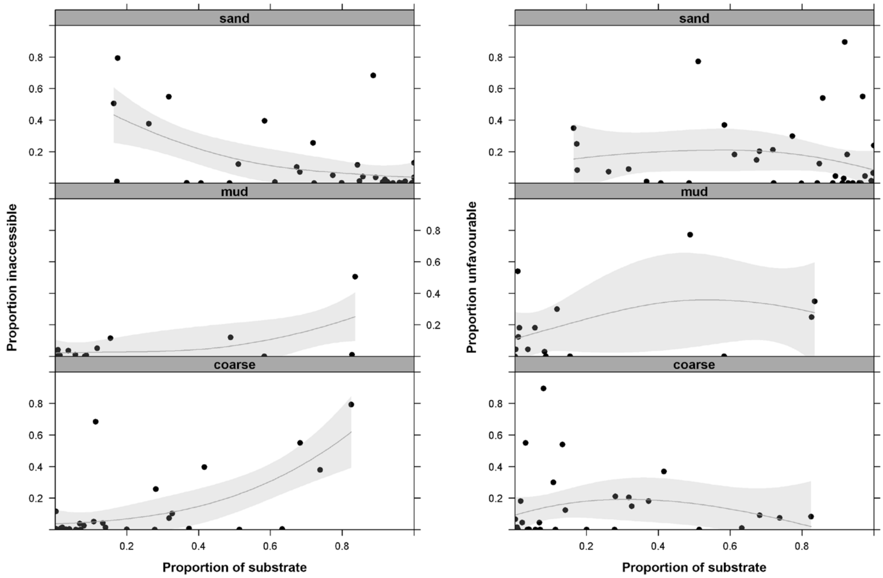

Figure 4.7 Proportion of inaccessible (left) and unfavourable (right) area in relation to the proportion of sand, mud, and coarse sediment. Each black dot represents an ICES rectangle, and a smoother (and its confidence interval – shaded area) has been added in light grey.

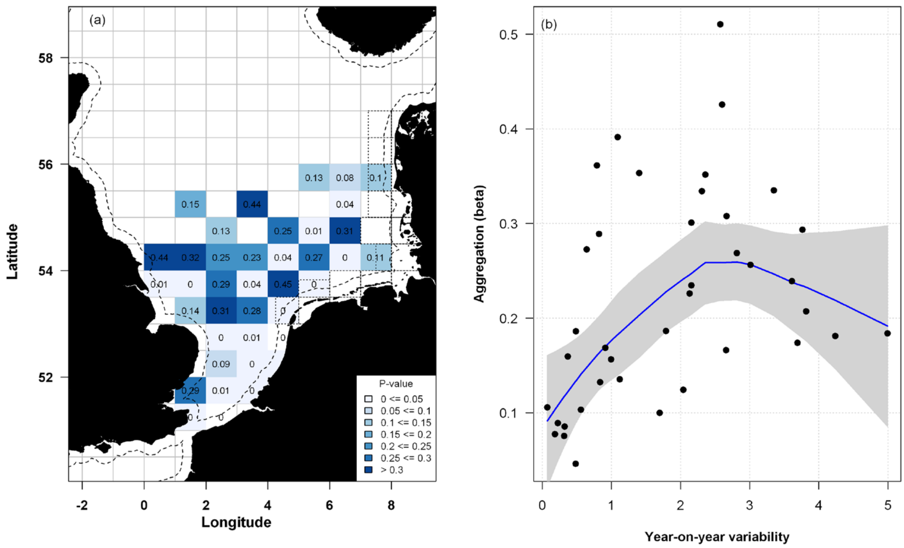

Figure 4.8 (a) *P*-values of test whether between-year variability is different from the variability observed under a random choice in fishing location. (b) Relationship between estimated between-year variability (θ) by ICES rectangle vs. the average aggregation over the study period (higher x-axis values indicate smaller changes from year to year). A smoother has been added as a solid line (and its confidence interval – shaded area).

Discussion

Stability of fishing ground

In this study, a method was developed that successfully estimated four characteristics of a fishing ground: (i) amount of untrawlable grounds within an ICES rectangle, (ii) aggregation of fisheries within a rectangle, (iii) temporal stability of this aggregation, and (iv) stability in spatial location of the fishery. The analysis showed that given the time-frame and fishery investigated, there is substantial stability in the aggregation of fishing effort both in time and space, even though fishing effort has fluctuated and declined by 40% during 2002–2009.

Aggregation tends to be higher in more southern areas, where more vessels target both sole and plaice. The aggregation of fishing effort could arise from dynamics described by the ideal free distribution (IFD) (Fretwell and Lucas, 1969), previously successfully used to describe the distribution of fishing effort in relation to the distribution of target species (Gillis *et al.*, 1993). The IFD predicts that fishers will distribute themselves in such a way that they equalize the catch rate, and a move to another ground will not yield a higher catch rate. Thus, whenever the resource is heterogeneously distributed in space, under the IDF, fisheries will aggregate. A heterogeneous distribution of the target species is more likely when their habitat is variable in space. The target species (sole and plaice) prey on benthic species, which are tightly linked to specific habitat characteristics (Barrio Froján *et al.*, 2012; Bolam *et al.*, 2017; Rijnsdorp *et al.*, 2018). Therefore, variability in habitat can be interpreted as a proxy for variability in fish resource distribution (Scott, 1982; Abookire and Norcross, 1998). In line with these findings, results from this study show an increasing relationship between aggregation and depth variability. The occurrence of sand dunes and tunnel valleys created in the glacial period, and hence changes in depth, typical for the southern North Sea, might explain the stability in aggregation in the southern North Sea. Although the exact location of sand dunes changes over time, due to e.g. stormy weather, their existence and approximate location at larger spatial scales remains stable (Caston, 1972), while the location of tunnel valleys is stable over time. In more northerly areas, the aggregation estimate is low, reflecting a more random distribution of the fishing fleet. Many of the untrawled gridcells in these northerly areas are estimated to be unfavourable or inaccessible. One possible explanation is that the distribution and biomass of the target species is low and less predictable, resulting in a more random (less aggregated) searching and fishing behaviour by the fishing fleet.

Estimates of the proportion of inaccessible and unfavourable areas are relatively stable in time for most ICES rectangles studied. Although there is some variability in the estimated aggregation in ICES rectangles with low fishing effort (e.g. the northerly regions), the variability is lower in rectangles with a high proportion of inaccessible areas. Rectangles with higher proportions of unfavourable conditions, and a lower proportion of inaccessible areas, show more change from year to year. The occurrence of inaccessible areas is often associated with the proportion of coarse or muddy substrates, which may hamper the safe operation of heavy bottom trawls. Stability in inaccessible areas over time can be explained by stability in the design and rigging of the traditional beam trawl during the study period. In recent years however, technological innovations have taken place. The beam and shoes of the traditional beam trawl were replaced by a foil-shaped wing to reduce the drag of the gear and subsequent fuel use, and the mechanical stimulation of the tickler chains was replaced by electrical stimulation (van Marlen *et al.*, 2014). As this may affect the stability in inaccessible areas, the study period was restricted to the years before this transition took place. The proportion of unfavourable areas seems unrelated to substrate composition since fishing activity is present, although irregular, in these areas.

Year to year stability in aggregation can occur even though fishers may fish in different parts of the ICES rectangle each year. Therefore, stability within gridcells over the years was investigated. Fishing effort allocation was more stable in areas closer to the Dutch coastline and are associated with higher aggregation. This relationship levels off near higher aggregation levels owing to either (i) interference competition, which reduces the catch efficiency of individual fishers causing them to start fishing elsewhere (i.e. hereby reducing aggregation) (Gillis *et al.*, 1993) or (ii) a limit on resource density, which would limit the number of vessels able to maintain a threshold catch per unit of effort (see Figure 4.8b). Stability is hence likely associated with high predictability and abundance of the resource, where areas with higher depth gradients may result in more clearly defined high-density resource patches. When a fisher knows where to find fish, he/she is likely to return to these spots year after year. Stability of the habitat and habitat preference of the two target fish stocks in the North Sea and their annual spawning and foraging migration results in predictable patches all over their distribution range in the North Sea (Hunter *et al.*, 2003), which are being targeted by the fishing fleet.

Uncertainty in aggregation estimates

Between-year variability in the estimated proportion of unfavourable/inaccessible grounds is overall higher in the more northerly ICES rectangles. Such between-year variability is particularly apparent where the proxy for inaccessible areas is low and the proportion of unfavourable areas is high. This reflects that fishers change their fishing grounds from year to year, but still aggregate. Our results do not explain why fishers irregularly avoid an area (i.e. unfavourable grounds), but we provide a mechanism to predict areas not impacted by beam trawl gear, given a certain fishing effort. Identifying inaccessible grounds can be achieved with a certain degree of confidence if time-series are of sufficient length. This study quantifies as a first the amount of unfavourable and inaccessible areas. Although it remains complex to distinguish with a high degree of confidence between unfavourable and inaccessible grounds.

Fixed structures such as oil rigs or wrecks likely do not affect the estimation of inaccessible grounds, as the surface they occupy in the study area (~300 km^2 in oil/gas platforms vs. 150 000 km^2 study area) is minimal compared to the surface area where fishing takes place. The estimation is further influenced by the change in TACs for the two main target species plaice and sole. Over the time-period, the TACs for plaice have gone down from more than 70 000 t in 2002 to around 50 000 t in the later years (ICES, 2018a, 2018b). Sole TACs have been more variable during this period. There is a negative correlation between the total estimated size of unfavourable area and total TACs, which may indicate that fishers increase focus on usual hotspots and engage less in exploratory fishing in unregularly trawled areas. This behaviour inflates the estimate of unfavourable areas.

Uncertainty in aggregation also stems from the use of the interpolation technique to reconstruct trawl tracks (Hintzen *et al.*, 2010). The reconstructed trawl tracks were used to derive a fishing intensity count process on the gridcell scale; hence, uncertainty in the true track affects the frequency distribution. This frequency distribution was used to estimate aggregation parameters. When fishers would aggregate in very small spatial units (e.g. narrow channels or ridges), the interpolation might lead to a more diffuse estimate of the distribution of fishing intensity and, as a consequence, an underestimate of the amount of aggregation. However, the size of the gridcells, being very small in this study, does not affect the accuracy of the interpolation since interpolated tracks are continuous in space and remain unaffected when zoomed in or out on predicted trawl tracks. For example, using 1-min GPS interval rate data (automatic identification system or AIS) to tune the interpolation routines did not differ from 6-min GPS interval rate data (automated position recording or APR, see Rijnsdorp *et al.*, 1998). Therefore, we conclude that processing data at the small 24-m spatial scale resembles the same accuracy as at much larger spatial scales (e.g. km scale). Nevertheless, the slight underestimate of the level of aggregation still remains. However, we expect this effect to be minor on the results of this study. For example, the effect of errors in the interpolation will apply to all ICES rectangles and years. Although the absolute aggregation estimate will be affected, the relative spatial and temporal changes, as depicted in Figure 4.2, should remain the same. Another result of this study was that increased variance in bottom topography lead to increased aggregation (Figure 4.4). If fishers would follow finescale topographic features, the effect of the variance in bottom topography on aggregation would even be higher, not smaller.

Estimating the historic and future fishing footprint

Studies focussing on the impact of bottom trawling on the benthic community, such as Frid *et al.* (2000), Hiddink *et al.* (2006), and Hinz *et al.* (2009), show the importance of quantifying bottom trawl activity to the fine spatial scale at which it causes a disturbance. With the framework developed here, the cumulative fishing intensity of local patches can be predicted and reconstructed for years in which effort data are available on the scale of, for instance, the ICES rectangle, but not on the more precise VMS level. The cumulative intensities should foster our understanding on how observed benthic communities were affected by trawling (Rijnsdorp *et al.*, 2016). When understanding aggregation for a diversity of bottom trawling fleets, estimating the footprint of fisheries (Eigaard *et al.*, 2016a) may become possible in areas where fishing effort information is only available at a coarse scale, such as the ICES rectangle, or where gaps in data exist, such as is often the case with AIS data (Kroodsma *et al.*, 2018). The main challenge herein was to demonstrate the persistence of hot-spots in addition to the identification of hot-times (Ellis *et al.*, 2014). The presented relationship between aggregation and hot-spots (low between-year variability) is key to the extrapolation of fishing footprints.

The aggregation parameters estimated for the rectangles can be directly applied in combination with the larger-scale effort allocation models (Poos *et al.*, 2010; Bastardie *et al.*, 2015; Batsleer *et al.*, 2016) to estimate small-scale footprints of fishing. Since the results of this study have no predictive power on fishing effort allocation, a combination of these fishing strategy models and the aggregation should be linked. This integration is a valuable approach to predict habitat use when certain parts of the North Sea are closed for fisheries, such as Natura 2000 or windmill areas. The benthic impact of enforced fisheries displacement can then be studied and evaluated in terms of their net effect on bottom trawling, given that aggregation is not stable across rectangles. Displacement, therefore, could lead to moving effort to areas where the distribution of fishing is random rather than aggregated, resulting in a lower proportion of unimpacted habitat. Furthermore, the estimated unfavourable/inaccessible habitat could be considered in spatial management, where these areas do yield economic or social interest for other users.

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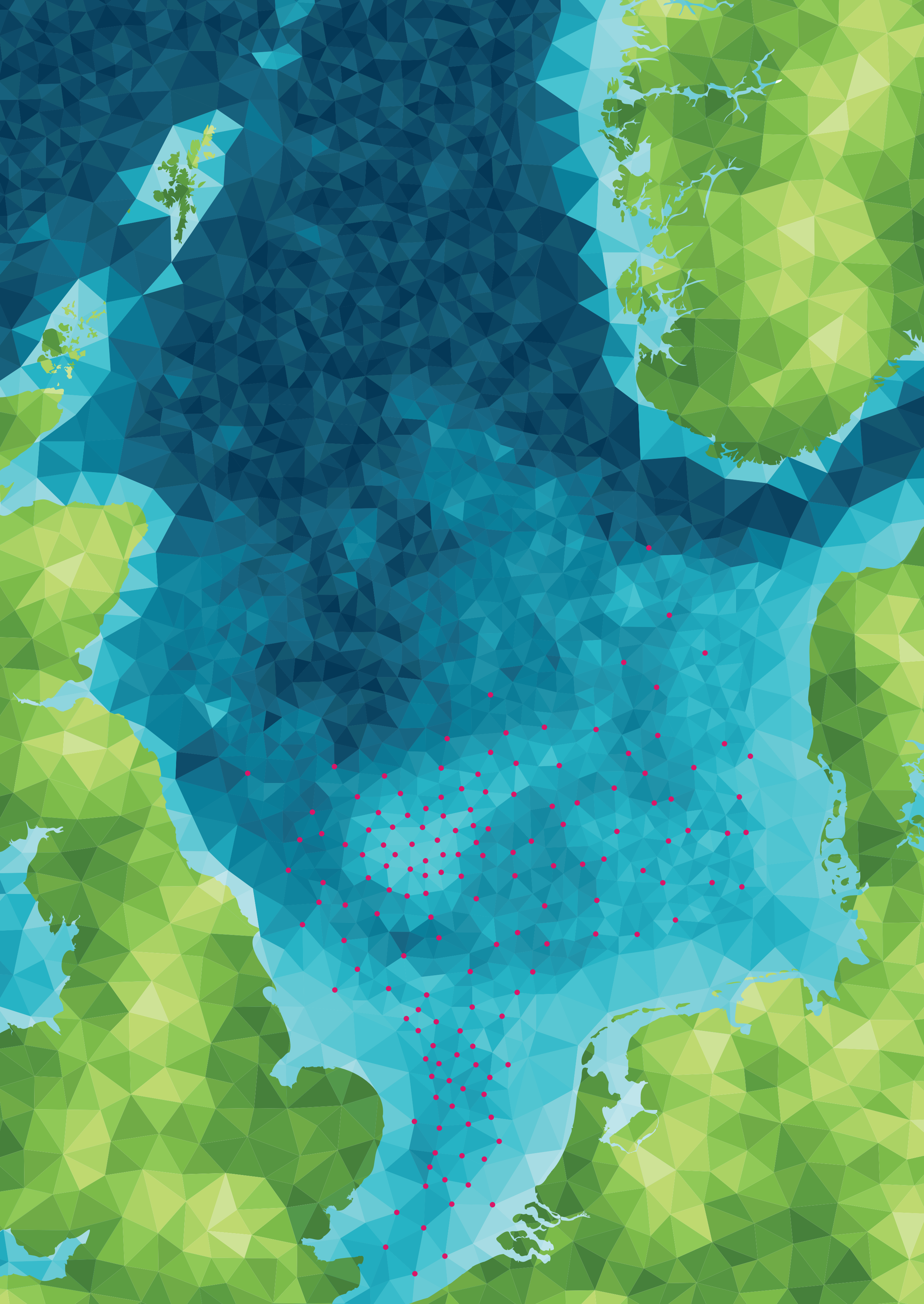

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Quantifying habitat preference of bottom trawling gear

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Abstract

Continental shelves around the world are subject to intensive bottom trawling. Demersal fish assemblages inhabiting these shelves account for one-fourth of landed wild marine species. Increasing spatial claims for nature protection and wind farm energy suppresses, however, the area available to fisheries. In this marine spatial planning discussion, it is essential to understand what defines suitable fishing grounds for bottom trawlers. We developed a statistical methodology to study the habitat preference of a fishery, accounting for spatial correlation naturally present in fisheries data using high-resolution location data of fishing vessels and environmental variables. We focused on two types of beam trawls to target sole using mechanical or electrical stimulation. Although results indicated only subtle differences in habitat preference between the two gear types, a clear difference in spatial distribution of the two gears was predicted. We argue that this change is driven by both changes in habitat preference as well as a change in target species distribution. We discuss modelling of fisheries' habitat preference in light of marine spatial planning and as support in benthic impact assessments.

Keywords

Beam trawl fishing
Benthic impact
Habitat preference
INLA, pulse fishing
VMS

Introduction

Continental shelves around the world are subject to intensive bottom trawling. Demersal fish assemblages inhabiting these shelves account for one-fourth of landed wild marine species (Amoroso *et al.*, 2018). The North Sea is part of the European continental shelf and is extensively trawled by different fishing gears. Increasing spatial claims for nature protection and wind farm energy suppresses, however, the area available to fisheries that may hamper the ambition to increase food production from marine environments. As such, it is essential to understand what defines suitable fishing grounds for bottom trawlers to allow for informed decisions on the location and design of windfarms and marine protected areas (Stelzenmuller *et al.*, 2008). This understanding is not only key for the spatial planning debate but also to illustrate that fishers are bound to certain hotspots in space and do not have the ability to move their activity without reducing the viability of their business. Beyond spatial planning, discussing the footprint of bottom fishing and comparing the impacts different types of fisheries have on seafloor integrity have increased in attention in recent years. This is likely driven by the Marine Strategy Framework Directive (MFSD) (EC, 2008) prescribing that member states in the EU need to ensure that seafloor integrity is at a level that ensures functioning of the ecosystem (Descriptor 6). Habitat characteristics, ecosystem functioning, and fishing impact are intertwined and hence all need to be appropriately addressed to evaluate the sixth MFSD descriptor. The societal debate also focusses on the ratio between seafloor impact (i.e. area impacted by a bottom trawl gear measured in km^2) and the amount of animal proteins obtained in the fishing activity, where generally fisheries with a lower ratio (i.e. footprint) are preferred. Studying habitat preference of bottom trawlers thus advances our understanding of benthic impact and ecosystem functioning as well as our ability to predict fishing impact at small spatial scales relevant for seafloor integrity, spatial planning, and fisheries footprint studies.

The spatial distribution of bottom trawlers differs among metiers (Eigaard *et al.*, 2017; ICES, 2018a) and reflects the broadscale distribution patterns of the targeted marine resources (ICES, 2018b, c). At a fine spatial scale (~1 km scale), the distribution of a fishery is often patchy (Rijnsdorp *et al.*, 1998; Murawski *et al.*, 2005; Lee *et al.*, 2010; Ellis *et al.*, 2014), reflecting habitat heterogeneity (van der Reijden *et al.*, 2018). Habitat heterogeneity will affect the local abundance of target species and determine the possibility to safely deploy a bottom trawl. As such, certain habitats are preferred over other habitats, i.e.

fished with higher intensity, as they yield higher catch rates. This is referred to here as habitat preference. Because sensitivity of the seafloor and the benthic communities differs across habitats, knowledge on habitat preference is important for the assessment of fisheries impact (Kaiser *et al.*, 2006; Lambert *et al.*, 2014; Hiddink *et al.*, 2017; Pitcher *et al.*, 2017; Rijnsdorp *et al.*, 2018; Hiddink *et al.*, 2019). Disentangling whether the spatial distribution of the fishing fleet is defined by either fishing gear type or target species habitat preference is challenging. However, such information is vital for fisheries management and spatial planning because changes in gear type (e.g. due to innovation or policy changes) may result in changes in the distribution of fishing effort and may alter the interactions with other stakeholders using the marine environment. Furthermore, understanding how habitat preferences change with modifications made to fishing gears could lead to more tailored gear design that reduces the seafloor impact. In fishing gear technology, one needs to be able however to objectively evaluate how changes in fishing gear design result in changes in fishing footprint, an approach for this is presented in this study.

This study focusses on the beam trawl fishery in the North Sea targeting sole (*Solea solea*) and plaice (*Pleuronectes platessa*). Beam trawls have been used from the 1960s onwards when they replaced the otter trawl as the dominant gear to catch sole and plaice (Rijnsdorp *et al.*, 2008). Although the large-scale spatial distribution of the beam trawl fisheries has shifted at decadal scales (Van der Pol *et al.*, in prep.), the fine-scale distribution of fishing activity has been very stable since the 2000s (Hintzen *et al.*, 2019). The fishery in the southern North Sea that primarily targets sole is known to be located in warmer, shallower, dynamic areas in the southern North Sea where sand ridges are common (van der Reijden *et al.*, 2018). In between these ridges, fishers tend to achieve good catches and therefore return to such grounds year after year. Fishers tend to avoid areas with coarser substrate (van der Reijden *et al.*, 2018; Hintzen *et al.*, 2019). Furthermore, their distribution is affected by the availability of sole and plaice quota (Poos *et al.*, 2010).

Traditionally, beam trawlers have fished with several tickler chains in front of their nets and a steel beam to keep the net open. Owing to increasing oil prices in the 2000s, the industry replaced the steel beam with a hydrodynamic foil (Sumwing) to reduce fuel consumption (Turenhout *et al.*, 2016b, Depestele *et al.*, 2019). A second innovation was the pulse trawl which replaced tickler chains with electrodes that emit electric pulses (van Marlen *et al.*, 2014, Depestele *et al.*, 2019). Although commercial electric fishing has been banned in

EU waters since 1998 (EU, 1998), a study fleet received a temporary exemption (Haasnoot *et al.*, 2016). Under this exemption, a large part of the Dutch beam trawl fleet switched to pulse fishing. Pulse trawling turned out to improve the economic profitability owing to a lower fuel consumption and improved catch efficiency for sole, although the catch efficiency for plaice and other species was reduced (van Marlen *et al.*, 2014; Turenhout *et al.*, 2016a; Poos *et al.*, 2020). A large part of the Dutch beam trawl fleet switched to pulse fishing between 2009 and 2015 and by 2016 about 95% of the Dutch sole quota were caught with the pulse trawl (ICES, 2018d). This large-scale switch to pulse allows us to study differences in habitat preference affected primarily by the change in gear design. Stakeholder information suggests that pulse fishers started to use different habitats compared to their distribution while using tickler chains (ICES, 2018d).

In this article, we study the interactions between gear developments, habitat heterogeneity, and habitat preference. Habitat preferences can be studied making use of statistical models (Rushton *et al.*, 2004; Bertrand *et al.*, 2016) that relate spatial count data to environmental variables. In this study, fishing vessel GPS data [vessel monitoring by satellite (VMS)] provided a detailed view of the spatial distribution of the fishing fleet. The micro-scale (tens of metres) at which the VMS data are available allowed testing for subtle differences in habitat preference when comparing two gear types. A study by van der Reijden *et al.* (2018) indicated already that among other factors, depth profile, sediment type, and natural disturbance were key indicators to explain habitat hotspots for beam trawl fishers. Noting that bathymetric information is available at very fine spatial scales (van der Reijden *et al.*, 2018), our ability to define habitat preference at micro-scale (tens of metres) is limited more by sediment and natural disturbance data, which are only available at lower resolutions (Wilson *et al.*, 2018).

The results show that there is a substantial difference (~50%) in spatial distribution between the pulse and tickler chain fisheries, where the first prefers habitat with higher gravel content and more elevated areas (relative to its surroundings) and shows fishing activity in between sand ridges. This shift in spatial distribution has caused some habitats to be more intensively impacted than before the switch to pulse gears while other areas are less frequently trawled. The benthic impact associated with the distributional shift is discussed. We argue that there is a clear role for habitat preference modelling in spatial fisheries management, such as tailoring the design of marine protected areas and supporting benthic impact assessments.

Material and methods

Case study

We study the Dutch beam trawl fleet targeting mainly sole in the southern North Sea. In this mixed fishery, sole is caught in a mixture with plaice, turbot, brill, and dab. Beam trawling has been used in the North Sea since the 1960s and has been a dominant fishery ever since in the Dutch fishing sector. On each side of the vessel, a 12-m wide steel beam fitted to a shoe on each side of the beam is dragged over the seafloor (see Eigaard *et al.*, 2016 for a graphical representation of the gear). The beam fixes the horizontal net opening and allows the fisher to deploy tickler chains perpendicular to the towing direction to chase flatfish from the seafloor into the net and increasing the catch efficiency of the gear (Daan, 1997; Rijnsdorp *et al.*, 2008). The pulse trawl is similar in design as the traditional tickler chain beam trawl but uses longitudinal cables that emit electric pulses which invokes a cramp response that immobilise the fish (de Haan *et al.*, 2016; Soetaert *et al.*, 2019). The pulse trawl gear is lighter and penetrates less deep into the sediments than the tickler chain gear and hence may provide access to softer habitats or more coarse habitats as the gear can be more easily pulled over these habitats (Depestele *et al.*, 2019, Rijnsdorp *et al.*, 2020). The fishery targets the same flatfish types, though catchability has increased fishing with the pulse trawl for sole and has been reduced for plaice compared to the tickler chain gear (Poos *et al.*, 2020). Both the tickler chain and the pulse trawl fleet belong to the same fleet segment TBB (beam trawls). We refer to the beam trawl fleet when speaking of both the tickler chain and pulse trawl combined while the two gear types are singled out when we discuss the differences between the two gear types.

Spatial fisheries data

The analyses included VMS data and mandatory catch and effort logbook data from all Dutch flagged vessels that fished during the transition from the tickler chain gear to the pulse trawl gear. Only vessels with engine power >221 kW were selected. These larger vessels were not allowed to trawl inside the 12-nm zone and in the so-called Plaice Box (see Figure 5.1). The study area was delineated by the 51º latitude line in the south and the 56º latitude line in the north (55º latitude west of 5º longitude), excluding the 12-nm zone and Plaice Box, corresponding to the area where beam trawlers are allowed to fish with 80-mm codend mesh size. The years 2009–2017 were included, as the first vessels switched to pulse trawling in 2009. From 2015 onwards, pulse trawling represented ~65–70% of the total area fished by the entire beam trawl fleet.

During the study period, fishing effort declined from ~14 000 fishing days in 2009 to ~11 000 fishing days from 2014 onwards.

VMS observations (i.e. pings, a signal from a fishing vessel transmitted via satellites to a ground station) include information about vessel name, speed and heading over ground, a date-time stamp, and a GPS position. Fishing activity was defined based on speed profiles (Poos *et al.*, 2013) and non-fishing pings were excluded from further analyses. Over time, the ping frequency of VMS has increased with more pings being submitted at 30-60-min intervals rather than the common 2-h interval rate (from 80% 2-h interval in 2009 to 63% by 2017). Daily catch and effort logbook records provided information on vessel length, engine horse power, trip information such as gear and mesh size used, and the catch by species. Usually, a fishing trip lasts around one working week. Although the tickler chain and pulse trawl share one common gear code in the logbooks, i.e. "TBB", an independent database was included which contains more details on gear specifications and their introduction date. Each fishing trip gear usage was further validated by analysing mean fishing speed during a trip as this was found to be highly indicative of gear usage (Poos *et al.*, 2020).

Creating count data

VMS and logbook data were carefully scrutinized for erroneous entries, following Hintzen *et al.* (2012). The final dataset included data from 70 vessels that were active during the transition from tickler chain to pulse trawl. This dataset was divided into two subsets: half of the vessels were randomly selected from the dataset and used for model fitting (training data), and the remaining vessels were used for cross-validation. Both subsets span all years and gears. The study area was divided into squares (i.e. grid cells) measuring one by one minute longitude–latitude (~2 km^2). For both the pulse trawl and tickler chain gear types separately, VMS pings within each square were summed and used as count data (i.e. counts) for the distribution model (Figure 5.1). As such, the number of VMS pings within a grid cell was used as a response variable in the statistical model.

Environmental covariates

A priori seven covariates were selected to be included in the model, which were shown to be relevant in determining the distribution of fishing effort of bottom trawl fisheries (van der Reijden *et al.*, 2018). Within the time-frame of this study the abiotic covariates are assumed to have remained constant. The following environmental variables were attributed to each of the grid cells in the study area: proportion gravel, proportion mud, proportion rock, depth,

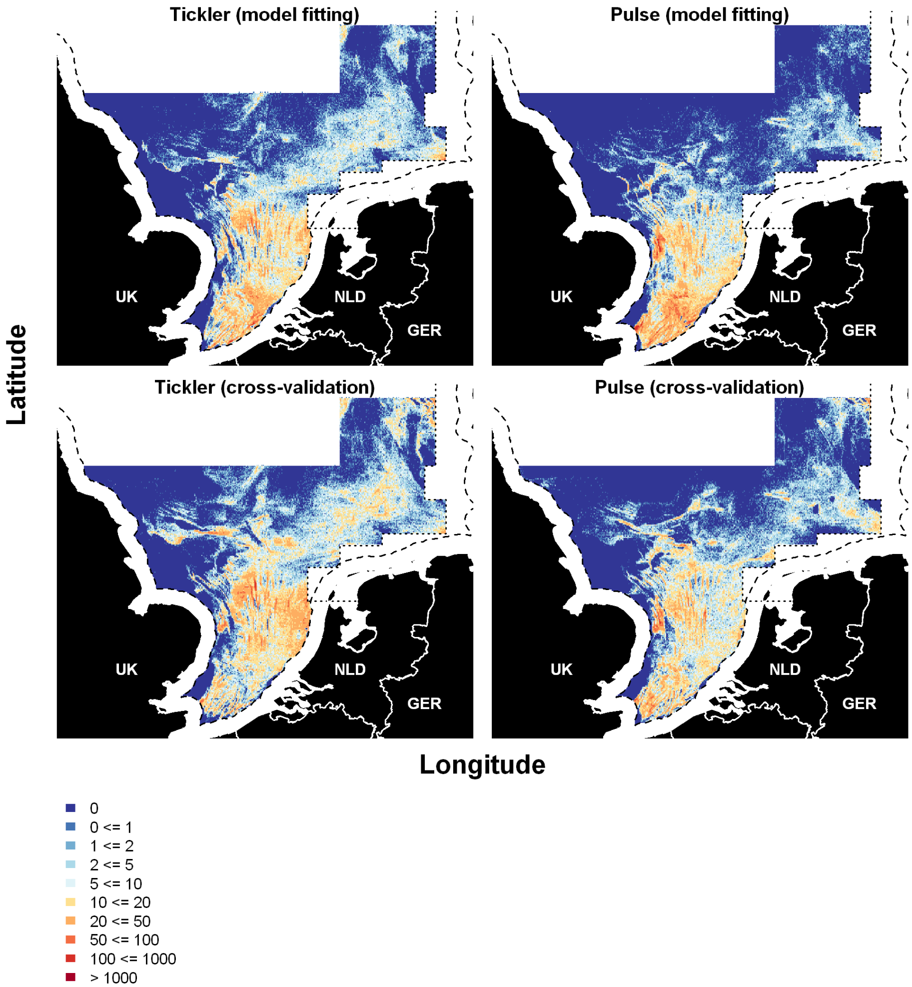

Figure 5.1 Colour-coded representation of VMS counts, associated with fishing, per grid cell. Darker red colours indicate higher values of fishing intensities while darker blue colours indicate zero to no fishing intensities. The top panels represent the data used for model fitting; the bottom panels represent the data used for cross validation. Left-hand panels show tickler chain trawling while right-hand panels show pulse trawling.

and mean tidal velocity as indictor of bed shear stress (bedstress). Note that proportion gravel, mud, and sand would sum to 100% and, for this reason, sand was excluded from the analyses to prevent having very high co-linearity among these. For each grid cell, distance to nearest Dutch harbour was calculated from the Euclidian distance between a grid cells' midpoint and the GPS midpoints of the Dutch harbours.

For depth, Bathymetric Positioning Index (BPI) was used, being a measure of the depth at a specific location relative to the depth in the surrounding grid cells maximum *r* km away (Figure 5.2). Two BPI values were used for each grid cell, with different *r* values: BPI 5 with *r* = 5 km (small-scale features) and BPI 75 with *r* = 75 km (large-scale features). These values were taken from (van der Reijden *et al.*, 2018). Gravel, mud, rock, and bed shear stress estimates were obtained from (Wilson *et al.*, 2018). Gear type (i.e. pulse trawl or tickler chain) was used as a covariate in the model (as a factorial covariate), which allows testing if there was a difference between the two gear types.

Furthermore, the inverse of average VMS interval time in each grid cell was used as a model offset. This offset was included to account for the change in a number of observations there are in the raw dataset owing to the decrease in interval rate of the VMS data from 2009 to 2017. There are more VMS observations when the interval time is low, resulting in higher VMS pings in a grid cell. This increased amount of pings should not be interpreted as an increase in fishing effort. The offset is a means to standardize the number of pings in each grid cell irrespective of the interval rate of the VMS data. Other available covariates such as sand proportion, depth, wave orbital velocity and intermediate BPI ranges were not considered owing to large co-linearity with the other covariates.

Model structure

We use a statistical framework to model the spatial distribution of fishing effort and hereby being able to objectively separate the response of fishing behaviour to different habitat characteristics. We used the Integrated Nested Laplace Approximation package in R, allowing for the inclusion of spatial latent fields to capture (residual) spatial autocorrelation in observations (Rue *et al.*, 2017). Both spatial and temporal correlation are, by the way VMS data are collected, present in the dataset, i.e. the location of consecutive VMS pings depends on the previous position and the maximum speed of a fishing vessel that allows it to move to another area. A correction for this correlation is necessary to prevent drawing incorrect conclusions on the preference of a fishing gear to a certain habitat characteristic. The spatial autocorrelation is modelled using a Matérn correlation function that is commonly used to model the statistical covariance between observations of two data points that are *x* km away from each other. Estimating the parameters in the Matérn correlation function requires dividing the study area into a large number of non-overlapping triangles, called a mesh. We used a mesh with an average leg length of ~14 km,

~¼ of a degree longitude. The mesh, with the maximum edge of 25 (i.e. the maximum leg length on the edge of the mesh) and a cutoff of 1 (i.e. the minimum leg length between data points), covers the North Sea delineated by the 51° latitude line in the south and the 56° latitude line in the north (55° latitude west of 5° longitude), expanding over the edges of the study area. The mesh was used as input to the stochastic partial differential equations approach to estimate spatial correlation in continuous space (Lindgren *et al.*, 2011).

For the distribution of the response variable, six options were explored: the Poisson, over-dispersed Poisson, Negative Binomial, Zero-inflated Poisson, and Zero-inflated Negative Binomial. Here, we started with a model including linear terms for all covariates and a separate spatial latent field for each gear type and selected one of the six statistical distributions leading to the lowest Watanabe–Akaike information criterion (WAIC, Watanabe, 2010) and Bayesian information criterion (BIC, Ghosh *et al.*, 2007) score while checking observed vs. fitted values to be reasonable. Both WAIC and BIC are statistical representations of goodness of fit and lower values indicate better statistical fits to the observations.

Model selection

First, the most appropriate distribution for the response was selected fitting a full model including a spatial correlation factor for each gear type. Next, we extended the linear terms for the covariates with multi-order (first to seventh) polynomials. Also, the interaction between gear type and each polynomial function of the covariates was included through testing if confidence intervals of the respective covariate or covariate interaction of the more complex model were outside the bounds of the less complex model. In the third and final iteration, all covariates were evaluated adding or reducing the polynomial degree by one, as changes in step 2 could have resulted in small changes in the fit of one of the other covariates. This led to a final model generically formulated in (Equation 5.1). Best models were selected based on fit (visual), lowest WAIC, and ability to estimate the cross-validation counts (R^2 on observed ~ fitted linear model).

The spatial correlation is estimated for both the pulse and the tickler chain gear types.

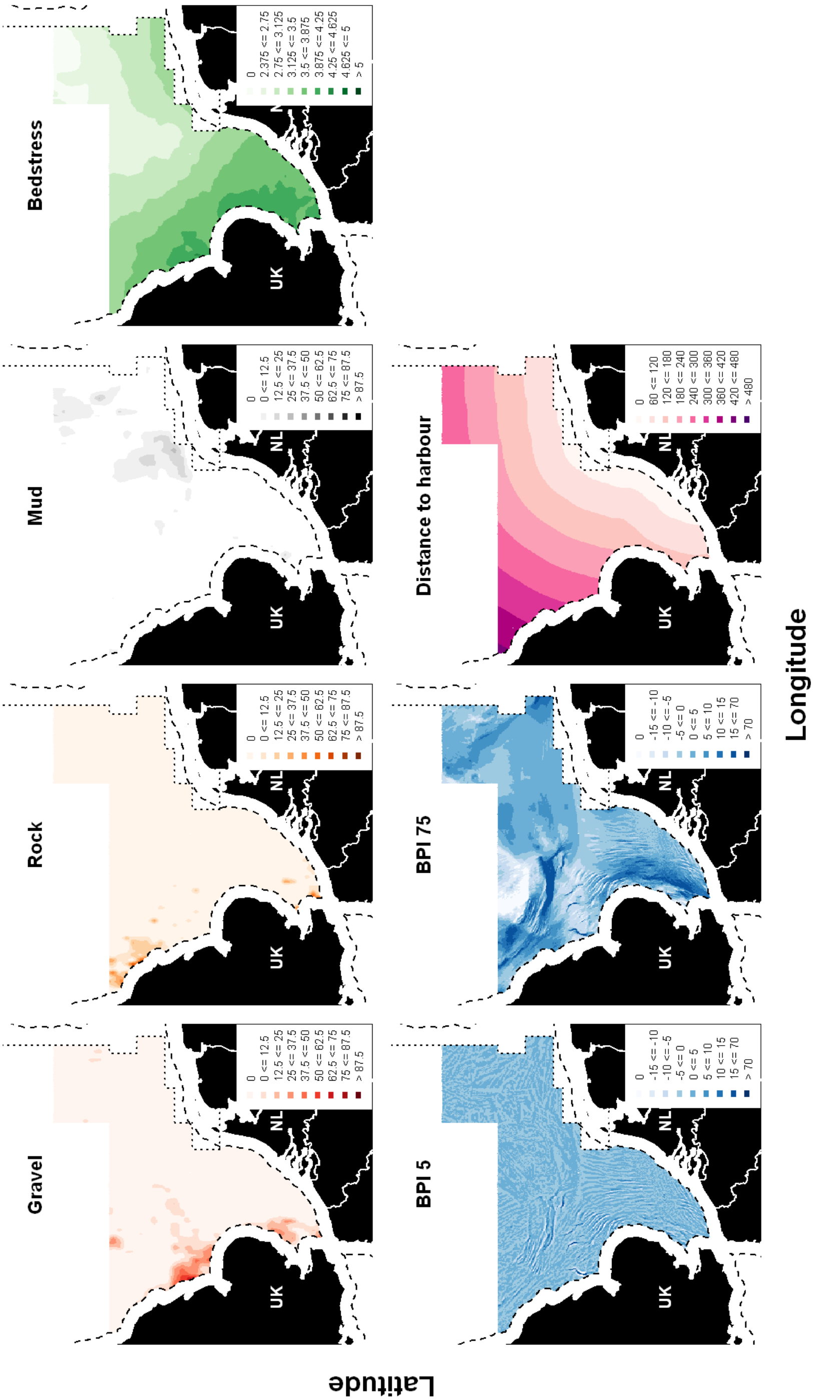

Figure 5.2 Colour-coded representation of the covariates in the study area. Darker colours indicate larger percentages/higher values of the covariate.

5

$$
\begin{aligned}
Y \sim\ & I + \mathrm{Mud} + f_p(\text{distance to harbour}) + \mathrm{Gear} \\
& \times \left[f_p(\mathrm{Gravel}) + f_p(\mathrm{Rock}) + f_p(\log(\mathrm{Bedstress})) \right. \\
& \left. + f_p(\mathrm{BPI5}) + f_p(\mathrm{BPI75}) \right] + \mathrm{offset}\left(\log\left(\frac{1}{\mathrm{intervalRate}} \right) \right) \\
& + \varepsilon + A(s;\ s_0)\, u(s_0),
\end{aligned}
\tag{5.1}
$$

where Y represents the predicted total number of VMS pings (counts), I is the intercept term, and $f_p(\cdot)$ is a pth-order polynomial, where p can vary between 1 (linear term) and 7 (seventh order polynomial). Spatial correlation is defined by $A(s;\ s_0)\ u(s_0)$ where $A(s;\ s_0)$ represents the projection matrix to project the process from the mesh nodes to the VMS locations. $u(s_0)$ represents the random field at the mesh nodes. Note that Y represents either counts of pulse trawl or tickler chain owing to the *Gear* factorial covariate in the equation.

Finally, an analysis was undertaken adding covariates one at a time, keeping in each iteration the covariate that explains most of the remaining variance (and is associated with the lowest WAIC value). This analysis indicates which covariate is most important in explaining the differences between habitat preference of the two different gear types. Covariates that did not result in a significant reduction in WAIC value were omitted from the model used to make predictions on the standardized spatial distribution of both gears.

After the model was fitted to the data, 10 000 new sets of model parameters were simulated using the uncertainty estimates of these parameters and their joint posterior distributions that describes the correlation between all estimated model parameters. These parameter sets were used to obtain 10 000 predictions of VMS pings for each grid cell. VMS pings are equal to fishing effort here as the predictions are standardized for interval rate and as such each ping represents 1 h worth of fishing activity. To be able to quantify differences in the estimated relative distribution of the tickler chain and pulse trawl, each of the 10 000 samples were scaled by its maximum value. As predicted values depend on the total effort of each of the gears, which is different for the pulse and tickler chain fisheries, the scaling is necessary to account for the effort difference. The proportion of effort allocated was calculated for tickler chain and pulse trawl and compared grid cell by grid cell, assuming that if either pulse trawl or tickler chain trawl intensities were outside 95% of the predictions of the other gear, they would be considered statistically different. In those cases where 97.5% of the samples of pulse trawl had a lower value than the lowest 2.5% of tickler chain fishing, the area was marked as significantly favoured by the tickler chain. The same was applied to cases where 2.5% of the pulse trawl samples had a higher value than the lowest 97.5% of the tickler chain fishing. These areas were marked as being statistically significantly favoured by the pulse trawl gear.

Results

Model fit

The observed and estimated counts are in good agreement and observations fit well within the uncertainty bounds as estimated in the model (Figure 5.3e and f). Although the spatial distribution of both the pulse and tickler chain trawling fleets in the model training data is markedly different from the data used for cross-validation (see Figure 5.1), the model fits well to the cross-validation data. There is a slight underestimation of grid cells with 2–5 counts and overestimation for grid cells with 5–15 counts in the cross-validation data (panel f), potentially caused by temporal effects that were ignored in the model.

Each of the covariates were modelled with increasing flexibility in polynomial design. Model selection let to conclude that BPI 5 was modelled as a second order polynomial, BPI 75 as a fourth order, mud as a linear term, gravel as a third order, distance to harbour as a fourth order, rock as a third order and bedstress as a fourth order polynomial. For each of the covariates, the model fitting procedure yields a relationship between the covariate itself and the preference for it for each gear type (Figure 5.4). If values exceed $y = 0$, including the confidence bounds, it is interpreted as a preference. This preference varies over the range of the covariate itself and can, e.g. illustrate negative preference at negative relative depths (BPI 75) and positive preference at positive relative depths (BPI 75).

Visual inspection of the residuals, including fitted loess smoothers through the residuals, did not highlight any apparent pattern or deviation of balanced residuals. Spatial residuals showed randomness on the model fitted data and some minor patterns for the cross-validation fit.

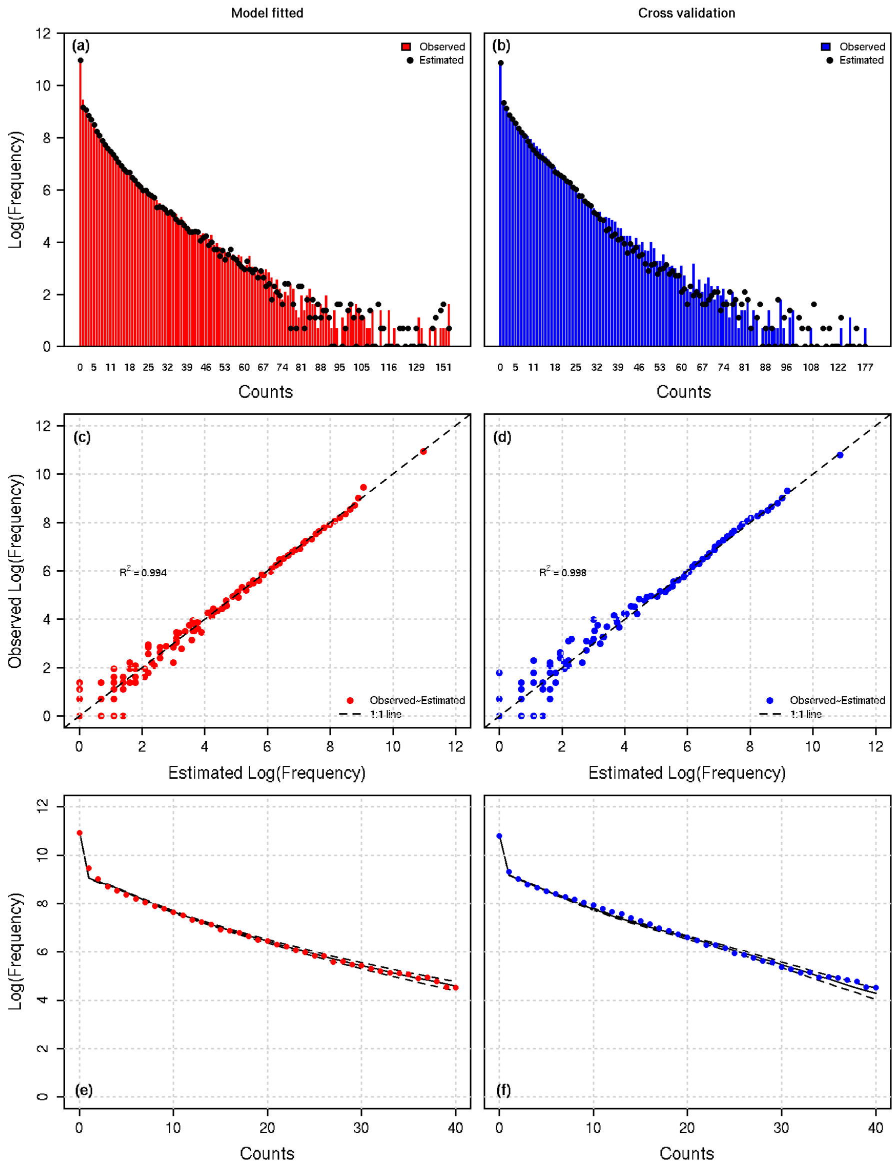

Figure 5.3 Diagnostic plots of the fit to the combined pulse and tickler chain trawling data. Panels (a), (c), and (e) refer to model fit to the training data while panels (b), (d), and (f) refer to model fit to the cross-validation data (data not used for model fitting). Panels (a) and (b) shows the observed log-frequency of 0, 1, 2, etc., counts in the dataset in red/blue bars, the black dots represent the estimated frequency of these counts by the model. Panels (c) and (d) show the 1:1 relationship between total observed and estimated counts. Panels (e) and (f) show the counts vs. log-frequency including a 95% confidence bound (dashed lines).

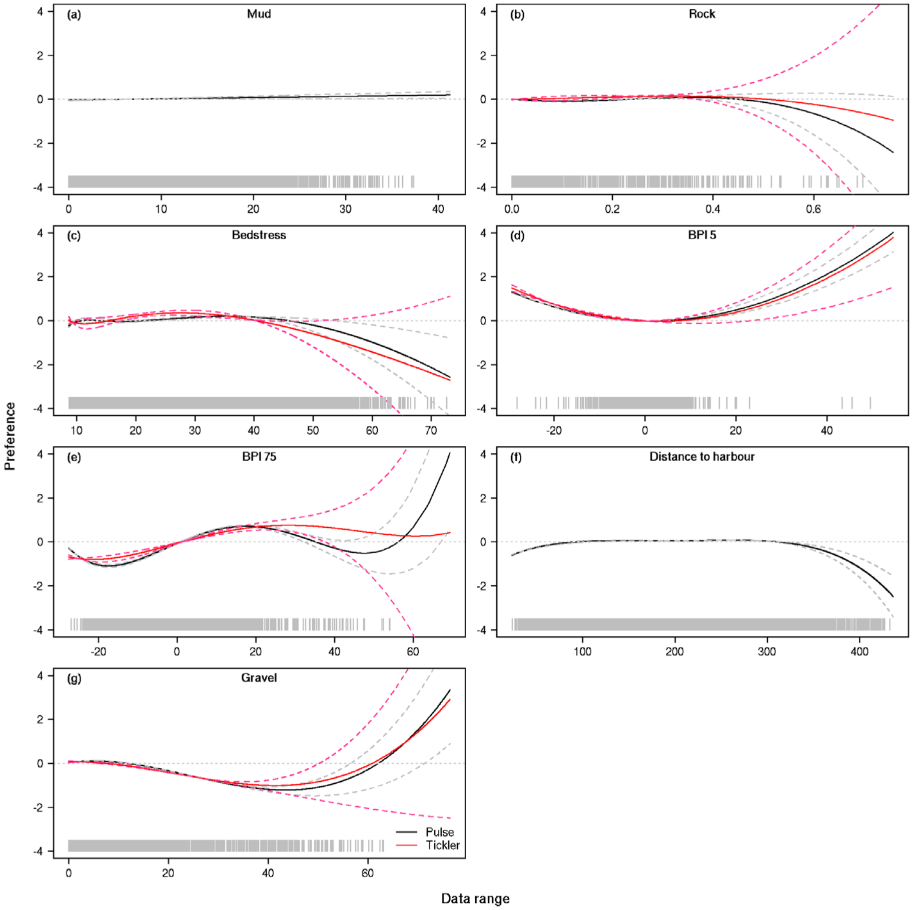

Figure 5.4 Estimated covariate effect (i.e. relationship between the covariate itself and the preference for it) by gear (red = tickler chain, black = pulse trawl) over the data range of each covariate (*x*-axis). Dashed lines show the 95% *CI* and the grey vertical bars at the bottom of each panel indicate where observations were available (5% random subsample to improve interpretation). A horizontal dashed line is added at preference = 0 for reference. Values greater than 0 indicate a preference for a specific condition relative to the mean, while values smaller than 0 indicate an aversion for a specific condition relative to the mean. Panel (a) shows the marginal effect (i.e. keeping the effect of other covariates constant) of muddy substrate for both gears combined, panel (b) shows the effect of rocky substrates for both tickler chain and pulse trawl gears, panel (c) shows the effect of bedstress, panels (d) and (e) show the effect of the bathymetric position index with range 5 and 75 km respectively, panel (f) shows the effect of distance to the nearest Dutch harbour for both gears combined, and panel (g) shows the effect of gravel substrates for both tickler chain and pulse trawl.

Habitat preference

There is a clear preference for both gear types to fish at slightly elevated areas (BPI 75), in between sand ridges (BPI 5), and in areas with higher bedstress (Figure 5.4). Fishing in areas with higher gravel content and (to a lesser extent) more rocks is generally avoided. No preference for a specific range of mud fractions was found. For the distance to harbour variable, preference was rather similar over a broad range of distances between 50 and 300 km from harbour representing the fishing area for sole outside the 12 nm zone and below the northern border of the study area.

The interaction between habitat variable and gear type was significant for the habitat variables BPI 5, BPI 75, bedstress, rock and gravel, while no significant difference was observed for distance to harbour and mud (Table 5.1). The relative depth, measured over a 75-km radius (BPI 75) is the most important explanatory variable, reducing the WAIC by 146 points. This represents 72% of the overall reduction in WAIC compared to the model without covariates. Furthermore, including distance to harbour and bedstress, up to ~95% of the reduction in WAIC is explained. A final 3% is explained by adding percentage gravel. Adding rock, BPI 5 and mud did not improve the model and resulted in a minor increase in WAIC.

Table 5.1 Estimated WAIC, the drop in WAIC when including more covariates and the contribution of each covariate to the model with the lowest WAIC expressed in percentages.

Covariate	WAIC	ΔWAIC	%ΔWAIC
Intercept + Gear + SpatialCorr	100 881	–	–
+ gear x BPI 75	100 735	146	72
+ distance to harbour	100 710	25	12
+ gear x log(Bedstress)	100 686	24	12
+ gear x Gravel	100 679	7	3
+ gear x Rock	100 681	-2	0
+ gear x BPI 5	100 683	-2	0
+ Mud	100 683	~0	0

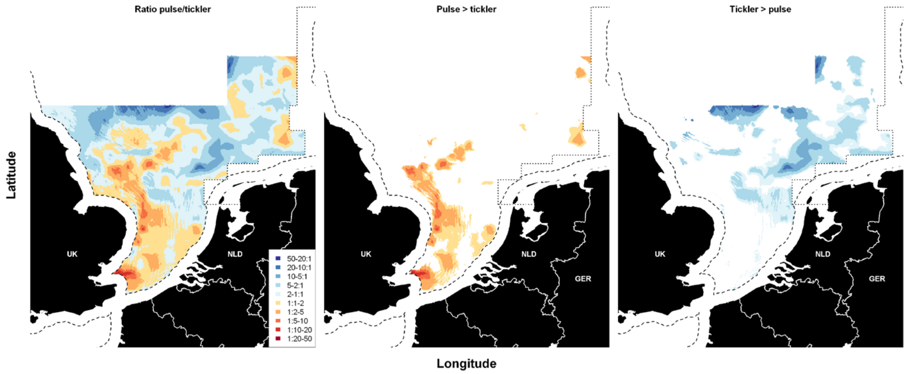

Figure 5.5 Effort of pulse trawl divided by effort of tickler chain trawlers (left panel). The areas significantly preferred by pulse trawls (middle panel) and the areas significantly preferred by tickler chain trawls (right panel) are coloured, all grid cells without significant differences are left white. Values smaller than 1:1 indicate a proportional lower effort investment in a grid cell for pulse trawlers compared to tickler chain trawlers. Values larger than 1:1 indicate a proportional higher effort investment in these grid cells for pulse trawlers.

Comparison of the preference curves between gear types shows that pulse trawling has a slight but significant stronger preference for the intermediate depths of BPI 75 and a lower preference for deeper and slightly elevated areas than tickler chain gear. Deeper troughs (BPI 5) are preferred by both types of fishers, while pulse fishers also have a preference to fish at tops of sand ridges (BPI 5). The additional explained variance by the BPI 5 covariate is low however. The preference curve for bedstress of the pulse gear is shifted to a slightly higher bedstress. For gravel habitats, pulse gear has a slight but significant preference for low gravel fractions (i.e. preference is just above the *y* = 0 line in Figure 5.4). Tickler chain gear tries to avoid gravel habitats under all circumstances.

A model consisting of fixed effects BPI 75, distance to harbour, bedstress, and gravel with a VMS interval rate set to 1 h was used to predict the pulse and tickler chain counts for each of the grid cells in our study area (hereby dropping rock, BPI 5 and mud given the minor contribution to overall gear differentiation and potential inflation of confidence intervals). Although the overall distribution of fishing activity is similar between the two gear types, there are areas where pulse trawls are more active, such as in the southwestern part of the North Sea, while tickler chains are more dominant in the south eastern part (i.e. German Bight) (Figure 5.5).

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Predicting spatial distribution

When determining the ratio in predicted pings between pulse and tickler chain gear, areas that show marked differences between the two gear types are given in darker colours (Figure 5.5). The middle and right-hand panels show the areas that are significantly different for both gears (middle panel shows significantly higher pulse, right-hand panel shows significantly higher tickler chain). The area where tickler chain or pulse activity differed significantly amounted to 49.7% of the study area, with 16.8% of the area associated with higher pulse activity and 32.9% associated with higher tickler chain activity. A breakdown of the ratios is given in Figure 5.6, showing that 80% of the grid cells with significantly different intensity are associated with ratios between 3:1 and 1:3. Only 7% of the grid cells not significantly different in intensity are associated with ratios outside this intensity range. Table 5.2 shows the main characteristics of areas where tickler chain or pulse activity differed significantly compared to the average of the study area. This shows that pulse trawling is significantly more active in areas with higher gravel content, in more elevated areas compared to its wider surroundings (BPI 75) and in areas with higher bedstress (southern North Sea, which is also located, on average, closer to shore than areas further north). Tickler chain fishers fish in areas with lower gravel content, on less elevated grounds compared to its wider surroundings (BPI 75) and in areas with lower bedstress. The tickler chain fishers do show a preference for areas with higher bedstress (see Figure 5.4) and both groups prefer to fish in between sand ridges (BPI 5) rather than on the slopes or top.

Table 5.2 Mean characteristics of the area significantly different between pulse and tickler chain fishing (e.g. areas significantly preferred by pulse fishers are on average 146.17 km from the harbour).

	Pulse trawl > tickler chain		Tickler chain > pulse trawl		
	Significant area	Ratio significant/ total	Significant area	Ratio significant/ total	Total area
Bedstress (ms^{-1})	38.47	1.44	20.56	0.77	26.80
BPI 75 (m)	3.52	2.50	1.04	0.74	1.41
Distance to harbour (km)	146.17	0.80	158.84	0.87	181.59
Gravel (%)	6.20	1.49	1.06	0.25	4.17

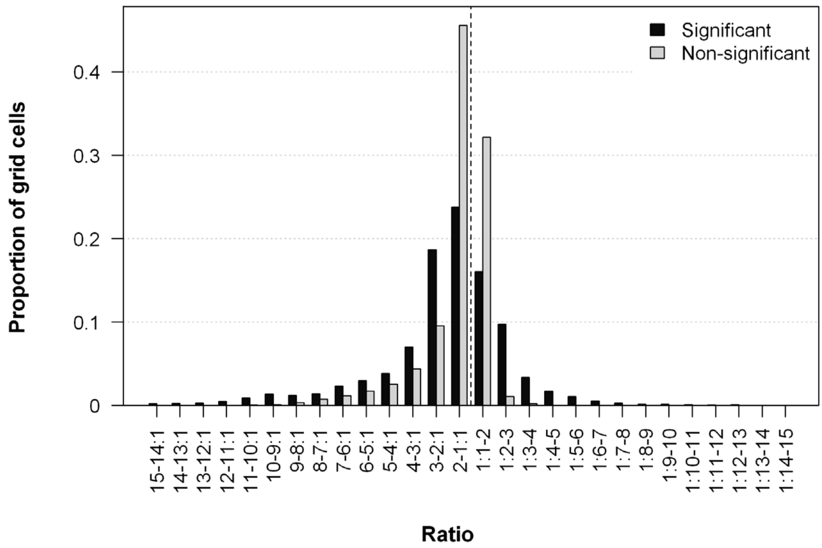

Figure 5.6 Effort of pulse trawl divided by effort of tickler chain trawlers for grid cells significantly preferred by either pulse or tickler chain trawls and grid cells not significantly different, scaled by the total number of grid cells in the area. Values larger than 1:1 (right of the vertical dashed line) indicate a proportional higher effort investment in these grid cells for pulse trawlers.

The difference in aggregation of fishing activity between the pulse trawl and tickler chain fishers is best illustrated when we assume that an average grid cell is fished with one unit of effort. Pulse fishers deploy around three units of effort in each of the significant grid cells (i.e. cluster a large part of their effort in these areas: 50% of all effort units in 16.8% of the study area). Tickler chain fishers only deploy an additional 0.35 units of effort in the areas they have significant higher counts (i.e. show a more evenly distributed effort all over the fishable areas: 44% of all effort units in 32.9% of the study area).

Discussion

Spatial distribution of bottom trawl fishery

The beam trawl fleet (both tickler chain and pulse trawl) preferentially selects elevated landscapes (i.e. higher BPI at large spatial scales, BPI 75), substrates with low gravel content and in-between sand ridges rather than on the top (lower BPI at small spatial scales, BPI 5). These results agree with the findings of van der Reijden *et al.* (2018) and suggest that habitat characteristics of fishing hotspots apply to areas with lower fishing intensity too. The beam trawl fleet seems to avoid either rocky or muddy substrates. Furthermore, there is no clear preference to fish closer or further from shore up till ~300 km where after preference shows a clear dip, associated with the area north of 56° where larger mesh sizes are obliged, limiting the ability to catch sole.

Differences between pulse trawl and tickler chain trawl fisheries

Predictions showed that the spatial distribution was significantly different for the two gear types in almost 50% of the entire study area. The tickler chain fishery was most abundant both in the southern North Sea and in the German Bight in the eastern part of the North Sea north of the Netherlands and Germany. The pulse fishery was more concentrated in the southern North Sea, closer to the United Kingdom 12-mile zone. This southern area is characterized by higher bedstress and has more gravel patches and sand ridges, which are reflected by the higher variability in bathymetric position index at large spatial scales (BPI 75). Since the pulse fishery is more concentrated in the southern North Sea, the region closest to most Dutch harbours, the overall distance to harbour is lower for pulse fishers too.

This spatial shift between tickler chain and pulse trawlers could be explained by the change in catchability of sole. Compared to the tickler chain trawlers, the pulse trawlers have a substantially higher catch efficiency for sole (and lower efficiency for plaice) (Poos *et al.*, 2020). Sole abundance in the German Bight has declined since the 90s and increased in the southern North Sea (Vansteenbrugge *et al.*, 2020); this change in the main distribution area of sole in the southern North Sea likely explains the observed spatial shift of effort. It is unlikely that the shift is a result of a change in habitat preference, as in general, habitat preference is similar for both gear types. The shape of the preference curves for abiotic variables such as BPI and gravel are very similar (Figure 5.4, e.g. for gravel the fitted preference curves are very close to each other over the entire range), though do occasionally differ significantly in absolute terms where, e.g. pulse trawl has a higher preference for BPI 75 in the range of 0–20 m.

Consequences of the transition from tickler chain to pulse trawl

The transition from tickler chain beam trawls to pulse trawls led to a higher catch efficiency, a lower towing speed, and a reduction in the impact on the benthic ecosystem (Poos *et al.*, 2020; Rijnsdorp *et al.*, 2020). Our study showed that pulse fishers spent around three times the effort per grid cell compared to an average grid cell in the study area, in areas where they have a significantly higher preference compared to the tickler chain fishers. Tickler chain fishers only spent an additional 35% of their effort per grid cell compared to an average grid cell in the study area. As such, they spatially aggregate their effort to a higher degree than the tickler chain fishers do, which implies that these areas are fished at higher fishing intensities (Ellis *et al.*, 2014; Hintzen *et al.*, 2019). The pulse preference areas are associated with higher gravel content. Coarser sediments have been shown to be more vulnerable to fishing (Hiddink *et al.*, 2017; Rijnsdorp *et al.*, 2018) because they generally contain more sessile and longer-lived organisms. These organisms decline more rapidly in biomass under higher fishing pressures compared to communities with mobile and short-lived organisms (Hiddink *et al.*, 2019). Furthermore, if pulse fishers moved to previously unfished areas, a substantial reduction in benthic biomass can be expected in those areas (Sciberras *et al.*, 2018). However, the impact depends not only on the trawling intensity but also on the penetration depth (Hiddink *et al.*, 2017; Sciberras *et al.*, 2018) and sensitivity of the benthic community, being related to the amount of natural disturbance (van Denderen *et al.*, 2015b; Rijnsdorp *et al.*, 2018; Hiddink *et al.*, 2019). Bedstress caused by currents is higher in a large part of the pulse fishing area, mostly in the southern North Sea, compared to the tickler chain spatial distribution. The penetration depth of the pulse trawl is less than half the penetration depth of the tickler chain beam trawl, and depletion rates of epi-benthos imposed by pulse trawls are ~50% less than tickler chain beam trawls (Depestele *et al.*, 2019). Indeed, direct mortality imposed by pulse trawling is less than by tickler chain beam trawling (Bergman and Meesters, 2020) and Rijnsdorp *et al.* (2020) demonstrated that overall benthic impact of pulse trawling was lower than that of tickler chains. In addition, further aggregation of fishing effort by the pulse fishers implies that a larger proportion of the seafloor outside of the preference areas remains unfished or is fished with lower intensity.

The importance of scale in habitat analysis

Here, we analysed habitat preference at a spatial resolution of 1 minute x 1 minute. Detailed studies in the southern North Sea, however, revealed small-scale heterogeneity in bathymetry and sediment composition with alternating ridges and troughs at scales well within the 1 minute x 1 minute grid cells (van Dijk *et al.*, 2012; Koop *et al.*, 2019; van der Reijden *et al.*, 2019). This micro-scale heterogeneity may have been used by pulse trawlers. Anecdotal information from fishers indicates that pulse trawlers may have been able to fish areas that could not be fished by tickler chain beam trawlers due to the softness or higher gravel content of the sediment. Higher resolution data on the habitat covariables are required to investigate this hypothesis and assess the consequences on the benthic ecosystem. Furthermore, higher resolution data also help in pinpointing the habitat preference of target species and identify how much habitat is available and may be in need of protection when fish stocks are in decline. For example, the possible occurrence of untrawlable habitat fragments may be relevant to understand the effect of trawling on the population dynamics of sole because these habitat fragments could provide a network of refugia where sole may have been safe from exploitation. At the same time, being yet unable to identify the exact size and characteristics of fisheries hotspots hampers decision-makers to accurately value fishing grounds in a trade-off with other uses such as nature reserve or offshore energy farms.

General use of habitat modelling

The methodology used in this study shows the added value of fitting habitat preference models to VMS data, which is now routinely available for a large part of the global fisheries (Amoroso *et al.*, 2018). Models like these allow testing for both spatial and temporal correlation in vessel abundance indicating the variability in time and space of specific fisheries. This information is valuable for bottom impact assessments where frequency of trawling and time for benthic communities to recover play an important role (van Denderen *et al.*, 2015a). Furthermore, they allow for different management strategies to be developed, such as habitat credit systems (Kraak *et al.*, 2012; Batsleer *et al.*, 2018) for which there is a need to quantify the spatial overlap in habitat preference between different fishing gears. A habitat credit system requires information, on a fine spatial scale, on the likelihood of other fishers to use a specific fishing spot, this to set a cost to each individual fishing area. The statistical framework developed here can provide this estimate but is also able to show if nearby areas are accessible to the fishery that could reduce pressure on traditionally heavily fished grounds.

Having detailed overviews of spatial distributions of fishing activity in relation to benthic (micro)habitats allows for the evaluation of ecosystem functioning of these habitats. This is required under the MSDF (EC, 2008) where member states need to bring the seafloor in such a state that it ensures appropriate functioning of the ecosystem. The methodology developed here provides standardized estimates of fishing impact (contrary to raw VMS-based estimates that are spatially correlated) per habitat type, which has a direct link to ecosystem functioning (Rijnsdorp *et al.*, 2018). It furthermore shows the likelihood that fishers are willing to move to other areas, i.e. if habitat preference to a specific abiotic factor is high, the willingness of fishers to move from those grounds is likely to be small. As such, the estimated habitat preference provides a fisher-independent view on where fishers like to fish, regardless of their home port or quota share.

In the spatial planning debate where managers need to decide where to make room for fishing activity and where to locate windfarms and marine protected areas requires reliable information on ecosystem functioning, suitability of areas to serve as wind farms and habitat preference for fish species and their fishers (Stelzenmuller *et al.*, 2008). The latter one is often inferred from recent observed distribution patterns while these could be biased due to other legal restrictions such as spatial closures and quota availability but also variability in the local productivity of fish stocks. For a long-term perspective, these variables need to be eliminated as can be achieved by making use of habitat preference models.

We demonstrated that changes in gear design had a marked impact on fishing distributions. However, these models could also be used to describe historic changes in distributions of fishing activity at small spatial scales in the absence of gear changes. In the marine spatial planning debate, optimizing the allocation of space for different uses such as energy production, nature conservation and fisheries is crucial. With help of habitat preference modelling, displacement of fisheries can be forecasted statistically, although longer-term forecasts would require inclusion of target species distribution. When predicting from the habitat model, a sum of total fishing effort is distributed over the grid cells according to each grid cells' preference, i.e. proportion of effort they will receive. If one wants to study how total effort would be distributed over space if certain grid cells would be closed, due to, e.g. windfarm development, the effort previously attributed to the windfarm area will be distributed over the remaining grid cells according to their preference. Such predictions are essential in decision-making by marine resource managers as decisions on, e.g. spatial closures or wind farm areas exclude other users. If there is a substantial change in target species distribution however, one needs to include this shift before making predictions based on habitat preference models. Even so, other factors such as temperature change or food availability for target species could become relevant covariates to include when studying the distribution of the fishing fleet over longer periods.

Beyond being able to predict spatial distributions from these statistical models is the ability to estimate the uncertainty of fishing intensity in relation to habitat use, i.e. for each grid cell, the uncertainty in habitat preference and hence uncertainty in predicted fishing counts are available. This is currently not possible with maps derived from raw VMS data. Given that VMS-based spatial analyses of fishing activity often include several assumptions (Hintzen *et al.*, 2012), accounting for uncertainty not only reflects reality, it also provides a range in the footprint of bottom trawling fisheries considering the uncertainty.

Data availability statement

Primary VMS data and catch and effort data of the mandatory logbook are subject to confidential, privacy related, agreements. One should contact Sieto Verver, Head of the Centre for Fisheries Research (sieto.verver@wur.nl) for permission using these data.

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5

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Author contributions

NTH and ADR conceived the ideas, NTH and KJVdR compiled the data, NTH, GA, and JJP designed the methodology, and NTH led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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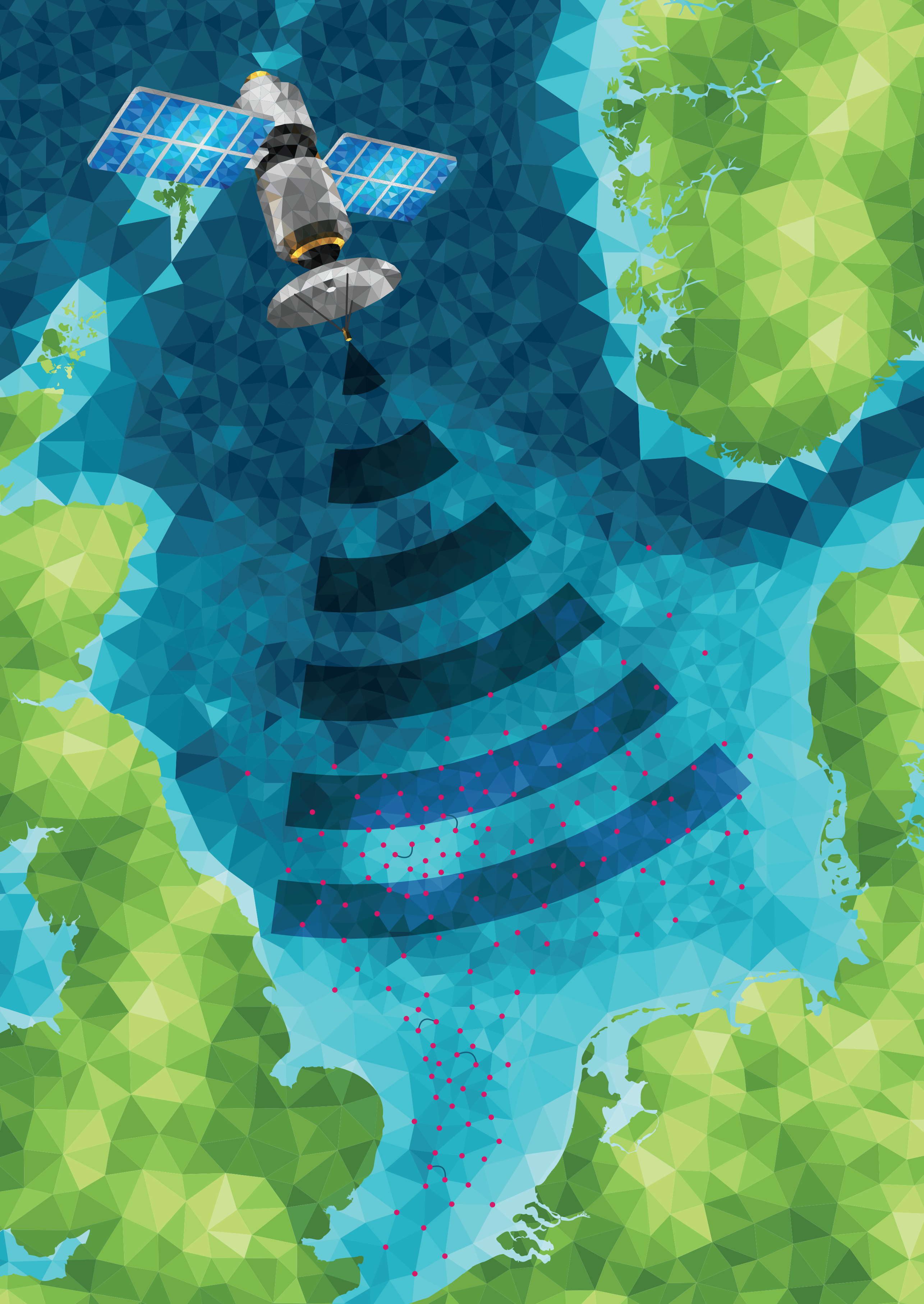

6

General discussion

General discussion

Studying marine fish and fisheries is complicated by the difficulty to directly and routinely observe fish behaviour in their natural habitat and the interaction with their natural environment and fisheries. Not only are there physical limitations to obtaining such observations, at-sea research cruises are expensive and data collection prone to e.g. weather conditions. Hence, fisheries scientists are often challenged to work from conceptual ecological mechanisms to explain the impact of fishing on fish stocks and the marine ecosystem. Statistics are then used to fit conceptual models to observations and to forecast future responses to fishing. It is therefore not surprising that fisheries management has banked on simple single species approaches for decades because single species models require a modest collection of data. The catch data for target fish stocks and effort data are collected throughout the year at spatial scales matching that of the distribution of a fish stock, such as the entire North Sea.

Managing just the target fish stocks, however, ignores the other aims of fisheries management: to protect the marine environment including sensitive habitats, non-target species, and system-wide processes (Link, 2010). Combining all these aims is often referred to in the literature as the Ecosystem Approach to Fisheries Management (EAFM). Although easily to identify as an aim for management, the knowledge needed to make an EAFM work is extensive (Skern-Mauritzen *et al.*, 2016). It requires for example an understanding of nutrient cycling in the oceans, primary production, marine food web dynamics relating predators and preys to each other, fish behaviour such as reproduction strategy, spawning and foraging habitats, and the alteration of all these processes when fishing takes place in terms of seafloor impact, removal of target and non-target species, bycatch of undersized fish or vulnerable species such as skates and rays. A further complicating factor to achieve an EAFM is the increased pressure for space on shelf areas such as the North Sea where various human activities such as aquaculture (Dempster and Sanchez-Jerez, 2008), nature reserves (Edgar *et al.*, 2014), wind energy (Stelzenmüller *et al.*, 2016), intensified shipping, oil and gas industry, and military are competing for marine space.

Without doubt, vast amounts of data are needed to scientifically underpin the interactions relevant for an EAFM such as between marine species and their habitats, with other species, and with human use like fisheries. Two sets of data, being logbook data and Vessel Monitoring by Satellite (VMS) data, are currently considered the backbone of fisheries dependent data for a vast range of research questions. Logbook data contains information on vessel ID, a date stamp, several vessel characteristics, such as departure and landing harbour, departure and landing time, gear information, and fishing location and their landings at ICES rectangle resolution. VMS data contains information on GPS position, a timestamp, vessel ID, speed, and heading. There is a wide variety of scientific papers making use of these datasets to study: the identification of spatial-temporal trends in unwanted bycatch (Uhlmann *et al.*, 2014; Sigurðardóttir *et al.*, 2015; Batsleer *et al.*, 2016), the impacts of fisheries on benthos (Reiss *et al.*, 2015; Rijnsdorp *et al.*, 2016; van Denderen *et al.*, 2014; Batsleer *et al.*, 2018), the changes of fishing gear technology and mixed fisheries (Eigaard *et al.*, 2014; Ulrich *et al.*, 2012; Poos *et al.*, 2013), the interactions with seabirds (Tyson *et al.*, 2015) and fleet behaviour (Poos and Rijnsdorp, 2007a; Vermard *et al.*, 2010), mapping fisheries catches at higher spatio-temporal scales by combining logbook and VMS data (Gerritsen and Lordan, 2011; Lee *et al.*, 2010; Maina *et al.*, 2016; Mills *et al.*, 2007; Murawski *et al.*, 2005; Witt, 2007), quantifying the impact of fishing on the seabed (Amoroso *et al.*, 2018; Eigaard *et al.*, 2016; Rijnsdorp *et al.*, 2016), studying the benthic response to fishing (Piet and Hintzen, 2012; van Denderen *et al.*, 2014; van der Reijden *et al.*, 2018) and many more topics. The number of scientific papers that zoom further into high spatial and temporal scale to provide an underpinning for the ecosystem approach to fisheries management is fast growing.

The ambition to zoom further into smaller spatial and temporal scales is internationally echoed given the growing number of publications using VMS and the Automatic Identification System (AIS) datasets (providing GPS at interval rates of several seconds) (Shepperson *et al.*, 2018, Natale *et al.*, 2015, Kroodsma *et al.*, 2018). Two main obstacles had to be dealth with however to be able to zoom in further and provide reliable estimate of fishing effort: the first was to combine fisheries data across countries while respecting privacy concerns associated with the data (Hinz *et al.* 2013), this has led to the development of dedicated software in R to automate and standardize VMS and logbook analyses (Chapter 2; Hintzen *et al.*, 2012). The standardization ensures that data is treated in a similar manner across countries and could, in final stages of a study, be combined and shared in more aggregated form that no longer is considered confidential. It furthermore allows unambiguous interpretation of results as variation in data preparation is brought back to a minimum. Ultimately, the transparency on exact working procedures as well as repeatability of the analyses allows continuous improvement on quality such as has become standard procedure with the ICES community delivering annual maps of fishing intensity across the ICES area (ICES, 2018). The second obstacle related to accounting for limited spatial and temporal coverage. AIS has shown to have gaps in spatial coverage throughout fishing trips (Shepperson *et al.*, 2018). VMS shows clear temporal gaps with data points being available every 30-120min and therefore interpolation routines had to be developed (Chapter 3; Hintzen *et al.*, 2010). With these technological advancements in place, two key questions can be answered: where do fishers allocate effort at small spatial scales and what drives fishers effort allocation. These two questions are further discussed below.

Where do fishers allocate effort at small spatial scales

At small spatial scales, bottom trawl fishers prefer to fish in specific benthic habitats (van der Reijden *et al.*, 2018; Chapter 5: Hintzen *et al.*, 2021), aggregated effort in space, and avoid unfavourable or inaccessible spots and effort distribution is remarkably stable over time (Chapter 4: Hintzen *et al.*, 2019). Interestingly, there is limited spatial overlap between the four main bottom trawl fleet segments in the North Sea (Eigaard *et al.*, 2017): seine, dredge, beam trawl and otter trawl (Figure 6.1). These fleet segments target different species with different distribution areas. For example, otter trawls target round fish such as cod, whiting and haddock, while beam trawls target sole and place (Eigaard *et al.*, 2016). Gear design also defines the area that can be fished by a fleet segment: Beam trawls are heavy in design and hence difficult to operate in muddy sediments. Where needed, gears can be modified to allow fishing on previously inaccessible grounds. Beam trawl for example that operate on hard bottoms deploy a chain mat to avoid catching large rocks (Eigaard *et al.*, 2016) and lighter gears such as pulse trawl were able to operate on softer, muddier grounds (van Marlen *et al.*, 2014). The combination of target species distribution and gear design define in what type of habitat a fishing fleet can operate. The type of gear components, their dimension, and penetration depth define the impact onto the seafloor (Eigaard *et al.*, 2016; Rijnsdorp *et al.*, 2020). Given that seabed substrate type and depth gradients hardly change over time, fishing effort allocation remains relatively stable too. Especially since most gear design innovations, although numerous, are small adaptations to existing gear types that do not lead to marked changes in focus on target species and

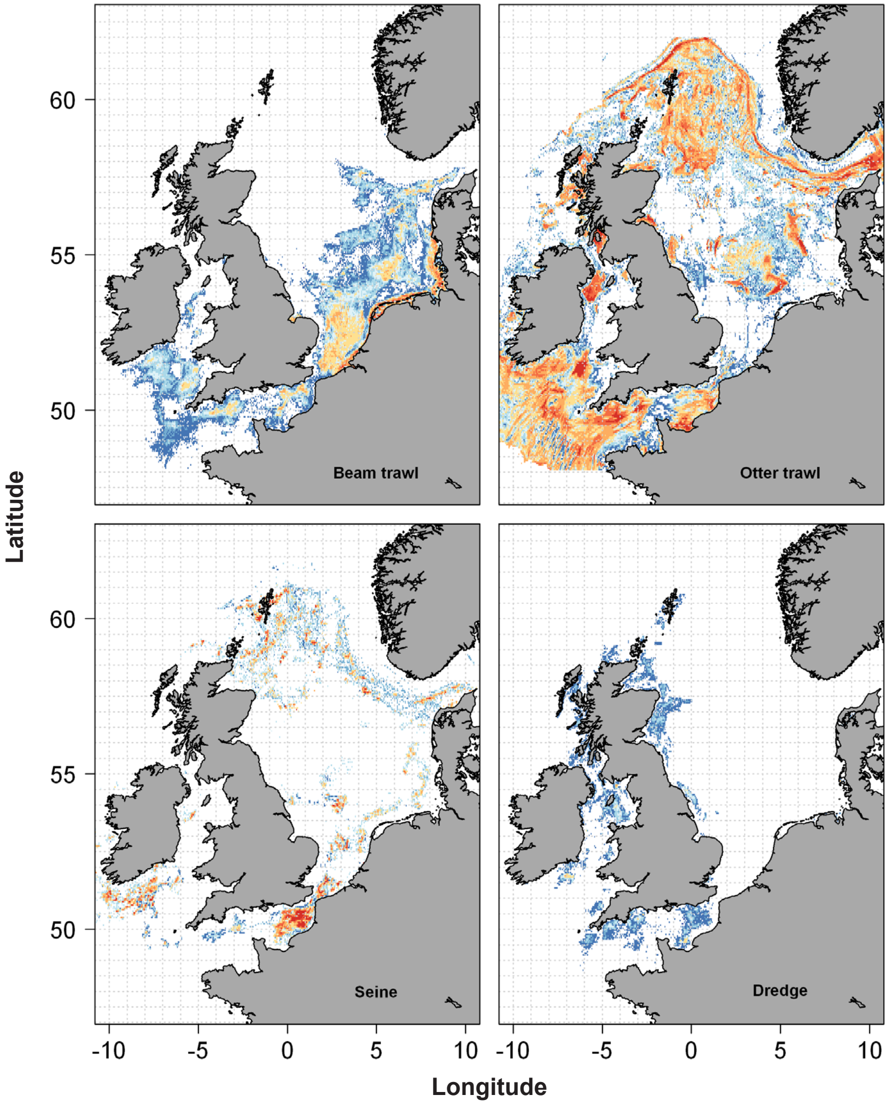

Figure 6.1 Spatial distribution and intensity (darker red indicates higher swept-area ratios) of four main bottom fisheries categories in 2017 in the north-east Atlantic region, reproduced from (ICES, 2018).

habitat association (ICES, 2020). For legal reasons, it may be advantageous to only develop small adaptations that would not classify as being sufficiently different from the what has been agreed as accepted types of fishing gear in the European Regulations (EC, 1998). Innovations beyond the accepted regulations require extensive ecological evaluations prior to admittance. These processes take many years, such as was required for an evaluation of the pulse trawl, a technique using electric stimulation to invoke a cramp response that immobilises fish (de Haan *et al.*, 2016; Soetaert *et al.*, 2019). First trials with the gear started in the 1970s, commercialisation was attempted in 1986 and a ban on electric fishing in the EU was instigated in 1988. Further development took place in the 1990s and only from 2004 onwards a project towards legalisation was initiated that led to large scale trials in 2009 (Haasnoot *et al.*, 2016) with a final ban on pulse fishing agreed by the EU in 2019. For most of the bottom trawl fisheries in Europe though, gear design has been relatively stable. Combined with generally unchanged seabed substrate and depth gradients the observed small-scale fishing effort distribution of many fleet segments has been rather consistent.

There is however variability in small scale effort distribution to be noted. Effort distribution (i.e. the observed resultant of fishing activity) is not homogenously distributed in space as was demonstrated by Ellis *et al.* (2014) and Hintzen *et al.* (2019, Chapter 4) and the degree by which fishers aggregate effort in space is different among fleet segments. Shrimp trawlers for example were shown to aggregate effort more strongly compared to beam trawlers (Hintzen and Beier, 2020). Variability in effort allocation (i.e. the spatial choice to fish in a certain spot) occurs over time because of unequal distribution of the resource being targeted but is also affected by spatial management measures such as Marine Protected Areas (MPAs) that lead to 'fishing the line' where fishers fish along the edge of marine reserves (Kelly *et al.*, 2002; McClanahan and Kaunda-Arara, 1996). Climate induced changes in the distribution of target species (Perry *et al.*, 2005) also affect the distribution of fishing fleets as they follow the movement of their target species (Cheung *et al.*, 2010). Although these processes are less profound at small temporal scales, annual temperature fluctuations contribute to changes in the fish species distribution (Teal *et al.*, 2012) and hence expected variability in effort allocation by fishing fleets. Variability in spatial effort allocation is furthermore driven by quota availability, where in a mixed fishery, such as the beam trawl fishery on plaice and sole, diverging development in stock size and hence quota, may push fishers to focus more on e.g. plaice grounds as quota is more abundantly available (Quirijns *et al.*, 2008). This could result in fishers having to move to lesser known grounds with associated variability in catch success (Poos and Rijnsdorp, 2007b).

We can hence conclude that there are many external factors that implicitly determine fishing effort allocation at intermediate to larger spatial scales. Fishers' behaviour is however expected to play an ever-larger role to determine effort allocation at small spatial scales. Fishers' behaviour is complex though and each individual acts differently (Salas and Gaertner *et al.* 2004). Several studies have attempted to capture this behaviour in models to more easily predict responses to fisheries management (Fulton *et al.* 2011, van Putten *et al.* 2013). These models are without doubt simplifications of reality and may ignore social constraints as data on these choices are more difficult to routinely collect. We need to acknowledge their shortcomings but also see the opportunity to study fishers' behaviour through the effort patterns that we can observe with help of VMS and logbook data.

What drives fishers' effort allocation

To analyse fishers effort allocation, it is useful to consider the more widely studied ecological concept of optimal foraging theory (OFT, Stephens and Krebs, 1986). In OFT, three components play a role to determine how animals search for food: i) decision rules, ii) the currency used to evaluate choices, and iii) the constraints that limit the set of choices.

Optimal foraging theory applied to fishers

The three components of the OFT are described below in relation to fishers' behaviour.

Decision rules: Fish occur in patches (aggregations). The decision that needs to be made by fishers is to evaluate if they want to stay in a particular patch or move on and find a better one. The fishery considered here targets flatfish that are undetectable with electronic equipment on-board the vessel. The echo sounder equipment on board does allow the fishers to determine the type of seafloor and bathymetry that may indicate preferred flatfish habitat. However, this implies that fishers need to 'sample' the area to see if they are on grounds with large abundances of preys or need to move to another patch (Rijnsdorp *et al.* 2011).

Currency used: A fisher will try to optimize its catch vs cost of fishing. If in a certain fishing patch, the catch per hour drops, it may become likely that a fisher will start to look for another patch. However, it needs to consider the time needed to travel to that other patch and time needed to find a new patch worthy to fish on. This mechanism is explained by the Marginal Value Theorem published by Charnov in the '70s (1976). Analyses from haul-by-haul studies indicate that fishers require a certain catch per unit of effort (CPUE) to stay on a fishing ground (Rijnsdorp *et al.*, 2011). As such, fishers work with the concept of expected catch rates and their foraging decisions result from trying to meet those expectations, in line with the theorem proposed by Charnov. A model study by Fauchald (Fauchald, 1999) indicated that a predator is most efficient in foraging when they operate in a patch with intermediate catch rates. This because the information that a skipper receives from 'sampling' the area time after time (i.e. haul after haul) is greatest when prey are not highly aggregated but one in which multiple sub-patches contain prey. It is yet to be tested if fishers indeed forage on multiple sub-patches for which clearly information at the smallest spatial scales on food availability to the target species of a fishery is needed.

Constraints: The efficiency of sampling an area can be improved when one has prior knowledge on catch rates, e.g. due to previous experiences. Part of this experience relates to processes that generally take place in the same area in the same period of the year such as migration of fish to spawning or foraging areas (Poos and Rijnsdorp, 2007a). Next to that, knowledge on the fishable area itself at small spatial scales is key as was found by Poos and Rijnsdorp (2007b). Especially in the Netherlands where fishing companies are often family owned and where knowledge is transferred from father to son, the latter can play a large role. This historical choice for a fishing location is to date still apparent (Figure 6.2) with clear clustering of fishing activity based on the port or registry of fishing vessels. If knowledge of small spatial patterns in the habitat are crucial to find high abundances of the target species, focussing on a relatively smaller area may be needed to thoroughly understand the distribution of the species and their seasonal fluctuations. Clearly though, there are communities, like those from Urk (bottom-left in Figure 6.2), that span the majority of the southern North Sea and show a lower spatial attachment. Part can be explained by the number of vessels in the fishing fleet by port of registry, those of Urk but also Texel (middle-right in Figure 6.2) holding most of the vessels and therefore different vessels depart for a fishing trip and land fish in different harbours (ICES, 2018) as well as different fishing style across ports of registration (Boonstra and Hentati-Sundberg, 2016). Although some ports show a wider distribution of vessels over the area, the small scale spatial allocation of fishing effort of all vessels combined shows substantial stability (Chapter 4; Hintzen *et al.*, 2019).

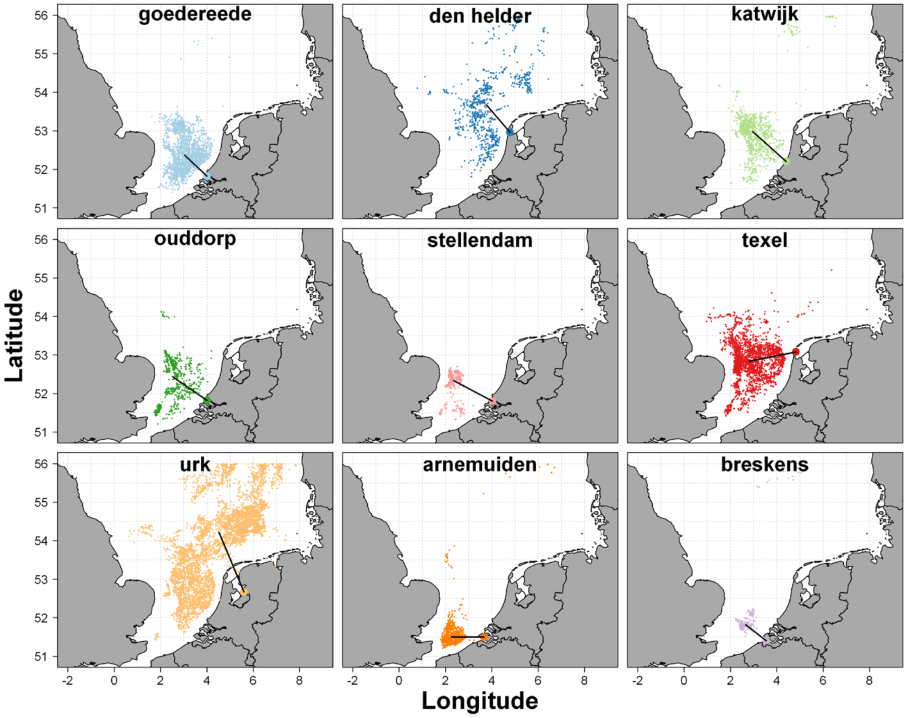

Figure 6.2 Spatial segregation in 2019 of the beam trawl fishing activity based on VMS data for different ports of Dutch fishers as identified based on their vessel registration ID. Black lines connect the mid-point of the distribution to the geographical location of the port.

This could imply that fishers, even from different ports, hold similar detailed information on where to find fish, but it could in addition imply that competition between fishing vessels results in a more evenly distribution of fishing effort in space, whereby all fishers maximise their catch rates while avoiding fishing on recently trawled (i.e. reduce interference competition (Poos and Rijnsdorp, 2007a)), and potentially exhausted, grounds.

The latter is much in line with the theory around the Ideal Free Distribution (Fretwell and Lucas, 1969; Gillis *et al.*, 1993; Poos *et al.*, 2010), which is one of the OFT models.

Ideal Free Distribution applied to fishers

Under the IFD, all individuals of a population will distribute themselves over the available resource patches proportionally to the resource density of the patches (see Gillis *et al.* 1993 for an application of the IFD in fisheries). Five elements play a key role: i) each resource patch has its own resource density (i.e. patch quality), ii) individuals can move freely to each of the patches, iii) individuals select a patch that is ideal to them and they hold perfect knowledge of all patch qualities, iv) patch quality is affected by competition (resource competition or interference competition) and v) all individuals have equal competitive strength. These concepts together form a way to explain how a predator forages, or fishers target fish, and here we relate these aspects to the small spatial use of fishing grounds. The five components of the IFD are described below in relation to fishers' behaviour.

Patch quality: the combination of VMS and logbook data provides clear proxies on patch quality in space and time, clearly indicating that patch quality is highly variable over both time and space (Poos and Rijnsdorp, 2007a, van Denderen *et al.*, 2015; Piet and Hintzen, 2012) mainly due to feeding and spawning migrations and availability of food for the target species that can be distributed in very small scale patches (Morrisey *et al.*, 1992; Ysebaert and Herman, 2002; Volckaert, 1987). The migratory aspect is considered relatively stable over time and can therefore be predicted with reasonable certainty (Hunter *et al.*, 2003). The latter aspect makes predicting small scale patch quality more difficult as food availability to target species can depend on the timing of spat from bivalve species that make up a large portion of food for both plaice and sole (Rijnsdorp and Vingerhoed, 2001) and the variability in food availability that varies based on climatic varying conditions (Teal *et al.*, 2012).

Free movement: Fishers can generally move among patches with limited restrictions. However, some areas are closed for certain fleet segments, such as the 12-mile zone and 'plaice box' (a closed area north of the Netherlands and Germany and west of Denmark) is limited exclusively to vessels with engine powers <300hp (Pastoors *et al.*, 2000). All movement activities, however, come at an increase in fuel consumption. This may limit frequent movement especially in times where fuel price is high (Poos *et al.*, 2013).

Perfect patch knowledge: Fishers are assumed to select those patches that are ideal to them while they do not generally exchange real-time information on their catch rates with the entire fleet via radio or other means. Only in recent years, with the introduction of AIS (Natale *et al.*, 2015), have fishers been enabled to keep a closer look at the spatial distribution of their competitors over the entire distribution area of the fleet. This could be used to infer patch quality information based on the behaviour of their competitors. Anecdotal information suggests that radar has been used in preceding years but range and precision of radar are more limited compared to AIS. As such, with the introduction of AIS, there is the potential that the fleet comes closer to the concept of perfect patch knowledge although only resident time as indicator of patch quality can be estimated from AIS and not the catch rates of fishing vessels.

Competition: Both exploitation competition and interference competition have been described as key factors defining the density of fishers exploiting a patch (Poos and Rijnsdorp, 2007b; Rijnsdorp *et al.*, 2000). Under exploitation competition, an increase in fishers targeting the same resource within a patch results in a reduction of the resource and hence fisher's catch rates. Interference competition reduces the catch rate as a result of an increase of competitors, without this being the effect of a reduction in resources (Ruxton, 1995; Abrahams and Healey, 1993). Noise of fishing vessels, sediment disturbance due to trawling or behavioural responses of neighbouring fish may result in the reduction in catch rates (Morgan *et al.*, 1997). Under the IDF both types of competition are expected to result in vessel densities fishing in resource patches proportional to patch quality.

Competitive strength: Even with perfect knowledge of the patches, resource densities and movements of competitors it is unlikely to expect identical behaviour from fishers owing to social and economic differences among individuals. The difference in competitive strength across Dutch beam trawlers resulted in large increases in sole and plaice catchability, and finally strong declines in stock status (Rijnsdorp *et al.* 2008). Roshier *et al.* (2008) demonstrated high variability in movement in ducks (*Anas gracilis)* under the same patterns of resource distribution, clearly indicating that the decision-making process of individuals includes aspects that are unknown or unquantified. The role of social constraints for selecting specific fishing habitat, such as safety at sea, are largely unknown. A study on oribi antelope demonstrated that under equal food availability over different patches, oribi would prefer feeding in the safest habitats (Stears and Shrader, 2015). Whether such dynamics add to the stability of fishing grounds is unknown.

It is challenging to scale down fleet dynamic studies such as those of Poos and Rijnsdorp (2007a) and Batsleer *et al.* (2018) that model fisheries behaviour at larger spatial scales to reflect fishing activity at small spatial scales. The choices, however, that are made by fishers at small spatial scales, and result in either stability of fishing hotspot or variability herein, are yet to be unravelled. It is clear that access to habitat and habitat type plays an important role, that classical foraging theory has a mechanism to describe aggregation of fishing effort, but it lacks in understanding of individual behaviour. To progress in this field, interviews with fishers are needed to gain a better understanding what drives fishers to select specific fishing grounds and should likely be supported by simulation studies to show how profitability may change if fishers are expected to move away from their historically favoured areas if conditions change (e.g. due to climate change or through spatial closures due to wind farm areas or Natura 2000 sites). Studies like those by Boonstra and Hentati-Sundberg (2016) already provide a semi-quantitative approach to structuring fisheries behaviour in such a way that it can be used in simulation studies.

Implications for fisheries management

Amoroso *et al.* (2018) demonstrated that in areas where fishing footprints (i.e. the area impacted by bottom gear) were small, fish stocks were generally in a good state. This leads to suggest that appropriate fish stock status could also be achieved through management of fishing footprint. Managers could put a cap on the total allowable trawled area and use tracking of fishing vessels through VMS to inform the fleet on real-time usage. Such a system is already in place, though using fishing hours as a limit, for Dutch shrimp fisheries in Natura2000 areas in the Netherlands (Hintzen, 2019). Corrections for improvements in gear design that enhance catchability of the target species (i.e. technical creep) would clearly be needed in such a situation (Eigaard *et al.*, 2014). Other options for the practical implementation of footprint management are closed areas or its opposite: fishing acres where fishers have to fish in designated areas similar to farmland use. Such an approach may not deliver on long-term sustainable and viable fisheries given that the fishery targets a mobile species that can change its distribution based on food availability and competition. It would, however, provide fishers with some 'ownership' of fishing grounds which may resonate well with fishers given the current heated debate on multi-use and sharing of the continental shelves. Alternatively, a system making use of habitat quota (such as Individual Habitat Quota, IHQ, Holland and Schnier, 2006; Batsleer *et al.*, 2018; Kraak *et al.*, 2012) where each patch of seafloor is associated with a cost to fish, could be an incentive to only fish in 'cheap' areas that are by design associated with areas with low ecological value.

Several studies have evaluated the consequences of using IHQ: an approach that limits the wider ecosystem effect of trawling by setting individual quota on fishing in sensitive habitats. The effectiveness of IHQ relies on 'good behaviour' from fishers to select those areas previously impacted by bottom trawl gear over 'pristine' areas as cumulative trawling impacts are generally considered to be less destructive to seafloor integrity than first encounters (Hiddink *et al.*, 2017). Prior knowledge on species distribution is essential however and changes herein, potentially altered by e.g. climate change (Perry *et al.*, 2005; ICES, 2017), may reduce the successfulness of such an approach. An IHQ approach will allow for a trade-off analysis between seafloor impact and fisheries resource landings, as was already highlighted by Eigaard *et al.* (2016) and Rijnsdorp *et al.* (2020) that showed that different habitats as well as different bottom-trawl fleet segments are associated with different footprints per kg landed resource. Managing according to this trade-off would provide insight into exploitation vs conservation goals of fisheries management and as such deliver to the need to move towards EAFM (Skern-Mauritzen *et al.*, 2016). In this analysis, the sensitivity of habitats should be incorporated as one km^2 of fishing does not result in similar impacts across a range of different habitats. A small spatial resolution needs to be used in this style of management as bottom trawling fishing fleets aggregate fishing effort on small spatial scales with distinct habitat characteristics (Chapter 4 and 5; Hintzen *et al.*, 2019, Hintzen *et al.*, 2021, van der Reijden *et al.*, 2018, Amoroso *et al.* 2018). Managing a bottom trawl fishery by constraining its footprint carries an incentive to reduce trawl gear impact on the bottom while maintaining catch rates. Reducing the footprint relates to one of the descriptors of Good Environmental Status (GES) as defined under the MSFD (EC, 2008) where integrity of the seafloor should ensure proper structure and function. Footprint based management may further lead to stronger focus on well-established fishing grounds, where annually the majority of catches are taken from, rather than fishing in peripheral areas.

A switch from quota based management to an IHQ system, however, is far from simple because of the mixed-fishery nature of many of the bottom trawl fleet segments (Eigaard *et al.*, 2016). Bottom fishers choose their fishing location based on quota availability of their main target species but also on economically interesting bycatch species such as e.g. turbot and brill. If quotas of the different target species develop in diverging directions, fishers may be forced to move to areas where mainly one of the target species can be caught with reduced catch of the other, more quota restrictive, target species.

Such a spatial reallocation may not necessarily contribute to seafloor GES. The development of marine protected areas at sea (i.e. Natura 2000 areas) with the ambition to protect 30% of a countries EEZ by 2030 will likely have an impact on the distribution of the fishing fleets and may result in a substantial displacement of fishing effort in the near future. The exact location to which fishing effort may be displaced however is highly uncertain. This is driven by a lack of understanding of the role of MPAs on target species, i.e. would these protected areas function as a refuge with associated boundary spill-over or would most of these MPAs be too small to trigger a behavioural response of the fish species. This example clearly illustrates the need for an integrated approach to fisheries management where mixed-fisheries TAC advice and the associated trawling footprint are evaluated simultaneously. One of the first steps to operationalize this integrated approach is to establish reference points for seafloor integrity, i.e. what constitutes an acceptable level of fishing impact. For TAC management, such reference points exist in the form of limit biomass levels as well as long-term sustainable exploitation rates (i.e. F_{MSY}). Only when clear targets are set, a quantitative framework can be designed incorporating IHQ systems next to existing single species or mixed-fisheries advice, that reduces the risk to both overexploitation of fisheries resources and seafloor adverse impacts.

It is yet undefined what the appropriate spatial and temporal scale of the IHQ approach should be. It has been argued that at a spatial scale as fine as $1km^2$ fishing activity becomes randomly distributed (Rijnsdorp *et al.*, 1998) while benthic communities may be organised in patches as small as several meters (van der Reijden *et al.*, 2019). Ellis *et al.* (2014) suggested to evaluate impact at the scale of fishing gear, i.e. 24m for beam trawls, ~100m for otter trawls, ~4-8m for dredges. Van Denderen *et al.* (2015) showed that temporal patterns in trawling frequency of a specific patch affect the recovery of the benthic community. Hence, any apparent seasonality in trawling frequency should be accounted for in analysing fishing impact on the wider ecosystem. The temporal scale of footprint management should likely be in the order of months to seasons rather than days or weeks as an analyses of Dutch beam trawl vessels in one of the most trawled sections of the Southern North Sea showed very limited repetitive trawling events within a week (0.05% of an ICES rectangle ~$2km^2$, Figure 6.3). For both spatial and temporal analyses to be appropriately refined, one needs to improve on observation resolution as well. I.e. currently VMS is being collected at only 30min interval basis and most habitat data, such as substrate type, is only available at km scale (Wilson *et al.*, 2018).

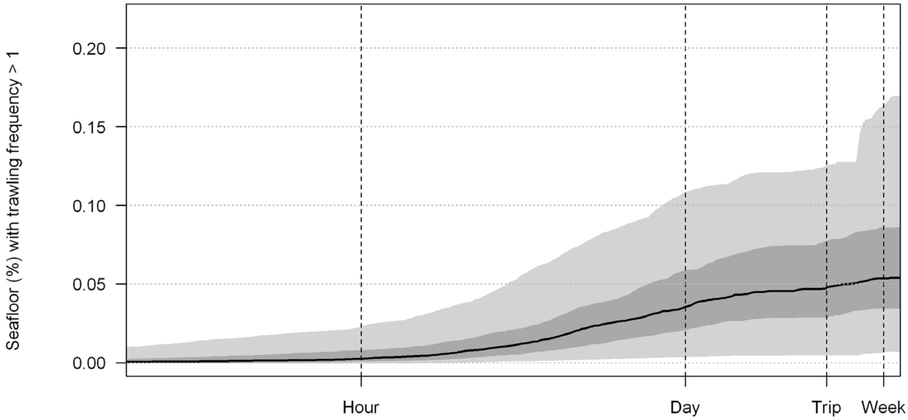

Figure 6.3 Percentage of seafloor being trawled by the Dutch beam trawl fleet in ICES rectangle 32F2. Black solid line presents the median interval-percentage relationship out of 2-years * 52-weeks combinations. The dark-grey area represents the 50% CI while the light grey area represents the 95% CI.

Future challenges

The number of scientific papers using VMS data since the introduction of the satellite system in the early 2000s has increased quadratically (Figure 6.4). In these papers, a great variety of topics has been studied such as the identification of spatial-temporal trends in unwanted bycatch (Uhlmann *et al.*, 2014; Siguróardóttir *et al.*, 2015; Batsleer *et al.*, 2016), the impacts of fisheries on benthos (Reiss *et al.*, 2015; Rijnsdorp *et al.*, 2016; van Denderen *et al.*, 2014; Batsleer *et al.*, 2018), the changes of fishing gear technology and mixed fisheries (Eigaard *et al.*, 2014; Ulrich *et al.*, 2012; Poos *et al.*, 2013), the interactions with seabirds (Tyson *et al.*, 2015) and fleet behaviour (Poos and Rijnsdorp, 2007a; Vermard *et al.*, 2010). Although the volume of research already conducted is vast, many questions remain. Two of these questions include one: the development of risk assessment methods for the interactions between pipelines and fisheries, and two: how historic small-scale fishing effort distributions have shaped the benthic ecosystem.

First: Fisheries form the highest external risk to the integrity of underwater pipelines and communication cables. Heavy bottom gear such as beam trawls and otter trawls can have a large impact on the pipelines and may cut through communication cables (Rouse *et al.*, 2018; Longva *et al.*, 2013; Fyrileiv *et al.*, 2006). Although most pipelines in the North Sea are either buried in the sand or covered by rocks, the dynamics of the sandy seafloor result in occasional

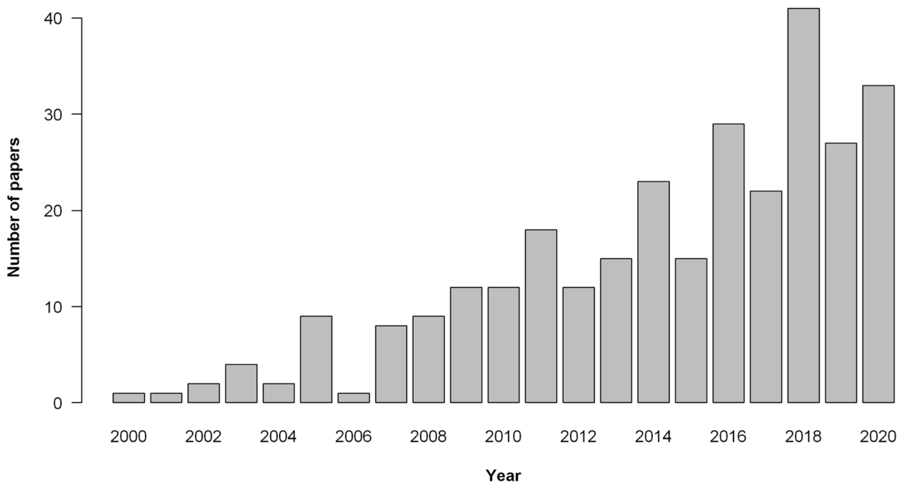

Figure 6.4 Number of papers published on topics directly associated with VMS and fisheries (Scopus search terms: TITLE-ABS-KEY ((Fisheries AND vessel monitoring satellite) OR (Fisheries AND VMS)), limited to year of publication 2000 - 2020).

free spans to emerge. These free spans, where pipelines are no longer covered by sand or rocks and sand is washed out underneath the pipelines are a potential danger to the fisher but also to the pipelines themselves. Dutch fishers do not actively avoid these pipelines and cables. An environmental catastrophe owing to a collision of fishing gear with a pipeline has been avoided in all these years while communication cables have been damaged several times a year in the past decade. With the tools developed to analyse VMS and logbook, data risk assessments could be performed indicating which pipelines and cables are at highest risk to fishing impact. These studies should account for gear design, towing speed and dynamics of the seafloor and could help oil, gas and communication companies to focus their maintenance in those areas with highest risks to prevent costly repairs out at sea. Although some local studies are focussing on the interaction between fisheries and pipelines (Rouse *et al.*, 2020) there is a clear void in risk assessment methodology and international collaboration.

Second: historic fishing has altered current day communities of benthos, fish, and marine mammals (Philippart, 1998; Thurstan *et al.*, 2010; Greenstreet and Hall, 1996). Studying ecosystem impacts of fishing thus requires an understanding of how exactly current day benthic ecosystems were shaped by fishing. The distribution area of a long-living species such as the bivalve mollusc

Arctica islandica L. (Witbaard and Bergman, 2003) or reef forming species such as *Sabellaria* spinulosa (van der Reijden *et al.*, 2019) may have been reduced due to intensive bottom trawling. The change in community composition over the years may result in a shifting baseline for conservation if only recent observations are considered to set reference points for sustainable exploitation. However, there is relatively little known about the small scale bottom impact of fishing, mainly due to a lack of high resolution spatial data such as VMS or AIS, in the years prior to 2000 with the exception for Rijnsdorp *et al.* (1998) who undertook a broad scale study with GPS loggers for a large part of the Dutch beam trawl fleet prior to the introduction of VMS. With our understanding however of recent small spatial scale fishing effort allocation and its relation to e.g. effort information available at lower spatial scales such as registered in logbooks (i.e. ICES rectangles, from ~1960 onwards for the Netherlands through the CBS), attempts should be made to reconstruct detailed maps of fishing effort since the 1960s when motor trawlers took over from sail and steam trawlers (Thurstan *et al.*, 2010; Engelhard, 2008).

The extrapolation of fishing effort at large spatial scales to small spatial scales for years before the introduction of VMS not only provides guidance on historic impact of fishing in areas close to the Netherlands, they may also provide a framework to estimate impact in areas where VMS and logbook data are less reliable or lacking. For the latter example, satellite images could be used to generate fishing effort snapshots and fishing impact can be studied in areas where both VMS and satellite images are available. The lessons learned in areas with extensive spatial data collection could help other areas to implement robust fisheries management making optimal use of the sparse data that is available. The same applies to fisheries operating passive gears such as gill nets or traps. Often, the sparse spatial data that is available is not representative of fishing activity (Stelzenmüller *et al.*, 2016) where soaking time and gear length are much better indicators of fishing activity than vessel presence. It is clear that dedicated studies are required to study the spatial and temporal hotspots of these gears resulting.

The ability to study fishing impact at the spatial scale of the gear size would benefit all studies highlighted above. For that however, the current VMS and logbook data collection will not suffice as the spatial-temporal resolution is too coarse. AIS with pings at the resolution of seconds, could fill this gap. The need for higher detail in fishing spatial-temporal information becomes especially eminent when higher resolution information on seabed characteristics and benthic community distribution becomes available. Although AIS data is not routinely available, and carries certain drawbacks, especially related to coverage (Shepperson *et al.*, 2018), it is by far the most routinely collected high resolution dataset used for fisheries science (Natale *et al.*, 2015). AIS and also VMS in itself are useful indicators of impact such as trawling intensity (Eigaard *et al.*, 2016) but lack information on target species and bycatch. Daily logbook reports, specifying species caught, provide some insight but haul-by-haul data is needed, preferably coupled with sampling of the catch, either manually or through electronic monitoring (van Helmond *et al.*, 2020), to gain a much more detailed picture of what part of the ecosystem is affected by different types of fisheries. With the help of machine learning (Nguyen *et al.*, 2019; French *et al.*, 2015), a lot of manual labour can be spared and we may be at the onset of a data availability revolution that allows individual behaviour to be characterized and used in simulation studies to set future goals for ecosystem based fisheries management. One large hurdle needs to be taken however, and that is of data confidentiality and associated privacy aspects of the data. Since this data is collected at the individual level and contains substantial detail on business operations and potentially their competitive status, only aggregated data over multiple fishers or over larger spatial-temporal grids can currently be exchanged by scientists. This is not only a limitation for science, it also hampers fishers to develop a fishing style completely based on best available data and science, to engage in a fishery with the lowest ecological impact possible and hereby earn a licence to produce that can count on wide-spread societal support.

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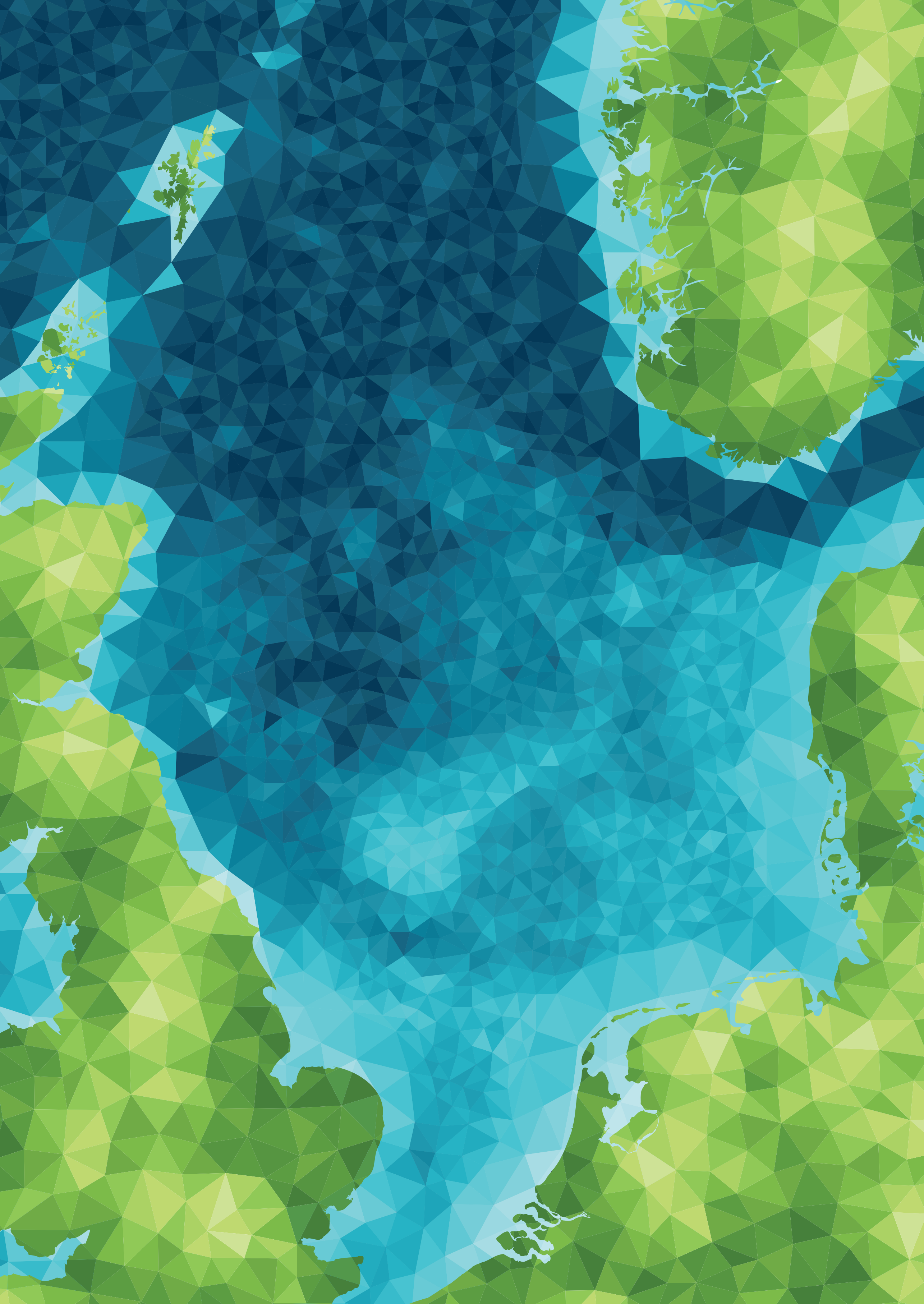

Addendum

Summary

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Summary

With the introduction of the European Vessel Monitoring by Satellite system (VMS), scientists could routinely access position data with an accuracy of around 100m. The introduction of VMS boosted the ability to explore the location of fishing activities (Murawski *et al.*, 2005; Stelzenmuller *et al.*, 2008; Fock, 2008), its relation to the habitat (Hiddink *et al.*, 2006; Kaiser *et al.*, 2006) and interaction with other fishing vessels (Poos and Rijnsdorp, 2007a) or users (Bastardie *et al.*, 2015). My research aimed at expanding the use of VMS data to study the impact of fishing at small spatial scales (tens of meters) to be used in an international context taking account of the issues of confidentiality and transparency, allow for analyses to take place at small spatial and temporal scales, and gain a mechanistical understanding of how small scale fishing patterns arise. This to allow for predictions of fleet distribution to be made at small spatial scales.

The PhD-thesis started with the development of transparent, generic and efficient methods to process fisheries data, both VMS and logbook data (**Chapter 2**). Provided that in most countries, but in the EU specific, VMS and logbook reports contain very similar fields of information, standardized data templates were designed at which a suite of analyses tools could be applied to gain understanding in fisheries behaviour and the impact of fishing. An R software package VMStools (**Chapter 2**) was developed. This contains a suite of standardized functions to clean VMS and logbook data from evident incorrect entries, link datasets together in time and space and allowed for activity tracking of fishing vessels. The package shows how data from multiple countries can be combined to provide a more complete overview of fishing intensity. Among the routines available in the VMStools package is a tool to interpolate in between successive VMS observations to artificially reduce the interval time of VMS data and hereby reconstruct a trawling track (**Chapter 3**). Although there is uncertainty associated with reconstructing trawling tracks, the methodology performs better than the more simple straight line interpolations applied in earlier studies (Stelzenmuller *et al.*, 2008). Making use of the tools designed in Chapter 2 and 3 we were able to reconstruct trawling tracks at meter scale for the Dutch beam trawl fleet and study the aggregation of fishing in time and space (**Chapter 4**). Zooming in to meter scale was recommended by Ellis *et al.* (2014) to allow counting the number of times a very small area (i.e. grid cell) was trawled by the entire fleet segment over a year. The resulting frequency distribution of counts was approximated by a statistical distribution (Negative

Binomial) and the degree of aggregation, one of the main outputs derived from this distribution, showed to be very stable over time at the ICES rectangle spatial scale. This suggest stable patterns in resource distribution and the attraction of fish resources to specific habitats that are routinely trawled by fishers. Since effort varied over the years, this shows that fishers visit in a predictable manner the small spatial scale of a grid cell. In addition to providing a measure for clustering (i.e. aggregation) on favourable fishing grounds, results also indicated the existence of untrawlable habitats and unfavourable grounds in a quantitative manner. This result provides context to areas that are hardly ever visited by fishers to whether these would constitute fishable areas or not, being relevant in the discussion on space available to fisheries in a crowded southern North Sea. First indications that untrawlable areas are associated with coarser habitat types was provided and let to the development of a habitat preference model for the Dutch beam trawl fleet (**Chapter 5**) in which the preference for fishers to fish in areas associated with certain environmental conditions was tested. Results of that study show that abiotic habitat characteristics describe well the fishing effort allocation made by beam trawl fishers (both traditional tickler chain fishers as the more recently developed fishery using electric stimuli: pulse fishing). Both types of fisheries prefer elevated landscapes with low gravel contents and often in-between sand ridges rather than on the top of larger scale sand dunes. Pulse fishers fished more in areas with higher gravel content, higher elevation differences and natural disturbance compared to tickler chain fishers which may be attributed to stronger focus on the southern North Sea. The results can be used to predict fishing effort distribution at high spatial scales under a range of scenarios such as closure of areal due to wind farm or Natura 2000 site development. The results also have a direct application in understanding the impact of fishing on ecosystem functioning as e.g. benthic community composition and function is often driven by habitat characteristics.

Samenvatting

Met de introductie van het Europese Vessel Monitoring by Satellite-systeem (VMS) konden wetenschappers routinematig toegang krijgen tot positiegegevens met een nauwkeurigheid van ongeveer 100 meter. De introductie van VMS versterkte het vermogen om de locatie van visserijactiviteiten te bestuderen (Murawski *et al.*, 2005; Stelzenmuller *et al.*, 2008; Fock, 2008), en de relatie met het habitat (Hiddink *et al.*, 2006; Kaiser *et al.*, 2006) en interactie met andere vissers (Poos en Rijnsdorp, 2007a) of gebruikers (Bastardie *et al.*, 2015) te onderzoeken. Mijn onderzoek was gericht op het uitbreiden van het gebruik van VMS-gegevens om de impact van visserij op kleine ruimtelijke schaal (tientallen meters) te bestuderen voor gebruik in een internationale context, rekening houdend met de vertrouwelijkheid van de data en transparantie van het verwerken ervan, zodat analyses mogelijk gemaakt konden worden op kleine ruimtelijke schaal. Ook bracht dit inzicht in het mechanisme achter het ontstaan van visserij patronen op kleine ruimtelijke schaal en hiermee ook voorspellingen van vlootverdeling op deze schaal mogelijk te maken.

Het proefschrift begon met de ontwikkeling van transparante, generieke en efficiënte methoden om visserijgegevens te verwerken, zowel VMS- als logboekgegevens **(Hoofdstuk 2)**. In veel landen, maar specifiek in de EU, bevatten VMS- en logboekrapporten zeer vergelijkbare informatie, waarvoor gestandaardiseerde datasjablonen ontworpen zijn waarmee een reeks analysetools kon worden toegepast om inzicht te krijgen in het visserijgedrag en de impact van de visserij. Er is een R-softwarepakket VMStools (**Hoofdstuk 2**) ontwikkeld. Dit bevat een reeks gestandaardiseerde functies om VMS- en logboekgegevens op te schonen van duidelijk onjuiste invoer, datasets aan elkaar te koppelen in tijd en ruimte en om activiteiten van vissersvaartuigen te volgen. Het pakket laat zien hoe gegevens uit meerdere landen kunnen worden gecombineerd om een completer overzicht van de visserijintensiteit te geven. Een van de routines die beschikbaar zijn in het VMStools-pakket is een hulpmiddel om tussen opeenvolgende VMS-waarnemingen te interpoleren om de intervaltijd van VMS-gegevens kunstmatig te verkorten en zo het beviste spoor te reconstrueren (**Hoofdstuk 3**). Hoewel er onzekerheid bestaat bij het reconstrueren van bevissingssporen, presteert de methodologie beter dan de eenvoudigere lineaire interpolaties die in eerdere studies werden toegepast (Stelzenmuller *et al.*, 2008). Gebruikmakend van de instrumenten die zijn ontworpen in Hoofdstuk 2 en 3, waren we in staat om bevissingssporen op meter schaal te reconstrueren voor de Nederlandse boomkorvloot en de aggregatie van visserij in tijd en ruimte te bestuderen (**Hoofdstuk 4**). Inzoomen op meterschaal werd aanbevolen door Ellis *et al.* (Ellis *et al.*, 2014) om het aantal keren te kunnen tellen dat een zeer klein gebied (d.w.z. rastercel) gedurende een jaar door het hele vlootsegment werd gesleept. De resulterende frequentieverdeling van tellingen werd benaderd door een statistische verdeling (Negatieve Binomiaal) en de mate van aggregatie, een van de belangrijkste uitkomsten afgeleid van deze verdeling, bleek zeer stabiel te zijn in de tijd op de ICES-vierkant ruimtelijke schaal. Dit suggereert stabiele patronen in de verdeling van de doelsoort en de aantrekkingskracht van visbestanden op specifieke habitats die routinematig door vissers worden bevist. Omdat de inspanning in de loop van de jaren varieerde, toont dit aan dat vissers op een voorspelbare manier de kleine ruimtelijke schaal van een rastercel bezoeken. De resultaten gaven niet alleen een maat voor clustering (d.w.z. aggregatie) op gunstige visgronden, maar wezen ook op het bestaan van ontoegankelijke habitats en ongunstige gronden op kwantitatieve wijze. Dit resultaat geeft context aan gebieden die nauwelijks door vissers worden bezocht om aan te geven of dit wel of niet bevaarbare gebieden zijn, wat relevant is in de discussie over de beschikbare ruimte voor de visserij in een drukke zuidelijke Noordzee. De eerste aanwijzingen dat ontoegankelijke gebieden geassocieerd zijn met grovere habitattypen werden verstrekt en leidden tot de ontwikkeling van een habitatvoorkeurmodel voor de Nederlandse boomkorvloot (**hoofdstuk 5**) waarin de voorkeur van vissers voor het vissen in gebieden die verband houden met bepaalde omgevingsomstandigheden werd getest. Resultaten van dat onderzoek laten zien dat abiotische habitatkenmerken de vislocatiekeuzes van boomkorvissers (zowel traditionele wekkerkettingvissers als de recentelijk ontwikkelde visserij met elektrische prikkels: pulsvissen) goed beschrijven. Beide soorten visserij geven de voorkeur aan hooggelegen landschappen met een laag grindgehalte en vaker tussen zandruggen in dan op grotere zandduinen. Pulsvissers visten meer in gebieden met een hoger grindgehalte, grotere hoogteverschillen en natuurlijke verstoring in vergelijking met wekkerkettingvissers, wat mogelijk kan worden toegeschreven aan een sterkere focus op de zuidelijke Noordzee. De resultaten kunnen worden gebruikt om de spreiding van de visserij-inspanning op grote ruimtelijke schaal te voorspellen onder een reeks scenario's, zoals sluiting van gebieden door windmolenparken of Natura 2000-gebiedsontwikkeling. De resultaten hebben ook een directe toepassing bij het begrijpen van de impact van visserij op het functioneren van ecosystemen zoals bv. samenstelling en functie van benthos gemeenschappen wordt vaak bepaald door habitatkenmerken.

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En eerlijk is eerlijk, dit was niet gelukt zonder de enorme steun van Marije. Een heel aantal vakanties werden de afgelopen jaren een mengelmoes van vrije tijd doorbrengen met Marije, Janneke en Jolein, en een paar dagen focussen op het schrijven van de hoofdstukken. De gulheid van Marije hierin om mij de tijd te geven te focussen op het proefschrift zijn enorm, zeker in de periode dat Janneke en Jolein ons leven kwamen verrijken. Maar naast tijd was ze ook mijn sparringpartner, en heeft ze me in onze gesprekken net zo lang kritisch bevraagd totdat ik een uitweg vond voor de wetenschappelijke uitdagingen. En stiekem, heel stiekem, voelt het ook wel goed om straks samen als dokter door het leven te gaan.

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Propositions

1. Confidentiality restrictions of VMS and logbook data should be waived after one year to improve science and management.
   (this thesis)

2. VMS is a more accurate data source for spatial fisheries research than AIS.
   (this thesis)

3. Any study on human behaviour should start with a formal model.

4. The lack of investments in science to study the COVID-19 pandemic in fields outside of epidemiology and healthcare will make the world ill prepared for a next pandemic.

5. A person's profile as built by large tech companies, and the personalized algorithms used to influence search results, should be shared with that person, to allow contemplation and alteration of the individual's behaviour.

6. Fact-checking by journalists should become part of the Services of General Interest (SGI) in the EU.

Propositions belonging to the thesis: 'Zooming into small-scale fishing patterns. The use of vessel monitoring by satellite in fisheries science'.

Niels T. Hintzen
Wageningen, 14 September 2021