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Estimating fishing effort from highly resolved geospatial data: Focusing on passive gears

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ABSTRACT

Increasing competition for marine space requires the appropriate development of indicators to best represent the use of marine areas and the value (whether economic, social and/or cultural) derived from such use. Fishers (the largest group of users) are often under-represented in marine spatial planning processes. Highly-resolved vessel tracking data provide opportunities to map the activities of fishing vessels at a level of detail never before available. Most effort mapping methods have focused on active gears such as trawls or dredges in large scale fisheries. For these fisheries, the time spent fishing at sea (hours) is usually a representative indicator of fishing effort, enabling a straightforward mapping of the most important fishing grounds. However, for passive gears generally used in small-scale fisheries, we show that spatial indicators of effort (here, length of vessel track) greatly outperform time-at-sea as an indicator of fishing effort. We further demonstrate and validate a method to estimate gear soak time from vessel tracking data and show how maps of effort that account for soak time can be different from those solely based on time spent fishing at sea. The development of adequate methods to quantify the spatial distribution of passive gear effort is particularly relevant to fisheries management because globally about a fifth of all catches (by weight) are landed by passive gears. Appropriate, fine scale effort maps will provide better tools for spatial planning to support sustainable fishing.

1. Introduction

Increasing competition for marine space and evolving spatial management regimes, particularly in coastal areas, demands objective spatial and temporal evidence of use and the "value" (economic, social and cultural) derived from such use. These data are critical to informed decision making if fisheries are to be adequately represented in these processes (Campbell et al., 2014; Metcalfe et al., 2018; Tidd et al., 2015) and can bring insights into the potential impacts or displacement that might result from the expansion of maritime activities such as offshore wind energy developments or Marine Protected Areas (Cabral et al., 2017). In addition, fine scale effort data are often used to assess compliance with area-based fishery regulations (Meyer et al., 2022) and to improve scientific assessments of the location and scale of logbook recorded catches (Gerritsen and Lordan, 2011). They have also enabled managers to assess the scale of fishery impacts on different benthic environments (Eastwood et al., 2007), and to delimit and protect vulnerable marine biotopes from damage by specific fishing gears (Hall-Spencer et al., 2009).

Traditionally, fishing effort data have been collated with low spatial resolution for the purposes of fishery management at fleet level. However, more detailed spatial information about resource distribution and fishing effort at the vessel level may be needed to enable the implementation of ecosystem based spatial management (Parnell et al., 2010; Stelzenmuller et al., 2008; Wilen, 2004). Recent technological developments have enabled the collection of spatially-detailed fishery-

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dependent effort data, initially through the use of vessel tracking systems such as Vessel Monitoring Systems (VMS) and Automated Identification Systems (AIS) (Gerritsen and Lordan, 2011; James et al., 2018; Lee et al., 2010; Natale et al., 2015a), and more recently through the deployment of Global Navigational Satellite System receivers coupled to General Packet Radio Service (GPRS) devices (mobile phone technology) (Behivoke et al., 2021; Burgos et al., 2013; Navarrete Forero et al., 2017), sometimes referred to as iVMS.

The growth in affordable electronic technologies to monitor the activity of fishing fleets in the last two decades constitutes a game-changing development for fisheries scientists and managers. Tracking devices are being increasingly used to obtain highly resolved geospatial data of fishing activities. AIS and GPRS-based trackers can report fishing vessel positions with frequencies from seconds to a few minutes (James et al., 2018; Kroodsma et al., 2018; Russo et al., 2016). In some countries it is mandatory to collect highly resolved geospatial data for small-scale fisheries (SSF), such as in England and Wales (MMO, 2022), while in the European Union (EU), mandatory tracking of SSF is under active consideration (EC, 2018). With these new data streams, activities taking place within a given trip can be classified into fishing or not fishing, based for example, on speed thresholds (Deng et al., 2005; Eastwood et al., 2007), or using more complex models that incorporate several descriptors of movement, such as speed and relative angle between successive locations to infer fishing activities (Joo et al., 2013; Mendo et al., 2019a; Vermard et al., 2010).

Positions classified as fishing can be aggregated into grid cells and provide highly resolved maps depicting proxies of fishing intensity or fishing effort. This aggregation is usually done by summing up the time a vessel (or vessels) spent within each grid cell (as in Kroodsma et al., 2018; Le Guyader et al., 2017; Natale et al., 2015b; Vespe et al., 2016). For active gears, where target species are captured following an aimed chase (e.g., trawls or dredges) (Bjordal, 2009), the time spent fishing estimated from highly resolved spatial information would be directly related to the amount of effort exerted when the gear effectively operates. This may be further refined by estimating the swept area and deriving metrics of swept area per unit time (Eigaard et al., 2015; Gerritsen et al., 2013).

For passive gears (e.g., traps, gillnets, longlines), where the gear is usually left underwater and retrieved after a specific amount of time, the United Nations Food and Agriculture Organisation (FAO) recommends alternative effort measure descriptors, such as number of pots deployed, net length, or number of hooks, associated to estimates of the time the gear spent in the water (FAO, 2020). These effort descriptors have been incorporated into the EU Data Collection Framework, which underpins the objectives of the Common Fishery Policy in the European Union (European Comission, 2008). Using highly resolved geo-positional data for passive gear fisheries opens up the potential to derive more accurate effort metrics. However, in contrast to active gears, time estimates associated with each position classified as fishing, only represent the amount of time a vessel has spent retrieving the gear and handling the catch. These operations effectively amount to a “time spent hauling”, which is affected by numerous factors such as the number of individual fish caught, eventual non-target catches, potential gear entanglements, broken ropes, etc. Therefore, using geospatial data to estimate fishing intensity or effort for passive gear fisheries is not as straightforward as it is for active gear fisheries. The development of adequate methods to quantify passive gear effort is particularly relevant to fisheries management, as globally about a fifth of all catches (by weight) are landed by passive gears (Watson, 2018, see Sup. Mat 1).

We believe that the potential of using highly resolved geospatial data to depict fishing effort more accurately in passive gears remains largely untapped. We demonstrate novel approaches to analyse highly spatially and temporally resolved data from passive gear vessels, which allow more accurate depiction of fishing effort indicators. We investigate whether the distance travelled by a fishing vessel while hauling gear is a better predictor of effort than the time spent retrieving the gear. We explore these relationships using highly resolved tracking data from five fisheries using various passive gears and from different geographical areas. In addition, we develop a method to estimate soak time from highly resolved geospatial data to further improve our estimates of fishing effort at spatial scales relevant to ecological studies and useful to inform fisheries management and support science-based decision making.

2. Methods

2.1. Case study fisheries

We used five case study fisheries from a variety of sites worldwide. They included several fishing gears and target species: pots in Scotland targeting Norway lobster *Nephrops norvegicus*, pots in Scotland targeting lobster *Hommarus gammarus* and brown crabs *Cancer pagurus*, gillnets in Peru targeting hake *Merluccius gayi peruanus,* gillnets in Denmark targeting multiple species including European plaice *Pleuronectes platessa*, Atlantic cod *Gadus morhua*, and lumpsucker *Cyclopterus lumpus*, and longlines in Iceland targeting Atlantic cod (*Gadus morhua*). Details of each fishery, how it operates and details about the number of vessels, trips and data collection can be found in Sup. Mat. 2.

2.2. Evaluating proxies for effort

For each case study, we compared fishing effort measured directly by observers or fishers, who recorded the number of pots, length of net, or number of hooks deployed, with (a) time spent hauling and (b) distance travelled by vessels based on vessel-tracking data during the observer-identified hauling events, based on vessel-tracking data. The start and end time stamp provided by the on-board observers, fishers or via video camera observations for each hauling event were used to estimate time spent hauling. To estimate the total distance covered during hauling, these time stamps were matched to the vessel track data to identify the segment of the trips which corresponded to hauling events. First, the Euclidean distance between consecutive positions (m) was calculated, and then the total distance travelled during hauling events (m) was estimated as the sum of each individual distances for each fishing trip.

We used linear regressions to model the relationship between observed fishing effort (number of pots, length of net, number of hooks), and time spent hauling, or distance covered during each haul (2 separate regressions). We then compared Goodness of Fit using the coefficient of determination R^2 (which measures the proportion of the total variation in the dependent variable that is explained by its relationship with the independent variable). All statistical analyses were conducted using the software R (R Core Team, 2022).

2.3. Estimating gear soak time

Four case studies were used to develop a method to estimate soak time in passive gears from highly resolved spatial data only: the hake gillnet fisheries in Peru, the lumpsucker gillnet fishery in Denmark, the pots and traps fishery in Scotland and the French gillnet fishery. The Peruvian dataset consists of highly resolved positional data (every 1 min) from 15 different vessels conducting 101 fishing trips with one setting and one corresponding hauling event (from now on called paired events). On board-observers recorded the time that the gear spent in the water. The Danish lumpsucker dataset consisted of information taken every 10 s, for 1 vessel conducting 16 trips and 59 associated paired events. Real soak time was estimated by looking at video data from remote electronic monitoring (REM). The Scottish dataset consisted of highly resolved data (every 1 min) from 4 different fishing vessels conducting 5 fishing trips each, for which validated information on soak time was available for 5 paired events, from fisher-led reporting. The French dataset consisted of positional data gathered every 15 min, for one vessel conducting 8 fishing trips, and 39 hauls. Soak time was annotated by a fisherman for each of these events.

To estimate soak time from geo-positional data alone, we first needed to identify the hauling activities. Several methods for inferring fishing or hauling activities from positional data already exist (Behivoke et al., 2021; Mendo et al., 2019a; Rufino et al., 2023), and we briefly detail how hauling was inferred for each case study. We used Random Forest models (Breiman, 2001) for all case studies to infer when the vessels were engaged in hauling gear, based on variables derived from positional data only (e.g. distance, relative angle, and the time of the day were used as predictors of hauling activities) following Mendo et al., (2022). The models were fitted using the R package randomForest (RF) (Liaw and Wiener, 2002). Accuracy was defined as the number of correctly classified instances (validated by on-board observers or Remote Electronic Monitoring (REM) data analyst, for both hauling and not hauling) with respect to their total number of locations.

2.3.1. Hake gillnet fisheries in Peru

As all hauling activities occur when there is sunlight (after 6 am) a subset of the data was used before applying RF models. The distance between observations, relative angle between positions, and the time of the day were used as predictors of hauling activities. We used information from 101 observer trips (see Sup. Mat. 2) to assess the performance of the model outputs compared with data ground-truthed by observers on hauling activities. We randomly selected 50 trips for training and 51 for prediction, to test for out-of-sample accuracy of the model. The model predicted hauling activities with 90% accuracy. All positions recorded after 06:00 were labelled as potential setting events, except for locations associated with speeds $<$1 knot, since we know from fishers that setting events occur on average at 2–3 knots.

2.3.2. Gillnet fishery in Denmark

The distance between observations, relative angle between positions, time of the day and month were used as predictors of hauling activities. We used information from 745 trips for one vessel (see Sup. Mat. 2) to assess the performance of the model outputs compared with data ground-truthed by observers on hauling activities. We randomly selected 603 trips from 5 years (2016, 2018, 2019, 2020, 2021) for training and 142 trips conducted in 2017 for prediction, to test for-out-of-sample accuracy of the model. The model predicted hauling activities with 80.5% accuracy.

2.3.3. Pots and traps fishery in Scotland

The distance between observations, relative angle between positions, and the proportion of time that had passed since the beginning of a trip were used as predictors of hauling activities. We used information from 95 trips conducted by 95 different vessels to assess the performance of the model outputs compared with data ground-truthed by on-board observers on hauling activities. We randomly selected 60 trips for training and 35 trips for prediction, to test for-out-of-sample accuracy of the model. The model predicted hauling activities with 91% accuracy.

2.3.4. French gillnet fishery

A random-forest predictor was built using a leave one fishing-trip out validation process. The covariates used were: speed, acceleration, bearing rate, speed change, sinuosity, turning-angle, direction change and a proximity index (ICES, 2023). A moving window of thirty minutes is used by adding the values for these variables for previous and next neighbours as covariates. The models were fitted with an out-of-sample accuracy estimated to 91.5% regarding the prediction of hauling events.

To estimate soak time from geo-positional data, new methods are needed. Ideally, we would be able to identify where the gear was set or deployed and then overlay subsequent hauling events. However, identifying when gear is being set is usually challenging (Mendo et al., 2019a), as the deployment of gear is usually conducted at speeds similar to those of steaming events. Therefore, for each trip, we must first infer hauling events (Fig. 1a in grey). As this is the starting point to be able to infer soak time, the accuracy of detecting hauling events must be high. In our four case studies, the accuracy to detect hauling events was greater than 80%, with three of four cases studies having an accuracy greater than 90%.

Once the hauling events have been identified, data not associated to a hauling event are removed, and a spatial buffer (input parameter, called *buffer_width* in R code, based on expert knowledge) is created around the hauling event to allow for a setting event not being exactly where the haul occurred (due to nets drifting for example, Fig. 1b). This spatial buffer depends on different factors, for example, how much “loose” rope is left between the bottom of the sea and the surface, the proximity between different sets of gear, the effect of tides in moving the buoy further away from the deployment event. Potential setting events from preceding trips are plotted (Fig. 1c) until there is a significant intersection (shown in blue) between a potential setting event and a

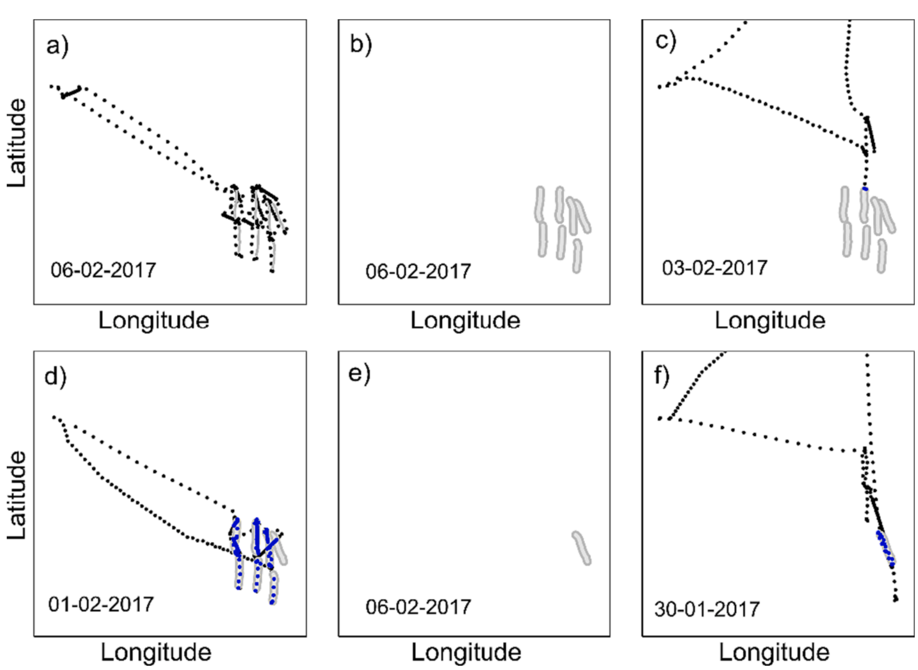

Fig. 1. Process used to infer soak time from geo-positional data only. Figures a – f show steps taken to infer soak time for a trip conducted on 06-02-2017. Coordinates not shown for confidentiality reasons. Gray lines or polygons represent hauling events, black dots represent non-hauling events, and intersections between a hauling event and a deployment event are presented in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

hauling event (Fig. 1d). The next input parameter required is *time_frame_fishing*, which sets a constraint on the maximum number of days before hauling, where a setting event could have. For example, if we know that the fishery will not usually leave the nets for more than 30 days in the water.

The threshold for the distance covered by the setting event that should intersect with the hauling event is set with expert knowledge. This is another user-defined parameter, called *overlap_threshold* in the R

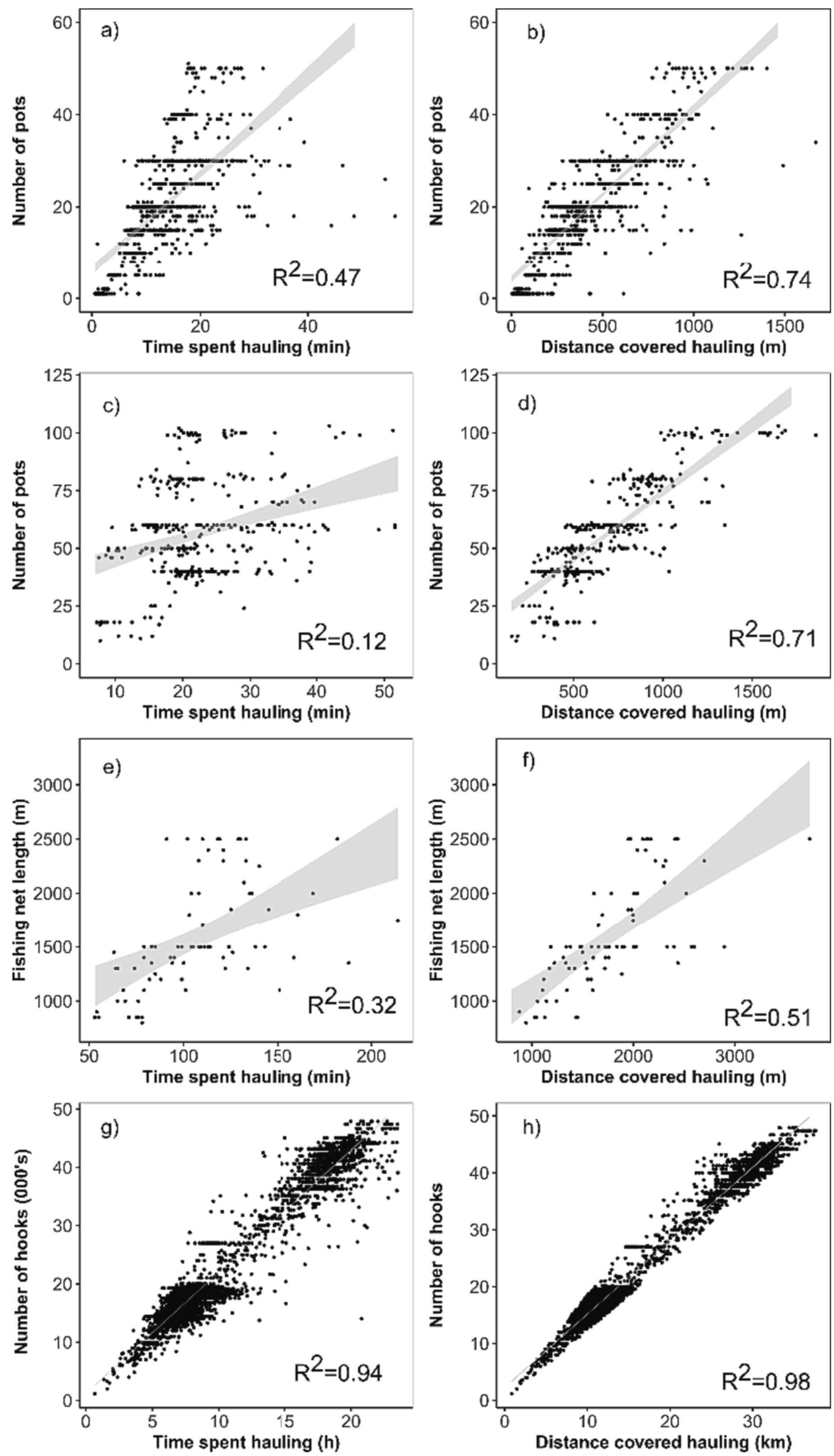

Fig. 2. Relationship between estimated time spent hauling (left) and estimated distance covered during hauling (right) and observed effort in fisheries targeting lobsters and crabs using pots (a,b), Norway lobster using pots (c,d), hake using gillnets (e,f), longline fisheries in Iceland (g,h).

code, and it represents the percentage of the distance covered during a hauling event, that should be inside the buffer created (Sup. Mat 3 and 4). This threshold is important as it helps distinguish between a sequence of non-fishing points that might fall inside a buffer, but which are not the actual deployment event. The difference in time stamps between deployment and hauling constitute soak time. The hauling events that are matched with a corresponding setting event are removed (Fig. 1e) and then the process is repeated until there as another intersection (Fig. 1f). This process is repeated until either, all hauling events are matched with a corresponding setting event or until a threshold date is reached (for example, from expert knowledge, nets will be retrieved up to a month after first being deployed). The R code for this new method is available as Sup. Mat. 3 (gillnet fishery Peru, setting and retrieving nets on the same day) and Sup. Mat. 4 (Danish gillnet fishery, setting and retrieving nets on same or different dates).

2.4. Spatial comparison of fishing effort

To demonstrate the differences in spatial distribution of effort that result from different metrics, we used on-board observers' data to develop the comparison with the best possible accuracy. We compared the spatial distribution of the fishing effort using different effort variables reported by on-board observers (gillnet fishery in Peru) and using an REM system for one gillnet vessel in Denmark. Three effort metrics compared were: (i) time spent hauling (h), (ii) net length (m) and (iii) net length (m) multiplied by soak time (h). All maps were plotted on a 500 × 500 grid. (i) Time spent hauling was calculated as the total number of positional records in each grid cell, using the R package *raster* (Hijmans, 2020), and multiplying it by the interval between vessel tracking data (180 s in the hake fishery and 60 s in the lumpsucker fishery). (ii) Net length was calculated as the proportion of the haul distance that occurred within the grid cell multiplied by the total net length as reported by fishers. (iii) Net length (m) was multiplied by soak time (h, unique for each haul). The soak time of any given net as reported by observers or REM analysts was multiplied by the length of the net in each cell to provide length of net in meters per unit time in hours (e.g. if there were 500 m of net in a grid and the soak time was 2 h, then 1000 m.h would be calculated). The same analysis could be repeated using the new method developed above to estimate soak time but is not shown here.

3. Results

3.1. Proxies to estimate fishing gear effort

Distance covered while hauling gear performed better in explaining the proportion of total variation in fishing effort for the four case studies (see R^2 in Fig. 2). This means that predictions of the number of pots, the length of the net, and the number of hooks deployed were more precise when using the distance covered hauling rather than the time spent fishing. In general, all linear models overestimated fishing effort at lower values of time spent hauling or distance covered. This could be due to the initial longer time and distance covered during hauling needed at the beginning of a hauling event, to get the gear out of the water which could be a function of water depth and or the length of the surface buoy rope.

3.2. Estimating gear soak time

Using the newly developed method for estimating soak time, estimation worked very well except in cases where the algorithm was not correctly able to match deployment and hauling events. This occurred in 2 of 39 cases in the French gill net fishery, and 1 out of 59 in the Danish lumpsucker fishery. This seems to be an issue with the spatial buffers, as the buffer around the hauling events did not entirely intersect the deployment events. For the hake gillnet fishery in Peru, all paired fishing events (a deployment and corresponding hauling) were identified. Gear soak time was generally estimated very accurately ($F = 710.9$, $df = 1{,}49$, $p < 0.001$, intercept $= -0.19$, slope $= 1.07$, $R^2 = 0.93$, Fig. 3a). In the gillnet fishery targeting lumpsucker in Denmark, the model also performed well in identifying paired events ($F = 147.5$, $df = 1{,}57$, $p < 0.001$, intercept $= 20.79$, slope $= 0.66$, $R^2 = 0.71$, Fig. 3b). Soak time was estimated very accurately in the Scottish pot and trap fishery ($F = 925{,}5$, $df = 1{,}18$, $p < 0.001$, intercept $= 9.99$, slope $= 0.92$, $R^2 = 0.98$, Fig. 3c) and in the French gillnet fishery ($F = 5583$, $df = 1{,}33$, $p < 0.001$, intercept $= 3.15$, slope $= 0.97$, $R^2 = 0.99$ (estimated without the outlier), Fig. 3d).

3.3. Spatial comparison of intensity of fishing effort

In our study examples, we found that the overall spatial patterns of effort did not change drastically over time, regardless of the estimation method used. There were differences between the three effort measures in the fine scale distributions of effort between cells, as shown in Fig. 4. For gillnet fisheries targeting hake in Peru, when using time spent hauling to depict fishing effort, one grid cell showed the highest level of fishing intensity (Fig. 4a), while using the length of the net or the length of the net multiplied by soak time resulted in a wider spread of the same high intensity area (Fig. 4b, c).For the Danish gillnet vessel targeting lumpsucker and the French gillnet vessel, using length of net multiplied by soak time resulted in the highest fishing intensity being located in an area approximately 1.5–2 km away from the high intensity areas estimated using the alternative estimation methods (Fig. 4, d–f, g–i). The French gillnet vessel showed a wider spread of similar intensity when using time spent hauling to depict effort (Fig. 4g).

4. Discussion

Based on a unique dataset from four different cases studies in different parts of the world, and using a variety of passive gears, we investigated best proxies of fishing effort. The work presented here analyses ground-truthed observations of fishing effort in passive gears (number of pots, nets, number of hooks) and their relationship with either time spent hauling or distance covered hauling from highly resolved geo-positional data. This work strongly suggests that estimation of gear effort is improved when using distance covered during hauling operations rather than time spent hauling. When elaborating maps of fishing effort distribution for passive gears, each grid cell should be assigned based on the distance covered during hauling operations, instead of the time spent hauling, as used in previous studies (e.g. James et al., 2018; Kroodsma et al., 2018). This simple step considerably improves estimations of nominal gear fishing effort (e.g. number of pots, length of nets, number of hooks). It mitigates the variability in hauling time introduced form artifacts such as snagged gear or differences in catch abundance and the associated handling time. In addition, if some information about the configuration of the gear is known, for example the distance between pots or hooks, then the total units of gear deployed during a haul or fishing trip can also be estimated (e.g. Mendo et al., 2019b).

For the first time, we present a method to estimate soak time in static gears from highly resolved geopositional data only. This method allows for soak time to be non-uniformly distributed across the study area. Generally, inferring deployment events directly from these data has proven challenging (Mendo et al., 2019a), so we developed a method where we first infer hauling events and then overlay these with deployment events from precedent trips. Following this initial step, we could estimate soak time by identifying the spatial overlap between inferred hauling events and matched deployment events. While the model performed generally very well for the four case studies presented here, a soak time value significantly greater than average was estimated on one occasion (out of 59) in the Danish fishery targeting lumpsucker (Fig. 3b) and on one occasion a soak time significantly lower than

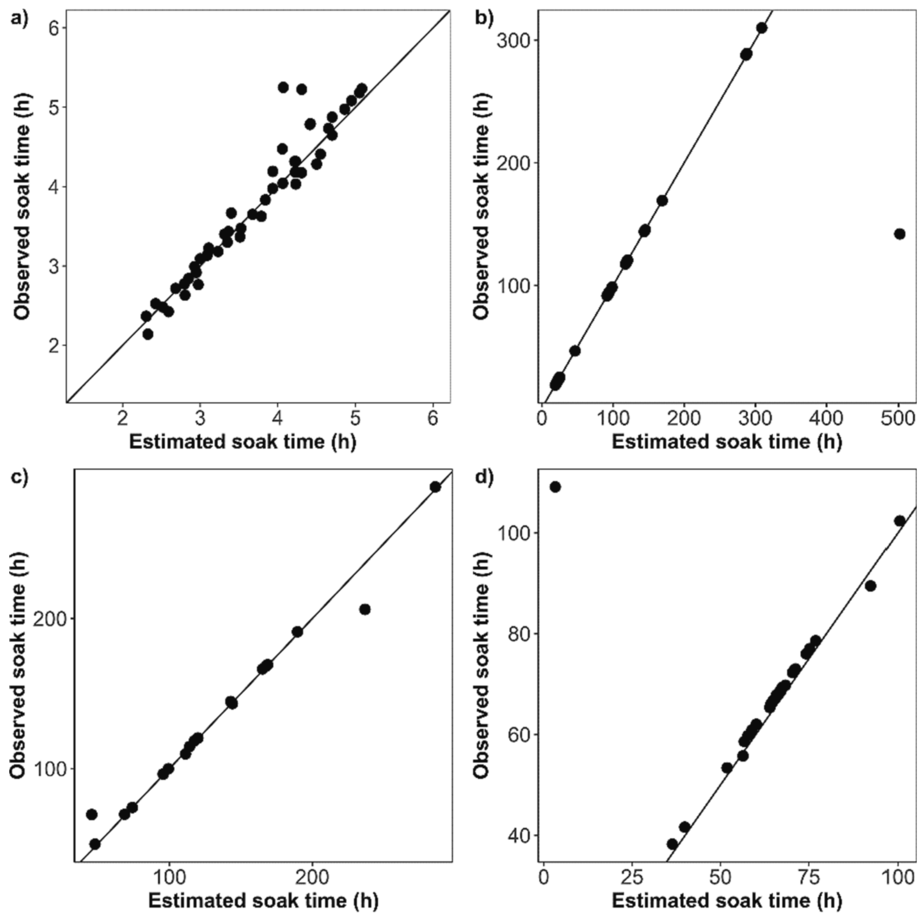

Fig. 3. Relationship between the estimated soak time and observed soak time for a) gillnet fishery targeting hake in Peru and b) gillnet fishery targeting lumpsucker in Denmark, c) pot and trap fishery in Scotland, d) gillnet fishery in France. Black lines denote an intercept = 0 and slope = 1.

average was estimated for French gillnet fishery (out of 39). In the first instance, the spatial buffer (that allows to match a deployment event to a hauling event) could not encompass the correct corresponding deployment event and wrongly matched the haul with an older overlapping vessel track. In the latter case, the overlap occurred with a deployment event that happened during the same trip. In this specific fishery, a net may be hauled on the same day it was set, therefore, the overlap between setting hand hauling was matched during the same trip. These parameters and rules are assigned *a priori* from expert knowledge, based on what is known from the fishery and that could be described as a "normal" fishing behaviour. In case of rare anomalies (deviations from the norm), this method may thus fail to match events correctly, which needs to be considered for heterogenous fisheries. Consequently, when deciding on a spatial buffer, experts must think carefully about the situations that might warrant an increase in the buffer length, for example, the amount of drifting of the gear due to tides and local currents, the length of the buoy or up-rope of the gear, and the depth at which the gear is being deployed.

Fine-scale depictions of fleet fishing effort distribution could benefit spatial management, especially when mapping specific fishing areas of particular interest for fisheries management and/or wildlife conservation (e.g. marine protected areas, fishing areas overlapping with the range of species of concern, etc.). A proper assessment of the risks fishers exert on marine and seabed biota and habitats requires finely resolved data, at spatial scales pertinent to the granularity of the habitat and also fishers' behaviours. Fishers targeting benthic species, for example, transfer knowledge over generations on location of suitable habitats for target species at a fine spatial scale. This information on effort distribution is often lost when aggregating fishing effort data at the low resolutions usually required by the legislator. Parnell et al. (2010) showed that incorporating recreational and commercial effort at scales of 250 × 250 m could account for the observed changes in biodiversity and community structure in kelp forest habitats. Similarly, exploiting information on fine-scale patterns of fishing effort will become very important for a transition to ecosystem-based management of fisheries and may have profound consequences for understanding ecosystem functioning and maintaining or rebuilding a healthy habitat and species biodiversity (Parnell et al., 2010).

Under the blue economy agenda, the increasing development of offshore renewable energy activities forces scientists and managers to understand fishing effort at scales pertinent to the proposed activities. For example, (Stelzenmüller et al., 2022) showed that coarse resolutions (e.g. 0.05 degrees) of gridded fishing effort tend to overestimate the actual overlap between fishing activities and offshore wind farms. In order to appropriately represent fishing activities, fine scale depictions of effort (0.01 × 0.01 degrees, roughly 1 × 1 km) are needed, as some offshore wind sites can cover areas of only few squared kilometres (Stelzenmüller et al., 2022). Higher resolution maps will improve the ability of policy makers to adequately represent the interests of fisher, which are often-neglected in the marine spatial planning process (Campbell et al., 2014; Stelzenmuller et al., 2008). While it is possible to estimate fishing activities over fine spatial scales using high resolution geopositional data, it is important to also consider that different effort variables derived from these data (time spent hauling, length of net, net. length days) can result in different fine scale depictions of the most important areas for fishers. This is an interesting avenue for future research, involving the fishing community and other stakeholders such as conservation scientists in discussing which type of effort metric is

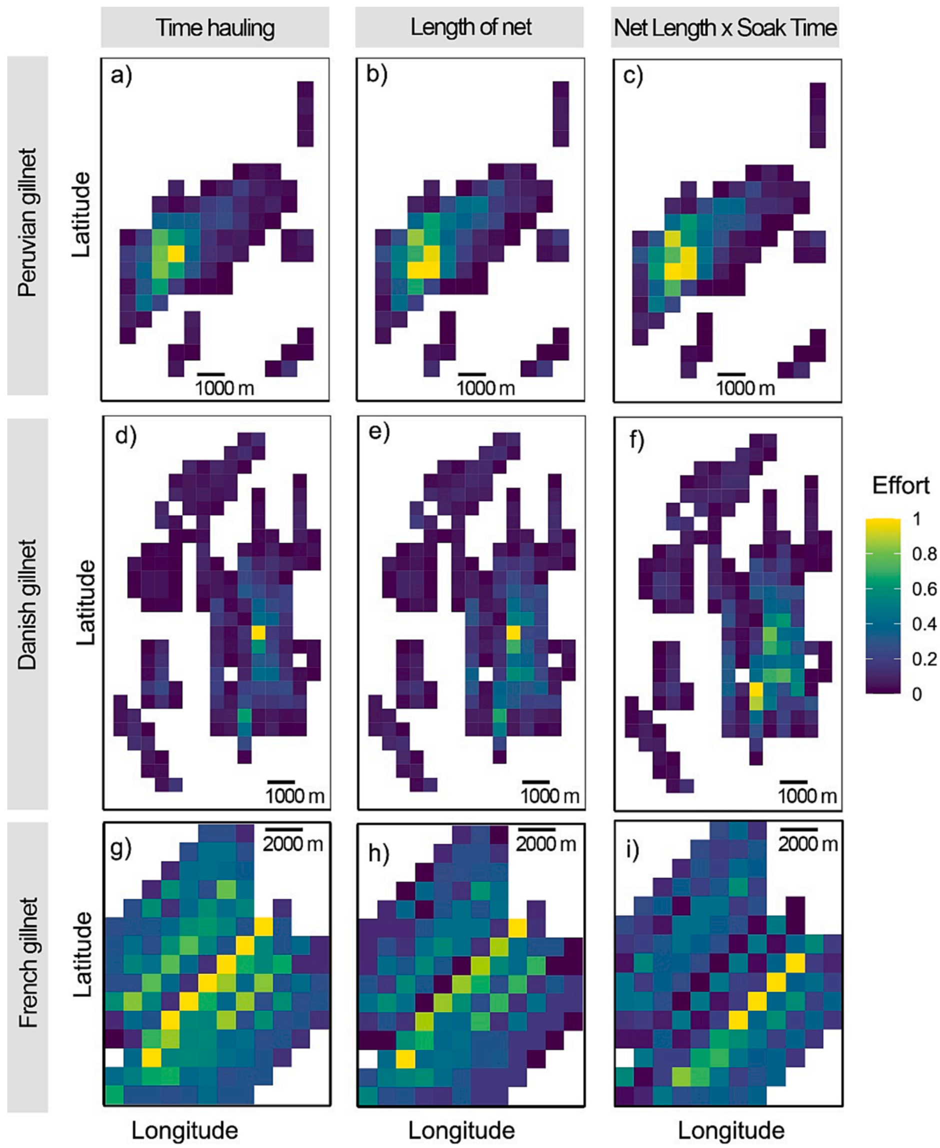

Fig. 4. Maps for the gillnet hake fishery (a–c) including 15 vessels operating between January and March 2019 in each grid cell (500 × 500 m); for one gillnet lumpsucker vessel, operating during 2017 in each grid cell (500 × 500 m) (d–f); and for one French vessel using gillnets in XX (g–i) in each grid cell (1000 × 1000 m), showing the proportion of effort (from 0 to 1) as a, d, g) time spent hauling nets, b, e, h) length of net (m), c, f, i) net length (m) × soak time (hours) in each grid cell.

most relevant to their activities and priorities.

The methods developed here to estimate soak time and proxies for number of pots, length of net or number of hooks from highly resolved geo-positional data fit the reporting requirements of the EU Data Collection Framework (EC, 2021). However, as soak time and catch are not linearly related, but rather increase towards an asymptote (Munro, 1974; Sundberg, 1985), derived effort metrics such as trap days or net length days may lead to overestimating fishing effort and fishing mortality. This declining fishing power with time for passive gears can provide serious bias in effort estimations. In particular, in fisheries with low stock densities, more gear with longer soak time will usually be favoured by fishers, while for stocks at high densities, less gear will be soaked for shorter periods as it will become saturated faster (Caddy, 1979). Fishery and gear-specific adjustments are therefore required to estimate soak time and effectively avoid overestimating fishing mortality (Caddy, 1979). Estimation of impacts on non-target species might also require alternative adjustments to effort estimation when soak time or number of hauls are not linearly related to bycatch.

From an ecosystem-based management perspective, detailed information on the intensity and distribution of passive gears fishing effort derived from the analysis of highly resolved geospatial data is particularly valuable to assess the level of incidental captures (bycatch) of sensitive species in some problematic fisheries (Moore et al., 2021). Bycatch of marine mammals, birds, or sea turtles in gears like gillnets and longlines are known to contribute disproportionally to overall mortality in some of these species' groups (Lewison et al., 2014). Many fisheries for which bycatch rates of marine megafauna are known to be high are not required to report their fishing effort at a fine scale (ICES, 2021). Knowing the precise location, gear length, and soak duration of the vessels operating high-risk gears would allow scientists and wildlife managers to better estimate bycatch mortality. Highly resolved geospatial data at fleet level (or at least for a representative sample of the fleet) would then contribute to a better understanding of the potential effects of fishing on impacted populations of non-target and protected species, and help in minimising bycatch, in line with the requirements enacted in many regions to conserve these species (e.g. Marine Wildlife Bycatch Mitigation Initiative in the UK, Marine Strategy Framework Directive in the EU, Marine Mammal Protection Act in the US).

Knowing the fine-scale variations in gear positions and soak time can shed a light into vessel-specific behaviours and how these change over time. In some areas, a common control measure for fisheries management is to limit the quantity of gear allowed in the water (Cochrane, 2002). However, these restrictions might have unintended consequences, such as provoking changes in fishing practices which may in turn negatively affect intended management measures. This is exemplified clearly in the Bristol Bay red king crab fishery, where pot limits were so low by 1997 that consequently, fishers reduced the average soak time from 2 days to 1, which, taking into consideration the catch per unit effort and soak time relationship, effectively increased mortality on crabs, as pots achieved more than 90% of a 2-day soak catch after a single day (Briand et al., 2004; Briand et al., 2001). Highly resolved geospatial data, which to date are often not collected in small-scale fisheries, could routinely and automatically be collected and used to estimate the number or the length of gear used over time using the methods presented in this paper.

The expansion in the use of tracking technologies that provide high resolution data (Burgos et al., 2013; EC, 2018; MMO, 2022), opens up the potential to further develop and apply robust methods to understand the spatial changes in fishing effort distribution. Highly resolved geopositional data demonstrate great potential for providing indicators of effort, fishing activities, and changes in fishing behaviours. Most method development has been oriented towards active gears, however, similar methods for passive gears are still in their infancy. Small-scale fisheries, which mainly use passive gears, generally operate at smaller spatial scales than large-scale industrial fisheries and are usually excluded from the marine spatial planning process. Understanding these nuances is increasingly important as globally, at least 40% of the catch is produced by this sector (FAO et al., 2023).

CRediT authorship contribution statement

T. Mendo: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Project administration, Writing – original draft. **G. Glemarec:** Validation, Formal analysis, Methodology, Writing – review & editing. **J. Mendo:** Conceptualization, Investigation, Funding acquisition, Project administration, Writing – review & editing. **E. Hjorleifsson:** Validation, Data curation, Formal analysis, Writing – review & editing. **S. Smout:** Conceptualization, Investigation, Methodology, Writing – review & editing. **S. Northridge:** Conceptualization, Methodology, Writing – review & editing. **J. Rodriguez:** Validation, Data curation, Formal analysis, Writing – review & editing. **A. Mujal-Colilles:** Validation, Conceptualization, Data curation, Formal analysis, Writing – review & editing. **M. James:** Conceptualization, Funding acquisition, Investigation, Project administration, Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Tania Mendo, Mark James reports financial support was provided by European Regional Development Fund. Tania Mendo reports financial support was provided by University of St Andrews.

Data availability

R code and sample data are provided in the Sup. mat.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.110822.

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