SIFIDS

Scottish Inshore Fisheries Integrated Data System

Work Package 8B Final Report

Identifying fishing activities and their associated drivers

Project code: WP00(8B) SIFIDS

EMFF: SCO1434

This project was supported by a grant from the European Maritime and Fisheries Fund

Published by

Marine Alliance for Science and Technology for Scotland (MASTS)

This report/document is available on

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Recommended citation style

Mendo, T., Smout, S. Ransijn, J., Durbach, I., McCann, P., Crowe, S. Carulla Fabrega, A., de Prado. I., James, M. (2019). Scottish Inshore Fisheries Integrated Data System (SIFIDS): Identifying fishing activities and their associated drivers. Published by MASTS. 67pp.

EMFF: SCO1434

This project was supported by a grant from the European Maritime and Fisheries Fund

EXECUTIVE SUMMARY

This Work Package (WP8B) of the SIFIDS project focused on vessels that are 12 m or under in length, use static gear (pots or creels), and primarily target lobsters (*Homarus gammarus*), crabs (*Cancer pagurus* and *Necora puber*), and prawns (*Nephrops norvegicus*).

WP8B had two principal objectives:

1. Identify fishing activity profiles for static gear vessels in the inshore fleet prosecuting lobsters, crabs and nephrops.
2. Incorporate effort, biological data, socio-economic data, environmental data to understand fishing behaviour

A total of 135 sea trips were conducted by on-board observers, including 117 different vessels from 43 different ports. These trips included the collection of a range of operational data including high resolution vessel tracks. Statistical models were then used to develop inference models to identify steaming and where and when fishing (gear hauling or shooting) was taking place, to estimate the number of pots or traps being used and to estimate the soak time of this gear.

Efficient algorithms which have an accuracy of greater than 90% were developed based on optimal polling rate for spatio-temoral position data and spatial grid cell sizes to process individual vessel movement profiles indicating when and where fishing is occurring. Focusing on methods that offered a combination of accuracy and computational efficiency could allow vessel tracks produced by the inshore fishing fleet (circa 1540 vessels) to be analysed in near real time with a conventional personal computer. Analysing data for the entire fleet on a daily basis recorded at a 60 second polling intervals was estimated to take ~40 seconds (~48 minutes annually).

By combining a range of fishing metrics derived from track data with FISH1 Form landings data for individual vessels it was possible to derive measures of Catch Per Unit Effort (CPUE).

A total of 105 fishers at 42 ports were interviewed to identify the main drivers that stopped fishers from going out on a particular day and placing their gear in a particular area. These responses were then used to inform a model which explored fisher's behaviour (probability of going fishing) based on several environmental and economic variables.

Environmental variables such as gust speed, temperature and wind direction affect the probability of going fishing on a particular week. Bad weather negatively affects the probability of going fishing but this depends on vessel size, with smaller vessels being more affected by high gust than larger vessels. The probability of going fishing is also affected by the expected landing (higher expected catch leads to greater number of fishing events) and increased fuel prices negatively affect fishing events.

A prototypic user-friendly interface has been developed that could be used to assist different stakeholders in decision making such as fishers, managers, Regional Inshore Fisheries Groups (RIFGs), and marine spatial planners. This tool incorporates modelling results to a) visualise boat track data on a map, highlighting the positional records that are most likely to be associated with hauling (b) visualise maps of the spatial distribution of boat positions and fishing effort; and (c) by linking FISH1 form landings data to effort estimates illustrate CPUE for individual boats.

A brief overview of the kind of management scenarios that could be informed by implementing the processes and systems developed by the SIFIDS project is included and describes potential analytical approaches that could be used.

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ACKNOWLEDGEMENTS

The authors would like to thank the many fishers who provided advice, support and access to their vessels for data collection purposes. Without their input, this work would not have been possible. In particular, we would like to acknowledge Andrew Whiston who has provided sage advice and insights as both fisher and a Regional Inshore Fisheries Group representative. Marine Scotland staff have encouraged and steadfastly supported this work providing both policy and practical support throughout. Nick Lake has provided sage advice and useful critique. Ariadna Carulla Fàbrega and Irene de Prado, two Erasmus students, undertook the first analysis of the drivers of fishing activity. Rene Swift, Swithun Crowe and Patrick McCann have been directly responsible for developing the equipment and software upon which much of the output from this project is based and we owe them a great debt. John Thompson and more recently Hannah Ladd-Jones, managed the SIFIDS project and helped to drive it to a successful conclusion. Kyla Orr, Ali McKnight and Kathryn Logan provided tireless and vital facilitation and outreach. We acknowledge Marine Scotland and the European Maritime and Fisheries Fund for supporting this project financially (Grant number EMFF: SCO1434).

1. INTRODUCTION

Increasing use of coastal marine areas may lead to future conflicts over space and resources. It is therefore, important to accurately map fishing activities to inform, local, regional and national fisheries management as well as marine planning and related policy commitments. In Europe, these commitments include the development of Marine Protected Areas (MPAs) and MPA networks which can displace fishing activities, or the installation of offshore renewable energy devices which can exclude certain fishing gear types. Assessing the spatio-temporal distribution of fishing activities can alert managers to the potential for spatial overlap between fisheries, which may help to reduce gear conflict. Quantifiable information on the interactions between fishing and the environment, including the spatial distribution of fishing effort, are also required to demonstrate good environmental status under the Marine Strategy Framework Directive.

In order to allocate space to specific uses, verifiable information on the location of different human activities is needed to determine interactions among users, and between users and their environment. This is particularly critical for inshore fishing activities, as they represent one of the main uses of the marine space, have considerable socio-economic importance and play a role in food security. Previous attempts to analyse space use and fishing effort in Scottish small scale vessels have been based on interviews with experts, sightings from shore, logbook data, fisheries protection vessels and aircraft patrolling (e.g. Kafas et al., 2014)[1]. These approaches however, provide limited data to inform management, e.g. location of vessels but no frequency of fishing, and limited information on fleet responses to management actions. Whilst an important point of reference, these data are static and therefore do not reflect change.he recent use of self-reporting systems such as Automatic Identification System (AIS) together with other forms of Global Navigation Satellite Systems (GNSS) tracking is providing an alternative source of data that can be used for spatial marine planning (James et al., 2018)[2]. The use of these and similar GNSS based systems can provide a large volume of high resolution spatial data. The challenge is to collate and analyse these data accurately in ways that are relevant to fisheries management and marine planning while ensuring computational efficiency.

One of the main aims of this Work Package (WP 8) was therefore to generate efficient algorithms to process individual vessel movement profiles in order to indicate when and where they are engaging in fishing activities. This WP focused on vessels that are 12 m or under in length, as they not required carry a Vessel Monitoring System (VMS), use static gear (pots or creels), and primarily target lobsters (*Homarus gammarus*), crabs (*Cancer pagurus* and *Necora puber*), and prawns (*Nephrops norvegicus*). This section of the fleet comprises approximately 80% of all inshore fishing vessels in Scotland. Once the locations of fishing activities have been inferred from positional data, the most important fishing grounds can be mapped on fine spatial scales.

Information on spatio-temporal distribution of effort in small scale fisheries (SSF) is important to inform marine planning and management that can protect both the marine ecosystem and the fishers. However, for SSF that use static or passive gears effort is usually related to the time it takes the vessel to recover gear, which is not a measure of how much gear is deployed or how long it was immersed (soak time). Therefore, to get a better idea of effort in SSF we

[1] Kafas. A., Mclay, A., Chimenti., M and Gubbins, M. (2014) ScotMap Inshore Fisheries Mapping in Scotland: Recording Fishermen's use of the Sea. Scottish Marine and Freshwater Science, Vol.5 No. 17. Publ. Marine Scotland ISSN: 2043-7722

[2] James, M.A., Mendo, T., Jones, E. L., Orr, K., McKnight, A., Thompson, J. (2018): AIS data to inform small scale fisheries management and marine spatial planning. Marine Policy, 91, 113-121.

aimed to develop methods that estimate the number of creels deployed and their soak time (i.e. effort).

Understanding the processes affecting fisher's behaviour is critical to the successful management of fisheries. Anticipating how a fishery will respond to management and other influences can reduce uncertainty in predicting the outcomes of management, but to date little has been done to understand and anticipate the human component of SSF in Scotland. This WP interviewed fishers to gain a better understanding of the main drivers affecting their decision to go fishing on any particular day. With this information, and including a number of variables that have been identified in other fisheries (i.e. vessel size, fuel price, meteorological and hydrographic variables) the probability of going fishing was estimated.

This WP contributes to the development of a preliminary decision support tool (user-friendly web-interface) to contribute towards a decision support framework which will inform fisheries management in Scotland. Fishing tracks, main fishing grounds, number of revisits to the same areas, and estimates of catch per unit effort can be visualised through the web interface for specified levels of granularity (subject to data access privileges). The final section of the report provides a brief overview of the kinds of fisheries management and marine spatial planning decisions that might be supported by data collected using systems and processes developed during the SIFIDS project. The document briefly reviews decision support and its ties to evidence-based decision making, summarizes the data produced by SIFIDS, and outlines several hypothetical management policy decisions to illustrate the kinds of decision that might be addressed in future with data derived from SIFIDS.

Decision support scenarios have to be determined by end user (decision maker, fishers, regional groups) requirements, but the capacity to integrate abiotic (i.e. weather, season, vessel characteristics) and biotic factors (e.g. stock, human behaviour) as covariates in statistical decision support models, opens up the potential to inform a wide range of management questions based on the best available evidence.

2. APPROACH

The main objectives of WP8B were to i) infer fishing (hauling) activities from positional data only, ii) estimate fishing effort at fine spatial scales, iii) understand main drivers affecting the probability of going fishing and iv) develop a preliminary decision support tool to assist in decision-making in Scottish SSF.

The following steps were conducted to meet these objectives(Fig. 1). The first step was to develop a protocol for data collection by the observers. This protocol was used by the on-board observers (WP8A) to collect the information required in this WP to identify fishing (hauling) behaviours and their locations as the trip was in progress, and to estimate different metrics of fishing effort. Survey questions were designed to identify the main drivers affecting a fisher's decision to fish (or not) on a particular day and where to place their creels. All this information was then combined to develop approaches towards a decision-support tool which will inform fisheries management in Scotland. Each step is described in detail in sections below.

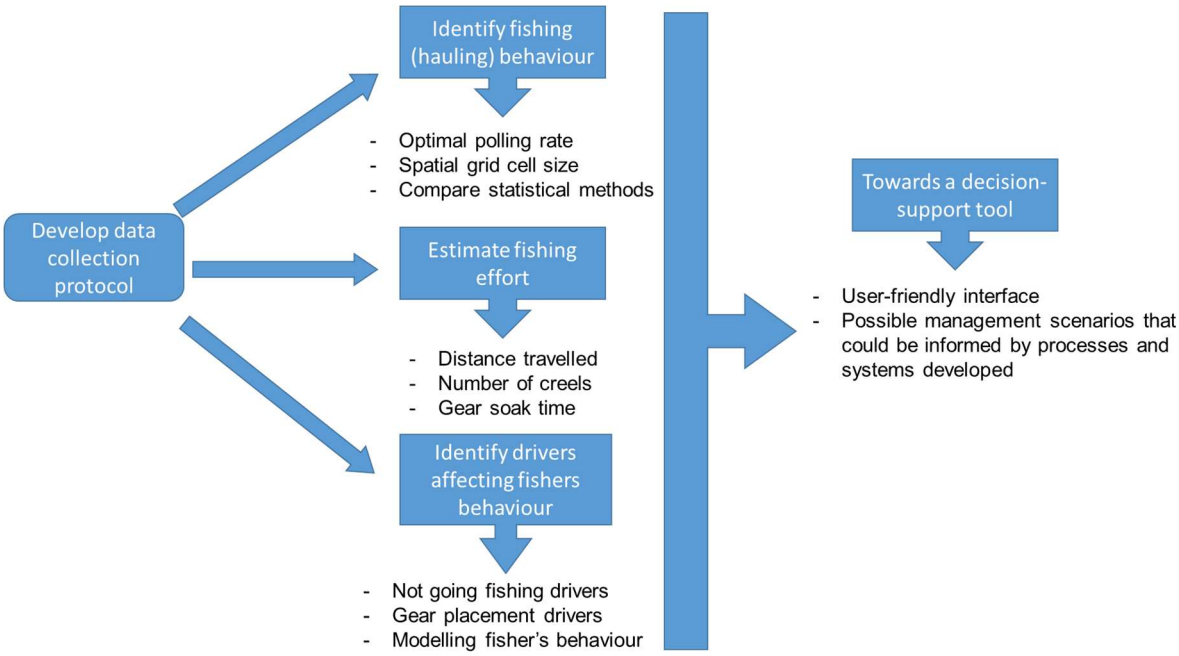

Fig. 1 Diagram showing the different steps conducted to meet aims of WP8b

3. DEVELOPMENT OF A DATA COLLECTION PROTOCOL

The first activity of the WP8B team was to develop a protocol that would capture information necessary to describe fishing vessel behaviours during a fishing trip. This included selecting a representative sample of ports around Scotland and making a detailed sampling protocol for on-board observers. A total of 43 different ports were selected from locations around Scotland. Ports were selected based on the number of annual fishing trips conducted by skippers, and then discussions with fishery Officers at Marine Scotland to ensure higher skipper participation rates and coverage of both the East and the West Coast. For logistical reasons, the north of Scotland (including Orkney and Shetland Islands) were excluded from the survey design (see Fig. 2 for map of locations, exact location not shown, subject to confidentiality agreements with fishers).

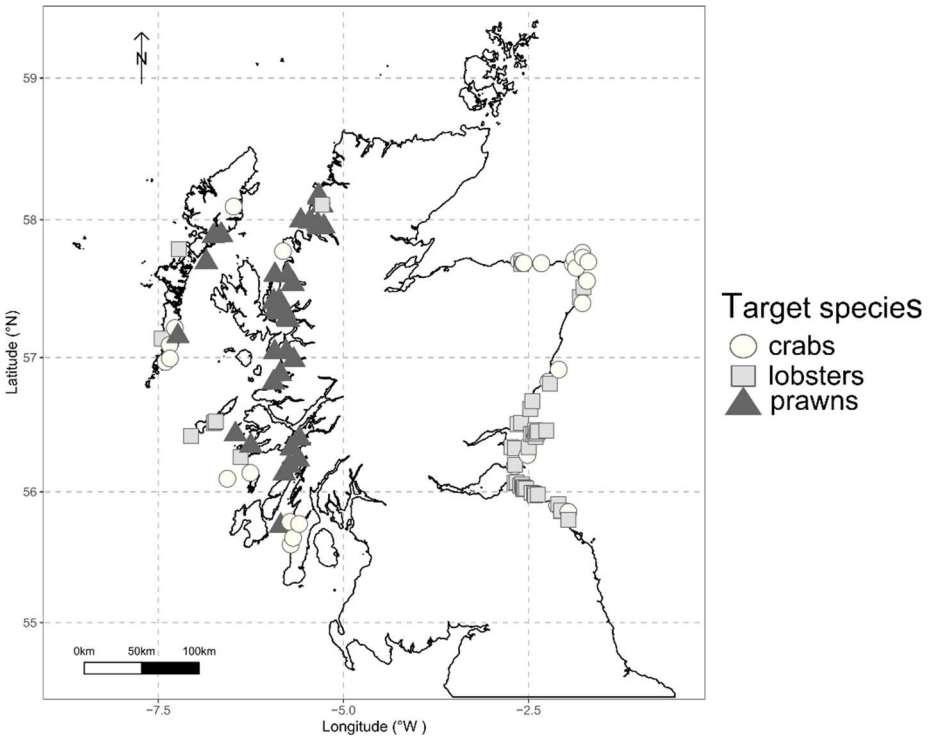

Fig. 2 Map showing locations of fishing trips with on-board observers. White circles show trips targeting crabs (brown and velvets), grey squares where the main species was lobster, and dark grey triangles where the main target species was prawns. For logistical reasons and subject to discussion with Marine Scotland, a decision was taken at the start of the project not to survey vessel in Orkney and Shetland.

The sampling protocol captures information necessary to describe fishing vessel behaviours for vessels undertaking creeling for crabs and lobsters (i.e. when the vessel is steaming, deploying or recovering gear, or handling catch). Effort was also recorded (number and type of creels used and soak time) to assess if fishing effort could be estimated from positional data. A semi-structured interview was conducted by on-board observers to identify the main drivers affecting the decision to go fishing on a particular day, and gear placement. The observers also asked for written consent from each skipper to allow access to their Fish 1 form[3] (catch landing) data from Marine Scotland, which was used to model the decision to go fishing on a particular day.

Five boat trips were conducted by members of the WP8B team on board inshore fishing vessels to develop an appropriate data collection protocol to be utilised by on-board observers in WP8A. These trips allowed the WP8B team to develop and assess the sampling protocol (Sup. Mat. 1) and to assure that it was suitable for capturing information necessary to adequately describe fishing vessel behaviour. Two of these trips were conducted with an observer from WP8A, to discuss the feasibility of data collection during a fishing trip. The protocol was explained to observers in detail and follow-ups were conducted immediately after initial observer deployments to receive feedback, check that surveys were undertaken properly and make any necessary amendments to the survey and the implementation. For each trip Global Navigation Satellite System (GNSS) data were collected by an on-board observer using a handheld Garmin Etrex 20 where GNSS positions were recorded at 1 second intervals. Observers also recorded the registry of shipping (RSS number), target species, departure time, and several vessel activities (time of hauling events, time of re-deployment of

[3] FISH1 is the name of a form that all inshore fishers must use to record the catch they land together with estimates of by-catch and the position where most of their fishing activity took place. The form must be submitted weekly to Marine Scotland. More detail is provided in section 4.2.1 of this report.

creels, and time when the vessel reached port at the end of each trip). A detailed protocol for data collection (step by step document) was also made available for observers (Sup. Mat. 2). A total of 135 sea trips were conducted by on-board observers, including 117 different vessels from 43 different ports.

3.1. Identify fishing vessel behaviours

Summary

Positional data was used to infer fishing activities. Several important methodological details are developed and explained in this section. The optimal polling interval to best infer fishing activities while limiting computational demands was determined. A number of possible analytical approaches were assessed to accurately and efficiently identify fishing. We discovered that it is feasible in near-real-time to identify fishing activity from a data set that would comprise the whole inshore fishing fleet in Scotland.

Introduction and background

Gathering positional data from the whole inshore fleet of Scotland (~1500 vessels) is challenging due to the large volumes of data that would have to be generated. It is important to consider the computational costs incurred when choosing an appropriate method for inferring fishing activities. SSF vessels in comparison to Large Scale Fisheries (LSF) make up the majority (80%) of the total fishing fleet in most European countries (1). Furthermore, the reporting frequency is higher for SSF (*e.g.* the razor clam dredge fishery in Ireland reports every 5 minutes (2)), compared to 30 – 120 minutes reporting from VMS units used for LSF. The standard reporting frequency being 120 minutes. It is therefore necessary to establish procedures that will secure effective identification of fishing activities, in computationally efficient ways.

3.1.1. Considerations on the optimal polling interval

Fishing activities in SSF usually occur at smaller temporal scales than in the LSF, therefore the location of fishing vessels must be collected at a finer temporal resolution. However, decreasing the polling interval (how often positional data are recorded) dramatically increases the amount of data collected, the amount of storage space required to house such data, and the computer processing time required for analysis. The optimum polling interval must therefore be short enough to effectively detect fishing activities, but long enough to allow for the data to be processed within a reasonable time frame using readily available and reasonably inexpensive computers.

In order to identify the optimal polling rate for smaller boats in a pot fishery, 66 vessels in the SSF from 29 separate ports volunteered to have observers on-board to record when fishing activities took place. Each haul was defined by the retrieval of the start and end buoy of a set of creels, and as times were recorded by on-board observers for each of these they could be combined with the GNSS tracking data to identify the location of hauling events. To evaluate the effect of polling rate on identification of hauls, the default 1 second polling rate at which all fishing operations were recorded was subsampled to different GNSS polling rates (5, 10, 30, 40, 60 seconds and , 2, 4, 6, 8, 9, 10, 15, 30 minutes seconds). Each subset of polling rates was further divided into a dataset that contained only the positional records categorised as hauling by the observers. Depending upon the polling rate, this process could result in, for example, just one positional record in each haul. As polling rate increased, more and more observed fishing activities would be missed by the positional data, introducing error. We sought to assess the polling rate at which positional records available would begin to inadequately describe observer's information on number of hauling events and area fished.

Vessels were split into 3 size categories based on length to assess any potential differences in their optimum polling rates: < 9.5 m ("small"), 9.5 – 10 m ("medium"), and > 10 m ("large"). The large category was created due to the increased reporting obligations given to > 10 m vessels, while the medium category corresponds to the "super-under-10s" which make up a significant proportion of the 10 m and under fleet (3).

The number of hauls were not affected by vessel size category but the area fished was generally greater for bigger vessels. The effect of different polling rates on the area fished was therefore assessed separately for each size category.

Review of the positional records from 66 trips (one per vessel) and 706 creel hauls indicated that a perfect haul detection rate can be maintained with polling rates up to 60 seconds (**Fig. 3**). The number of detected creel hauls decreased at larger temporal rates, and spatial records every 600, 900, and 1800 seconds showed significantly fewer creel hauls than those recorded by observers (F=4067.3; df=1,13; p<0.001; **Fig. 3**) (4).

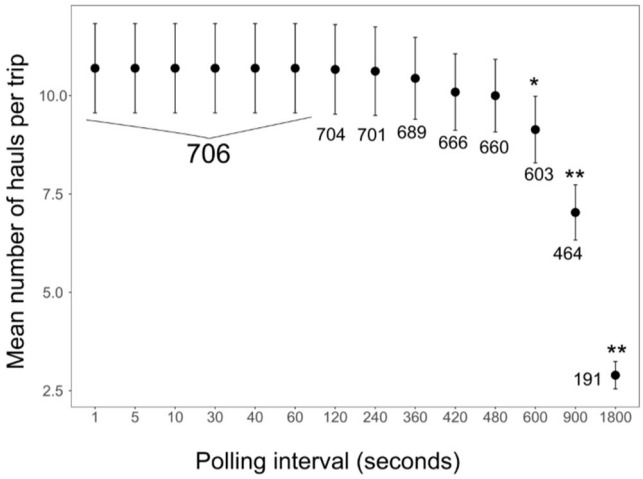

Fig. 3 Estimation of mean number of hauls per trip (+/- SD) for 66 trips at different polling rates. Asterisks above error bars show which polling rates resulted in significant (*<0.05, **<0.001) differences to the real mean number of hauls reported by observers (1 second rates). Numbers below error bars indicate number of hauls estimated for each polling rate (from (4)).

As polling rate increased, estimates of the total area fished per trip began to show significant differences for small and medium-sized vessels at the 240 second rate, while these differences were only evident at 420 seconds in large vessels (Fig. 4 a,c,e).The mean area fished per haul showed significant differences from the area estimated from observer data at the 60 second rate for small vessels and at 120 seconds for medium and large vessels (b,d,f).

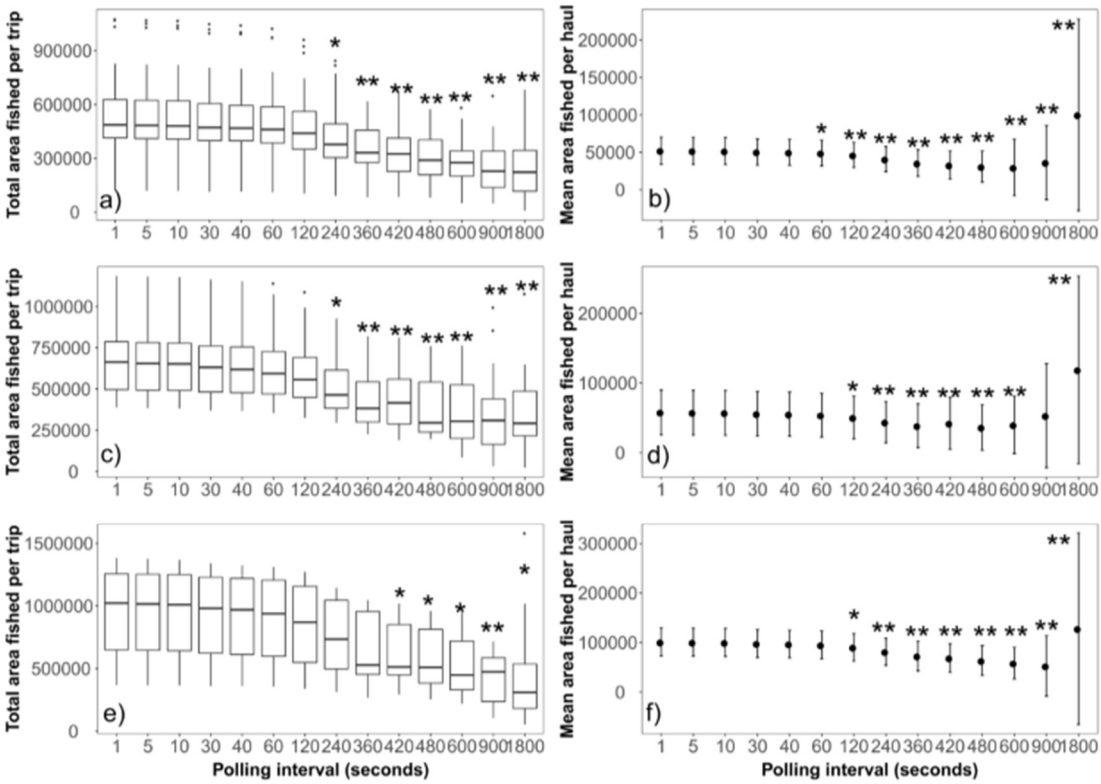

Fig. 4 Total area fished per trip (+/- SD) for a) small, c) medium, and e) large fishing vessels. Mean area fished per haul (+/- SD) in b) small, d) medium, f) large fishing vessels. Asterisks above error bars show which polling rates resulted in significant ((*<0.05, **<0.001) differences to the area fished estimated from observer's records (at 1 second rates) (from4)).

A polling rate of 60 seconds would be optimal to estimate the number of hauls, total area fished per trip, and mean area fished for vessels using pots and traps in Scotland. At this temporal resolution, 29,566 GNSS observations were recorded for 66 trips. When expanded to the entire fleet, an estimated 50,135,232 GNSS observations are expected annually (assuming 111,909 trips as in 2016, Marine Scotland, unpublished data). This would require a storage capacity of approximately 21Gb per year. Free open source software such as PostgreSQL and R can handle this volume of data, making remote collection and analysis of GNSS data a low-cost and efficient way to improve the management of these fisheries (4).

3.1.2. Considerations on the spatial grid cell size

To effectively estimate the area fished (whether it is the total area per trip or the mean area per haul), spatial grid cell size must also be considered. The optimum cell size has similar constraints to the optimum polling rate: it must be small enough to adequately describe the area fished, but large enough to be easily stored and analysed.

A comparison of grid cell resolutions (100x100, 200x200, 400x400, 500x500, 1000x1000, and 1500x1500 metres) was performed on a subarea of the West Coast of Scotland that comprised 30% of the total effective area fished during the study (13.2 km^2) by (4). The area fished at each resolution was calculated by counting the number of cells with at least one observed hauling record and multiplying that number by the area of a grid cell at that resolution.

Increasing the cell grid size from 100x100 m to 200x200 m resulted in a ~200% increase in the total area fished (from 13.2 km^2 to 25.8 km^2). A further increase to 1000x1000 m caused an almost 14-fold increase in the total area fished (**Fig. 5**). Changes to spatial grid cell size had more profound effects on area estimation than changes to polling rate (see (4)).

The decision on the cell grid size will depend on the objectives of each stakeholder, confidentiality requirements and the amount of error they are willing to accept. For example, a smaller cell grid size might be necessary to assess the impact of an offshore activity on the access to fishing grounds by fishers, but might not be appropriate to convey information at a national scale.

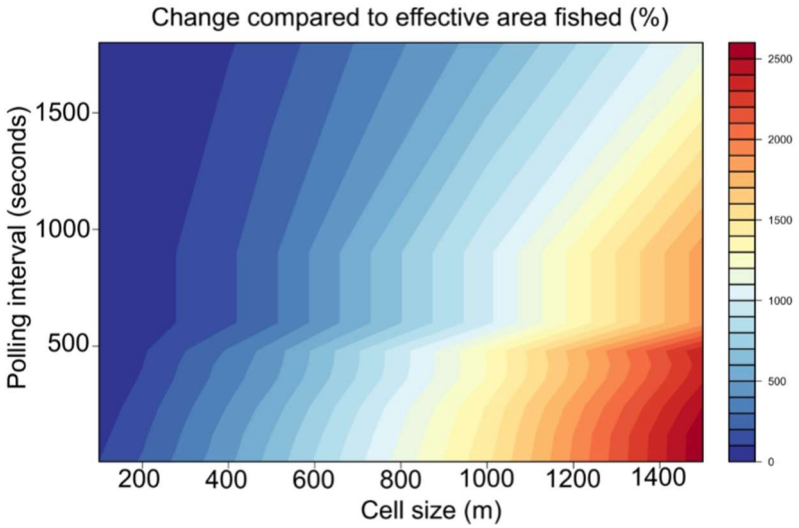

Fig. 5 Effect of cell size (metres) and polling interval (seconds) on distribution of fishing activities, compared to the effective area fished calculated from observer's data (from (4)).

3.1.3. Compare different statistical methods to identify hauling activities

Different methods have been used to identify when and where fishing activities occur (*i.e.* fishing or not, steaming, or in port) from positional data. Different fishing activities are characterised by different movement behaviour of the vessel. Fishing activities can be distinguished from steaming by having lower speeds and higher turning angles. The most common methods use these differences to identify fishing and include i) an overall speed threshold inferred from a sample of vessel movements and known activities, or estimated from expert knowledge (5-8); ii) mixture models fitted using an Expectation Maximisation algorithm (9), and iii) Hidden Markov models (10-13). The expectation maximisation (EM) algorithm implements an iterative procedure that uses maximum likelihood estimates to cluster the data based on a mixture of normal distributions (14). Hidden Markov Models (HMM) have been used in animal movement ecology as a method for classifying different movement behaviours such as travelling and foraging (15, 16). HMM models are stochastic and are used for discrete time steps, an unobserved state process (*e.g.* fishing) would generate each observation (location) and the probability of the current time step depends on the previous one. These models assume that observations are independent and conditional on the underlying state (17). For fishing vessels, the characteristic distinguishability between steaming and fishing are frequently associated with each hidden state (e.g. low speed and high turning angle corresponding to fishing).

One of the challenges to a complete coverage of the inshore fleet is the large amount of data that would be produced, therefore it is important to consider the computational costs incurred when choosing an appropriate method for their analysis. Therefore, we aimed to infer activities of fishing vessels using pots and traps from positional data collected by on-board observers, while prioritising computational efficiency.

We compared five approaches with varying levels of complexity: a single overall speed filter, two EM algorithms capable of assigning a speed threshold value for each vessel, a univariate HMM that used only speed, and a multivariate HMM including speed and turning angle (Sup. Mat. 3). We judged the performance of each approach by comparing its outputs to observers' ground-truthed data, and by its computational efficiency (model run time for each approach). The ground-truthed data came from 115 fishing trips, conducted by vessels using static gear (pots and traps) and targeting lobsters and crabs.

All five approaches performed well in identifying fishing activities. The best overall accuracy (proportion of correctly classified instances) was similar across approaches (Table 1) but was highest for the trip-based EM algorithm and lowest when using an overall speed threshold. The trip-based EM was considered to achieve most satisfactory results in terms of an overall accuracy rate, maximum error rate per trip, false positive rate, and computing time. The computational time was based on the use of a desktop computer (Intel® Core™ i7–5820K @3.30 GHz with 32 Gb RAM x64-bit Windows 10 Pro OS).

Table 1 Accuracy, per trip error rate (%), false positive rate, false negative rate and time elapsed for computation of 115 trips using five different approaches (from Mendo et al, in prep)

	Overall speed	**Trip_based_EM**	**Embc**	**HMM speed**	**HMM speed and angle**
Accuracy (%)	91.14	92.3	91.37	91.97	91.68
Per trip error rate (% range)	(2.16 – 33.33)	(2.05-28.95)	(1.57 – 33.7)	(1.81-25.92)	(1.80 – 35.94)
True positive rate	94.23	95.69	97.37	97.58	97.19
False positive rate	11.28	10.34	13.23	12.37	11.95
Time elapsed (seconds)	1.56	3.06	15.48	197.09	352.20

The area covered during 115 fishing trips was 63.21 km^2. The trip-based EM resulted in 68.12 km^2 (~7.7% difference compared to the area estimated from observer's data). The trip-based EM algorithm resulted in about 10.8% overestimation of the real area fished (e.g. Fig. 6, false positives) and about 3.04% underestimation of the real area fished (e.g. Fig. 6, false negatives), however, these areas were mostly located nearby real fished areas.

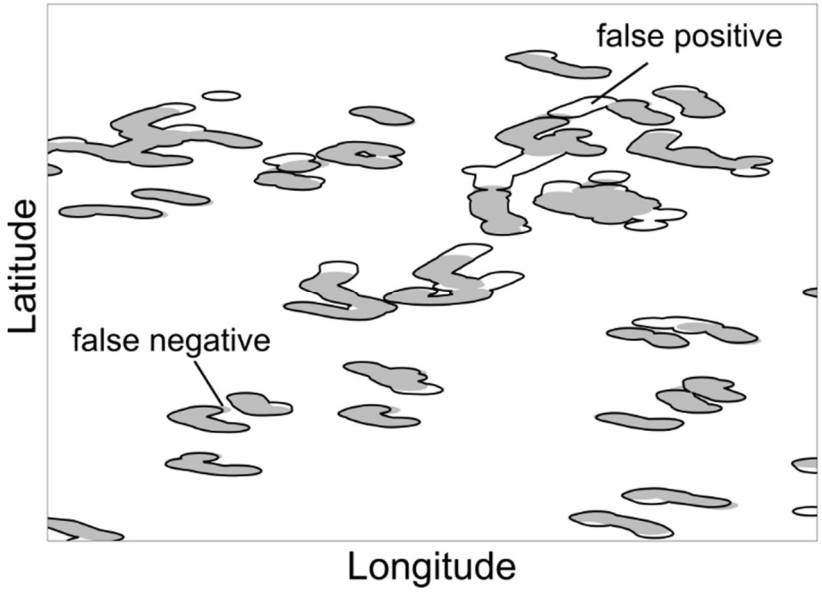

Fig. 6 Map showing a subset of areas fished identified by observers (grey areas) and identified by the trip-based EM algorithm (black contour lines), showing false positives (white areas inside a black line) and false negatives (grey areas outside the black con the black contour line). Coordinates not shown due to confidentiality agreements with fishers (from Mendo et al, in prep).

The 155 trips classifying positional records into hauling and not hauling activities took the trip-based EM algorithm approach ~ 3 seconds to complete (~0.026 seconds per trip). If we would assume that these 155 trips are representative of the total fleet in Scotland and the entire fleet would be fitted with a similar device (*i.e.* device to record positional data at a 60 second polling interval) it would take ~40 seconds a day to classify the fishing activities of the circa 1540 SSF vessels if they would all be engaged in fishing activities. If we scale this up by looking at the total number of fishing trips annually conducted in Scotland (111,909 trips in 2016, Marine Scotland, unpublished data), it would take ~ 48 minutes to classify. This highlights the feasibility of designing a monitoring system that could efficiently generate information on main fishing grounds, fishing effort, or monitoring of compliance to regulations for the Scottish SSF fleet without using the computational power of a relatively conventional personal computer.

4. CHARACTERISE FISHING EFFORT

4.1. Summary

We present three types of effort estimates:

1) Distance travelled per trip, calculated based on positional data.
2) Number of creels deployed during each trip: Numbers were estimated by looking at the relationship between the number of creels deployed (as recorded by on-board observers) and the distance covered during each haul (estimated from positional data and on-board observer's records).
3) Gear soak-time. Gear soak time is the time the gear spent underwater and imputes fishing. This was estimated by looking at successive trips to identify deployment followed by hauling events.

The relationship between soak time and catch may not be straightforward (18, 19) and deserves further data collection and analysis which are out of the scope of this WP.

4.2. Introduction and background

Information on spatio-temporal distribution of effort in SSF is important to protect both the livelihoods of fishers and people that depend on these fisheries and the ecosystem. Whilst in general SSF are recognised as having less impact to stocks and habitats than LSF, there is some evidence of the contrary: in West Africa, the artisanal sector exerts more fishing effort than the industrial sector, due mainly to the increasing number and size of boats (20). There is also growing evidence that SSF are directly responsible for a significant decrease in abundances and biomass of target (21, 22) and non-target species (23, 24) and have impacts on habitats at magnitudes comparable to those of large scale industrial fisheries (e.g. set gillnets damage to kelps and gorgonian corals in Baja California) (25)). In fact, impact to habitats is more likely related to quantities and types of gear, rather than overall boat length (25).

However, SSF offer a key source of livelihoods in coastal communities (26). Knowledge of spatio-temporal distribution of effort can better represent space use in the marine environment by SSF to inform marine planning and avoid conflicts. Spatio-temporal distribution of effort can better represent SSF fleets in order that boundaries established for marine spatial planning can, as far as possible, respect the needs of fishers.

Once hauling events are identified, different effort metrics can be calculated. In mobile gears, such as trawlers and dredgers, effort maps have been generated based on the estimation of time spent fishing. However, most SSF use passive or static gears, such as pots and traps, and in these fleets, time spent fishing is a description of how long it took the fishers to recover their gear, but not necessarily of the quantities deployed and the time they were immersed. We aimed to estimate the spatial distribution of fishing effort in passive gears at small spatial scales, based solely on positional data. The specific objectives were to: i) estimate distance travelled per trip, ii) estimate the number of creels deployed per haul; iii) estimate the amount of time gear was immersed (soak time).

4.3. Estimate distance travelled per trip

The Euclidean distance between consecutive positional observations (every 60 seconds) was calculated and added to estimate the total distance travelled in each trip. For the 115 trips conducted with on-board observers, the average distance travelled per trip was 47.9 km, ranging from 7.5 – 123 km.

Linear mixed models (LMMs) were applied to explore the effect of vessel overall length and main species targeted (crabs and lobsters or langoustines) on the distance travelled in each trip. Vessel ID was incorporated as a random factor, as the distance travelled was likely depend on a skipper's preference. Model validation was undertaken by evaluating diagnostic plots and residual variance using normalised residuals. Model selection was based on the lowest Akaike Information Criteria (AIC).

The selected model included only vessel length. For every metre increase in vessel length, the mean distance travelled per trip increased by about 9 km (*Fig. 7*). This relationship was not affected by the main species targeted during a trip. The intra-class correlation for the random effect (vessel ID) was 0.52, indicating that about half of the total variance in distance travelled was among vessels.

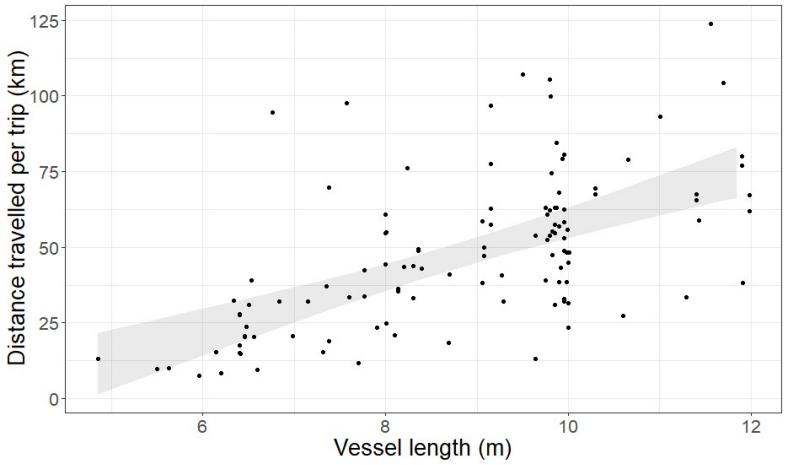

Fig. 7 Relationship between vessels length (m) and distance travelled per trip (km)

4.4. Estimating number of creels

We first estimated the distance covered during a hauling event and evaluated the relationship between this distance and the number of creels deployed (observer's data). The distance covered during a hauling event was estimated by identifying the first and last positional record of each haul (recorded by observers), and calculating the shortest distance between the two points according to the harvesine method, which assumes a spherical earth, ignoring ellipsoidal effects using the R package 'geosphere' (27). Linear mixed models were applied to explore the effect of hauling distance, vessel overall length and species targeted on the numbers of creels deployed in each haul. Trip id was incorporated as a random factor, as the number of creels were likely depend on a skipper's preference, or the vessel's capacity to held creels. Model validation was undertaken by evaluating diagnostic plots and residual variance using normalised residuals.

Distance covered during hauling, target species and the length of the vessel explained 83% of the variability in the numbers of creels deployed in each haul (Table 2). For every metre increase in overall length of the vessel, the number of creels deployed in each haul increased by ~3 in vessels targeting lobsters and crabs and by 5 creels in vessels targeting prawns (*Fig. 8*). Overall, there was a positive relationship between the distance hauled and the number of creels (*Fig. 8*).This is logical as the longer the hauling events, the more likely it is that more creels were deployed.

Table 2 Model results for the analysis of variation in number of creels. A random effect of form ~1|vessel_ID was included. SE = Standard error; SD = Standard deviation; ci = confidence interval

Random effect:	SD				
1|vessel	6.98				
Residual	5.687				
Fixed-effects	Estimate	SE	t-value	2.5%c.i.	97.5%c.i.
Intercept	24.14	0.84	28.66	22.50	25.79
Distance hauled (m)	8.58	0.34	24.82	7.90	9.30
Overall vessel length (m)^	4.25	0.68	6.16	2.91	5.60
Target species Nephrops	27.44	1.47	18.6	24.57	30.32

^Standardized to have a mean of zero and a SD of 1

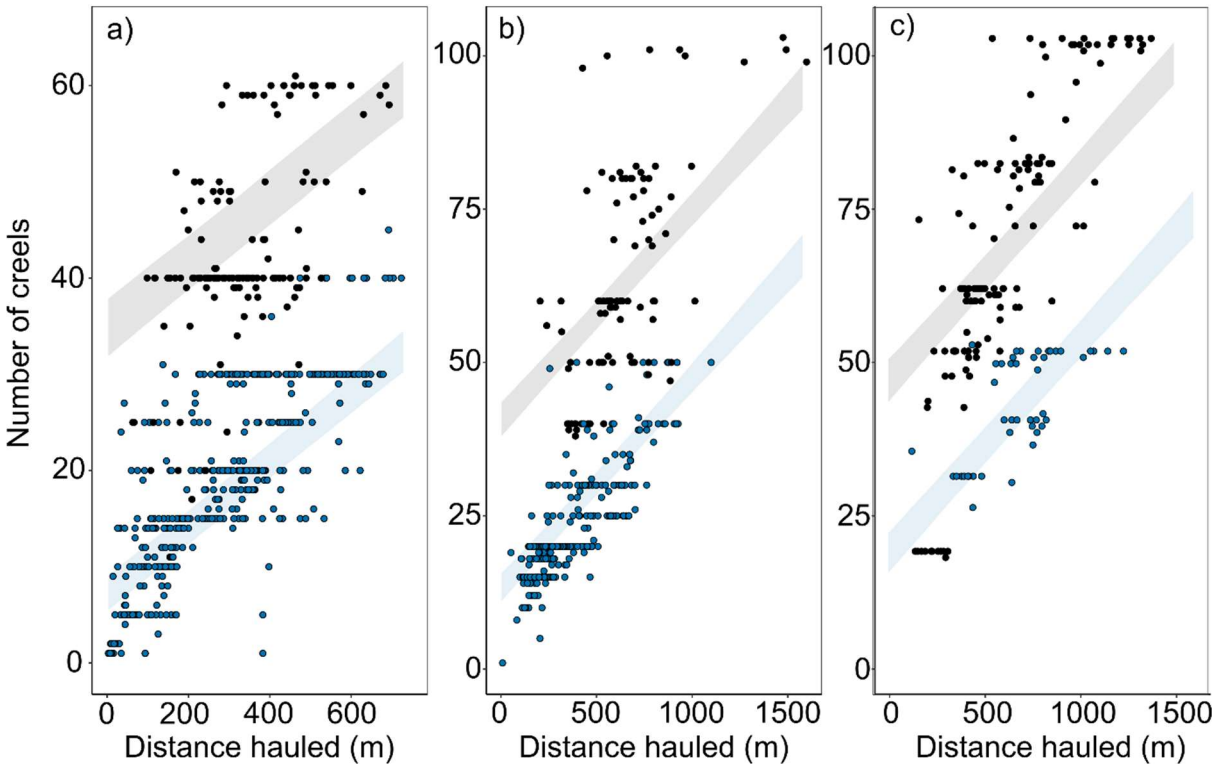

Fig. 8 Predicted 95% confidence interval of the mean number of creels deployed during each haul in relation to distance hauled in a) small (< 9.5 m in length; 7.6 m vessel shown) , b) super under 10's (9.5-10m; 9.8 m vessel shown) and c) larger (>10-12m; 11.5 m vessel shown) vessels targeting crabs and lobsters (blue) or prawns (black).

This model was then used to predict the number of creels deployed during a haul, but estimated using the trip-based EM algorithm (i.e. assuming no observer's data would have been available). Finally, we compared the total number of creels deployed during a trip from observer's data to the total number of creels per trip estimated from the model to assess how well we could estimate numbers of creels by using positional records only. The relationship between the estimated and observed number of creels was linear and the model parameters are listed in Table 3. The number of creels was consistently but just slightly underestimated by the model. This means that calculating distance hauled by using the trip-based EM algorithm can give us a good indication of the number of creels deployed in each trip.

Table 3 Model result for the relationship between numbers of creels estimated by the model and observed (real) number of creels (R2=0.83).

	Estimate	SE	t-value	p value	2.5%c.i.	97.5%c.i.
Intercept	41.14	19.38	2.12	0.03	2.70	79.57
Number of creels estimated	1.06	0.046	23.01	<0.001	0.97	1.15

4.5. Estimating gear soak time

We used AIS data and data collected by the on-board observers to estimate and evaluate the possibility of using positional data to identify the time each string of creels was immersed. AIS

data were collected by UltraMap Ltd (http://www.ultra-map.org/) between May 2017 and July 2018 and added to a database in PostgreSQL. These data came from SSF vessels equipped with Class B AIS units under the 2014/15 EFF funded project 'Evidence Gathering in Support of Sustainable Scottish Fisheries' in 2015. While the use of AIS data for SSF in Scotland has some limitations (including the lack of AIS reception in several coastal areas, and differences in sampling rates across regions (28)) this was the only source of positional data available which could record trips on a consecutive basis. Out of the 105 vessels participating in the project, 40 were equipped with one of these AIS units. Of these, 8 had been transmitting AIS records regularly enough to identify consecutive fishing trips, and data from these vessels were therefore used to evaluate the methods.

4.5.1. Identifying soak time using on-board observer data

For each of the 8 vessel trips, the positional records of the deployment events registered by on-board observers were plotted (Fig. 9a). The trip-based EM algorithm was used to identify hauling events from positional data from subsequent dates (AIS data, Fig. 9b). If there was no overlap between the hauling events and the deployment events for a subsequent date (Fig. 9 c), then the next date was selected. If there was an overlap between hauling events and deployment events (Fig. 9 d) then the hauling event was selected and the deployment event removed from further analyses. This procedure was repeated until no deployment event was left without a complementary hauling event. The date and mean time for each hauling event were recorded, matched to the deployment event (Fig. 9 e), and soak time was calculated as the difference between the time stamp from the hauling event and the time stamp of the deployment event (e.g. Table 4). The mean soak time for all hauls conducted during the 8 fishing trips was 5.7 days, and ranged from 18 hours to 15 days. The median soak time was 4.0 days.

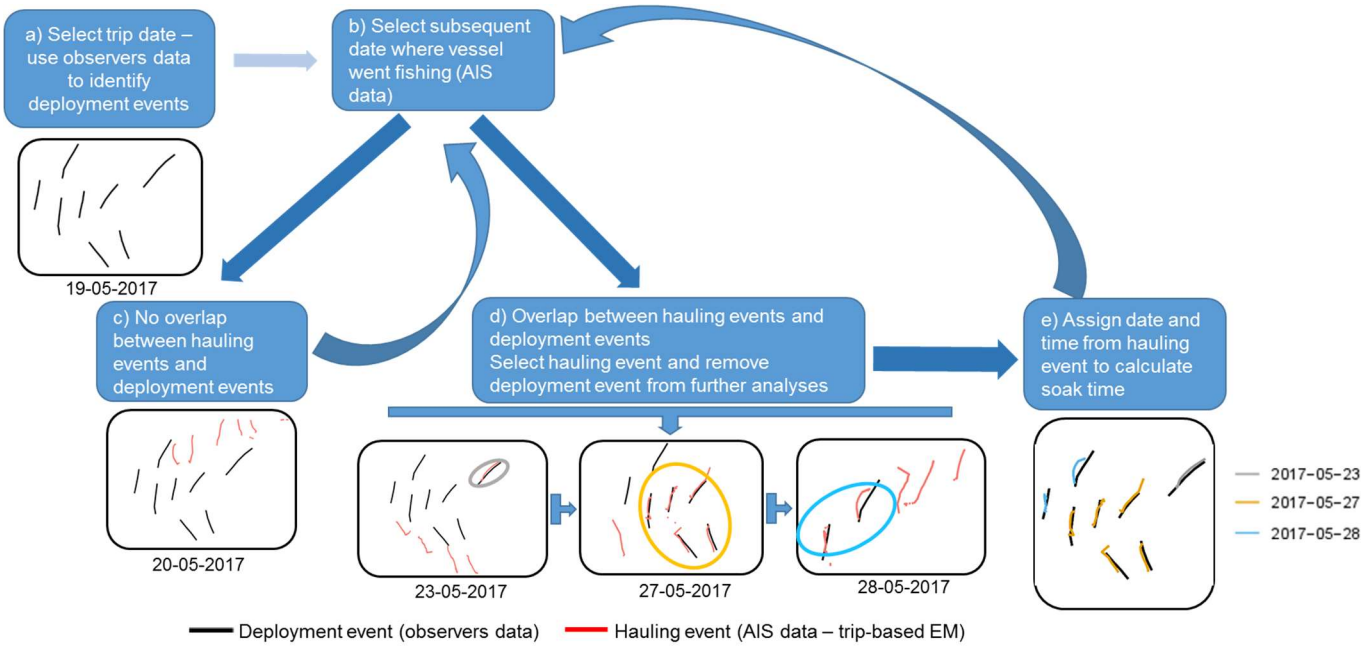

Fig. 9 Example of procedures used to estimate soak time using on-board observer records of deployment events and overlapping AIS data for subsequent fishing trip dates. This procedure was followed for each vessel

Table 4 Example of soak times calculated using on-board observer's records of deployment events for vessel A.

Deployment event	Deployment date and time	Hauling date and time	Soak time (days)
1	2017-05-19 08:45:58	2017-05-27 08:15:08	7.97
2	2017-05-19 09:44:58	2017-05-27 07:20:08	7.89
3	2017-05-19 10:40:58	2017-05-27 11:26:38	8.03
4	2017-05-19 11:38:28	2017-05-27 10:20:08	7.94
5	2017-05-19 12:30:58	2017-05-27 12:24:38	7.99
6	2017-05-19 13:25:28	2017-05-23 07:47:38	3.76
7	2017-05-19 14:32:58	2017-05-28 07:26:08	8.70
8	2017-05-19 15:23:28	2017-05-28 08:26:38	8.71

4.5.2. Identifying soak time without on-board observer's data

Once we had identified the hauling event that corresponded each deployment event occurred, we estimated soak time using only AIS data, we would later compare these estimates with on-board observer's data. We have demonstrated above that the trip-based EM algorithm performs well in identifying hauling activities with low error rates. However, identification of deployment events of creels is not as precise, as several vessels show very similar movement patterns during deployment and steaming (see section above).

In order to match hauling events to their corresponding deployment events several selection procedures were used (Sup. Mat. 4). In brief, we used a series of rules that were informed by the length of hauling and deployment events, and the distance of the up-rope of a string of creels (rope that joins ground rope with the surface buoy), initially recorded by on-board observers. We used the soak times estimated with on-board observer's data to assess the performance of a method (how well the method was identifying real deployment events and soak time).

These procedures performed well in estimating soak times, albeit there is still room for improvement. Out of the 70 hauls performed during the 8 trips, 66 were correctly identified by these procedures (94.3% true positives). Of these 66, two hauls did not match the correct date of hauling and one haul was identified were no actual deployment event had occurred (Sup. Mat. 5). The main reason for these errors corresponded to errors in the identification of hauling events from AIS data, where a few positional records misclassified as steaming or deployment during an actual hauling event would divide the hauling event into two and make it shorter than required to be kept as a real hauling event.

5. IDENTIFICATION OF DRIVERS AFFECTING THE DECISION TO GO FISHING AND WHERE TO FISH

5.1. Summary

This section analyses fisher's interview responses to identify the main drivers that stopped fishers from going out on a particular day and placing their gear in a particular area. These responses were then used to inform a model which explored fisher's behaviour (probability of going fishing) based on several environmental and economic variables. We discovered inconsistencies between the dates reported as fishing from FISH1 forms and the actual fishing trip dates as recorded by on-board positional systems, therefore we grouped the data on a fishing week basis.

We discovered that environmental variables such as gust speed, temperature and wind direction affect the probability of going fishing on a particular week. Bad weather negatively affects the probability of going fishing but this depends on vessel size, with smaller vessels being more affected by high gust than larger vessels. The probability of going fishing is also affected by the expected landing (higher expected catch leads to greater number of fishing events) and increased fuel prices negatively affect fishing events.

5.2. Introduction and background

It is important to understand the decision making process of fishers as these have an impact on fisheries management. The decision making processes involved in small-scale fisheries needs to be highly adaptable and varies with individual fishers. Fishers have different preferences and switch tactics by, for instance, selecting different fishing grounds, target species, gear type or even engage in other activities that generate income (29). Fishers' short-term behaviour is affected by economic, social, cultural, weather and/or ecological factors (30, 31). In order to manage the fishery effectively we have to understand what motivates fishers to fish in a given manner at any point in time. However, we currently have a limited knowledge of what drives fishers to go fishing or not and this limits our ability to understand and thus effectively manage this dynamic fishery.

In principle, using the sort of outputs that WP8b could generate, it should be possible to explore policy options and estimate which vessels might be affected by different prevailing weather conditions for example. This would allow to more accurately assess the potential adverse effects of the predicted increase in storm intensity and frequency around the UK due to future climate change. This information could inform strategic investment decisions to facilitate transition to a Scottish fleet that is better suited to future weather scenarios. Relevant economic data on fishing activity can be linked to individual vessels, classes of fishing activity or region, to model what the consequences of different impact scenarios (*e.g.* changes in fuel price) will be on fishing behaviour. Furthermore, this type of analysis would identify who might be more vulnerable to these changes (*e.g.* smaller vessels) and could help to inform the scale and equitable distribution of publicly funded compensation for example. The ability to predict fishing activity, likely success and landings would have implications for markets and logistics support, particularly where complex, costly and time sensitive supply chains may be involved. By capturing and understanding some of the key drivers for fishing behaviour we should be able to provide more robust and timely information to support decision making.

This study identified key drivers for creel fishers in Scotland by conducting interviews with fishers. FISH1 form data from Scottish creel fishers was then used to model the probability of fishers going to sea according to different factors identified as potentially important by the

interviewees or expert knowledge *e.g.* season, vessel length, revenue, weather conditions, and fuel prices.

5.3. Interview results

A semi-structured interview was conducted by on-board observers to identify the main drivers affecting the decision to go fishing on a particular day, and gear placement. 105 fishermen from 42 ports on the East and West Coasts of Scotland were interviewed to assess what drove them to stop fishing or change fishing locations. Fishermen were asked, “What would have stopped you from going to sea today?” and, “How do you pick where to place creels?” For each question, fishermen were encouraged to provide at least 5 answers, identify the thresholds at which the driver would affect fishing activity (*e.g.* wind over 20 knots), and rank them from most to least important. Similar responses were grouped into categories (*Fig. 10*).

A Fisher’s Exact test of independence was conducted to assess if there were any difference in the proportion of driver categories mentioned by fishers and region (West or East Coast), vessel size (“small”: <9.5 m, “medium”: 9.5-10 m, and “large”: >10 metres), or main target species (edible crab (CRE), European lobster (LBE), velvet swim crab (LIO), and Norway lobster (NEP)).

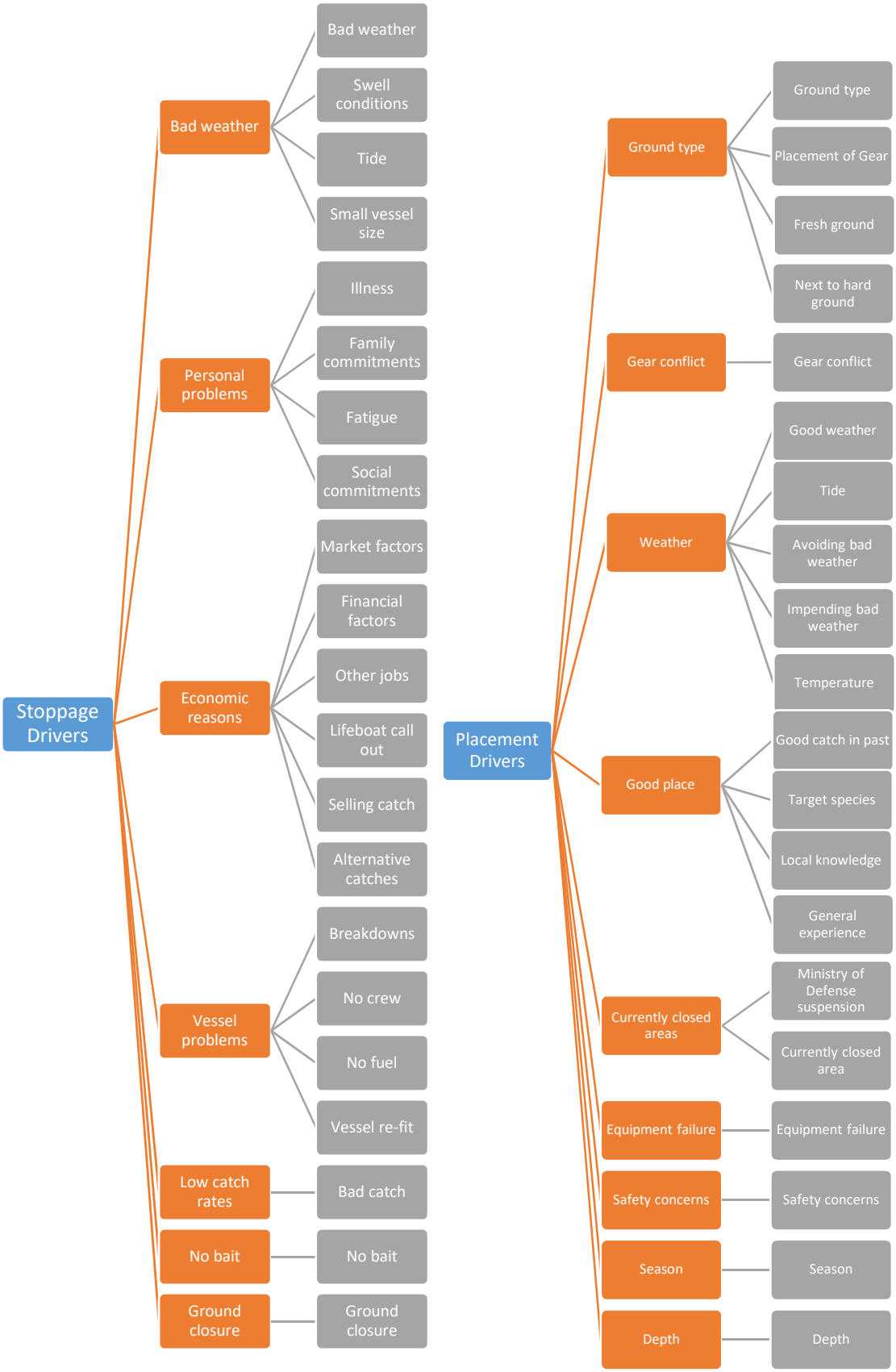

Fig. 10 Regrouped drivers that would stop fishing (left) and placement drivers (right). Grey indicates the drivers supplied by fishermen. Orange indicates the new regrouped drivers.

5.3.1. Drivers stopping fishing activities

The most common driver category that stopped fishers from going out on a particular day was bad weather (95.2% of fishermen surveyed), followed by low catch rates (37.1%) and vessel problems (32.4%) (**Fig. 11**). Other driver categories mentioned were personal problems (28.6%), economic reasons (14.3%), lack of bait (6.7%), and ground closure (1.0%).

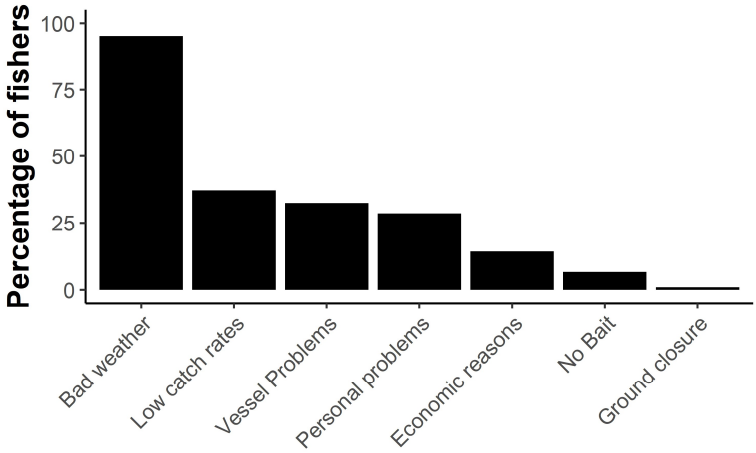

Fig. 11 Percentage of fishers that identified a particular driver as important in affecting their decision to go fishing on a particular day

When asked what defined “bad weather”, 60.6% of fishers explicitly mentioned wind and 19.1% mentioned “shelter” [from the wind]. The wind direction that prevented fishermen from fishing varied by area. On the west coast, in the Outer Hebrides, easterly to southerly wind directions mainly prevented fishers from going fishing, while on the western mainland, westerly and northerly wind directions were mentioned more frequently (**Fig. 12**). On the east coast, north-easterly to south-easterly wind directions prevented fishers from going out fishing, while on the northern east coast, north-northeasterly wind directions were mentioned more frequently (Fig. 12).

Fig. 12 Reported wind directions associated with decisions to avoid fishing on a given day, by area and port. West coast - blue, Outer Hebrides – light blue, east coast – red, and northern east coast- orange

The second most mentioned driver category for stopping fishing was low catch rates. Fishers that commented mentioned seasonal change (18.9%) and leaving pots in the water for longer to improve catch rates (24.3%).

The main drivers mentioned by fishers were not significantly different by region (Fig. 13, p = 0.13, Fisher's Exact Test), targeted species (Fig. 14, p = 0.15, Fisher's Exact Test) or vessel size category (Fig. 15, p = 0.38, Fisher's Exact Test).

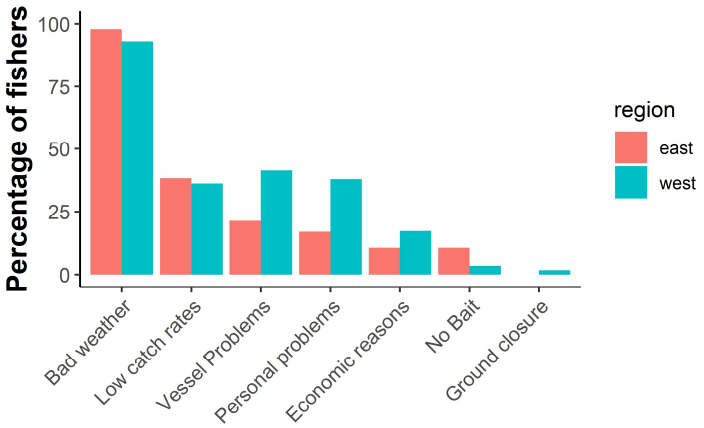

Fig. 13 Percentage of fishers identifying a particular driver as important in affecting their decision to go fishing on a particular day according to region.

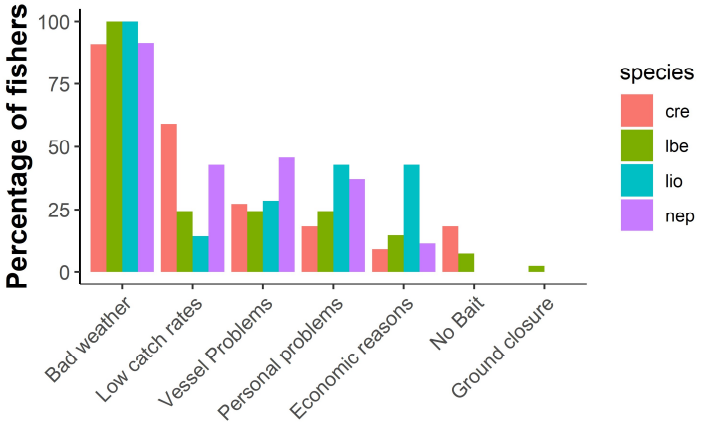

Fig. 14 Percentage of fishers identifying a particular driver as important in affecting their decision to go fishing on a particular day according to target species.

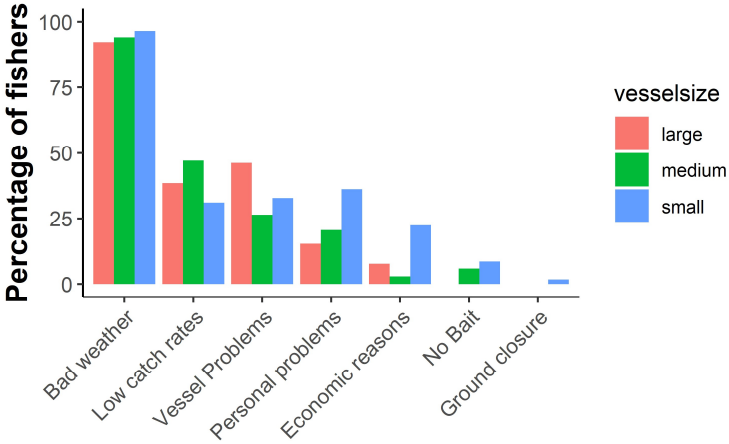

Fig. 15 Percentage of fishers identifying a particular driver as important in affecting their decision to go fishing on a particular day according to vessel size.

5.3.2. Drivers that influence gear placement

The most mentioned driver category that determined creel placement were “good place” (62.8%) and “ground type” (50.4%) (**Fig. 16**). Gear conflict (39.5%), impending bad weather (24.0%), and depth (20.2%) were also mentioned often, while season (6.2%) and the other driver categories were mentioned the less frequently.

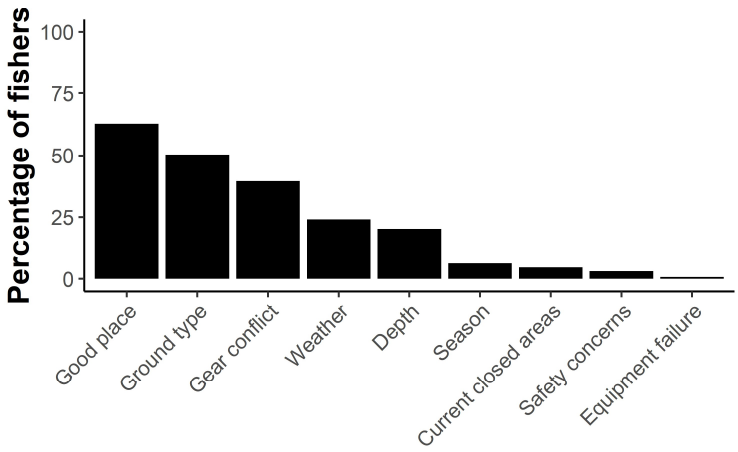

Fig. 16 Percentage of fishers identifying a particular driver as important in affecting their decision of where to place their gear.

The relative proportion of drivers affecting creel placement was not affected by region (*Fig. 17*, p = 0.87, Fisher's Exact Test), main target species (*Fig. 18*, p = 0.54, Fisher's Exact Test), or vessel size category (*Fig. 19*, p = 0.33, Fisher's Exact Test).

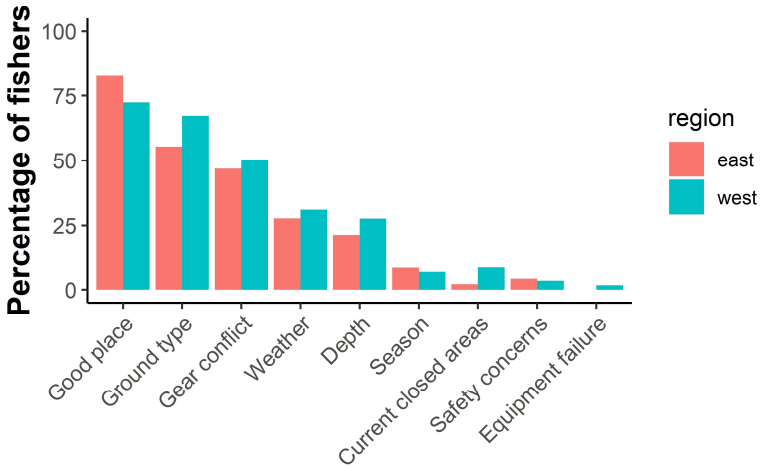

Fig. 17 Percentage of fishers identifying a particular driver as important in affecting their decision of where to place their gear according to region.

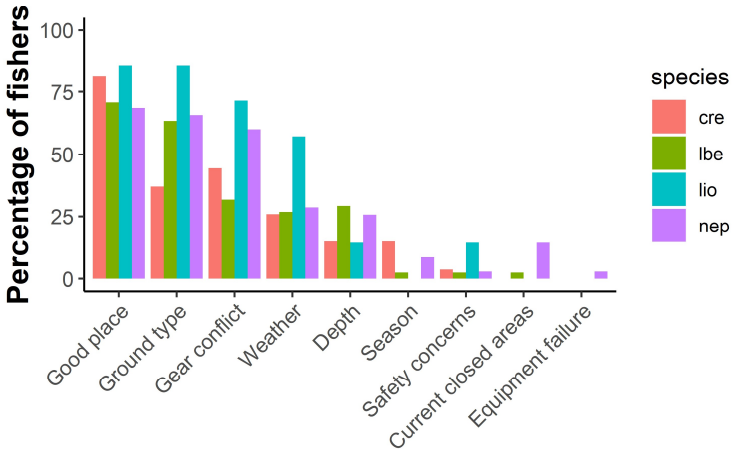

Fig. 18 Percentage of fishers identifying a particular driver as important in affecting their decision of where to place their gear according to target species.

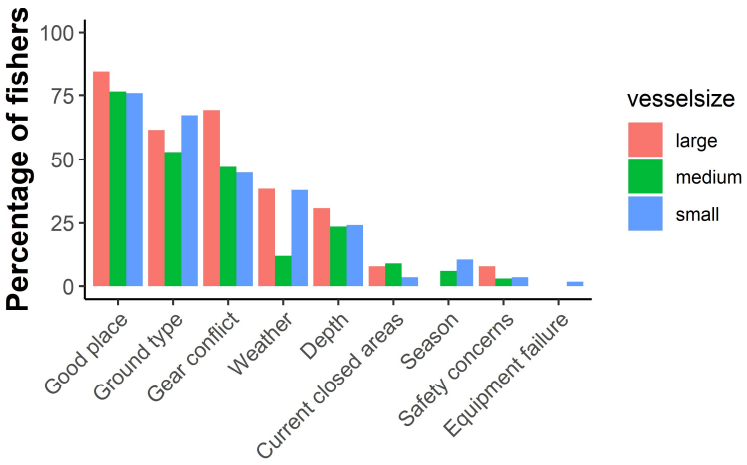

Fig. 19 Percentage of fishers identifying a particular driver as important in affecting their decision of where to place their gear according to vessel size.

5.4. Probability of going fishing

In this study, we evaluated which factors influenced the probability of Scottish creel fishers going fishing (ie the factors that would stop them fishing) and what factors would influence where they placed gear. We used the drivers identified from interviews with fishers as explanatory variables: weather (wind, gust and temperature); economic factors (a proxy for expected catches was developed, fuel price); geographic area (east, north east, west and Outer Hebrides); target species (lobsters, crabs or prawns); vessel length; and season.

The probability of going fishing was modelled using a hierarchical Generalised Additive Models (GAMs) (32). Vessel ID was incorporated as a random effect smoother, to account for potential variability between skippers. An interaction between wind direction and area was added as for this four areas different wind directions were flagged as preventing fisher's from going fishing (see interview results section above). An interaction between gust and vessel size was also incorporated, as small vessel size was flagged by fisher's as limiting their operating capabilities under windier weather conditions. To account for additional correlation amongst vessels, a random effect was included. The Akaike information criterion (AIC) was used to select optimal models while reducing overfitting. Residual temporal autocorrelation was checked using autocorrelation function (ACF) plots and spatial autocorrelation was investigated using variograms and bubble plots. All plots indicated very weak autocorrelation.

5.4.1. Data sources and preparation

FISH1 form

Fishers that use vessels of 10 meters or under are required to report their catch by completing and weekly submitting a FISH1 form. This form records *e.g.* vessel information, activity data, start and end location of the fishing trip (by port), gear type used, and weight of species caught. FISH1 forms from 2017-2018 were available from 93 vessels (for which we got the skipper's consent to access their data for the duration of the project) based in 39 different ports. Only fishers that spent more than 10% of the total number of days fishing were selected for analyses. The number of days recorded as fishing for each individual skipper ranged from 64-459 days during the two year-period. A few outliers (n=27) were detected when plotting the weight of the species caught for each individual vessel, these were removed from the dataset and the mean weight caught during the two year period was used instead.

The main species targeted was defined as the most frequently caught species. One vessel mostly caught mackerel and was therefore excluded from the dataset, as it was deemed that the factors affecting the decision to go fishing might be affected by the different way his vessel may operate (using hand lines in contrast to creels). The main targeted species included lobsters (*Homarus gammarus*), brown crab (*Cancer pagurus*), velvet crabs *(Necora puber*), and prawns (*Nephrops norvegicus*).

A proxy for expected landing was estimated by plotting the weight of the catch (kg) per trip per month for each species in each region (east and west of Scotland). The minimum monthly value for each subset was set as a baseline, and the proportion above this baseline (catch per trip in all other months divided by the minimum monthly value) was estimated for each month. This represented a proxy for expected catch per trip with the rationale that greater expected catches would positively influence a fisher's decision to go fishing on a particular day.

Environmental variables change drastically on a daily basis, therefore it is necessary to have high quality data of the date that each fishing trip occurred. To explore how well fishers reported the dates they went fishing we used vessels for which we had positional reporting systems installed (the On-Board Data Collection System developed by Seascope Ltd. in WP2b) to compare the date of the trips as logged in the systems against the date of the fishing trips reported in the FISH1 forms. We had permission to access FISH1 form data for 11 out of the 15 vessels in which the systems were installed. We found inconsistencies between the dates were the vessels went fishing and the dates reported in the FISH1 forms (Table 5). This mismatch between dates reported in the FISH1 forms and dates where trips occurred ranged between 3% - ~90%. This could be due to errors in reporting the dates, underreporting the number of trips or catches being less than the level required to be reported. Due to these inconsistencies, we decided to group the trips on a weekly basis (a fishing week according to the FISH1 form runs from 0001 hours Sunday to 2359 hours Saturday), to avoid associating the wrong environmental variable to a date.

Table 5 Proportion of dates where mismatch occurred between FISH1 Forms and vessel activity data recorded by the On-Board Data Collection System. A fake vessel ID is used to confidentially agreements with fishers.

Vessel_ID	Proportion of dates where mismatch occurred
J	3.84
M	7.52
F	8.33
I	8.69
H	9.09
C	20.45
L	58.82
K	69.56
D	78.78
E	86.48
G	89.47

Weather information

The ERA5 dataset which is publicly available was used to extract weather variables (33). ERA5 is a climate reanalysis dataset developed through the Copernicus Climate Change Service and processed by ECMWF, available from the Copernicus website (cds.climate.copernicus.eu). The dataset currently released starts from 1979 and goes up to

2-3 months before the present. We used “surface or single level” hourly data for wind gust (m/s^{-1}), U and V wind components (m/s^{-1}) (can be transformed to speed and direction), and sea surface temperature ($m/s^{-}1$). The data had a resolution of ~31 km or 0.3°x0.3° and was pre-interpolated to a regular grid (see *Fig. 20*).

Because fishers go out mainly during day-light hours, when it is light the day length was calculated for Scotland and the largest range (*i.e.* earliest sunrise and latest sunset) was assigned per day. The ERA5 raster data was subsetted by daylight hours and for each day and port location the closest grid cell was extracted from the raster. Thereafter, the mean sea surface temperature, maximum gust, maximum wind speed, and 75% upper quantile wind direction was estimated for each day and port.

Wind speed and direction were calculated using the U and V wind components:

$$Wind\ speed = \sqrt{u^2 + v^2}$$

$$Wind\ direction = atan2(u, v) * \left(\frac{180}{\pi}\right) + 180$$

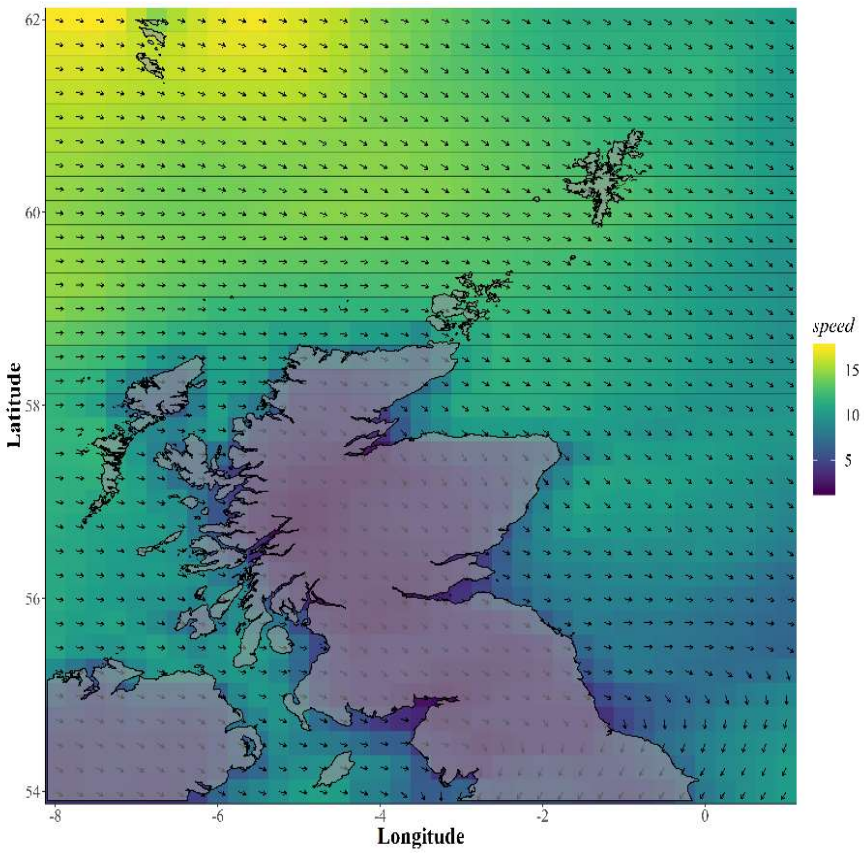

Fig. 20 Wind speed (m/s-1) and direction [2017-01-01 00:00:00] from the ERA5 dataset, providing an example of grid resolution.

The description of the weekly estimates for weather variables are shown in Table 6. Mean temperature was estimated for each fishing week. A variable called weekly gust was estimated as the number of days that the maximum gust exceeded the speed threshold value for Beaufort scale 4, 5, 6, and 7 (see Beaufort scale in Sup. Mat. 1). Wind speed was highly correlated with gust, and was therefore not included in the models.

Wind direction was identified as a variable that would prevent fishers from going fishing (see section 4.1), but this direction depended on where fishers were based in Scotland (Outer

Hebrides, west coast, north east coast, and the east coast). The weekly wind direction variable was calculated as the number of days in each fishing week for which the 75% quantile wind direction fell within the wind direction specified by fishers as preventing them from going fishing.

Table 6 Weekly estimates for weather variables.

Variable	Description
Weekly temperature	mean sea surface temperature during a fishing week
Weekly gust	number of days gust > 5.5m/s (Beaufort scale 4) during a fishing week
	number of days gust > 8.0m/s (Beaufort scale 5) during a fishing week
	number of days gust > 10.8m/s (Beaufort scale 6) during a fishing week
	number of days gust > 13.9m/s (Beaufort scale 7) during a fishing week
Weekly wind direction	Number of days where 75% quantile wind direction identified as preventing fishers from going fishing during a fishing week

Diesel fuel prices (diesel in pence per litre) in Scotland were available per month (34). Whilst some smaller vessels using outboard engines will use petrol rather than diesel, the price of these fuels generally increases or decreases by a similar amount.

5.5. Results and discussion

The final model included weekly wind direction, fuel price, expected landing, mean weekly temperature, an interaction between gust and vessel length, and an interaction between season and main target species (Table 7, Fig. 21). The deviance explained was 31.5%.The probability of going fishing increased with increasing temperatures up to 8 degrees (°C) and then decreased. An interaction between gust and vessel length was evident, the probability of going fishing decreased with gust but this was dependent on vessel size, the longer the vessel the more likely it could still go out fishing compared to smaller vessels during the same gust conditions (Fig. 21). Weekly wind direction affected the probability of going fishing. In general, the more days that were identified as having detrimental wind direction the less the probability of going fishing during that particular week. Increased fuel prices decreased the probabilities of going fishing, while increased expected landings increased the probability of going fishing. Season influenced the probability of going fishing but this depended on which species was mainly targeted: the probability of going fishing was larger for vessels targeting velvet crabs but they were more likely to go fishing in fall and spring. The probability of going fishing for lobsters, in contrast, was lower in general but higher in summer.

The variables retained in the model explained 31.5% of the deviance. The rest of the deviance explained might be due to skipper-specific characteristics that are harder to quantitatively

incorporate in the model but that were mentioned during the fisher's interviews, such as family or social commitments, or fishers having other jobs, which affected their decision to go fishing.

Table 7 Model results for the analysis of variation in the probability of going fishing during a particular week. Coefficient estimates are shown for the best fit model. Df= degrees of freedom, F=F statistic, edf=estimated degrees of freedom.

Parametric terms	**df**	**F**	**p-value**
Weekly wind direction	1	29.23	<0.001
Season	3	17.09	<0.001
Target species	3	16.12	<0.001
Season*target species	9	90.18	<0.001
Approximate significance of smooth terms			
	edf	**Chi.sq**	**p-value**
te (weekly gust, vessel length)	7.66	168.11	<0.001
s (fuel price)	1.98	170.38	<0.001
s (expected landing)	2.34	74.47	<0.001
S (weekly temperature)	3.87	57.25	<0.001

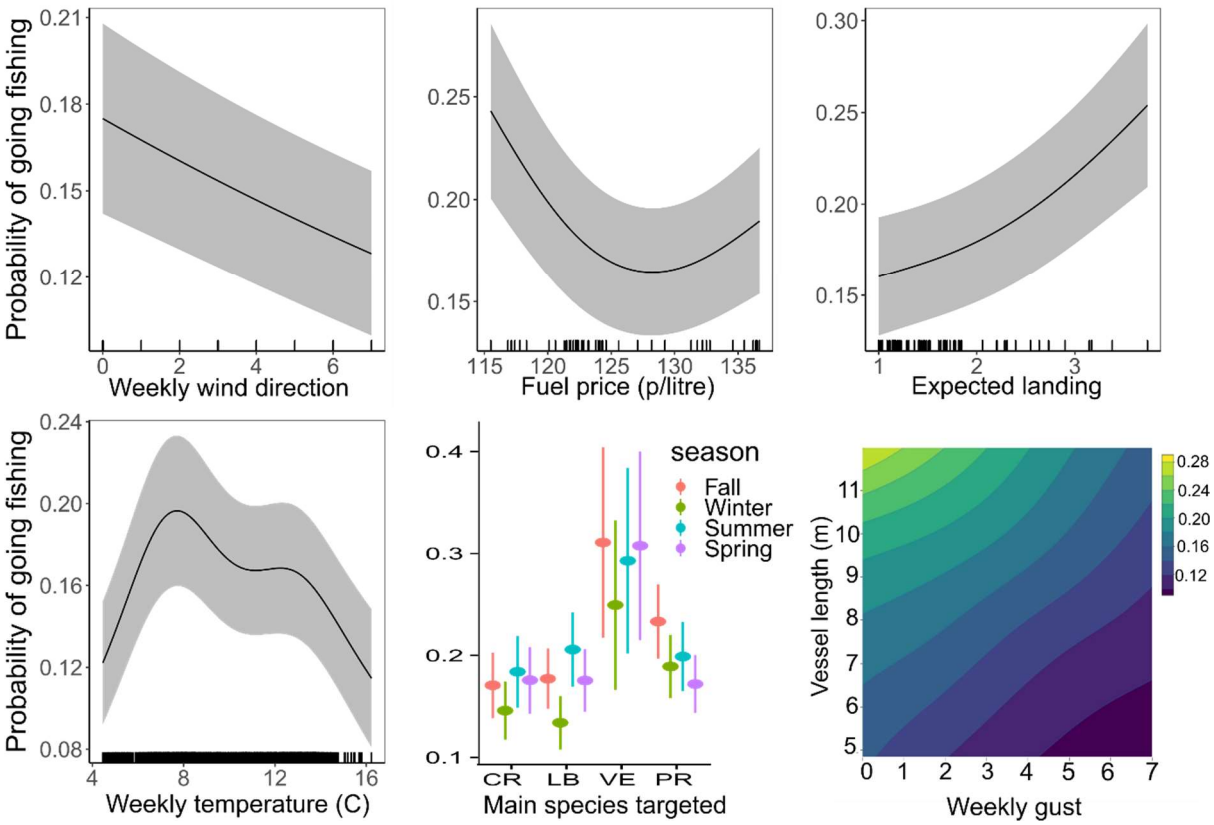

Fig. 21 Relationship between the predicted probability of going fishing (proportion of days per fishing week) and each explanatory variable in final model.

6. TOWARDS A DECISION-SUPPORT TOOL

6.1. Summary

This WP contributes towards the development of the "SIFIDS Application", which is a user-friendly web interface that could be used to assist different stakeholders in decision making

such as fishers, managers, RFIGs, and marine spatial planners. This tool incorporates modelling results to a) visualise boat track data on a map, highlighting the positional records that are most likely to be associated with hauling (b) visualise maps of the spatial distribution of boat positions and fishing effort; and (c) by linking FISH1 form landings data to effort estimates illustrate CPUE for individual boats. A final section provides a brief overview of the kind of management scenarios that could be informed by implementing the processes and systems developed by the SIFIDS project and describes potential analytical approaches that could be used.

6.2. Introduction and background

The Scottish Inshore Fisheries Integrated Data System (SIFIDS) project collectively produces several data resources across a range of fishing-related activities. These data include , highly spatially and temporally resolved vessel position, speed and direction , capture data, effort data, biological data of the catch, together with attitudinal information on perceptions and factors affecting fishing activities. Socio-economic data has also been collected as part of a Sustainable Livelihoods Assessment. Much of these data could be collected routinely in the future for at least part of the inshore fleet and used to inform a range of fisheries management and marine spatial planning decisions. However, once the principle and practice or collecting these data is established, it is likely that they could be used to aid decision support in a much wider spectrum of applications including day to day and strategic business management by fishers, buyers, processors and logistics companies. The ability to link some of these data to the entire value chain has profound implications and opportunities with respect to traceability and provenance. With some modifications, the equipment developed as part of SIFIDS could also be used to improve crew safety and inform actuarial decisions for insurance companies.

The purpose of this section is to provide a brief overview of the kinds of fisheries management and marine spatial planning decisions that might be supported by data collected by processes and systems developed by the SIFIDS project. This section includes the development of a pilot user-friendly interface for standard queries that could support managing decision at a fisher's, regional managers, or governmental level. Possible management scenarios that could be addressed in the future with SIFIDS data are then discussed.

6.3. Developing a user-friendly interface for standard queries

The WP8B team contributed to the development of the "SIFIDS Application", which is the user-friendly interface to the SIFIDS database (with a PostgreSQL backend). This interface could potentially be used by different stakeholders such as fishers, managers, RFIGs, marine spatial planners. Depending on the user, the level of access to data could be modified.

Under the Track data tab, we have four different outputs:

6.3.1. Track data and activity

This function plots the track data on a map. The time frame and vessel id required can be specified. The trip-based EM algorithm (described above) automatically assigns "hauling" (in red) to the positional records that are most likely to be hauling in each trip. The numbers of creels (95% lower and upper confidence interval) are shown per trip, as well as the distance in km travelled in each trip.

Individual fishers could access their own tracks per day and look at how much effort they spent in specific grounds (Fig. 22), while regional managers could access all trips conducted in a specific month for all vessels grouped (Fig. 23). It is important to consider not only where hauling activities are occurring but also the main transited areas for marine spatial planning. As evidenced in the models above, the probability of going fishing is affected by fuel prices, therefore developments affecting the transit routes of the SSF could potentially also alter their fishing practices.

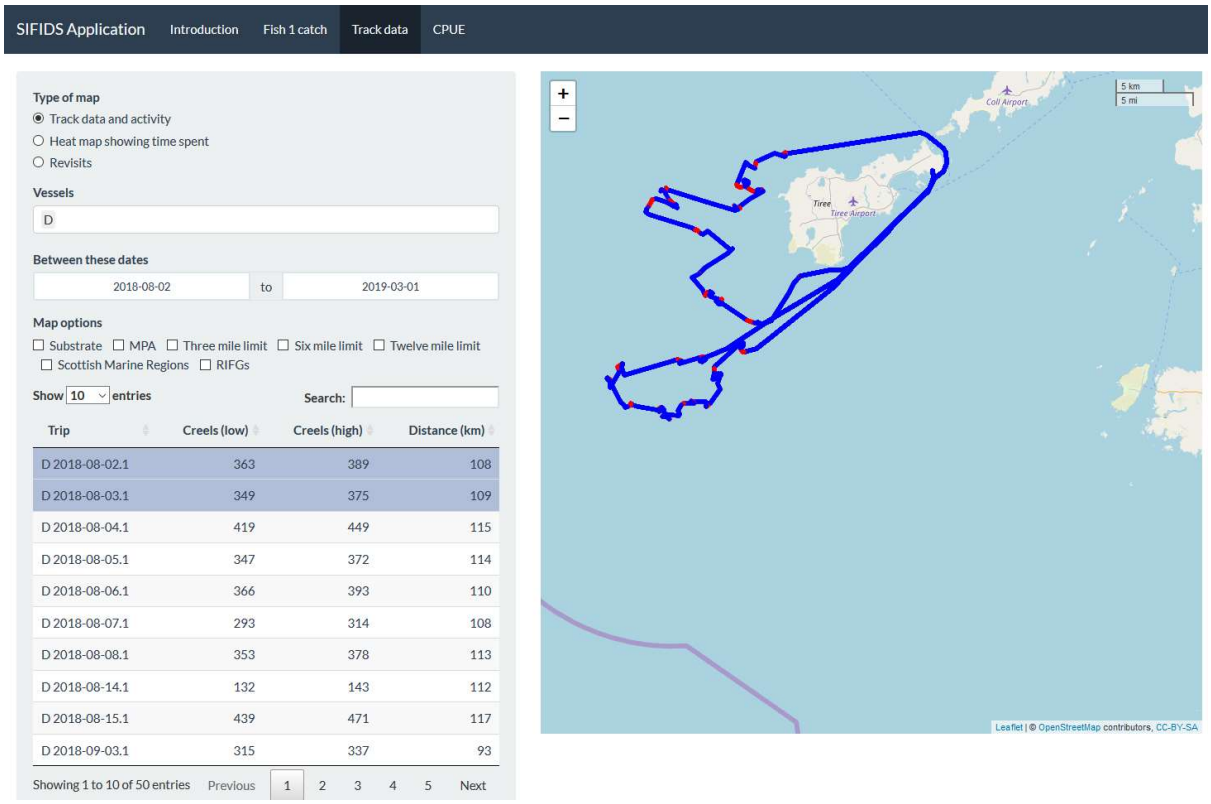

Fig. 22 Map showing track data (blue) and hauling activities (red points) identified from models developed in WP8B for 2 trips conducted by one vessel. Confidence intervals (95%) are shown for the estimated number of creels and the distance covered during each trip has been calculated.

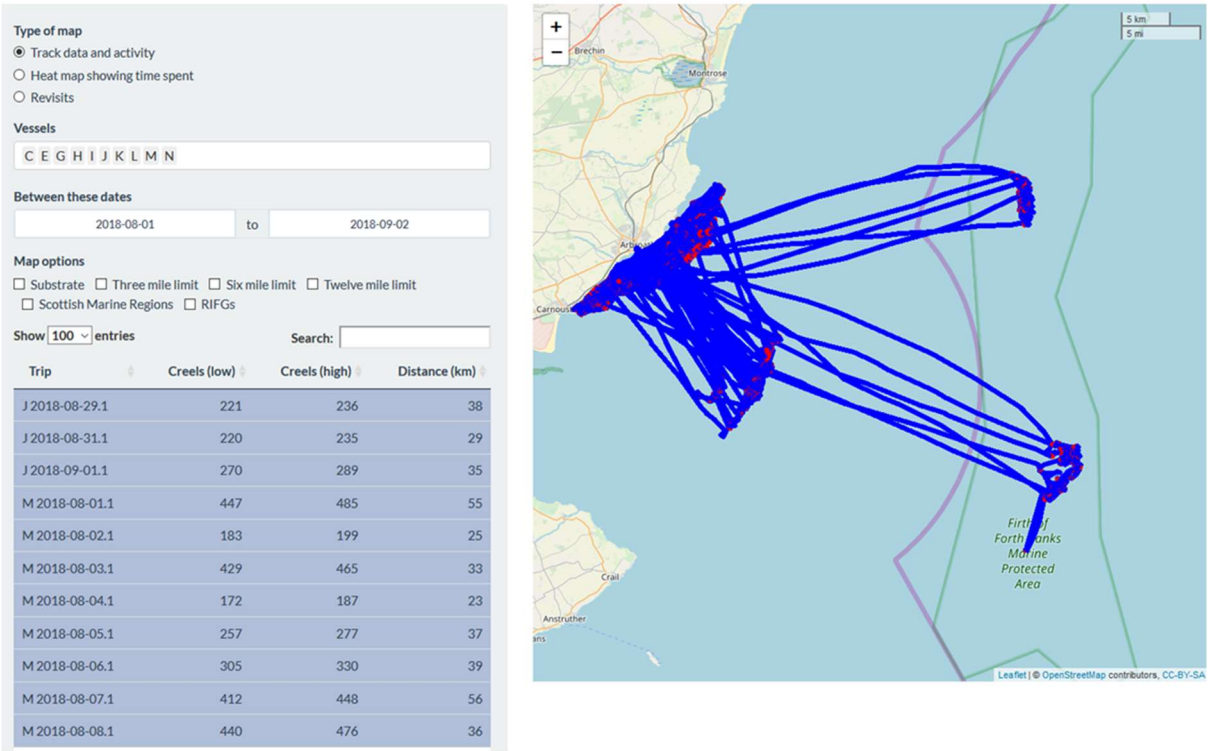

Fig. 23 Map showing track data (blue) and hauling activities (red) identified from models developed in WP8B for all trips conducted by 5 vessels from 01/08/2018 – 01/09/2018. Confidence intervals (95%) are shown for the estimated number of creels and the distance covered during each trip has been calculated.

6.3.2. Heat map showing time spent fishing:

A heat map showing time spent hauling for each vessel (or joining vessels if more than one specified) can be visualised in this feature. Individual fishers would access their own data (Fig. 24) while regional managers and marine spatial planners would benefit from aggregated data from different vessels operating in different regions and for specific time frames (Fig. 25).

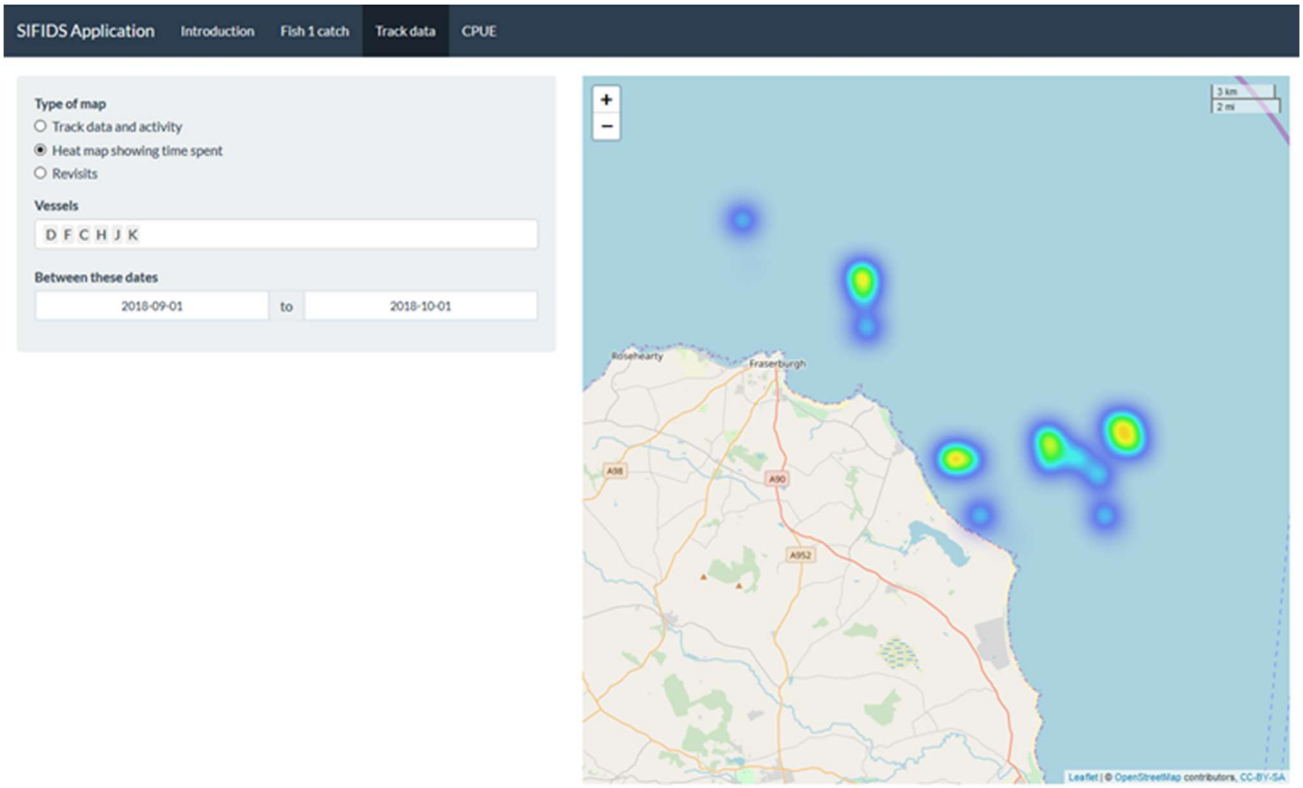

Fig. 24 Heat map showing kernel density estimates of the relative time spent fishing from 01/09/2018-01/10/2018 for 1 vessel operating in the East Coast of Scotland.

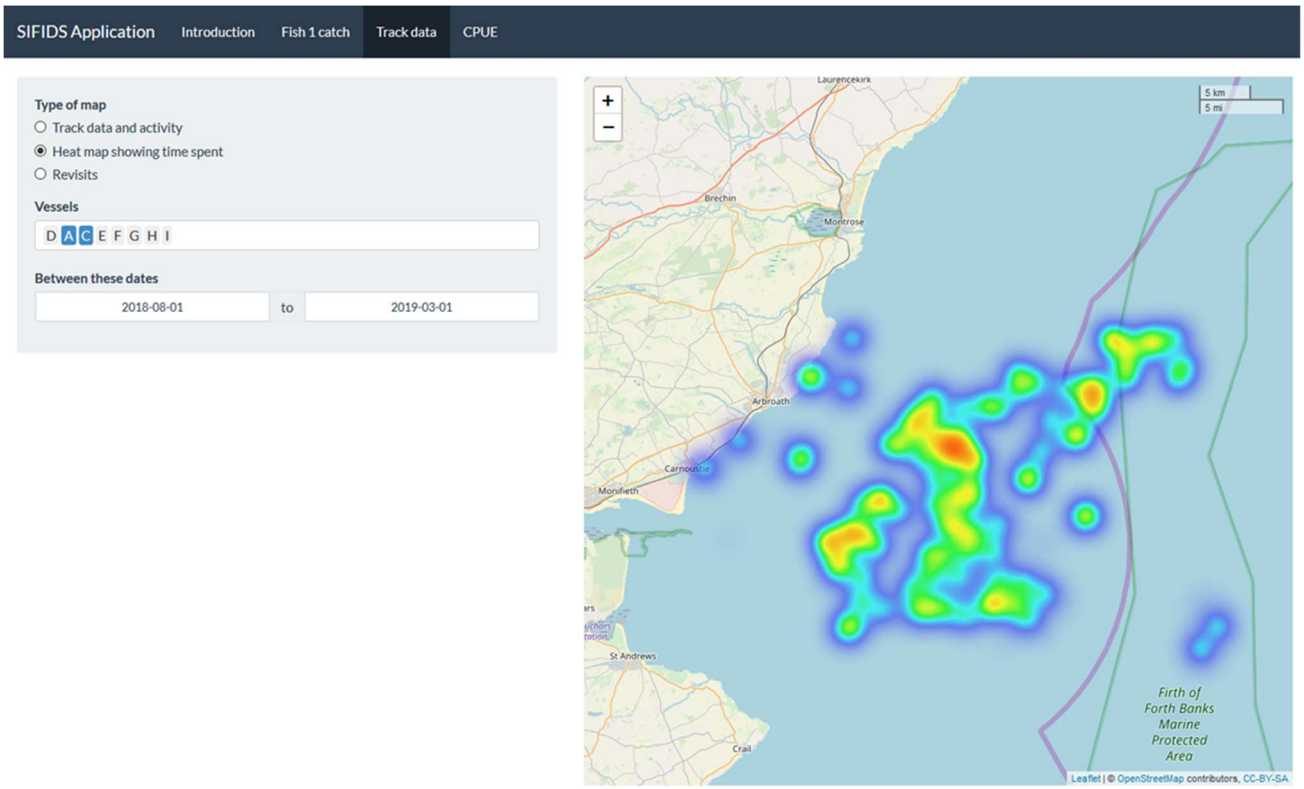

Fig. 25 Heat map showing the relative time spent fishing from 01/08/2018-01/03/2019 for 6 vessels operating in the East Coast of Scotland

6.3.3. Number of revisits:

Number of revisits to the same area is a better estimator of the importance of a particular fishing ground to each vessel, as time spent fishing might be affected by, for example, gear entanglements, which could increase the estimate of time fishing.

Fishing areas were defined as 200 metre square grid cells in order to understand the number of revisits to a potential group of creels (strings) (see Fig. 26 and Mendo et al., 2019)[4]. Each positional point identified as hauling is assigned to a square grid and when a consecutive fishing point moves to a different cell this change was recorded in the database. The number of revisits was defined as the sum of all these records for each grid cell.

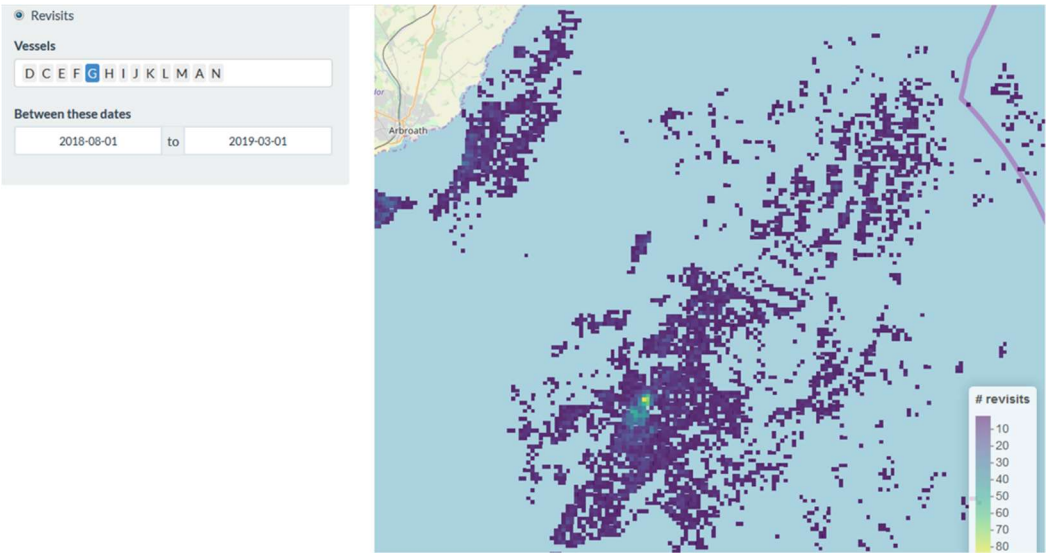

Fig. 26 Number of revisits estimated for 13 vessels operating from 01/08/2018-01/03/2019 in east Scotland.

6.3.4. Catch per Unit Effort:

CPUE can be used as an indirect measure of stock abundance and of the state of the fishery. By joining information on the landings (kg) per species per vessel (from FISH1 forms) and several descriptors of fishing effort (i.e. distance travelled, or number of creels, or trips per week) estimated in WP8B, trends of Catch per Unit Effort (CPUE) can be estimated (Fig. 27). The dates of trips reported in the FISH1 1 forms did not always match the date of the fishing activity as recorded by on-board electronic systems, therefore catch and effort data were aggregated on a weekly basis.

[4] Mendo, T., Smout, S., Russo, T., D'Andrea, L., and **James, M.** (2019) Effect of temporal and spatial resolution on identification of fishing activities in small-scale fisheries using pots and traps. – ICES Journal of Marine Science, doi:10.1093/icesjms/fsz073.

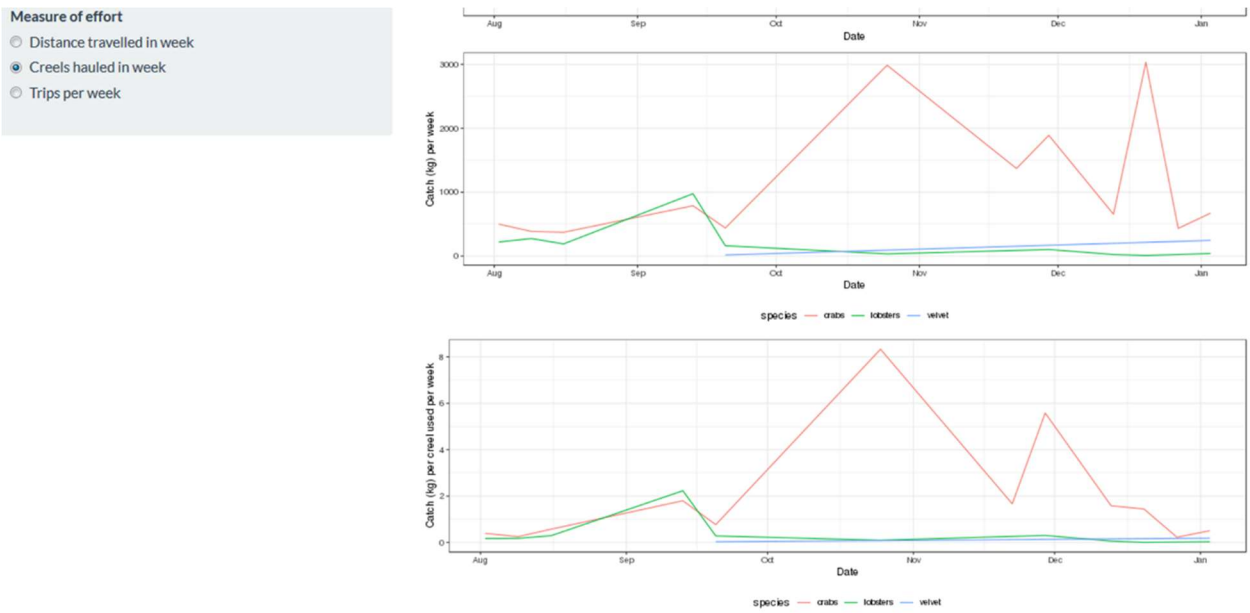

Fig. 27 Trends in weekly CPUE (catch per unit effort) from Aug 2018 to March 2019 per species for one fishing vessel. Effort here is presented as number of creels hauled in a week.

6.4. Possible management scenarios that could be informed by processes and systems developed by the SIFIDS project

6.4.1. Detecting and inferring fishing activity

The SIFIDS project has successfully demonstrated that it is possible to infer fishing (hauling) activities from positional data for inshore fishing vessels using pots and creels and targeting mainly lobsters, crabs, and prawns. The installation of a tracking device which provides positional data for the whole fleet, would allow for detection of potential fishing behaviour to identify adherence to compliance, estimate most important fishing grounds, most important transit areas for inshore vessels, estimate the potential conflict in area use between this fleet and large vessels. The information derived from this process would revolutionise marine spatial planning and represent inshore fisheries in an evidence based manner.

Extending from this work, as different gear types (i.e. trawlers, dredgers, diving) potentially have different “signatures” in terms of their vessel movement metrics like velocity, acceleration, and changes in bearing, algorithms could be developed to infer not only when fishing is occurring but also which gear is being used and potentially which species are being targeted on a particular trip.

6.4.2. Improving fishing efficiency

The data collected by SIFIDS offers the potential to improve the efficiency of fishing and sustainability of fishing activities. Higher spatially and temporally resolved fishing activity and catch data coupled to localized environmental data could provide a range of fisheries management and fishing business relevant information. Knowing the location of strings of pots together with weather and tide/current information could be used to provide fishers with optimal track and speed for gear recovery, reducing fuel use and time taken to recover gear.

Recording environmental data such as water temperature, wind, state of tide and sea could also be factored into estimates and indicators such as CPUE. By modelling these data it may be possible to detect hitherto unrecognized patterns in catch which could be used to manage and direct fishing effort more efficiently – even on a localised basis.

Many static gear fishers prosecute the same grounds repetitively. Providing them with predictions of catch per unit effort or, form a business perspective, cost versus return could help to improve efficiency and profitability. At present, there is no limit on the number of pots that may be deployed in a given area. Collection of the data outlined above, which could attribute catch at high spatial resolution could inform optimal pot numbers – not as an imposed form of management, but as a basic fisher's business decision based on predicted return on effort/investment.

More reliable, spatially and temporally resolved catch data (possibly coupled to traceability measures) also has implications for stock assessment and the setting of local and regionally meaningful catch limits.

6.4.3. Predicting and influencing fishing behaviour

Some of the most difficult policy decisions involve securing the long-term sustainability of the fishing industry. These decisions involve both forecasting and behavioural components. Two key challenges that could be addressed by SIFIDS data resources are how fishing activity might change with long-term changes in climate, and anticipating the effects of management interventions on fishing activities. Climate is predicted to change significantly over the next decades. As evidenced in the models above, the probability of going fishing is negatively affected by increasing wind gust and regionally by wind direction.

At present, the evidence for increased wind speed resulting from climate change is equivocal, and such changes may be masked by high inter-annual variability. However, the Met Office predict an increase in near surface wind speeds over the UK for the second half of the 21st century for the winter season when more significant impacts of wind are experienced. This is accompanied by an increase in frequency of winter storms over the UK (https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/research/ukcp/ukcp18-fact-sheet-wind.pdf).

One potential scenario would use data collected by SIFIDS to construct models linking various metrics of fishing activity (e.g. days at sea, time spent at sea, gear deployed, CPUE) to weather patterns. Constructed models can be used for "what if" analyses to assess the effects of changes in weather patterns. For example, under what climate scenarios will inshore fishing remain economically viable? Will it become riskier, and thus more costly to insure fishing vessels? Which geographical areas are most at risk?

A second kind of "what if" analysis involves anticipating potentially unexpected responses to management interventions. Management actions like spatial planning decisions, fishing spatial and temporal restrictions and quotas are all intended to influence fishing-related actions. Data collected by SIFIDS can be used to assess the impact of these decisions on fishing activity. Such analyses perform both monitoring and predictive functions. The ability to predict potential displacement of fishing activity is increasingly important. Coastal developments including marine renewable energy and aquaculture, together with gear conflict results in displacement of fishing effort and in some cases direct impacts on livelihoods. Predicting these changes has both policy, regulatory and economic implications. Recent

evidence suggests that marine organisms are likely to be more vulnerable to climate change than terrestrial animals (41, 42). Shifts in species distribution may therefore become apparent more swiftly than previously thought which will have impacts on fishing – particularly in coastal waters where temperatures for example will change most rapidly. Some of these changes could well occur within the time horizon of some loans and mortgages for example. Mitigating these medium to longer term financial risks with more highly resolved data will become increasingly important, as it will have profound implications for policy and strategic investment in the fishing sector and its supply chain.

6.4.4. Enabling citizen science

As part of the SIFIDS project, a mobile App (see WP5 Report) allowing fishers to log a species list of marine and bird species seen at sea has been developed. Data collected in this way, without structured sampling and by a diverse set of observers, is often referred to as "citizen science" data and can be used in a number of ways. First, it can be used to inform models of species distribution and diversity and to analyze changes in these over time (35, 36). Secondly, it can be used to identify unusual events, in the manner of an early warning system. As climate changes more rapidly, and ecosystems with it, it will be increasingly important to learn even from one, or a small number, of extreme observations (see 37). Interactions between fishing and Protected Endangered and Threatened species is also an area of increasing concern, but there is little reliable data to support informed policy, regulation or best practice in this area. Utilizing fishers as observers of marine species could significantly increase our understanding provided we can verify the quality and consistency of the data provided. Mobile Apps coupled to the array of ancillary sensor data that these devices can supply could offer some verification and offer feedback to fishers about the observation they make, thus enhancing the potential for further data recording.

6.4.5. Potential analytical approaches

The decision support process depends critically on being able to assess the consequences of different courses of action. Transforming raw data (e.g. fishing vessel tracks, images of caught species) to outcomes that are of interest to decision makers (e.g. vessel behaviour, abundance estimates) requires some form of predictive modelling. The past decade has seen an explosion in the application of machine learning to solve problems for which large volumes of data are collected. The promise of modern machine and deep learning algorithms is that they can learn important predictive features directly from the data; that is there is no longer a need for the modeller to hand-craft these features as part of an initial data pre-processing step. For example, a traditional approach might predict the behaviour of a fishing vessel by developing a number of metrics such as acceleration and persistence of turning angle; machine learning would learn these directly from the positional co-ordinates of the vessel. Machine learning methods now consistently outperform both humans and traditional modelling approaches across a wide range of prediction tasks, provided that they have access to large amounts of data.

Modern machine learning models were originally developed in the areas of computer vision, but recent years have seen these developments spread to ecology, where these approaches have been successfully used for a range of species and animal individual identification tasks (38). Machine learning has been applied in fisheries management to, for example,

automatically detect species from sonar screenshots and from video mounted above a chute, measure individuals for determination of size and sex, for habitat classification from multi-beam sonar, to classify the behaviour of fishing vessels from tracks, to automatically assess biomass of planktonic organisms from images, and to forecast recruitment patterns (see review in 39).

The application of automated identification systems is challenging and likely to be fishery dependent. Operational constraints, vessel size, water clarity and weather can all confound image acquisition and quality and impact on the utility of these systems in real world conditions. Nevertheless, the recent uptake of machine learning in fisheries management, and ecology more generally, coupled with the increasing accessibility of various forms of collecting image, audio, and video data, is almost certainly just the beginning of a major trend that has the potential to revolutionize the way in which data is incorporated into the management process.

Machine learning is perhaps most evident in object identification from still images or video. Successful image classification tasks often have several thousand images for each possible outcome (for example, each species). However, more recent advances using YOLO (You Only Look Once) object detection algorithms are opening up the potential for applications in the marine environment where the availability of training images may be limited.

Several of the scenarios described above involve a two-step process. The first step involves building a statistical model to infer a fishing-related outcome (e.g. CPUE, gear deployed, a decision to fish on a day) from explanatory variables (e.g. location, date, time, environmental and other covariates that may also vary spatio-temporally). Predicting gear use from movement patterns or classifying species from images are similar in structure to other standard classification problems for which methods like hidden Markov models, tree-based approaches (CART, random forests, boosting), and various kinds of neural networks have proved successful. Fitting spatio-temporal models can be challenging but methods such as generalized additive models, or those based on Integrated Nested Laplace Approximation (INLA) are appropriate. Most of the scenarios described above require specialized statistical or machine learning skills.

The second step involves extrapolating from these models to answer a particular management question. In some cases this may be fairly straightforward but care would be needed when (a) translating the variables of a management decision into variables amenable to statistical modelling (i.e. variables on which data is available, at least indirectly), and (b) extrapolating beyond the range of the data, which might be required in order to assess potential effects of e.g. climate change. These task require knowledge of techniques for decision analysis and support, particularly around problem formulation and structuring, and facilitating the process of managerial decision making.

7. CONCLUSIONS AND RECOMMENDATIONS:

7.1. Inferring fishing activities

- It is possible to infer fishing activities from positional data only for vessels using creels and traps. Through calculation of the optimal polling frequency and identification of best statistical methods we have proven that it is computationally feasible to estimate the spatial distribution of vessels for the entire SSF in Scotland.

- We recommend that this approach is further expanded to other inshore fishing fleets (i.e. dredging, trawling, scallop divers) in order to accurately map their main fishing grounds, possible impacts to the ecosystem, and possible conflict among fleets in terms of space use. An observer scheme such as deployed during the project offers validation of the model results and this approach is recommended for other fleets as well.
- Preliminary data from 15 observer trips on a limited number of scallop dive vessels and trawl vessels has been collected, but the analyses of these data will not be possible within the existing SIFIDS project.

7.2. Estimate fishing effort

- We have produced different indicators of fishing effort, such as distance travelled during a trip, number of creels deployed, and gear soak time.
- The relationship between catch and soak time is not straightforward and deserves further exploration. Field experiments determining the catch rate as a function of soak time for different types of creels could enhance our understanding for example of CPUE, and ecosystem impacts of fishing.
- The disparity between the actual date of catch and the reported landing on the FISH1 Form needs to be addressed if more temporally and spatially resolved fishing activity data is to be used to full effect. This is particularly important in terms of linking catch to effort for individual vessels.

7.3. Identify drivers affecting fisher behaviour

- The interviews conducted by on-board observers resulted in useful information and has allowed us to model the probability of a fisher going fishing in any givenweek.
- We would recommend that further fisher behaviour related studies are conducted as our research suggests that some factors affecting fishing behaviour need to be disaggregated to inform behavioural insights which could be used to promote changes in behaviour.
- Use of SIFIDS App to record FISH1 Form data – would greatly improve the data quality and not only automatically record date but also where fishing is taking place.
- With greater access to highly resolved spatio-temporal movement, catch, ancillary environmental data and behavioural insights, there is considerable potential to further develop Individual Based Models[5] to represent boat movements, decisions, and use of space under current circumstances and potential future scenarios.
- Incorporating social, economic and cultural drivers into models of fisher's behaviour represents an important shift in fisheries management as it acknowledges that need to manage people in relation to the fishery rather than the fishery (stock) in isolation.

7.4. Towards a decision support tool

- SIFIDS has created a basic decision support interface that is designed to provide tiered access to data aggregated at different levels of granularity based upon user needs

[5] **Individual-based models** (IBM; also known as "agent-based" models) is a way of modelling populations such that all individuals are considered explicitly. We no longer need to group individuals into populations - each individual can potentially have a different propensity for displaying a given behaviour (e.g. fishing/not fishing).

whilst respecting commercial sensitivity. There is considerable potential to develop this interface to provide a range of decision support information relevant to fisher's individual businesses, fisheries managers, compliance, and marine planners. There is potential to engage other stakeholders with interest in these data, subject to appropriate agreement with those that own the data.

- Ownership of data and access to these data is an area that will require further clarification and agreement – principally between the industry (individual fishers) and Government. Government will continue to have statutory data requirements that individual vessel owners will be obliged to supply. However, there is considerable value to the industry that could be realized through the appropriate processing and feeding back of data to the industry individually, collectively and to other relevant stakeholders to support decision making.
- In many respects, the decision support interface is a supply led opportunity. Only through exposure of stakeholders to this facility are we likely to gain an understanding of what users will require from it in the future both in terms of near real time reports and more strategic outputs.
- The SIFIDS approach to data collection, combining high resolution spatio-temporal fishing track data, catch data and verifiable reference fleet data has significant potential to inform decisions. The capacity to integrate abiotic (eg weather, season, vessel characteristics) and biotic factors (including human behavior) as covariates in statistical decision support models, opens up the potential to inform a wide range of decision support questions based on the best available evidence.

7.5. Data and infrastructure

- Inferring complex relationships generally requires large amounts of data, particularly in systems where there is a large amount of randomness present. Machine learning methods are also known to be data intensive. At present there are approximately 110 000 fishing trips per year for the entire inshore fleet. Positional data, collected at 60 second intervals, represents some 50 million observations collected per year. Depending on how much information is collected at each sampling occasion, specialized data storage, manipulation and analysis routines may be required.
- The recent ICES workshop on machine learning in marine science identified several structural issues impeding the application of machine learning: insufficient data quality and organization, insufficient labeling of datasets, and the lack of a centrally organized repository for data, models, and results. All of these issues offer important lessons for future use of SIFIDS data.
- If the SIFIDS approach is to be rolled out across the Scottish inshore fleet, it is important for data and infrastructure considerations to be addressed at the outset with a scaled trial.

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Supplementary Material 1.

Survey protocols and formats used during on-board observer trips

**********TRIP-SPECIFIC DETAILS**********

Researcher's initials: Date:

Trip ID: Vessel name: Vessel PLN:

Port out: Port in:

# crew members today including skipper	Experience fishing (years)

Fisher arrived as agreed? Yes/No Going to sea? Yes/No If no, why?

List main target species of this trip? Total number of creels in water?

Type of hauler? Deck tank?: Y/N Size of deck tank?

"Behaviours"*	Time
Working day start (time when fisher goes on board of vessel)	
Trip start (time when vessel starts engine)	
Trip end (time when vessel returns to port –docking time):	
Final engine off time (time when engine is turned off):	
Working day end (time when fisher leaves the vessel):	

*Any other vessel activities? Bait fishing?; manoeuvring to find pots; anchor or drift for periods for breaks or to lay up whilst awaiting tide to rise or turn? Please record the time.

Retained catch by marketable species:

Species name	Numbers	Weight (kg)/#bins?	Retained or landed?

Notes: Catch stored in keep pots (by species - GPS location)
Notes on any birds, mammals, turtles, and unusual fish observed during this fishing trip. Record the time.
Also, note if there is any destruction of pots by seals. Record the time.

**********FISHER SPECIFIC INFORMATION – IDENTIFYING DRIVERS**********

Trip ID: Vessel name: Vessel PLN:

1) **What would have stopped you going to sea today?**

Importance **(order from most important to least)**	Driver or reason	Likelihood of happening **(1-5)** ***1= almost impossible*** ***5= very likely***	Extra comments (can you identify thresholds?)

2) **How do you pick where to place creels? (list the 5 most important factors)**

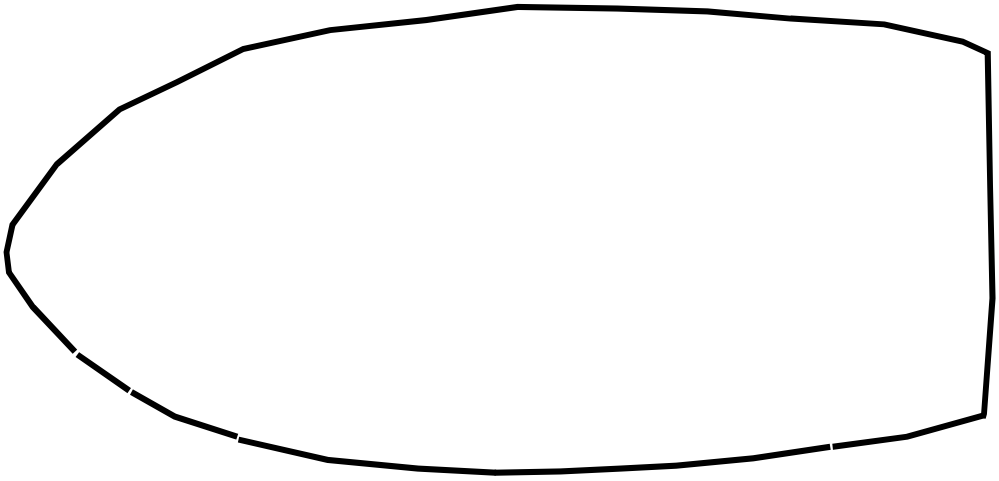
Importance **(order from most important to least)**	Driver or reason	Likelihood of happening **(1-5)** ***1= almost impossible*** ***5= very likely***	Extra comments (can you identify thresholds?)

Question 3: is there anything else that has influenced your choice of where to go today?

**********VESSEL CHARACTERISTICS**********

Trip ID: ☐ Vessel name: Vessel PLN:

Please provide a diagram depicting the main working components and arrangements of boat (hauling area, haul, working table, creel platform). Provide rough measurements of working table and operating areas



Photos of (remember to use ruler provided as scale). Tick box if photo was taken.

Hauling area ☐ Plan view ☐ Wide angle view ☐

Back of vessel to front ☐ Front of vessel to back ☐

Which other equipment (sonar, GPS, echo-sounder, etc) is present in vessel?

**********HAUL-SPECIFIC DETAILS**********

Trip ID

Haul ID	Soak time	Water depth	Wind direction	Sea state	Ground-rope (length/material/diameter)	Up-rope (length/material/diameter)	Length-rope (length/material/diameter)	Distance between creels	Weak links?	Creel identifier
001										
002										
003										
004										
005										
006										
007										
008										
009										
010										
011										
012										
013										
014										
015										
016										
017										
018										
019										
020										
021										
022										
023										
024										
025										

Creel used in this trip – take pictures of each type of creels

Creel identifier	Creel type	Size	Opening size	Soft-hard eye	Top/side entry	Escape vents	Mesh size	Bait used	Other characteristics?
A									
B									
C									
D									

**********CATCH DETAILS**********

Trip ID: Haul ID:

Creel Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
LOBSTERS																				
Retained lobsters (#)																				
Discarded lobsters(#):																				
BROWN CRABS																				
Retained crabs (#)																				
Discarded crabs (#)																				
VELVET CRABS																				
Retained crabs (#)																				
Discarded crabs (#)																				
OTHER SPECIES																				

Creel Number	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
LOBSTERS																				
Retained lobsters (#)																				
Discarded lobsters(#):																				
BROWN CRABS																				
Retained crabs (#)																				
Discarded crabs (#)																				
VELVET CRABS																				
Retained crabs (#)																				
Discarded crabs (#)																				
OTHER SPECIES																				

Supplementary Material 2.

Protocol for data collection – step by step

If you arrive 15 minutes earlier than convened, there are a number of things you can start recording, specifically in regards to vessel characteristics (see form).

Once the fisherman arrives, please give a brief explanation of the project, why it is important and how it can benefit industry.

Once on board, place GPS unit at the **midline** of the vessel (bow-stern orientation and should be secured to prevent from moving). Make sure there is enough satellite coverage in vessel. Start recording position **as soon as** you are on the vessel.

Ask the skipper if it is OK to take video recordings of the catch/discarding process. Explain you will need to access the camera twice, in case this interferes with fishing operations. Once he has agreed, place camera so that the "creel handling area" can be seen clearly from above if possible.
Record time when skipper starts the engine and follow survey forms. All fields are explained below in detail.

You might have time to talk to the skipper while he is steaming to fishing grounds – complete trip specific details form.

Use "Activity Logger Pro" app to record the time stamp of;

- Trip Start: Depart port
- Trip End: Docking time
- Trip Comment: Anything that may better describe vessels activity in GPS log (eg. Ground-rope parted during haul, dropping off keep pots, gear tangles etc.)
- Buoy Haul: Time buoy is hauled over gunwhale
- Buoy Shoot: Time buoy leaves vessel
- Pot Haul: Time creel is hauled over gunwhale
- Pot Shoot: Time creel leaves vessel
- Pot Cleared: Time catch has been cleared from pot.

Record catch and discard data using the voice recorder and headset provided. Do this on a creel basis.

Equipment checklist

Equipment	Check?
GPS unit	
Voice recorder	
Headset	
Extra AA batteries for GPS	
Extra AAA batteries for voice recorder	
Camera	
Camera straps/attachments/zip mount	
Camera boom	
Survey forms (with extra copies)	
Clipboard	
Pencils, pens	
Quick grip clamps (2)	
Cable ties	
Mobile phone (2)	
Allen key (2)	
Extra camera batteries (2)	
Extra phone battery	
Safety equipment (waterproof clothes and floatation device)	

TRIP SPECIFIC DETAILS

- Date: Format dd/mm/yyyy
- Home port: Ask the skipper about the vessel's home port.
- Trip ID: Observer's initials followed by the trip number (e.g. Guy Pasco's first trip : GP – 001)
- Vessel name: Record vessel's name
- Vessel PLN: Record vessel's plate number
- Port out/port in: Please record the name of the port you are leaving from and coming back to.
- Crew members: Write down number of crew members including skipper.
- Fishing experience. For each crew member record the total number of years fishing (either creeling or other fishing gears)
- Fisher arrived as agreed? Yes or No answer. (A date and time was set and when arriving at port the fisher was there as planned).
- Going to sea? If fisher arrived as agreed, are you going to sea yes or no.
- If no then please list the reasons behind the change of mind. – Also proceed to complete the Fisher specific information – identifying drivers form (for WP8B), Trip-specific details form (as much as you can) and vessel characteristics form (for WP2 and WP8).
- Main target species in this trip? What are the main species targeted in this trip (for which the creels/pots are being set in that day)
- Number of creels in the water? Ask the skipper about how many of his creels are currently in the water.
- Type of hauler?: electric/hydraulic –Power. E.g. 2 tonnes?
- Deck tank/vivier tank: Does the vessel have a built-in deck tank? Or a bin/tank that works like one?
- Size of deck tank? Please give rough dimension of deck tank
- Trip start: is the time to the nearest minute when the fisher starts engine.
- Trip end (time when vessel returns to port –docking time)
- Engine off time: Time to nearest minute when the engine is turned off.
- Work day end: Is the time to the nearest minute when fisher leaves the vessel
- Any other vessel activities? Record the time of other activities taking place, e.g. fuelling, bait fishing, anchor or drift for periods for breaks or to lay up whilst awaiting tide to rise or turn? Please record the time. We need to be able to look at the track and know if there was something different happening at the time- please write time start time end for each different behaviour recorded.
- Retained catch by marketable species: Specify for each one of these: lobster, crabs, velvet crabs, prawns (*Nephrops*) and any other marketable catch the numbers and/or weight of catch. If the number of boxes or bins are given then please provide a description of what each box/bin means in terms of quantity or weight
- Notes: Catch stored in keep pots? Was the catch stored in keep-pots or landed? Mark GPS location.
- Notes on any birds, mammals, turtles, and unusual fish observed during this fishing trip. Record the time.
- Also, note if there is any destruction of pots by seals. Record the time.

FISHER SPECIFIC INFORMATION – IDENTIFYING DRIVERS

- Trip ID:
- Vessel name: Record vessel's name
- Vessel PLN: Record vessel's PLN

Question 1: **What would have stopped you going to sea today? (list the 5 most important factors)** With this question we want to capture information about which sort of factors would have stopped them from going to sea. **If the trip is cancelled on the day please also take the opportunity to complete this question. Try to get information about the actual threshold values.** For example, a fisher may say they would not go fishing when wind speed is more than 30 knots, or they can try a different bay with South winds at 25 knots, etc.

Question 2**:** **How do you pick where to place creels? (list the 5 most important factors)**

This question aims to determine why the skipper chose going to a particular area – was it any of the listed drivers or was the area picked based on a rotational system to pick up creels?

Question 3: is there anything else that has influenced your choice of where to go today?

Any other factors that could have affected their decision on where to place creels? E.g. they work in cycles of 1 week for each string, etc.

<u>For each of the drivers mentioned, please specify:</u>

- Their importance, e.g. which drivers have a greater impact on your decision to go to sea today?
- The likelihood of it happening, e.g. does it occur very frequently? Use a scale from 1 – 5 where 1=almost impossible, 2=highly unlikely, 3 = same chance of happening as not happening, 4=likely to occur; 5 = very likely to occur)
- Thresholds, e.g. if swell greater than 2 metres will not go out fishing, or if fishing for 4 days that week won't go fishing an extra day; or I don't fish on a Friday?

An example of possible drivers is presented in Figure 1. Please avoid giving examples of possible drivers unless you are really struggling to get information from fishers!

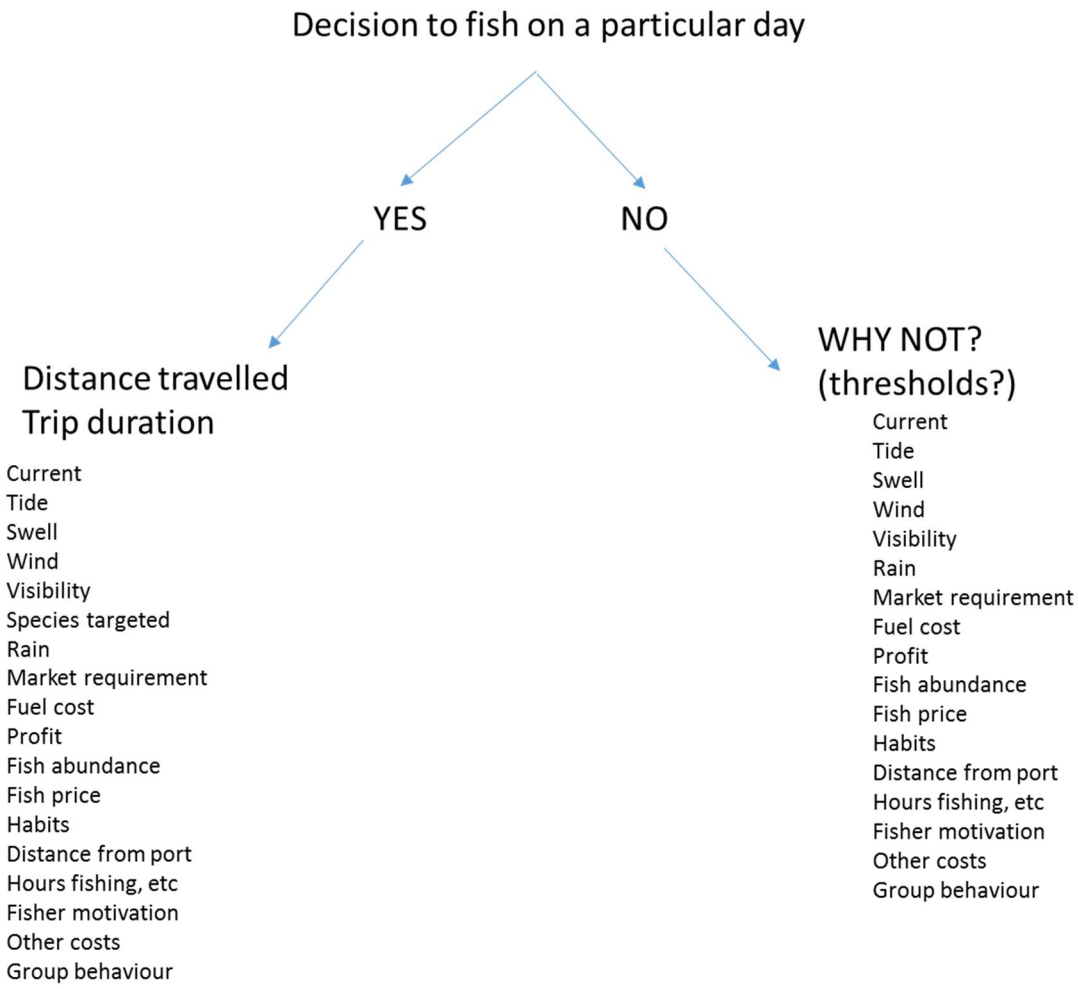


Fig. 1 List of possible drivers affecting their decision to fish in a particular day

Vessel characteristics for WP2

- Trip ID:

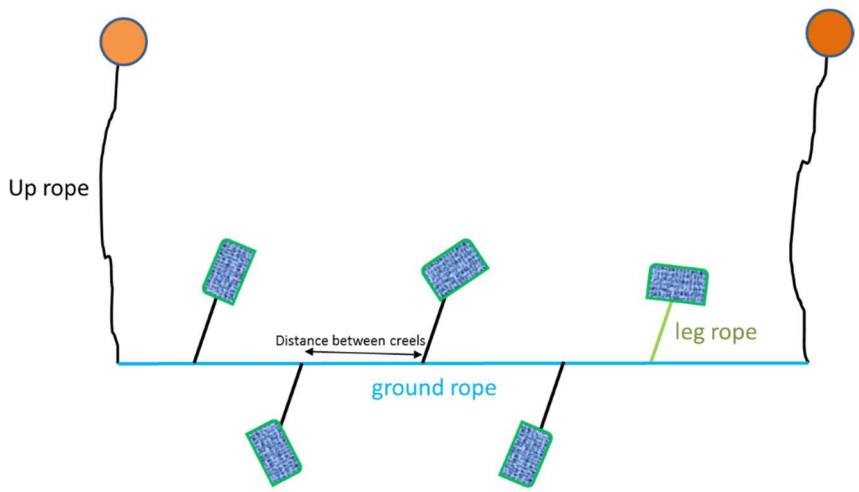
- Vessel name: Record vessel's name
- Vessel PLN: Record vessel's PLN
- Diagram of boat: Can you roughly sketch each component (hauling area, haul position, working table, creel platform, etc) and provide rough estimates of size?
- Location where discards occur
- Locations where retained catch is stored (by species/grade if applicable)
- Remember to take photos of different areas of the boat (hauling area, plan view, wide angle view, back of vessel to front, front of vessel to back
- Record which other equipment is present on boat (GPS, radio, echo-sounder).

HAUL-SPECIFIC DETAILS

- Trip ID: Observer's initials followed by the trip number (e.g. Guy Pasco's first trip : GP – 001)
- Haul ID: 1 – 25 included in form.
- Soak time: In hours or nearest possible time estimate of how many hours the fleet was submerged.
- Water depth: record depth either from sonar or ask for rough estimate if not available
- Wind direction: E.g. North, East, West, NorthWest, etc
- Sea state: Use the Beaufort scale to describe sea state (attached)
- Bottom type: Ask the skipper about the bottom substrate (e.g. rocky, sandy, muddy, shingle)

<u>Ropes used:</u>

- Ground rope is the rope from one anchor to the other (metres). Please record its length, material and diameter – rough estimates of length are fine.
- Up rope/tailing is the rope length from anchor (or first pot if anchors are not used) to buoy (metres) – rough estimate of length is fine
- Legs/strops is the average distance from creel to ground rope (metres). Rough estimate is fine.
- Distance between creels: Distance for creel to creel.
- Weak links: Are there any weak links that will break if a pressure over XX is applied to avoid entanglement with marine mammals or sharks?



<u>Creel types used in this fleet:</u>

- Creel identifier: A,B, C, D
- Type: E.g. parlour, no parlour, inkwell pot, *Nephrops* creel
- Size: Record creel size – inches?, volume?
- Opening size: rough estimates of opening sizes
- Soft/hard eye: Hard eye has the apex of the entrance funnel held open with a plastic ring attached to the netting, held in place by twine strops. The soft eye has an entrance entirely made from netting.

- Top /side entry: Where on the pots are the entries for lobsters – at the top or at the sides?
- Escape vents: are any escape vents/ grids present?
- Mesh size: Record mesh size (mm?) of netting around creel
- Bait used: Predominant bait used for each type of creel
- Other characteristics: Any other descriptors you make think are relevant to describe the gear.
- Include notes filed – add anything of note – especially sightings of marine mammals etc, seal damage, whales nearby. Destruction of pots by seals: Please make notes on any evidence of destruction of pots by seals – count numbers of creels. Take pictures

CATCH DETAILS

- Trip ID: Observer's initials followed by the trip number (e.g. Guy Pasco's first trip : GP – 001)
- Haul ID: Trip ID followed by the haul number (e.g. Guy Pasco's first trip, second haul : GP – 001-02)
- Creel ID: 1,2,3,4,5, etc…

Lobsters:

- Retained lobsters (#) Number of lobsters (European lobster, *Homarus gammarus*) per creel
- Discarded lobsters (#) Number of lobsters not retained

Brown crabs:

- Retained crabs (#) Number of crabs (edible crabs, *Cancer pagurus*) per creel
- Discarded crabs (#) Number of crabs not retained

Velvet crabs:

- Retained crabs (#) Number of crabs (velvet crabs, *Necora puber*) per creel
- Discarded crabs (#) Number of crabs not retained

OTHER SPECIES:

- Prawns (#): Numbers? Or weight?
- Whelk *(#)*: Number/estimates of whelks in each creel (only required for targeted whelk fishery).
- Wrasse: Number of wrasse in each creel – please specify with an R if they were retained or B if used for bait
- Cod: Number of cod in each creel – please specify with an R if they were retained
- Squid eggs: Please specify the number of egg batches in each creel.
- Complete the other fields with other species caught, e.g. coalfish, sea scorpion, shore crabs, ling, spider crab, etc??
- Any diseased animals: please specify if any of the lobsters or crabs showed signs of disease (e.g. shell necrosis/carapace lesions) – and if so please ask skipper if he has further information on this.

Beaufort wind force scale

The Beaufort scale, which is used in Met Office marine forecasts, is an empirical measure for describing wind intensity based on observed sea conditions.

Specifications and equivalent speeds

Beaufort wind scale	Mean Wind Speed		Limits of wind speed		Wind descriptive terms	Probable wave height	Probable maximum wave height	Seastate	Sea descriptive terms
	Knots	ms^{-1}	Knots	ms^{-1}		in metres	in metres		
0	0	0	<1	<1	Calm	-	-	0	Calm (glassy)
1	2	1	1-3	1-2	Light air	0.1	0.1	1	Calm (rippled)
2	5	3	4-6	2-3	Light breeze	0.2	0.3	2	Smooth (wavelets)
3	9	5	7-10	4-5	Gentle breeze	0.6	1.0	3	Slight
4	13	7	11-16	6-8	Moderate breeze	1.0	1.5	3-4	Slight - Moderate
5	19	10	17-21	9-11	Fresh breeze	2.0	2.5	4	Moderate
6	24	12	22-27	11-14	Strong breeze	3.0	4.0	5	Rough
7	30	15	28-33	14-17	Near gale	4.0	5.5	5-6	Rough-Very rough
8	37	19	34-40	17-21	Gale	5.5	7.5	6-7	Very rough - High
9	44	23	41-47	21-24	Strong gale	7.0	10.0	7	High
10	52	27	48-55	25-28	Storm	9.0	12.5	8	Very High
11	60	31	56-63	29-32	Violent storm	11.5	16.0	8	Very High
12	-		64+	33+	Hurricane	14+	-	9	Phenomenal

Supplementary Material 3

The five methods used to identify fishing activities are described below:

a.- “Overall” speed threshold: Speed data for all trips were combined, and in order to estimate the parameters of the mixture models, an Expectation Maximisation (EM) algorithm was fitted to the multimodal distribution using the mixtools package (14) in R. Three univariate underlying normal distributions were assumed to correspond to hauling, deploying gear and steaming (k=3). Even though in some vessels the distribution of vessel speeds overlapped between steaming and deployment, we couldn’t anticipate which vessels would show two (combined steaming and deployment) rather than three distributions (hauling, deployment, steaming) therefore, for the model to be applicable to the whole fleet, we chose to use three underlying behaviours for all vessels. Starting values for the mean and the standard deviations for each underlying distribution were estimated visually using a histogram showing the multimodal distribution of speed.

b.- Trip-based speed threshold: To estimate the parameters of the mixture models, an EM algorithm was fitted to the speed frequency distribution resulting from each trip. Means and standard deviations for the normal distributions were estimated by fitting the EM algorithm were used as starting values but the algorithm was applied independently to each fishing trip. While normal distributions might predict negative speed values during hauling, the upper threshold of the upper threshold for the overall and the trip-based threshold was calculated as the mean of the distribution plus 2 times the standard deviation. Hauling speed distributions were not close enough to zero to result in a negative mean.

c.- Trip-based EMbc classification. The EM behavioural clustering algorithm is based on Maximum likelihood estimation of a Gaussian mixture model (40). This classification uses speed and angle and clusters the observations into high/low speed and high/low angles using Maximum Likelihood Expectation producing 4 possible combinations: speeds can be high with large or small angles, or speeds can be low, either with low or high values for turning angle (14, 40).

d.- Trip-based HMM with speed only: The package moveHMM (16) was used to classify the movement of each vessel during a fishing trip into three underlying states (steaming, hauling and deploying). The HMM is fitted via numerical optimization of the likelihood, which requires setting initial values for the model parameters (e.g. mean and standard deviation for each distribution, 16). Due to the great variability in vessel overall length and engine power in the fleet, starting values for the mean and standard deviation of each underlying state distribution for step length were estimated using an EM algorithm. The numerical maximisation routine to identify the global maximum failed to converge for all trips, therefore different sets of initial values the standard deviation of the step length distribution were tested. We analysed different starting values and the only instance that yielded a fit for all vessels where when we empirically forced the standard deviation estimated by the EM algorithm for deployment to be smaller (specifically divided the standard deviation by 4 and subtracting this from the estimated standard

deviation), forced the standard deviation for steaming to be greater (we added two units to the standard deviation estimated for steaming in each trip). This was informed by the spread that we noticed from observer records for each distribution. A gamma distribution was used to model step lengths, which are strictly positive. We assessed model fit based on corresponding fit with true states.

e.- Trip-based HMM with speed and turning angle: Same as above except that turning angle was also included as a variable using the wrapped Cauchy distribution.

Supplementary Material 4

Identifying soak time without on-board observer's data – step by step procedure

Pre-processing steps

Without observer's data, we need first to identify where deployment events occurred in each trip to be able to match them to hauling events in subsequent trips. First, using the trip-based EM algorithm, we identified hauling events for each trip (Fig. S1a) and removed them. The resulting segments are a combination of deployment of gear and steaming activities (Fig. S1b). From observer's data (for 131 trips) we knew that 95% of deployment activities cover distances greater than 123 metres, therefore we eliminated segments shorter than this threshold. After a hauling event, skippers will usually turn into the direction where they want to deploy the gear, therefore a turning event will be visible in the track. Therefore, if the standard deviation of the turning angle was below 5 degrees (resembling a straight line), then these segments were also removed (Fig. S1c).

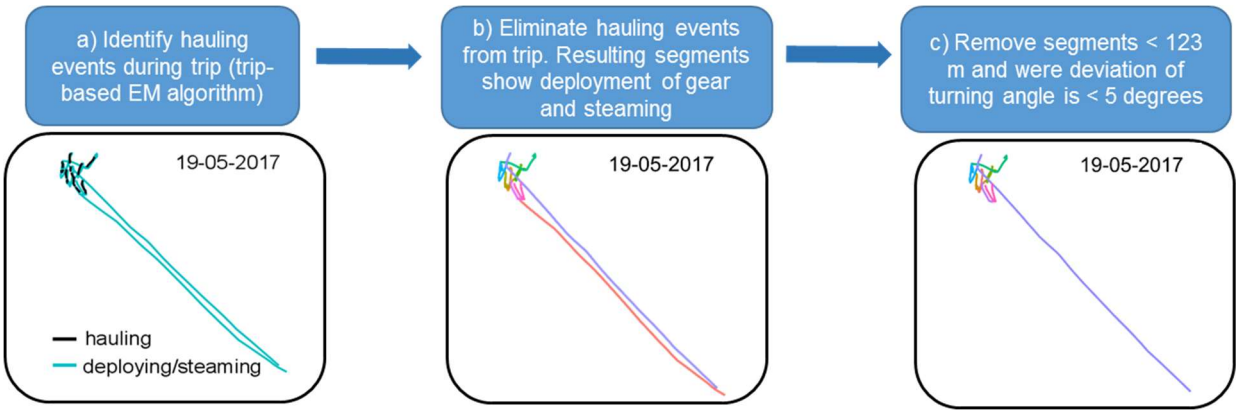


Fig. S1 Pre-processing of trip information to identify deployment events during a fishing trip.

Once we have established potential deployment segments, we look at the next date for which spatial information was available for that vessel (using positional data from AIS units) and overlaid the hauling events (identified by the trip-based EM algorithm) during this fishing trip to the segments identified above. From on-board observer's data, we know that 100% of the hauling events were shorter than 2468 metres and 95% were longer than 118 metres. We used these two values as thresholds to eliminate potential erroneous hauling events identified by the model. We then added a buffer area of 157 metres around each hauling event before overlaying them to the deployment segments (Fig. S2a). This buffer distance was used because the difference between the length of the up-rope used for the strings of creels and the water depth is about 157 metres or less in 99% of the hauls. We considered that a buffer radius to each side of the hauling event was necessary to include this potential distance between the deployment of a string of creels and the start of the hauling event. Only hauls that overlap deployment segments were selected (Fig. S2b).

Each deployment segment inside the buffer area had to be longer than the buffer diameter (2x 157 m = 314 metres), as observer data shows that hauling events and deployment events occur in a mostly parallel manner. We chose 35 degrees as the maximum angle for the intersection between the

deployment segment and each hauling event as it maximised the number of correctly identified hauling events (compared to observer's data), which resulted in a distance greater than 547 meters as a minimum threshold for the length of each deployment segment inside each buffer area. If the intersect between the hauling buffer and the deployment segment was shorter than 547 metres, then the hauling events were not considered and the next date for which spatial information was available was used to again overlay hauling events to segments combining deployment and steaming activities (Fig. S2c). Fishers repeatedly return to same fishing grounds in subsequent trips but might not haul a string of creels due to time constraints, or tide making it difficult to spot the buoys. If the intersect between the hauling buffer and the segment was longer than 547 metres (Fig. S2d), then the hauling event was considered to correspond with the deployment segment, the date and time of the hauling event was stored, and the deployment segment was removed from consecutive analyses. Consecutive dates were tried in this manner (Fig. S2d) until no remaining deployment/steaming segments were left (Fig. S2e). The identified hauling events were then compared to the deployment events recorded by the observers to assess the performance of the method.

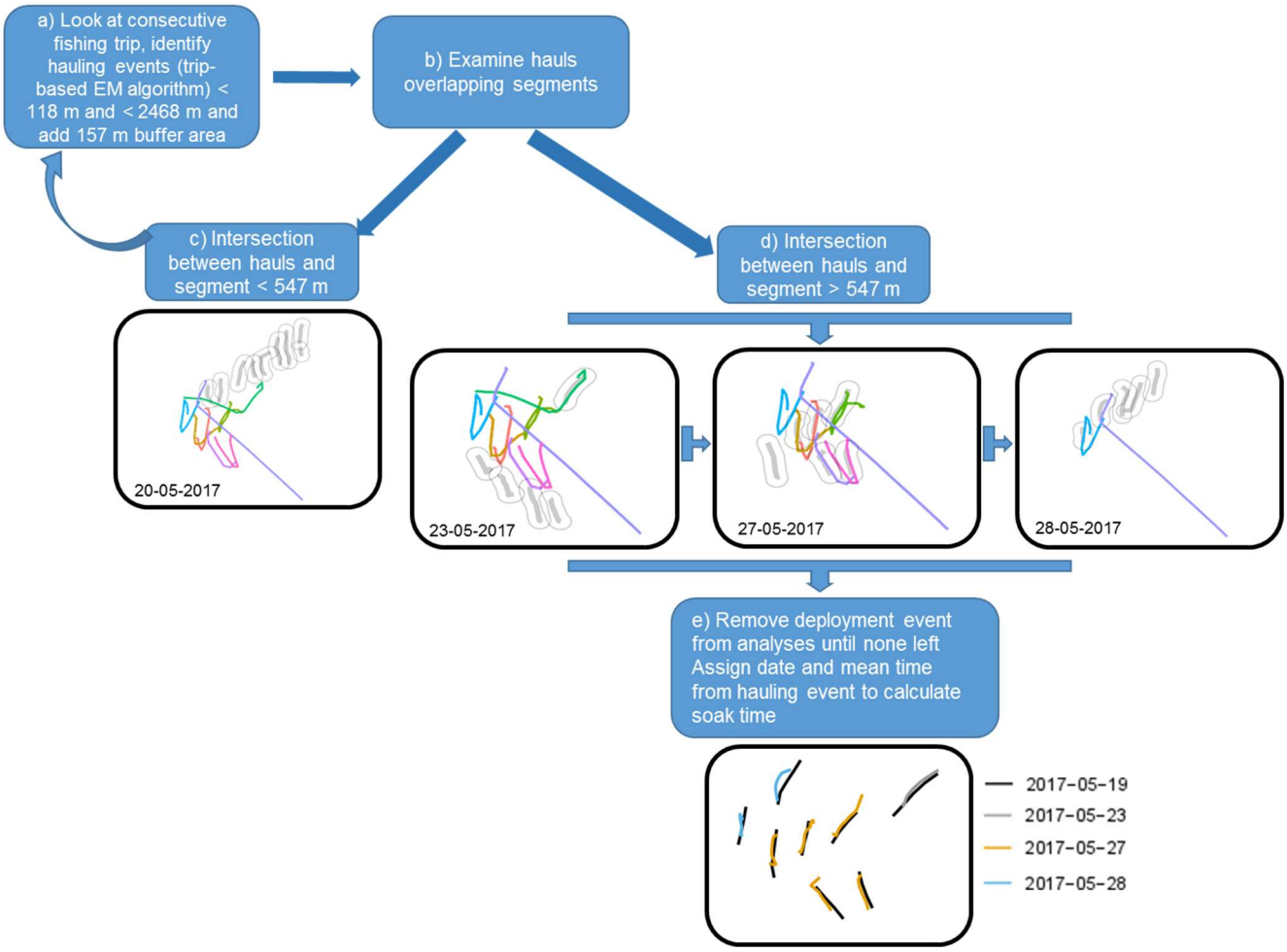


Fig. S2. Sequence of rules and procedures used to estimate soak time without on-board observer's data. Deployment segments are shown in different colours, while overlapping hauling events with a buffer are showed in grey, except for Figure 2e, where hauling event dates are shown in colours and overlapped to on-board observer's deployment events to assess method performance.

Supplementary Material 5

Fig. S1. Comparison between hauling events corresponding to each deployment event with observers data (left side) against hauling events identified using set of procedures (right side)

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ISBN

MASTS Company Number: SC485726; Charity Number: SC045259

EMFF: SCO1434

This project was supported by a grant from the European Maritime and Fisheries Fund