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Enhancing fishery-dependent information in data-poor fisheries; integrating gear-in–gear-out sensors and mobile reporting technology in a mixed Irish Sea static-gear fishery

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Inshore static gear fisheries such as those targeting predominately shellfish play an import socio-economic role across the northeast Atlantic. Despite this, assessment techniques are heavily reliant on fishery dependent data which is typically aggregated over large spatial scales and lacking in key environmental and biotic data. In this study, we trialled the implementation of an enhanced electronic reporting system (EERS) and gear-in–gear-out (GIGO) technology in a data-limited, mixed species, static gear fishery for brown crab *Cancer pagurus* and European lobster *Homarus gammarus*. EERS/GIGO systems were deployed on two commercial vessels for 12 months and collected data from 812 strings, equating to 29826 pots, with precise geo-located landings per unit effort (LPUE) and environmental data. Cluster analysis identified spatially distinct patterns in fishing activity, corresponding to different target species. Generalized additive modelling was used to investigate the effect of environmental variables, inter-specific interactions and geo-location on LPUE in both species. Sea bottom temperatures had a significant positive effect on LPUE in both *C. pagurus* and *H. gammarus*. In addition, GAM analysis showed the importance of inter-specific interactions; increases in capture of competing non-target commercial species (*H. gammarus*/*C. pagurus*) resulted in the decreases in target species LPUE (*C. pagurus*/*H. gammarus*).The significant effect of environmental variables and inter-specific interactions demonstrate the value of understanding these interactions in order to produce robust standardized LPUE metrics. The EERS/GIGO system successfully demonstrated its application, and value in collecting geospatially defined fishery dependent data in historically data limited fisheries. Co-development of such an approach between fisheries administrations and industry has the potential to significantly enhance data collection and management in many data poor fisheries.

Keywords: brown crab, data-storage-tags, electronic reporting, e-logbook, European lobster, gear-in–gear-out technology, mobile technology.

Introduction

Effective management of wild capture fisheries combines consideration of both ecological and economic viability. In order to achieve this, fisheries managers rely on a suite of data to inform and support decision-making. This approach ideally incorporates bio economic models and scientific stock-assessments which, through use of biological reference points can inform harvest control rules for a sustainable fishery (Jensen and Marshall, 1982; Caddy, 2004; Shertzer *et al.*, 2008) In the northeast Atlantic ~78% of stock fishes are currently classed as being fished within biological sustainable limits (Stankus, 2021). This number, however, can provide an inaccurate assessment of small scale inshore fisheries such as those targeting crab and lobster. Such fisheries are historically overexploited (Mesquita *et al.*, 2017; CEFAS, 2020a), classed as data-poor and are assessed using data limited methods or receive no formal level of assessment (Lart, 2019).

Whilst stock assessments are a critical component of the evidence required to achieve the goal of sustainable fisheries (Gebremedhin *et al.*, 2021), the development of "indicators" that track trends in fisheries-dependent data are becoming more accepted in the provision of management advice, particularly for data-poor fisheries (Trenkel *et al.*, 2007; Ye *et al.*, 2011; Tidd, 2013; Trenkel *et al.*, 2013; Miethe *et al.*, 2016). Miethe *et al.* (2016) highlighted a number of possible fisheries-dependent indices that may be considered as proxies for traditional biological reference points (BRP), including the use of landings-per-unit-effort (LPUE) as an indicator to inform BRP development. For example, two Marine Stewardship Council certified fisheries, for *Cancer pagurus* in Shetland (Cappell and Addison, 2021) and *Homarus gammarus* in Normandy and Jersey (Ernst and Addison, 2020) use such indicators as the primary mechanism in assessment and management. However, there are a number of methodological concerns associated with the use of fisheries-dependent LPUE as a BRP in static gear fisheries (e.g. green crab *Carcinus maenas*—Murray and Seed 2010; king scallop *Pecten maximus*—Murray et al. (2013); brown crab *C. pagurus*; and European lobster *H. gammarus*—Skerritt *et al.* 2020), as well as underlying issues of data resolution, precision, and accuracy of reporting systems. These concerns relate to the effect of both environmental and biotic factors affecting overall catchability and interaction of the target species with the fishery/gear, such as inter- and intra-specific interactions (Skerritt *et al.*, 2020), bait attraction (McQuinn *et al.*, 1988), temperature (Lizárraga-Cubedo *et al.*, 2015; Mullowney, 2016; Bakke *et al.*, 2019), soak time (Bennett, 1974), and fisher targeting behaviours and associated local ecological knowledge (Santos *et al.*, 2019). Factors that

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create variability in commercial LPUE are often overlooked because of over-simplistic approaches and static-environment assumptions, which are frequently built into traditional assessment and management tools (Szuwalski and Hollowed, 2016). Complexity within fisheries-dependent data is often ignored in data-poor fisheries (Mangi *et al.*, 2018; Bradley *et al.*, 2019). Here, we look to address this issue by piloting an enhanced electronic reporting system (EERS) in a data-poor static gear (baited pot) fishery targeting *C. pagurus* and *H. gammarus* in the northern Irish Sea (ICES Area VIIa).

Accurate geolocations would help improve the integration of fisheries-dependent LPUE into assessments of data-poor fisheries (Skerrit *et al.*, 2020). In the EU, vessel monitoring systems (VMS) have been useful for monitoring, control, and surveillance purposes as well as producing evidence for some ecological indicators (EC, 2008). However, the usefulness of VMS in enabling spatially defined LPUE is limited by the low-frequency of reports that are unable to take account of fine-scale spatial data clusters (Gerritsen *et al.*, 2012; Murray *et al.*, 2013) and the exclusion of smaller vessels. In the EU, for example vessels <12 m, which make up 70% of the registered fishing fleet, are not required to use VMS (Needle *et al.*, 2015; Russo *et al.*, 2016; STECF, 2016). While similar technology is being adopted in smaller inshore fleets [e.g. inshore vessel monitoring systems (iVMS)], which are typically more likely to be targeting data-poor stocks (Rossiter, 2015; Coleman and Rodrigues, 2017), the value of iVMS/VMS for assessment purposes may be limited considering that catch-data is typically reported for entire fishing trips, and individual data points cannot therefore be verified against specific catch and effort data.

In the UK, pot fisheries have historically had a lower profile than well-documented fin-fisheries, although many have undergone significant expansions in effort and landings. The main *C. pagurus* and *H. gammarus* fisheries in the UK are considered to be either fully exploited or over-exploited (Mesquita *et al.*, 2017; CEFAS, 2020a, b), although due to the open access nature of these fisheries and lack of total allowable catch limits, regulatory responses to overfishing currently hinges primarily on access/effort limitations and implementation of technical measures (Skerrit *et al.*, 2020). Furthermore, mandatory reporting systems for the majority of inshore vessels <12 m targeting these fisheries have been at low spatial resolution and relied on paper submissions which are prone to (unintentional) inaccuracies. Even, where efforts have been made to improve reporting through app based logbooks (e.g Catch App—MMO 2019; FISH1—Marine Scotland, 2018), such records fail to capture important fishing activity variables (e.g. pot-type/pot-volume, bait-species, soak-time, pot-density), observations of the physical environment (e.g. sea-bottom-temperature; SBT, tidal conditions, depth), ecological parameters (e.g. by-catch, discarding, population structure), or precise fishing activity locations among potentially highly heterogeneous fishing grounds. The inclusion of such variables are known to play a significant role on target species behaviour and subsequent interaction with fishing gear (Lizárraga-Cubedo *et al.*, 2015) with consequent impacts on catchability and perceived abundance derived from fishery dependant data. Such variables are currently not routinely included in standardization of fishery-dependant data in part due to their lack of availability (Ernst and Addison, 2020). Development and widespread use of EERs that integrate gear-in–gear-out (GIGO) technology, passive environmental sensors, and mobile technology may provide such high-resolution data to be collected.

Here, we describe an integrated EERS for pot fisheries that allows submission of effort and catch reports at high spatial-temporal resolution in a historically data poor fishery. The system developed is enhanced through GIGO sensor technology that passively records potentially important environmental and abiotic variables. We show how such a system can be used to assess drivers of variability in LPUE, thus, providing insight into the added value of utilizing such variables in the standardization of fisheries-dependent data that could be applied at either a fleet level or via a reference fleet programme.

Material and methods

Fishery

The Isle of Man (IoM) is situated in the northern Irish Sea (ICES statistical Area VIIa), with the territorial sea (TS) encompassing six ICES statistical rectangles (Figure 1). *C. pagurus* and *H. gammarus* are both targeted using a net-enclosed metal-bar based trap, commonly referred to as a pot or creel. Active targeting behaviour by fishers occurs between target species, i.e. Bait type and/or spatial distribution of fishing activity mirroring species-specific preferential habitat (Skerritt *et al.*, 2020). The targeted IoM crab fishery typically occurs outside of the 1 nm limit, on sandy to mud substrate at depths ≥25 m. Conversely, the targeted lobster fishery occurs primarily within the 1nm limit, typically at depths ≈20 m on rocky/sublittoral reef habitats (Emmerson, person obv). The IoM inshore fishery is populated by mainly <10 m vessels, with several vessels 10–12 m and >12 m; each component complies with different statutory data collection systems in accordance with IoM, UK and EU legislation and licence conditions (Table 1). The data provides the Department for Environment, Food and Agriculture (DEFA; fisheries authority for the IoM) with the ability to view daily landings and effort by ICES Rectangle one month retrospectively. Since, the IoM TS is composed of several partial ICES Rectangles (see Figure 1), resolving landings inside and outside the management jurisdiction is problematic. The fishery is not currently subject to harvest control rules and there are no agreed biological reference points. The IoM static gear fisheries is managed through species-specific authorization and the use of effort (input) limits. Vessels with crab and lobster authorization are entitled to fish no more than 500 pots, of which no more than 300 can be within the 3 NM zone. Technical measures include a minimum conservation reference size (MCRS) of 140 mm carapace width (CW) for crab and 90 mm carapace length (CL) for lobster and mandatory escape gaps fitted to all pots fished within the 3 NM zone.

GIGO and EERS technology

From September 2018 to September 2019, two IoM licensed static-gear vessels (one under 10 m total length and one 10–12 m total length) were invited to participate in a trial to improve data collection and reporting in IoM static-gear fisheries. The technology used in the trial, developed by Zebra-Tech© (www.zebra-tech.co.nz), offered an integrated enhanced electronic reporting system that is centred on a Zebra-Tech© Decklogger device. This technology has been utilized and trialled primarily in New Zealand fisheries (Neubauer, 2017; Middleton *et al.*, 2021). This system collects and stores data through

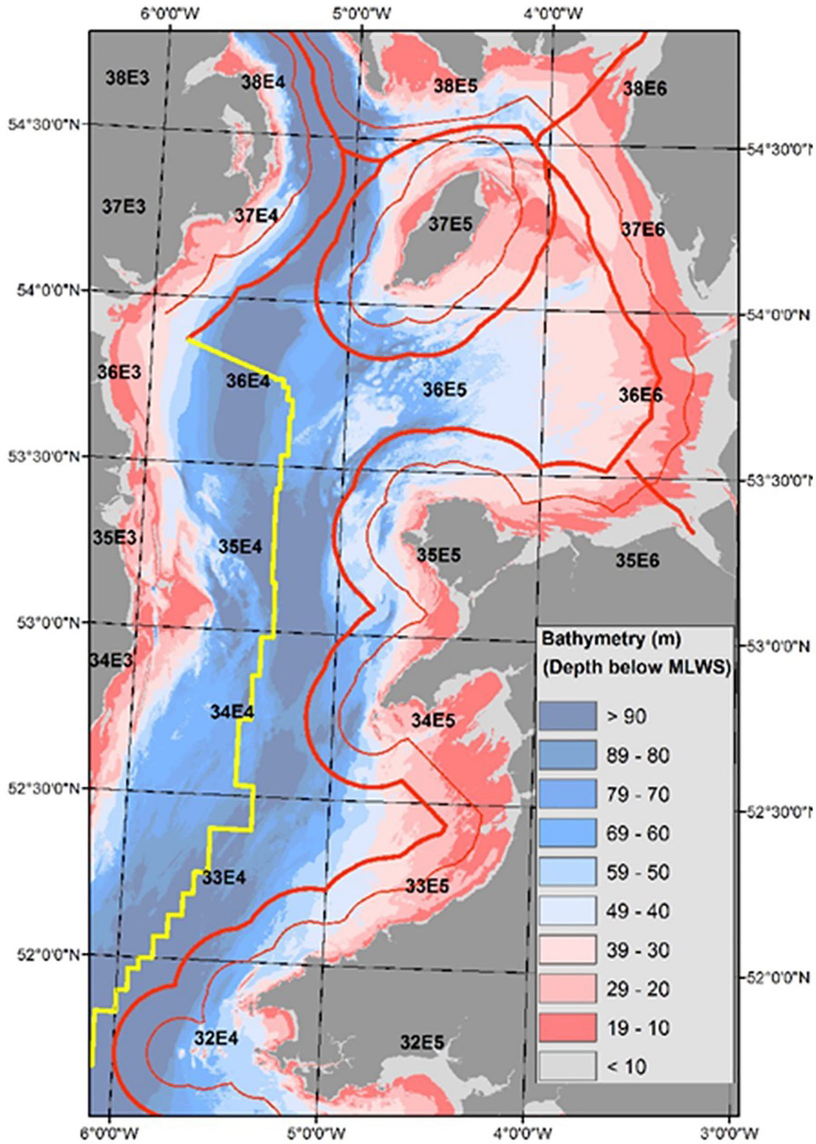

Figure 1. The Irish Sea showing British Fishing Administration territorial limits (12 NM—thick red line and 6 NM—thin red line) against a bathymetry layer. Yellow line represents the median-line between the British and Irish EEZ. Bold text shows ICES Statistical Rectangles.

Table 1. Current data reporting requirements imposed on the IoM static-gear sector by length category.

Sector	Spatial data (iVMS/VMS)	Electronic reporting	Effort data	Legislation
<10 m	NO (ICES rectangle)	NO (Monthly paper logbook)	YES	IOM/UK
10–12 m	NO (ICES rectangle)	NO (Daily paper logbook)	YES	UK/EU
>12 m	YES (2 h poll)	YES (Daily e-logbook)	NO	UK/EU

manual input and by automatically synchronizing with wireless GIGO environmental sensors called Zebra-Tech© wet-tags (Figure 2).

Upon surfacing, wet tag data including geopositional information is wirelessly transferred to the Decklogger and is linked with manually entered data on total number of pots in that string (string specific effort) along with quantities of retained catch by species (landings). For the purposes of this trial, the firmware was designed to capture the same information as demanded by existing mandatory logbooks (landings and effort only—albeit at a string by string resolution as opposed to an amalgamated daily total) in addition to the automatic GIGO-captured wet tag data. Recordings were taken every two minutes with the accuracy of depth data stated as +/-1% of the full depth range or better, and temperature accuracy +/-0.1°C. Wet tags were rated to a depth of 150 m.

At the beginning of each fishing trip, the fisher is prompted to enter information on sea-state and wind-direction, after which the Decklogger searches for a valid GPS signal. At the end of the fishing trip, which typically lasts 7–9 h in the IoM

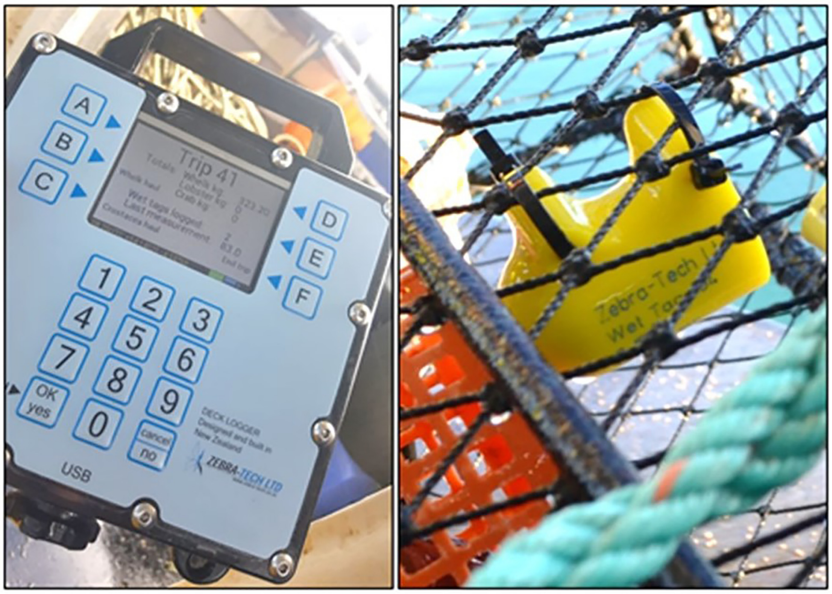

Figure 2. Left: The Zebra-Tech© decklogger and right: Zebra-Tech© wet-tag (Zebra-Tech, 2017).

inshore fishery, the fisher is prompted to review a catch summary page on the Decklogger. If the data are accurate, the skipper offloads the data from the device via cellular mobile signal. The data is sent as a .csv file to a specified email address. Each Decklogger and wet tag record has a unique identifier, which is appended to data so that vessel and string can be identified day-by-day.

EERS data analysis

A total of 340 daily records of haul-events were generated by the two participating vessels; 190 and 150 d for the under 10 and the 10–12 m vessels, respectively. In total, 812 individual string-lifts were reported, equating to 29826 pot-hauls. The total harvest reported from these pots was 45 tonnes of *C. pagurus* and 4 tonnes of *H. gammarus*, equating to 7% of effort and 10% of landings during the same period for the whole fishery (DEFA, IoM logbook submissions).

Data generated by the two vessels were used to explore spatial clustering of fishing activity and assess spatial and temporal variability in parameters (temperature, soak time) revealed by the Wet Tags. General additive modelling (GAM) approaches were then used to explore the effect of environmental drivers on LPUE and hence, gain insight into variables driving catch rates and the potential usage of such variables in the standardization of fisheries dependant data.

All data analyses were run in (R Core Team, 2017).

Spatial analysis

Cluster analysis techniques were used to investigate whether groupings existed within the spatial data using the cluster package in R (Maechler *et al.*, 2013). The latitude and longitude, hereafter referred to as geolocation, of each wet tag record was mapped and analysed using Euclidean geometry. The total within cluster sum of squares value was calculated from the Euclidean distance between haul-events and a range of clustering scenarios, ranging from one to ten cluster-centroids (K). An elbow plot was visually inspected to determine the value of K at which the total within sum of squares value reaches an asymptote, i.e. additional cluster-centroids do not identify statistically different groups of haul-events. The elbow plot method was supported by silhouette analysis, which determines how well each haul-event location fits into its K-means determined cluster group. For each clustering scenario, the silhouette width, $S(i)$, was calculated for each haul-event. Values range from -1 to 1, where a value of 1 indicates that the observation is well matched to the assigned cluster, 0 indicates it is on the border between two clusters and -1 indicates that a better cluster assignment is possible. $S(i)$, is calculated using the Cluster Distance (the average Euclidean distance of each observation to every other observation within the same cluster; C) and the closest Neighbour Distance (the average Euclidean distance from each point to the closest neighbouring cluster; N) and is described using the formula:

$$S(i)\begin{cases} 1-\frac{C(i)}{N(i)} & , \text{if} C(i) < N(i) \\ 0 & , \text{if} C(i) = N(i) \\ \frac{N(i)}{C(i)} - 1 & , \text{if} C(i) > N(i) \end{cases}.$$

Visual interpretation of the average $S(i)$ value over a range of K values was used in conjunction with the "elbow plot" to estimate the number of spatial clusters in the data. Each haul-event was then assigned to a named fishing area.

Statistical analysis

Fishery descriptive statistics

Prior to statistical comparisons data were tested for normality using the Shapiro–Wilk Test for normality and inspected visually using Kernel Density and Normal Q-diagnostic plots. Heteroscedasticity was tested using Levene's test and outliers identified using the Cook's distance plot. Kruskal–Wallis rank sum tests were used to test for differences in SBT, soak-time, depth, and LPUE by fishing area (assigned via cluster analysis) with post-hoc pairwise comparisons conducted using Wilcoxon rank sum tests (R-package: stats) due to data listed failing normality assumptions (Shapiro–Wilks normality test: SBT—W = 0.86; $p < 0.001$; Soak Time—W = 0.71;

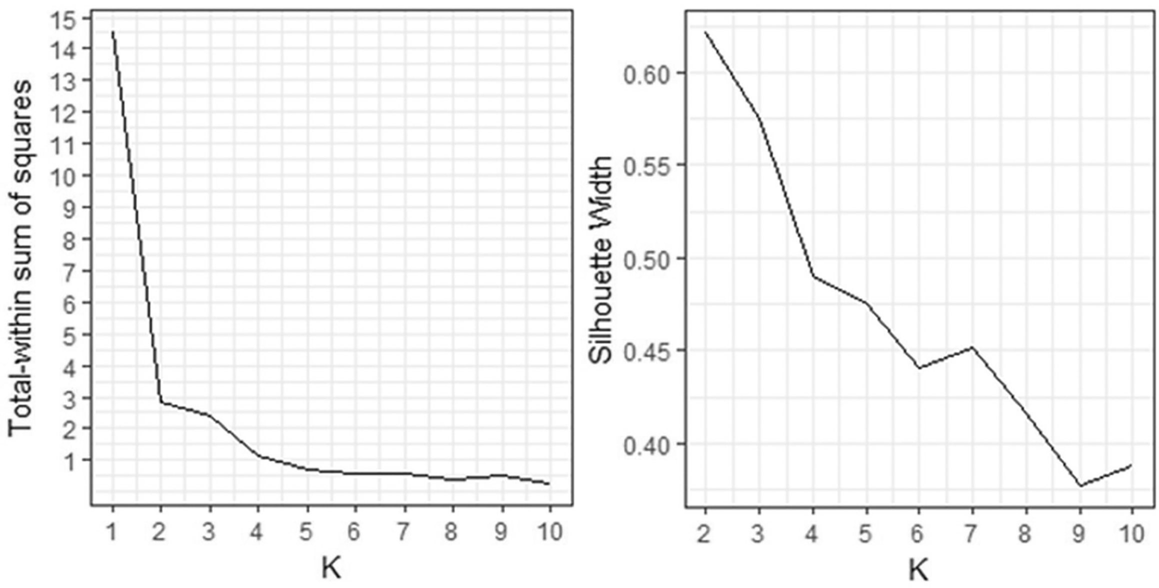

Figure 3. The total-within sum of squares for one to ten cluster centroids of WT data collected during the trial (elbow plot, left). The silhouette width for the same *K*-means determined cluster centroids (right).

$p < 0.001$; depth—$W = 0.94$; $p < 0.001$; and LPUE—Crab $W = 0.92$; $p < 0.001$ and lobster $W = 0.70$; $p < 0.001$).

General additive modelling

A generalized additive model (GAM) was used to investigate the relationship between both brown crab and lobster LPUE, geolocation and environmental variables using a Gaussian distribution of errors within the mgcv package in R (Wood, 2015). A 2D smoothed interaction term (Latitude and Longitude) was used to characterize geolocation data. The starting model constructed for both *C. pagarus* and *H. gammarus* was:

Brown crab *C. pagarus*:

$$\text{LPUE} \sim \text{s(Longitude, Latitude, by} = \text{Month)}$$
$$+ \text{s(averagebottomtemperature)} + \text{s(SoakTime)}$$
$$+ \text{s(LobsterLPUE)} + \text{Vessel} + \text{Month)}.$$

European lobster *H. gammarus*:

$$\text{LPUE} \sim \text{s(Longitude, Latitude, by} = \text{Month)}$$
$$+\text{s(averagebottomtemperature)} + \text{s(SoakTime)}$$
$$+\text{s(BrownCrabLPUE)} + \text{Vessel} + \text{Month)}.$$

Smoothing parameterization within the GAM was reached via the restricted maximum likelihood method (REML). The relationship between species LPUE and all predictors (SBT, depth, soak time, month, Vessel, and bycatch species) including the 2D smoothed term for geolocation was also modelled using a GAM approach. Model complexity was reduced using a backward selection approach by comparing AIC values. Model diagnostics were run using the "mgcViz" package in R (Fasiolo *et al.*, 2020) to plot linear predictors against residuals, residual frequency distributions, and fitted values against response values, and determine that basis dimension choices were adequate. Covariate dependence in fitted GAM models was also tested using the concurvity function in the mgcv package in R (Wood, 2015).

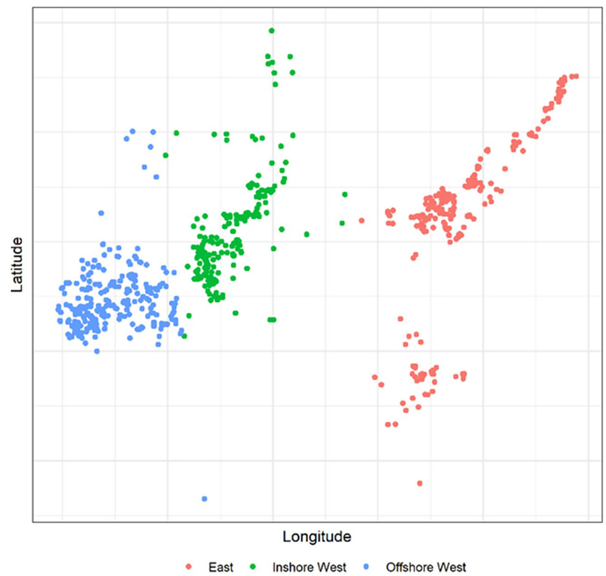

Figure 4. Idenfititfcation of three distinct clusters of fishing activity based on geolocation derived from EERS deckloggers. Spatial identifiers are omitted due to the commercial sensitivy of the data.

Results

EERS data

The geolocation was successfully appended to each haul-event recorded by the decklogger. Elbow plots indicated that activity of the two vessels took place in three discrete spatial clusters within 37E5 (Figure 3), categorized as "East", "Inshore Southwest", and "Offshore Southwest" (Figure 4). Further analysis using the average silhouette width shows $S(i) = 0.62$ and 0.57 for $K = 2$ and $K = 3$, respectively, confirming that spatial data are well matched to several cluster groups. Where data are assigned to four or more cluster groups, spatial data become less well matched to assigned cluster centroids

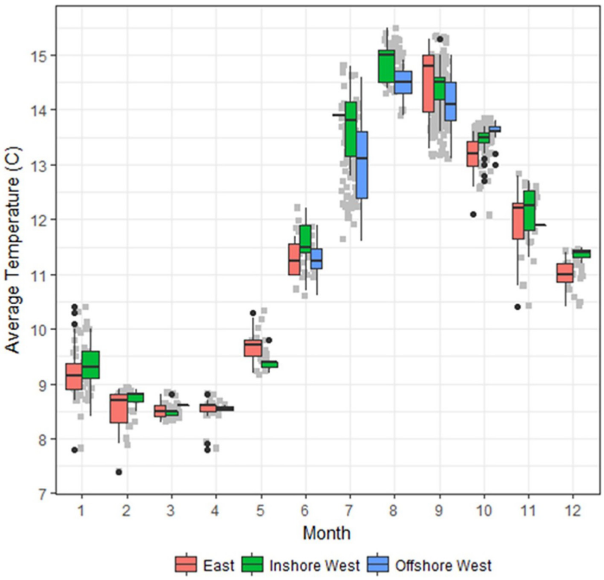

Figure 5. Median monthly sea bottom temperature (°C) recorded by wet tags, by fishing ground. Boxplots denote median and 95% *CI*. Residuals denoted in grey, outliers denoted in black.

(Figure 3), although the fact that silhouette width values remain above 0 for K values up to 10, suggests that spatial data are well matched to fine-scale clustering even when using many cluster groups (Figure 3). Three distinct clusters were chosen as this best described known fishery distributions between grounds and targeting behaviour of vessels.

Fishery descriptive statistics

Temperature data from wet tags showed spatial and temporal differences between fishing areas identified through cluster analysis (Figure 5). All three grounds showed spring/early summer warming and autumnal cooling, indicating the potential for spatial variation in temperature to drive activity and hence catchability of crabs/lobsters.

Soak time varied both within and among the three fishing areas (Figure 6). There was a significant difference in median soak time between different areas (Kruskal–Wallis rank sum test; $\chi^2 = 15$, df = 2; $p < 0.001$). Pots were soaked for shorter periods in the Offshore West (median = 2.1 d) ground compared to both Inshore West (median = 2.9 d, Pairwise Wilcoxon rank sum test; $p = 0.012$) and East fishing grounds (3.1 d, Pairwise Wilcoxon rank sum test; $p < 0.001$). The three fishing grounds were also characterized by significantly different depth profiles (Kruskal–Wallis rank sum test, $\chi^2 = 455$, df = 2; $p < 0.001$), with the deepest fishing areas in the western grounds, which were generally deeper in the offshore cluster (Figure 6).

Brown crab

Across the 12-month time series, average monthly LPUE data ranged from 0.29 to 3.46 kg pot^{-1} haul, with an annual mean of 1.45 kg pot^{-1} haul across all areas (Figure 7). The average weight of brown crab at MLS (140 mm CW) is ~0.5 kg, suggesting that an average of ~3 crabs were caught every pot-haul. The temporal trend in LPUE data shows a clear seasonal pattern with a peak occurring in September and October and depressed catch rates from December through to April. Monthly average LPUE peaked during the autumn fishery (3.46 kg pot^{-1} haul) corresponding to a 138% increase from the annual average catch-rate (Figure 7). LPUE varied significantly between all fishing grounds (Kruskal–Wallis rank sum test, $\chi^2 = 135$, df = 2; $p < 0.001$), with the greatest catch rate recorded in the Offshore West area and poorest in the East (Figure 7). Catch rates showed a significant difference of 0.5 kg pot^{-1} between Inshore and Offshore Southwest areas (Pairwise Wilcoxon rank sum test; $p = 0.011$).

European lobster

Across the 12-month time series, monthly average LPUE ranged from 0.09 to 0.58 kg pot^{-1} haul, with an annual mean of 0.305 kg pot^{-1} haul across all areas (Figure 8). The average weight of European lobster at MLS (90 mm CL) is ~0.4 kg, suggesting an average catch rate over the year of less than one lobster per pot. There was a clear seasonal pattern in mean LPUE with a peak occurring in September to December and depressed catch rates from January through to August. Monthly average LPUE peaked during the autumn fishery (October–0.58 kg pot^{-1} haul) corresponding to a 90% increase from the annual average catch-rate (Figure 7). LPUE varied significantly between all fishing grounds (Kruskal–Wallis rank sum test, $\chi^2 = 64$, df = 2; $p < 0.001$), with

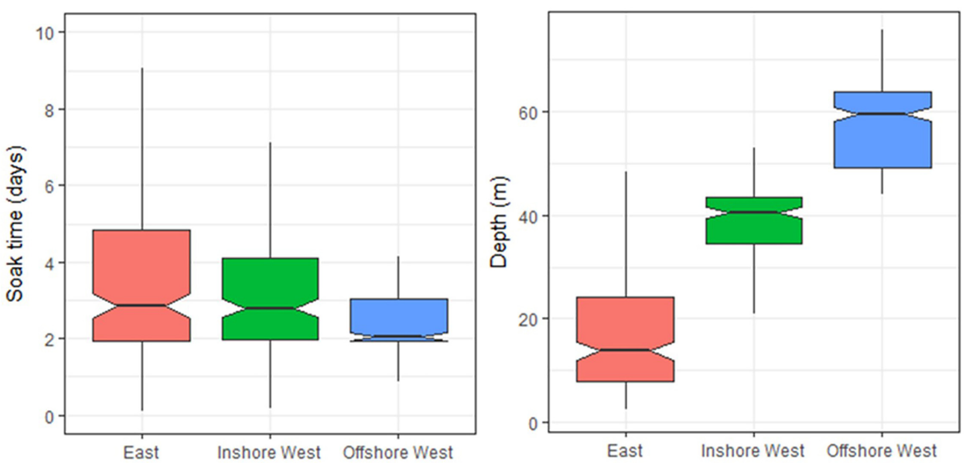

Figure 6. Median soak-time and mean depth associated with fishing activity recorded by wet tags via the EERS.

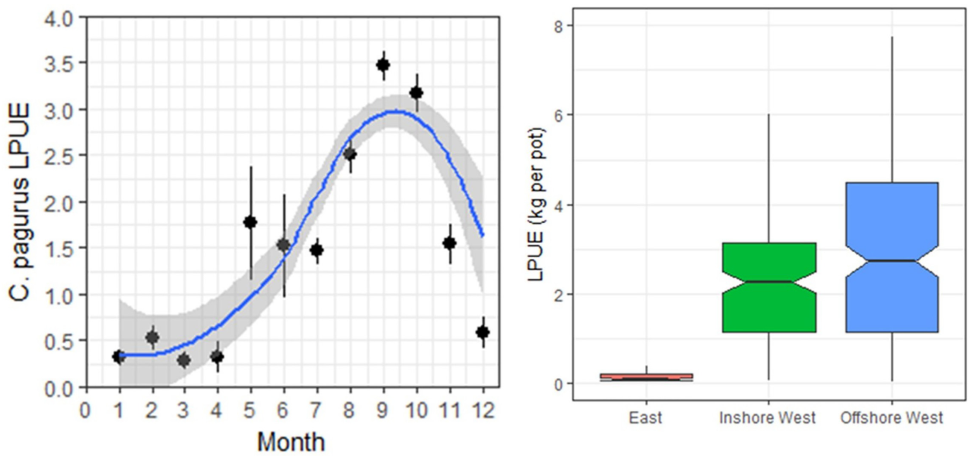

Figure 7. Mean LPUE of the *C. pagurus* fishery through the 12-month sampling programme undertaken with ERS ± standard error (left) with smoother. Median LPUE by fishing area (right). Boxplots denote median and 95% *CI*.

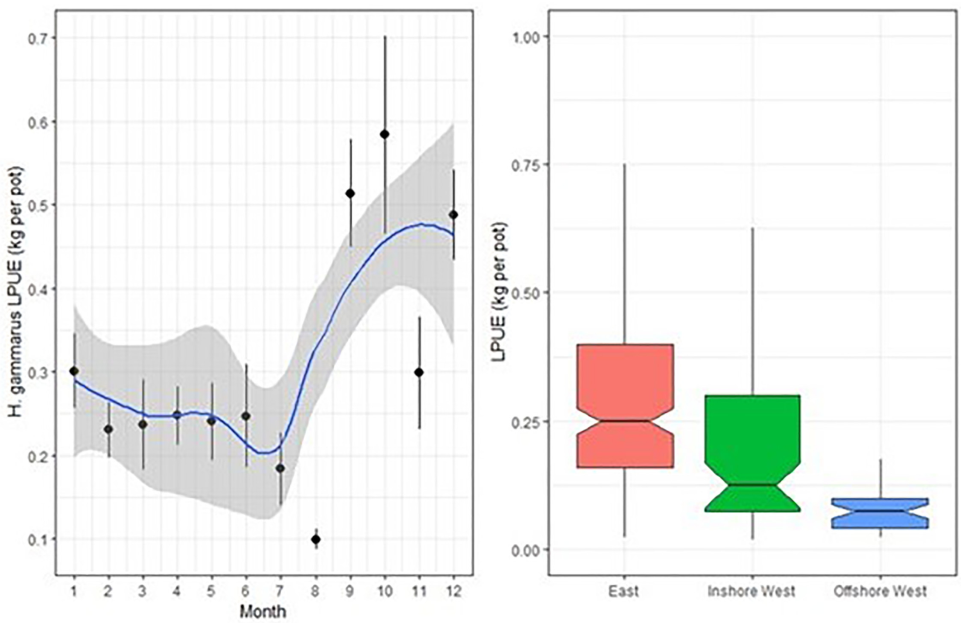

Figure 8. Mean LPUE of the *H. gammarus* fishery through the 12-month sampling programme undertaken with ERS ± standard error (left) with smoother. Median LPUE by fishing area (right). Boxplots denote median and 95% *CI*.

the greatest catch rate recorded in the east, followed by inshore west and poorest in offshore west (Figure 8). Catch rates showed a significant difference of 0.125 kg pot^{-1} haul between East and Inshore Southwest areas (Pairwise Wilcoxon rank sum test; $p < 0.001$).

Landing-per-unit-effort (LPUE) GAM model

Brown crab

GAM selection (by minimum AIC; Table 2) identified Geolocation, SBT, *H. gammarus* bycatch and Vessel as having a significant effect on crab LPUE (Figure 9). This model accounted for 68% ($r^2 = 0.64$) of the deviance explained. Geolocation had a significant effect on LPUE, with significant differences in LPUE geospatially [edf = 14.941, F (19.499) = 5.777; $p <$ 0.001]. Similar patterns are observed in raw fisheries descriptive statistics for *C. pagurus*, with LPUE greater in the offshore area compared to inshore areas (Figure 7; Figure 9). Average sea bottom temperature was a significant smoother contributor [edf = 2.17, F (2.66) = 4.227; p = 0.009] indicating a strong non-linear positive effect of temperature on LPUE (Figure 9). The effect of *H. gammarus* LPUE on *C. pagurus* LPUE was significant [edf = 2.33, F (2.9) = 3.6; p = 0.02] with increasing catch rates of *H. gammarus* negativley influencing *C. pagurus* catch rates. Low covariate dependence was recorded in the estimates for the final model (Table 3), with values observed to be <0.6.

European lobster

GAM selection (by minimum AIC; Table 2) identified Geolocation, SBT, crab bycatch, and Vessel effect as having a significant effect on European lobster LPUE (Figure 10). This model accounted for 41.8% ($r^2 = 0.40$) of the deviance explained. SBT was the most significant smoother contributor [edf = 1.2, F (4.37) = 31.3; p = 0.001] indicating a positive near linear

Table 2. Generalized additive model selection for *C. pagurus* and *H. gammarus* LPUE models using backwards stepwise selection approach using AIC values.

Predictor	Model	AIC	R^2
Crab LPUE	s(Longitude, Latitude)+s(AV_temp)+s(Soak_time)+s(Lob_LPUE)+Month + Vessel	476.87	0.63
	s(Longitude, Latitude)+s(AV_temp)+s(Lob_LPUE)+Month + Vessel	475.69	0.63
	s(Longitude, Latitude)+s(AV_temp)+s(Lob_LPUE)+Vessel	467.10	0.63
Lobster LPUE	s(Longitude, Latitude)+s(AV_temp)+s(Soak_time)+s(Lob_LPUE)+Month + Vessel	26.67	0.38
	s(Longitude, Latitude)+s(AV_temp)+s(Lob_LPUE)+Month + Vessel	25.19	0.37
	s(Longitude, Latitude)+s(AV_temp)+s(Lob_LPUE) +Vessel	11.43	0.39

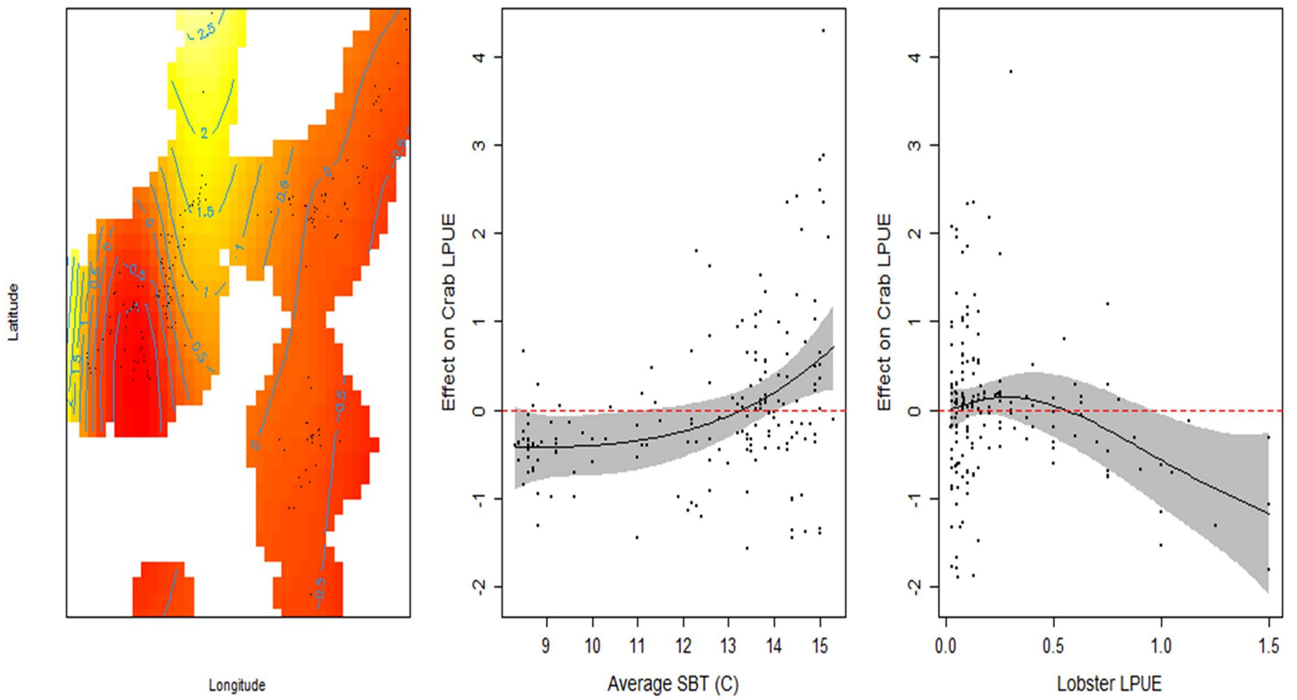

Figure 9. GAM smoothed term outputs for the effect of; (left) geolocation by month; (middle) average sea bottom temperature °C; (right) *H. gammarus* LPUE on *C. pagurus* LPUE. Buffered lines denoted 95% *CI* and residuals. Gradient in 2D plot should be interpreted with gradient of red positive and yellow negative effect on LPUE.

Table 3. Concurvity test results from generalized additive models for the effects of geolocation and environmental variables on *C. pagurus* and *H. gammarus* LPUE.

GAM model	Variables	Factor variable	Longitude × Latitude	Sea bottom temperature	Lobster/Crab bycatch
Crab	Factor variable	1	<0	<0	<0
	Longitude × Latitude		1	0.51	0.57
	Sea bottom temperature			0.12	0.1
	Lobster bycatch				1
Lobster	Factor variable	1	<0	<0	<0
	Longitude × Latitude		1	0.59	0.48
	Sea bottom temperature			1	0.22
	Crab bycatch				1

effect of temperature on LPUE. *C. pagurus* bycatch rates had a significant non-linear effect on LPUE [edf = 3.1, F (3.8) = 6.7; p < 0.001]. In addition, there was a significant effect of "Vessel" (p < 0.001) and Geolocation [edf = 2.153, F (2.29) = 4.382; p = 0.01]. Geospatial LPUE was seen to vary longitudinally, with an increasing positive effect on LPUE. Low covariate dependence was recorded in the estimates for the final model (Table 3), with values observed to be <0.6.

Discussion

This technology trial, designed in collaboration with the fishing industry, demonstrates the utility of an EERS that allows skippers to remotely submit high-resolution catch and effort data electronically to a central database on a daily basis. Data resolved at the scale of individual haul-events is a step-change in resolution compared to aggregated daily reports resolved to ICES Statistical Rectangles (30 NM^2 areas),

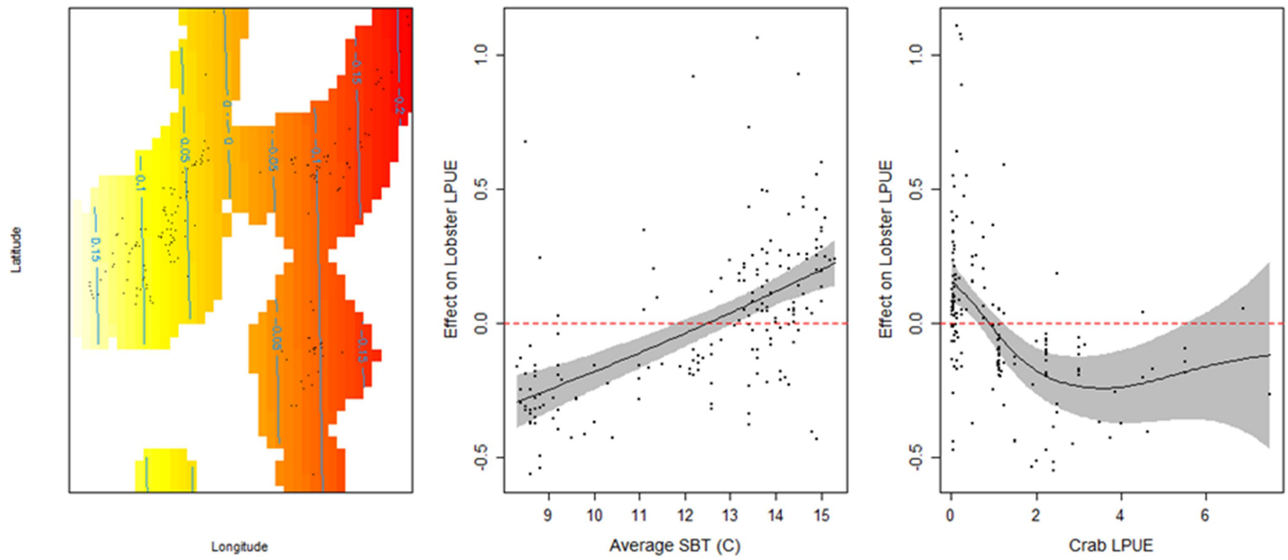

Figure 10. GAM smoothed term outputs for the effect of (left) geolocation; (middle) average sea bottom temperature; and (right) *C. pagurus* LPUE on *H. gammarus* LPUE. Buffered lines denote 95% *CI* and residuals. Gradient in 2D plot should be interpreted with gradient of red postive and yellow negative effect on LPUE.

at no greater burden on the fishing vessels standard operating procedures. In addition, passive monitoring of additional variables has enabled statistical modelling of both *C. pagurus and H. gammarus* LPUE using a generalized additive modelling approach, demonstrating the significant effect of spatial, biotic and abiotic variables. More generally, the precision and modelling capacity of the fisheries-dependent data collected through this trial demonstrates the utility that GIGO and mobile technologies can offer to management of data-poor fisheries that lack fisheries-independent stock assessment approaches and/or funding for on-board observer programmes.

High spatial-resolution GIGO data

In contrast to the spatial data collected in this trial, which is the precise geolocation of hauling activity triggered by GIGO technology, previous studies investigating spatial data requirements in data-poor pot fisheries have mostly focussed on the utility of continuous polling GPS and iVMS systems (Mendo *et al.*, 2019a, b). Mendo *et al.* (2019a) found that an optimal polling interval of 1 min is required in order to accurately estimate effort metrics such as the number of hauls, total area fished per trip, and spatial extent of fishing activities in static-gear fisheries. This is 120 times greater than current EU VMS requirements for >12 m vessels (EC, 2011) and greater than trials in other data-poor fisheries (e.g. Shelmerdine and Leslie, 2015), some of which required an especially high frequency poll-rate to monitor potentially damaging fishing activity within sensitive European Marine Sites (ICES, 2016). Mendo *et al.* (2019b) found that iVMS/GPS with a low polling frequency made it increasingly challenging to detect discrete hauling events in pot fisheries, as well as producing increasingly erroneous estimates of the spatial distribution of fishing activity since many data are recorded during transitory activity. An EERS that integrates GIGO technology can overcome many of the approximation issues associated with VMS data. For example, in the case of a pot-fishery as used in this case-study, each GIGO record represents the exact location of a haul-event associated with a declared number of pots, which could more simply and accurately be used to calculate the effective area fished with basic information on fishing gear configuration (e.g. distance between consecutive pots).

The EERS technology provided high-resolution data on the spatial-temporal distribution of fishing activity over the 12-month trial. Existing logbook requirements, which report fishing activity data to ICES statistical rectangle (30 NM^2 areas), results in aggregation of data into arbitrary delineations that do not reflect stock boundaries, the spatial dynamics of commercial activity, or jurisdictional/territorial limits. Our approach represents a step-change in data resolution with consequent benefits for provision of effective management advice. When considering temporal trends in catch data (e.g. declining landings), fisheries advice must necessarily take into account fine-scale spatial dynamics of fishing activity in order for management decisions to reflect any requirement for intervention. For example, the three fishing grounds identified through our work occur within the same ICES statistical rectangle but differ in their characteristics, LPUE and associated fisher targeting behaviours. A shift in fishing effort and targeting behaviour, for example, from west coast to east coast grounds, perhaps driven by economic factors (decrease in value of crab compared to other species caught with the same gear-type, such as European lobster) and displacement effects (i.e. exclusion from favourable fishing grounds due to competition with mobile gear or other marine developments) would likely lead to a significant decline in *C. pagurus* LPUE within ICES Rectangle 37E5. In the absence of spatially resolved fisheries-dependent data, a biological reference point based on an LPUE threshold for the whole of 37E5 may trigger harvest control rules such as catch restriction, effort restrictions, or spatial closures that are neither necessary nor appropriate for protecting crab stocks because the LPUE data that triggered the harvest control rules reflects aspects of behavioural change in the fishing fleet rather than that of stock decline. This hypothetical example highlights the need for highly resolved spatial data to inform area-based assessment, advice, and management (Babcock *et al.*, 2005).

Integrating environmental observations into EERS

The inclusion of SBT in the LPUE model has provided valuable insight into the thermoregulatory dynamics of the fishery; there was a clear positive effect of temperature on LPUE for *C. pagurus* and *H. gammarus*, increasing linearly from ∼9°C to the maximum observed temperature of 15°C (Figure 9; Figure 10). Our measurements showed the clear large seasonal variation in temperature, which drives LPUE, but also more subtle variation over local spatial scales (Figure 5). Temperature has an important effect on a range of processes in both *C. pagurus* and *H. gammarus* including moulting, mating, and migration (Bennett, 1995; Tallack, 2007; Bakke *et al*., 2018; Coleman *et al*., 2021) which is linked to catchability (Lizárraga-Cubedo *et al*., 2015) and hence to fishing activity (seasonal and spatially defined effort). Our empirical observations and modelling approach suggest that abiotic drivers of catch can theoretically be used to standardize fisheries-dependent indicators. Such an approach has been recommended for stock assessments of baited fishing gear for some time (see Stoner 2004). Similarly, utilization of LPUE as part of an inter-annual abundance survey for crustacean stocks using baited traps (e.g. for the assessment of impacts of offshore developments; Roach *et al*. 2018) should also seek to incorporate *in-situ* monitoring of SBT to accurately perform post-hoc adjustments of LPUE indices for temporal-spatial comparisons. More generally, the inclusion of SBT monitoring as part of EERSs may assist scientists, fisheries authorities, and industry to develop a greater understanding of thermoregulatory dynamics that affect fisheries. Such understanding will naturally facilitate development of long-term management plans that take into account environmental triggers and thresholds relating to stock health, which will be particularly important within the context of ocean warming (Cheng *et al*., 2019).

Haul-specific catch and effort data

The EERS trial has also demonstrated the utility of highly resolved spatial-temporal fisheries-dependent catch and effort data within the context of data-poor mixed-species fisheries. As opposed to current statutory logbooks that report the landed weight of individual species for an entire fishing trip, the EERS data contain information on the catches of multiple species for each individual haul event. In this case, *C. pagurus* and *H. gammarus* populations are often targeted within a mixed fishery owing to their overlapping spatial distribution (Smith *et al*., 2001). Historically, fisheries-dependent catch analysis has failed to address the potential for inter-specific interactions among multiple captured species to distort estimates of relative abundance using LPUE data. The potential for this has been highlighted clearly by Skerritt *et al*. (2020) working on a mixed brown crab and European lobster fishery on the north east coast of the English coast. They showed that pots pre-loaded with European lobster had significantly lower catchability of brown crab compared to control pots. In contrast, they found no effect of C. *pagurus* on the catchability of *H. gammarus*.

Our analyses are in partial agreement with those of Skerrit et al. (2020). In the brown crab fishery increases in *H. gammarus* LPUE resulted in declining *C. pagurus* LPUE. Interestingly, the model suggests that the negative effect on *C. pagurus* LPUE is minimal until *H. gammarus* LPUE reaches 0.75 kg (Figure 10), which is approximately the average weight of a single lobster at MLS (87 mm carapace length) (*unpublished data*, J. Emmerson). Thereafter, the effect of *H. gammarus LPUE* on brown crab LPUE showed a negative linear relationship to the point where *C. pagurus* LPUE average reaches zero when *H. gammarus* LPUE reaches 1.5 kg pot^{-1}, i.e. when there are approximately three above-MCRS *H. gammarus* caught per trap. We found a similar relationship in the opposite direction; *H. gammarus* LPUE declined with increasing *C. pagurus* LPUE (Figure 10). The apparent contradiction with Skerrit et al. (2020) observation of no effect of the presence of *C. pagurus* on *H. gammarus* catch may be explained by the density/biomass utilized in the experimental work. Skerrit et al. (2020) used a maximum pre-loaded pot threshold for *C. pagurus* of ≈1kg; our observations suggest that negative effects of *C. pagurus* on *H. gammarus* start once this density/biomass is exceeded. The work of Rayner and McGaw (2019) is in general agreement for the potential of negative impacts of crab bycatch on lobster catch. They showed that high densities of *C. maenas* around and within pots reduced overall *H. americanus* interaction and catchability.

Our work shows clearly that inclusion of "commercial bycatch" alongside more traditional data such as sea temperature will clearly be beneficial in deriving standardized LPUE for *C. pagurus* and *H. gammarus*. However, the importance of considering inter-specific effects is not unique to this fishery, and is becoming increasingly pertinent as ecosystem approaches to fisheries (EAF) continue to be developed (Bianchi and Skjoldal, 2008). Our data comes from a spatially and temporally limited EERS trial within a specific mixed fishery, but the analysis and results have demonstrated that inter-specific effects within a mixed fishery are possible to capture, model, and estimate. We envisage that this level of reporting would be beneficial for other mixed fisheries using a wide variety of fishing methods.

Feeding into scientific advice and fisheries management

Increased application of area-appropriate fisheries advice and management tools are needed in order to sustain stock abundance and fisheries harvests in data-poor fisheries (Hilborn *et al*., 2020). If fisheries-dependent data, in the form of indicators such as LPUE, are to be used as a foundation for the delivery of scientific recommendations and management in these fisheries (Miethe *et al*., 2016), catch reporting systems must necessarily be sufficiently capable of capturing the relevant data at an appropriate resolution. EERS-derived indices have the potential to provide this and in so doing could enable highly responsive, accurately informed and proportionate management for many fisheries, including but not limited to data-poor contexts. For example, continuous data from commercial activity could trigger the need for intervention harvest control rules in near-real-time, as opposed, or, in addition to FAs setting fixed harvest control rules resulting from annual fisheries-independent scientific surveys. For data-poor fisheries specifically, GIGO technology and well-designed EERSs generally represent an opportunity for step-change in data acquisition and consequently management, with minimal additional data submission demands on skippers. The system described is also cost-effective when considered against the resource requirements of collecting data with a similar spatial-temporal resolution using fisheries-independent methods (e.g. survey vessels and observer programmes).

Conclusion and recommendations

To summarize, we have demonstrated through the use of readily available technology, the value in providing accurate geolocated catch and effort data combined with environmental variables and information on the effect of species interactions in a data poor fishery. Such data allow the estimation of reliable fisheries-dependent indices and address the call from Skerritt *et al*. (2020) for commercial providers to develop onboard electronic data logging and retrieval kit as part of a fully documented strategy to fill data gaps.

We recommend that fisheries authorities and fisheries scientists work with the fishing industry to co-develop fisheries-specific EERS solutions for trials. As in this study, initial tests should use sentinel fleets of fisheries in key areas in order to assess whether EERSs can fulfil the data-requirements needed to provide fisheries advice for data-poor fisheries. The EERS trial reported here demonstrates the considerable potential for EERSs to harness GIGO sensory technology and mobile communications to (1) increase the spatial-temporal resolution of catch and effort data to exact locations of haul-events and identify discrete fishing and management areas without complicated analytical methods that introduce error, (2) monitor and model significant drivers of variation in fisheries-dependent LPUE with no substantial changes to standard fishing procedures, and (3) provide high-precision daily reports with little administrative and resource burden. We acknowledge that EERSs are a panacea for all of the issues facing data-poor fisheries; sound fisheries advice is only one element of the pre-requisites for effective fisheries management; the others include appropriate institutional and legal frameworks, monitoring, control, and surveillance capacity, and good stakeholder engagement through co-management. Nonetheless, we see EERS as being a valuable tool in the development of appropriate fisheries advice for data-poor fisheries.

Conflict of interest statement

All authors declare no conflict of interest.

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Data availability statement

The data underlying this article cannot be shared publicly due to its commercial nature.

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