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Identifying partners at sea from joint movement metrics of pelagic pair trawlers

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Abstract :

Here, we present an approach to identify partners at sea based on fishing track analysis, and describe this behaviour in several fleets: pelagic pair trawlers, large and small bottom otter trawlers, mid-water otter trawlers, all in the North-East Atlantic Ocean, anchovy purse-seiners in the South-East Pacific Ocean, and tuna purse-seiners in the western Indian Ocean. This type of behaviour is known to exist within pair trawlers, since these vessels are in pairs at least during their fishing operations. To identify partners at sea, we used a heuristic approach based on joint-movement metrics computed from vessel monitoring system data and Gaussian mixture models. The models were fitted to joint-movement metrics of the pelagic pair trawlers, and subsequently used to identify partners at sea in other fleets. We found partners at sea in all of the fleets except for the tuna purse-seiners. We then analysed the connections between vessels and identified exclusive partners. Exclusiveness was more common in pelagic pair trawlers and small bottom otter trawlers, with 82% and 74% of the vessels involved in partnerships having exclusive partners. This work shows that there are collective tactics at least at a pairwise level in diverse fisheries in the world.

Keywords : collective behaviour, dyadic joint movement metrics, fishing tactics, Gaussian mixture model, vessel monitoring system

Introduction

Understanding fisher spatial behaviour contributes to the development of effective spatial management tools. The increasing availability of georeferenced data from sources like Automatic Identification System (AIS; Robards *et al.* (2016)) and Vessel Monitoring System (VMS; Hinz *et al.* (2013)) has enabled a proliferation of studies that characterise fisher spatial dynamics (e.g. Bertrand *et al.* (2005); Joo *et al.* (2014)), propose movement models (e.g. Vermard *et al.* (2010); Walker and Bez (2010); Joo *et al.* (2013); Gloaguen *et al.* (2015)), account for it in stock assessment models for fisheries management (e.g. Vigier *et al.* (2018)) and discuss management measures based on it (e.g. Gerritsen *et al.* (2012); Holmes *et al.* (2011)). While individual movement of fishers has been extensively studied by means of trajectory data, the collective behaviour of fishermen has been rather neglected. Fishers are social individuals that may develop collaboration or competing strategies (e.g. Horta and Defeo (2012); Hancock *et al.* (1995)). The characterisation of their collective behaviour could provide valuable inputs that would increase the realism of movement models and make management measures more effective (Salas and Gaertner, 2004; Gezelius, 2007; Rijnsdorp *et al.*, 2011).

Collective behaviour can emerge at large or small group scales, and may be reflected in a variety of movement patterns. Here, we focused on a particular collective behaviour, which is dyadic or pairwise joint movement behaviour, and more specifically, aimed at identifying partners at sea, defined as two fishing vessels that move together at sea. An extensive review and comparison of metrics for assessing dyadic joint movement (Joo *et al.*, 2018) showed that the metrics varied in their sensitivity to three aspects of joint movement: proximity, coordination in direction and coordination in speed. Here, we defined partners at sea as showing coordinated and proximal joint movement. To account for all of these aspects, we chose one metric for each of the three dimensions of joint movement, from the ones recommended in Joo *et al.* (2018), to characterise the dyadic movement of fishing vessels.

Strong partnership at sea was expected to be found in pelagic pair trawlers: since they need to be in pairs at least during each fishing operation, they are likely to be paring throughout their entire fishing trips. For that reason, in this study, we aimed at defining the model parameters that would allow us to identify strong partnership at sea in pelagic pair trawlers in the North-East Atlantic Ocean through the analysis of their VMS data. After that, the goal was two-fold: assessing whether the same patterns of partnership were present in other fleets; and, if present, assessing the level of exclusiveness in the partnership within each fleet.

Dyads, or potential candidates for partners at sea, were defined as pairs of segments of VMS tracks at sea at the same time. For each dyad, three joint movement metrics were calculated. Then, we fitted a Gaussian mixture model (GMM) to distinguish three groups of dyads sharing the same types of behaviour. One of these components was expected to correspond to partners at sea patterns. After characterising at-sea partnership in this fleet, we used the fitted model to identify partners at sea in several other fisheries: bottom and mid-water otter trawlers in the North-East Atlantic Ocean, anchovy purse-seiners in the South-East Pacific Ocean, and tuna purse-seiners in the Western Indian Ocean. We showed that this type of behaviour is not exclusive to pelagic pair trawlers, and discuss possible implications of this behaviour in terms of fishing strategies. Perspectives opened by this work for further research in collective spatial behaviour are also discussed.

Materials and Methods

Fishing vessels trajectory data

In this section, the VMS data and fishing trip characteristics of the analysed fleets are briefly described. These are: 1) French pelagic pair trawlers, 2) French large bottom otter trawlers, 3) French small bottom otter trawlers, 4) French mid-water otter trawlers, all operating in the North-East Atlantic Ocean, 5) French tuna purse-seiners in the Western Indian Ocean, and 6) Peruvian anchovy purse-seiners in the South-East Pacific Ocean.

For the French fleets, the use of VMS started to be legislated and mandatory in the European Union since 2000. In practice, records are transmitted at ∼ 1 h intervals. In the North-East Atlantic Ocean, we analysed VMS data from fishing trips performed between 2012 and 2013 within the English Channel and the Celtic Sea, while in the Indian Ocean, we analysed fishing trips from 2011 to 2013. In Peru, industrial purse-seiners are also legally obliged to use VMS tracking devices since 2000, transmitting their positions at ∼ 1 h intervals, but since 2015, VMS positions are recorded each 10 minutes. We focus on Peruvian fishing trips during a specific fishing season in 2016.

French pelagic pair trawlers

A pelagic pair trawl is a gear defined by one trawl towed in midwater by two vessels to target pelagic fish. Thus, vessels of the pelagic pair trawler fleet remain close performing almost synchronous movements while operating the trawl. The distance between vessels during this operation varies between 50 m and 250 m, depending on the warp length (which in turn depends on several factors such as the fishing depth and technique) (Prado, 1988). The vessels do not need to move together throughout their whole fishing trips, especially when steaming, using single trawls or exploring the sea individually looking for shoals (Sainsbury, 1996). These vessels can spend part of their fishing trips on individual activities, even targetting other fish that do not require pair trawling. Most of the pair-trawler fishing trips in the dataset were performed by relatively large vessels (18-24 m; ~80%), and they last ~99h on average, according to fisher logbooks.

French large and small bottom otter trawlers

The bottom otter trawl gear is a trawl towed by a single vessel; these vessels target bottom and demersal species. Vessels performing bottom otter trawl fishing trips had a large variability in their sizes: from 10 to 40 m. The duration of the trips were proportionally related to the size of the vessels: larger vessels performed longer trips and generally offshore. Since, for this type of gear, the spatial behaviour from smaller vessels differs from that of larger vessels (e.g. the trips are not only shorter but also closer to the coast), we separated bottom otter trawlers into two groups: one with vessels smaller than 12 m or performing trips of less than 20 h (we assume that in very short trips even large vessels act like the small ones), and another one with vessels larger than 12 m or performing trips of larger duration; vessels with these characteristics are considered as composing the small otter trawl and large otter trawl fishing fleets, respectively. The average duration of fishing trips for both fleets were ~16 and ~105 hours, respectively, according to fisher logbooks.

French mid-water otter trawlers

A mid-water otter trawl gear is also operated by an individual vessel. As the vessels in the pair trawler fleet, mid-water otter trawlers target pelagic fish mostly. As with bottom trawlers, vessels performing mid-water trawling trips had sizes ranging from 10 to 40 m; larger vessels exist (e.g. 90 m long targeting blue whiting) but were not found in this dataset. However, the spatial behaviour of these vessels was not conditioned by their size, so they were not separated by size. The average duration of a fishing trip was ~ 31 hours (fisher logbooks). Since fishing with mid-water or bottom otter trawls does not require pair-work, if it exists, it would reflect a strategic/tactical choice.

French tuna purse-seiners

The fleet is composed of ten to twenty vessels operating in the Indian Ocean and the size of the purse seiners is typically of sixty meters. Tuna purse-seiners' fishing trips usually last several tens of days. The time windows targeted in the present study (2011-2013) followed a harsh period of strong security issues induced by piracy attacks in the Indian Ocean. During the second half of 2009, it became mandatory for fishing vessels operating in the Indian Ocean to fish in pairs before some military protection were enforced. However, some vessels could have decided to continue moving more or less in pairs as a precautionary approach. Since tuna purse-seiners perform long fishing trips, we did not expect vessels to move together throughout their whole fishing trips, but rather over some shorter opportunist periods of time, eventually changing partners.

Peruvian anchovy purse-seiners

The ten-minutes frequency of data recording is particularly suiting for monitoring the anchovy (*Engraulis ringens*) industrial fishery, where fishing trips usually last less than 24 hours (a median of 17 hours for the analysed data), since fish tends to distribute close to the coast in dense patches (Bertrand *et al.*, 2008; Joo *et al.*, 2014). In this fishery, vessel size is measured in terms of its hold capacity, which varies from 32.5 MT to 900 MT, with a median at ~ 100 MT. We used data from the first fishing season of 2016 (39 days between June and July). Though the race for fish stopped in

2009 (the total allowable catch was replaced by an individual vessel quota system; Aranda (2009)), the high abundance of anchovy, the eagerness to save fuel oil and the habit of performing very short fishing trips, make it common for vessels to go to the same fishing zones or to follow each other as a fishing tactic. Thus here as well, we expected to find some patterns of joint movement, although not perfectly synchronous or remaining close to each other all the time.

Methods

Identifying partners at sea basically consists of 1) data pre-processing and dyad constitution (i.e. the VMS data was first cleaned and interpolated, and then dyadic segments of trajectories were identified); 2) joint-movement metrics derivation for each dyad; 3) identification of clusters of dyadic joint movement –and particularly partners at sea– via GMMs; and 4) characterisation of partnership at vessel and fleet scales. All the analyses were performed in R (R Core Team, 2015).

Data Pre-processing

From the trawler VMS data, fishing trips where at least one pair of consecutive records were lagged by more than three hours were removed (≈ 9% of the total number of fishing trips). For tuna purse-seiners, we used a one-hour threshold. If there were consecutive records separated for more than one hour, those differences had to represent less than 10% of the trip duration to keep the trip in the dataset (≈ 7% of the total number of fishing trips were removed). Then, since location records had irregular time steps, we linearly interpolated tracks to obtain regular 1-hour time steps and simultaneous VMS positions (i.e. fixes) from vessels at sea. The anchovy purse-seine data was processed using the vmsR R package (Marin and Joo, 2021) prior to this study. The vmsR algorithms apply a two-hour threshold for consecutive records and use a linear interpolation at 10-minute time steps. From the (interpolated) fixes, we derived motion variables such as displacement (distance between consecutive fixes) and absolute angle (between the direction of the x-axis and the locations at consecutive fixes). The adehabitatLT package in R (Calenge, 2006) was used to compute those metrics.

We then formed the dyads that would be candidates for partners at sea. Dyads were defined as the concomitant parts of two vessel tracks crossing each other at least once during their fishing trips. We considered that, to 'cross each other', vessels had to be at a proximity of <5 km at least once for all fleets, except tuna purse-seiners. The latter have a greater range of motion and do not get so close; for them, the distance threshold was set to 60 km. If both vessels departed from port and then arrived to port at the same time, the dyad was to be composed of the two tracks of their whole fishing trips; if not, the dyad would have been composed by track segments of their fishing trips corresponding to moments when both vessels were at sea. To keep only dyads with segments that were long enough for the analysis, an arbitrary 10-hour threshold was set for all trawlers and anchovy purse-seiner fleets. Tuna purse-seiners performed longer trips, so the 10th percentile, i.e. 106 hours, was used as their threshold. The number of vessels, dyads and the median duration of a dyad are shown in Table 1.

Table 1. Statistics per fleet of number of vessels, number of dyads, their duration (median in hours), the δ threshold for Prox, and the frequency of record transmission. The first three statistics are also displayed for each cluster.

		Total	Cluster 1	Cluster 2	Cluster 3
Pelagic pair	Vessels	59	56 (94.9%)	57 (96.6%)	58 (98.3%)

		Total	Cluster 1	Cluster 2	Cluster 3
trawlers	Dyads	6,457	495	1681	4281
(δ = 5km			(7.7%)	(26.0%)	(66.3%)
Δt = 1h)	Duration	87	74	68	97
Large	Vessels	266	38	254	261
bottom			(14.3%)	(95.5%)	(98.1%)
otter trawlers	Dyads	54,478	312	16205	37961
(δ = 5km			(0.6%)	(29.8%)	(69.7%)
Δt = 1h)	Duration	65	60	47	73
Small	Vessels	202	52	185	183
bottom			(25.7%)	(91.6%)	(90.6%)
otter trawlers	Dyads	17,300	93	7051	10156
(δ = 5km			(0.5%)	(40.8%)	(58.7%)
Δt = 1h)	Duration	12	12	12	12
Mid(water	Vessels	70	4	56	65
otter			(5.7%)	(80.0%)	(92.9%)
trawlers	Dyads	844	3	409	432
(δ = 5km			(0.4%)	(48.5%)	(51.2%)
Δt = 1h)	Duration	12	11	12	12
Anchovy	Vessels	757	327	756	756
purse-			(43.2%)	(99.9%)	(99.9%)
seiners	Dyads	572,804	568	168284	403952
(δ = 5km			(0.1%)	(29.4%)	(70.5%)
Δt = 1h)	Duration	17	16	16	17
Tuna	Vessels	15	0	15	15
purse-				(100.0%)	(100.0%)
seiners	Dyads	1,523	0	39	1484

		Total	Cluster 1	Cluster 2	Cluster 3
(δ = 5km				(2.6%)	(97.4%)
Δt = 1h)	Duration	357		224	362

Joint movement metrics

The review made by Joo *et al.* (2018) defined three dimensions of joint movement: proximity (closeness in space-time), coordination in direction and coordination in speed. The article evaluated ten metrics used in the literature to assess joint movement and showed that some metrics were either redundant or inaccurate for characterising joint movement, some others were better suited to assess proximity, and others were more sensitive to coordination. Based on that work, we chose three metrics that were positively evaluated and that – together – account for the different aspects of joint movement: 1) the proximity index (proximity), 2) dynamic interaction in displacement (coordination in speed, and in displacement when time steps are regularly spaced), and 3) dynamic interaction in direction (coordination in direction).

The proximity index (Prox) is defined as the proportion of simultaneous fixes that are spatially close. To define closeness, we needed to fix a distance threshold δ. For pair trawlers, it is expected that at the very moment of fishing, vessels working together are separated by less than 1 km from each other. When they were not fishing, they could still move together but not necessarily at <1km. Thus, a 5km threshold was used for this fleet. We also used a 5km threshold for large bottom otter trawlers to get comparable results to those of pair trawlers. Anchovy purse-seiners, mid-water, and small bottom otter trawlers usually perform short and coastal fishing trips, meaning that vessels would not necessarily move together as a strategy, but could sometimes coincide in places due to their short coastal movements. For that reason, we chose a smaller threshold, 3km, for those three fleets. For tuna purse-seiners, we chose 10km, as it is roughly the limit of visual detection of neighbouring vessels.

The calculation of the other two metrics did not require an *ad hoc* parametrization as for Prox. The dynamic interaction in direction (DI_θ) and in displacement (DI_d) measured similarity in direction and speed/displacement, respectively, between simultaneous fixes (i.e. records of locations) in a dyad. The mathematical definition of each metric is shown in Table 2.

Table 2. Joint movement metrics

Metric	Range	Interpretation for joint movement
$Prox = (\Sigma_t 1\{d_t(A,B) < \delta\})/T$	[0,1]	From always distant (0) to always close (1)
$DI_d = (\Sigma_t[1 - (\lvert d_{t,t+1}(A) - d_{t,t+1}(B)\rvert / (d_{t,t+1}(A) + d_{t,t+1}(B)))^\beta]) / (T-1)$	[0,1]	From non-cohesive (0) to cohesive (1) movement in displacement
$DI_\theta = (\Sigma_t \cos(\theta_{At}-\theta_{Bt})) / (T-1)$	[-1,1]	From opposite (-1) to cohesive (1) movement in azimuth

Note: A, B: vessels in the dyad; T: number of fixes in the dyad; $d_t(A,B)$: distance in km between vessels A and B at t-th fixes; $1\{\}$: index function; δ: distance threshold; $d_{t,t+1}(A)$ (resp. $d_{t,t+1}(B)$): displacement of A (resp. B) in km between fixes t and t + 1 ; β is a scaling parameter for which we assume to take the default value of 1 (Long and Nelson, 2013; Joo *et al.*, 2018); θ_{A_t} (resp. θ_{B_t}): heading of vessel A (resp. B) at time t.

Identification of partners at see with Gaussian mixture models

Partner identification was addressed through a probabilistic clustering approach using GMMs (Biernacki *et al.*, 2006). In this approach, each dyad i was characterised by its three dimensional metrics $X_i = (\mathrm{Prox}_i, \mathrm{DI}_{di}, \mathrm{DI}_{\theta i})$ which were assumed to be a realisation of a three-dimensional normal distribution. The mean vector and the variance matrix of this distribution depended on the unknown cluster Z_i to which the dyad i belonged. Given a fixed number of clusters (G) and the three metrics, there were three elements to estimate for each cluster g $(g = 1,...,G)$: a three-dimensional mean (μ_g), a 3 × 3 covariance matrix (Σ_g), and the proportion of the cluster in the observed dyad population (π_g).

In this set-up, the probability density function of given metric values x_i of a dyad i ($\phi(x_i)$) can be expressed as:

$$\phi(x_i) = \sum_{g=1}^{G} \pi_g f_g(x_i, \mu_g, \Sigma_g)$$

where $\pi_g = P(Z_i = g)$ and $f_g(x_i, \mu_g, \Sigma_g)$ is a three-dimensional Gaussian density function.

The probability of being in cluster g for each dyad i given the observed metrics, $P(Z_i = g | X_i = x_i)$, also called posterior probability, was obtained as a by-product of the global estimation of the model and is expressed as follows:

$$P(Z_i = g | X_i = x_i) = \frac{\pi_g f_g(x_i, \hat{\mu}_g, \hat{\Sigma}_g)}{\sum_{k=1}^{G} \pi_k f_g(x_i, \hat{\mu}_k, \hat{\Sigma}_k)},$$

where $\hat{\mu}_g$ and $\hat{\Sigma}_g$ stand respectively for the estimated mean in cluster g and the corresponding estimated covariance matrix.

In GMMs, the total number of clusters are chosen according to either statistical selection criteria (mostly likelihood-based) or case-study goals. A three-component GMM structure, i.e. $G = 3$, was chosen in order to obtain higher discrepancies between two extreme dyadic-behaviour clusters by allowing to have a cluster in between corresponding to an intermediate behaviour. This pattern would be consistent with our expectations of joint movement within the pelagic pair trawler fleet: dyads moving together all along, some others joining each other at some moments–like fishing operations, and others moving independently from each other–likely paired with other vessels.

Each covariance matrix Σ_g can be expressed as the product of different components which specify its orientation, shape and volume (see Biernacki *et al.* (2006)). We chose a general GMM structure of 3 dyadic-behaviour clusters allowing for the volume, orientation and shape of the clusters to differ from one another, called Gaussian_pk_Lk_Ck in Biernacki *et al.* (2006).

The GMMs were fitted to the pelagic pair trawlers dataset, composed of 6457 dyads. Parameter estimation was achieved via the iterative EM algorithm. Because EM is known to be sensitive to initial conditions (Dempster *et al.*, 1977), we fitted 30 different GMMs and kept the one that minimised the integrated complete likelihood criterion, using the Rmixmod package (Langrognet *et al.*, 2019) and based on Biernacki *et al.* (2006). From the fitted model, henceforth denoted by $\mathrm{GMM}_{\mathrm{pairtrawlers}}$, we obtained the posterior probability $P(Z_i = g|X_i = x_i)$ of each dyad i to belong to each cluster g given the metric values x_i. We considered that a dyad was classified as part of the cluster g that maximised the posterior probability $P(Z_i = g|X_i = x_i)$. The level of mixture between pairs of clusters in the final model was quantified as the overlapping volume between the tri-Gaussian distributions of each cluster. This index ranges between 0 (no mixture) and 1 full (mixing). High levels of mixture would indicate that the clusters are difficult to distinguish from each other, making the classification poorly relevant.

For each cluster, we computed a global average of the Z-scores (i.e. centred and scaled transformation) of their $(Prox_i, DI_{d_i}, DI_{\theta_i})$-features, and ordered them accordingly. Based on the definitions of the metrics (Joo *et al.*, 2018), the cluster with the highest average was associated to partners at sea behaviour.

The GMM fitted on pelagic pair trawlers ($GMM_{pairtrawlers}$) was then used on each of the other fleets to classify their dyads, into the three identified groups. For each dyad i of the other fleets, we computed $P(Z_i = g|X_i = x_i)$ for $g = \{1,2,3\}$ and assigned the dyad to the most plausible cluster.

Using GMMs provided several advantages compared to other common clustering algorithms. Since it is a model-based clustering approach, we obtained posterior probabilities of belonging to each cluster; it is thus a probabilistic classification instead of a hard classification. The k-means algorithm can actually be seen as a particular case of a GMM: the former optimizes a loss function which could be seen as the negative log likelihood of a GMM with spherical shape and same variance among clusters (Steinley, 2006). The GMM fitted to the pair trawler data allowed for different variances and was not constrained to spherical structures, thus being more flexible than k-means, which should give a better classification performance (Qiu, 2010). Moreover, the EM algorithm used to estimate the parameters in the GMM runs a k-mean algorithm to find a suitable starting point (Bishop, 2006).

Vessel and fleet characterisation

We focused on the dyads of each fleet classified as cluster one, i.e. partners at sea. Their relative importance in the fleets were represented by the proportions of vessels and dyads involved in the cluster. For each fleet, the social relationships between vessels that engaged at least once in partners at sea behaviour were visually represented as a social network (Scott, 1988; Jacoby and Freeman, 2016). The elements of the sociomatrix of the network, i.e. adjacency matrix, represented the number of partner-at-sea dyads between the vessels —that had at least one dyad in the cluster. The Fruchterman and Reingold algorithm was chosen to draw the graph. It positions the nodes of the graph in the space so that all edges are more or less equal length and there are as few crossing edges as possible, aiming at an aesthetic representation (Fruchterman and Reingold, 1991). The igraph package was used for this purpose (Csardi and Nepusz, 2006).

We identified which and how many vessels were exclusive, i.e. only formed partners at sea with one vessel throughout the whole period of study. In the adjacency matrix this corresponded to the rows with 0 everywhere except once. To assess how exclusive were partnerships at the fleet level, a loyalty index was defined as the proportion of vessels that showed exclusiveness in partnership. For this calculation we excluded vessels with only one dyad in the group.

All the R codes for partner-at-sea identification via GMMs and vessel and fleet characterisation are available at https://rociojoo.github.io/partners-at-sea (doi:10.5281/zenodo.4016377)

Results

Pelagic pair trawlers

Table 3. Parameter estimates of GMM for pair trawlers

		Cluster 1	Cluster 2	Cluster 3
π		0.077	0.330	0.593
μ	Prox	0.939	0.204	0.086
	DI_θ	0.928	0.235	0.177
	DI_d	0.915	0.703	0.626
Σ_{ii}	Prox	0.007	0.016	0.003
	DI_θ	0.005	0.063	0.024
	DI_d	0.002	0.004	0.010

Table 4. Correlations between metrics per cluster obtained from Σ estimates of the GMM for pair trawlers

	Cluster 1			Cluster 2			Cluster 3		
	Prox	DI_θ	DI_d	Prox	DI_θ	DI_d	Prox	DI_θ	DI_d
Prox		0.48	0.36		0.46	0.3		0.35	0.1
DI_θ	0.48		0.79	0.46		0.34	0.35		0.47
DI_d	0.36	0.79		0.3	0.34		0.1	0.47	

After pre-processing, 6457 dyads were classified with GMMs. The estimated parameters are shown in Table 3. The correlations between features (Table 4) were not negligible, which supports the joint use of metrics that evaluate different aspects of dyadic movement. There was little overlap between cluster 1 and the other two: 1.9

$\times 10^{-3}$ and 3.7×10^{-10}, between clusters 1 and 2, and 1 and 3, respectively. There was higher overlap (0.32) between clusters 2 and 3. Moreover, most dyads were classified based on high values of their posteriors (1.00, 0.95, and 0.86 as median posteriors for each group, respectively; Fig. 3), and all of them above 0.5.

The three clusters obtained corresponded to distinct levels of joint movement (Fig. 1). The first one (purple in Fig. 1) corresponded to high joint movement in its three dimensions: proximity, coordination in direction and in speed/displacement. This was the expected pattern for partnership at sea. The second one (green in Fig. 1) was associated to a lower degree of joint movement in all dimensions. The third cluster (yellow in Fig. 1) was overall characterised by low proximity, relatively low coordination in direction, and low coordination in displacement. In these two metrics, there was a considerable amount of overlap, with Prox being the metric that made these two groups distinguishable. The tracks of the most representative dyad of each cluster, i.e. the one with the largest $P(Z = g|X = x)$, are shown in Fig. 2. Animations of the trajectories and time series related to the three metrics can be found in https://rociojoo.github.io/partners-at-sea/.

In total, 8%, 26% and 66% of the examined dyads were classified in the first, second and third cluster, respectively (Table 1). The examined dyads were couples of vessel tracks coinciding in a common area at the same time. Not all pairs of vessels that cross their paths should be necessarily working together. On the other hand, most of the vessels of the fleet, 56 (95%), participated at least once in dyads classified as partners at sea. From them, 46 had exclusive partners (Fig. 5), which translated into a 0.82 loyalty index for the fleet.

Dyads from other fleets

In this section, we focused only on the first group, i.e. partners at sea. The proportion of dyads classified in each cluster is presented in Table 1, and examples of dyads in each cluster for all fleets can be found in https://rociojoo.github.io/partners-at-sea/, a companion website for the manuscript.

When using $\text{GMM}_{\text{pairtrawlers}}$ to classify dyads from the other fleets, we found partners at sea in all of them except for tuna purse seiners. In all the fleets, the posterior probabilities computed for classification were relatively high (medians were >0.65 and all posteriors were >0.5; Fig. 3) showing low ambiguity for classification in all groups.

For large, small bottom, mid-water otter trawlers and anchovy purse-seiners, 312, 93, 3 and 568 dyads were classified as partners at sea, respectively (Table 1). In all cases, it represented less than 1% of the examined dyads, showing that vessels in the same area do not always move together, and when they do, they do not do it in large groups.

We compared the distribution of values of the metrics in the first group between pelagic pair trawlers and the other fleets (large and small bottom otter trawlers, and anchovy purse-seiners; Fig. 4). Large bottom otter trawlers showed the most similar shapes of the distributions to pair trawlers, for all metrics, though the values of DI_d were less skewed to the right than for pair trawlers. This difference in skewness for DI_d was also true for the other two fleets. Moreover, 'partners at sea' among anchovy purse-seiners took lower values of all the metrics (more skewed to the left). Since both fleets target pelagic species, one might have expected to find similar metric values for their partners at sea. This difference is not related to the different sampling rate (10 minutes), which we confirmed by re-running the analyses for 60 minute interpolated dyads. It could rather be an indication of a joint movement that does not occur at a dyadic scale, i.e. a couple of vessels that decide to move together; if larger groups were moving together, this pattern would not have necessarily reflected in very high values in the dyadic movement metrics.

The percentage of vessels engaged in at-sea partnership and their exclusiveness varied greatly among fleets (Fig. 5). 38 out of 266 large bottom otter trawlers (14%) showed at-sea partnership at least once, and from them, 19 had exclusive partners (loyalty = 0.54). A larger percentage of small bottom otter trawlers engaged in partnership (26% , or 52 out of 202). From them, 38 had exclusive partners (35 with >1 dyad; loyalty = 0.74). Only 4 out of 70 mid-water otter trawlers engaged in partnership, which was exclusive (loyalty = 1) and only occurred three times. In contrast, 43% of the anchovy purse-seiners engaged in partnership (or 327 out of 757 vessels). 134 of these vessels were exclusive (132 with >1 dyad; loyalty = 0.44). Most anchovy purse-seiners showed joint-movement links with large groups of vessels (Fig. 5d), which would be consistent with the differences in the metrics distribution (Fig. 4).

Discussion

In this work, we aimed at identifying partners at sea in different fleets around the world. We presented a simple heuristic approach to identify them by means of joint movement metrics (Joo *et al.*, 2018), use of Gaussian mixture modelling, and taking pelagic pair trawlers as a 'training' dataset.

Partners at sea were identified in all the examined fisheries, except for tuna purse-seiners. This could be partly explained by the long duration of their fishing trips and large range of movement. While the trip duration in the other fleets ranged between less than a day and four days, tuna purse-seiner fishing trips lasted about 30 or 40 days. Tuna purse-seiners, not bounded to fish together, showed that there was no strategy involving dyadic joint movement throughout their whole trips. However, data exploration showed that some vessels moved together in pairs for parts of their trips (see https://rociojoo.github.io/partners-at-sea/ for an example in group 2). The identification of trip segments associated to joint movement (i.e. redefining a dyad) was out of the scope of this work, and remains open for future research.

Mid-water and small bottom otter trawlers performed equally in terms of trip duration and distances covered. However, the mid-water otter trawler dataset only contained three partners at sea dyads, suggesting that individual competition could be higher in this fleet, or that working together would bring them no benefit, which could be due to their smaller fishing zones or the spatial behaviour of their targeted fish. Compared to mid-water trawlers, a higher percentage of both small and large bottom otter trawlers participated in partnerships, showing that this is a strategy used in these fleets, though it has not been adopted by the majority of the vessels. These three trawler fleets are composed of vessels that engage in fishing activities (métiers) that target demersal or benthic species (fish, crustaceans, cephalopods). From empirical observations, these métiers are likely to require less synchronous collaboration than pelagic métiers. Instead, the observed partner-at-sea behaviours could have been shaped by environmental or physical constraints (e.g. currents, Gloaguen *et al.* (2016)) that the vessels would be facing in the same fishing area at the same time, rather than a collaborative fishing strategy.

A third of anchovy purse-seiners moved in partnership at least once during the analysed fishing season. Though the trips had a short duration (~ 17 hours), the sampling rate from these VMS data was very high (~ 10 minutes). At such resolution, joint movement patterns were identified. In this intensive and highly dynamic monospecific fishery, these findings are somehow a surprise that may be worth studying in more detail in the future. The high number of vessels in this fleet showing joint movement, and the high number of connections displayed in its social network, makes it appealing to study joint movement in larger groups for this fleet.

While it was expected to find partnership in pelagic pair trawlers, the degree of loyalty in this fleet was previously unknown, thus revealing about their partnership strategies. 82% of the vessels (or fishers) opted for exclusive partnerships, and the ones who did not, exchanged partners in very reduced groups. In large and small bottom otter trawlers, the loyalty between vessels involved in the partner at sea cluster was lower; small bottom otter trawlers are involved in larger groups (Fig. 5). Non-exclusive partnerships involved even larger groups in the anchovy purse-seine fleet. These fleets may be revealing two opposed partnership strategies: exclusiveness, which would involve commitment or long-term partnership, and opportunism, in which a vessel would move jointly with another one (or even a group of vessels) without any previous history or commitment. We did not assess the associations between partnerships and belonging to a same company, and it could be appealing for future studies to analyse if this would correspond to a strategy where the ship-owner requires his fishing masters to work together.

This work represents a first approach into studying joint movement behaviour and strategies in fisheries. It highlights the fact that not all trajectories can be considered as independent, an assumption made in most modelling studies (e.g. using state space models; Joo *et al.* (2013); Gloaguen *et al.* (2015)). Furthermore, it could be appealing to apply this approach to select, from a set of trajectories, those that do not show any partnership at sea. This could allow computing Catch per Unit of Effort only drawn from independent fishing operations. It could also be used to evaluate potential errors in modelling fleet dynamics. For instance, one could fit state-space models using independent tracks on one hand and using all the tracks on the other, and compare the goodness of fit of both models –and simulation results –to evaluate the biases in state estimations linked to the dependence between vessels.

In this study, we focused on a very specific scale of joint movement, the dyad, defined as a unit composed of fishing trip segments of two vessels occurring at the same time and in a common area. Studying the strategies of fleets like the tuna purse-seiners could benefit from the development of methods to identify joint movement at smaller scales (e.g. segments of fishing trips). The computation of Prox for each dyad depended on a fixed distance threshold. Here, we made an ad hoc choice of the threshold for each fleet. This choice is not straightforward; more in-depth studies of dyadic movement should focus on sensitivity analysis and the development of an automatic choice of the threshold.

We consider this work as a first approach to studying partnership at sea, with pelagic pair trawlers' joint movement as a starting point. Future studies could focus on other types of partnership at sea, pairwise or not. In many fisheries, like the anchovy purse-seine fishery, the characterisation of joint movement in larger groups could help understanding the scales of collective behaviour in the fisheries. Besides joint movement, leader/following dynamics would also be worth exploring (see a brief discussion in Joo *et al.* (2018)). All of these components would help characterising spatial behaviour patterns, but it would not be enough to understand the triggers of these behaviours. A next step would be to understand the associations between joint movement (or following movement) and external factors such as the spatial aggregation of the targeted species, the direction of currents, or management and economic policies. Ultimately, understanding and modelling fisher movement including its collective components will contribute to better estimations of local exploitation of resources. More realistic movement models would allow better simulations of fisher spatial behaviour and effort for different management scenarios, thus improving decisions for management.

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Authors' contributions

RJ, SM and NB conceived the study. NG gave valuable insights on fishing behaviour at sea that were key to the study design and interpretation of results. RJ led the data processing and analysis, with contributions from PM and JR. MPE suggested and helped implementing the GMM. RJ led the writing of the manuscript. SM, NB and MPE made major contributions to the manuscript, and NG and PM made minor contributions to it.

Data and codes availability statement

The dyads' metrics along with all of the R codes for GMM and computation of the fleet characteristics are available on Zenodo: https://doi.org/10.5281/zenodo.4016377. The codes can also be viewed from https://rociojoo.github.io/partners-at-sea/data-processing-and-analysis.html. Due to confidentiality agreements, the raw VMS data cannot be shared.

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Figure captions

Fig. 1. Histograms of the joint movement metrics for the three clusters (in purple, green and yellow) for pelagic pair trawlers. It should be noted that only DI_θ ranges from -1 to 1, while Prox and DI_d take values from 0 to 1.

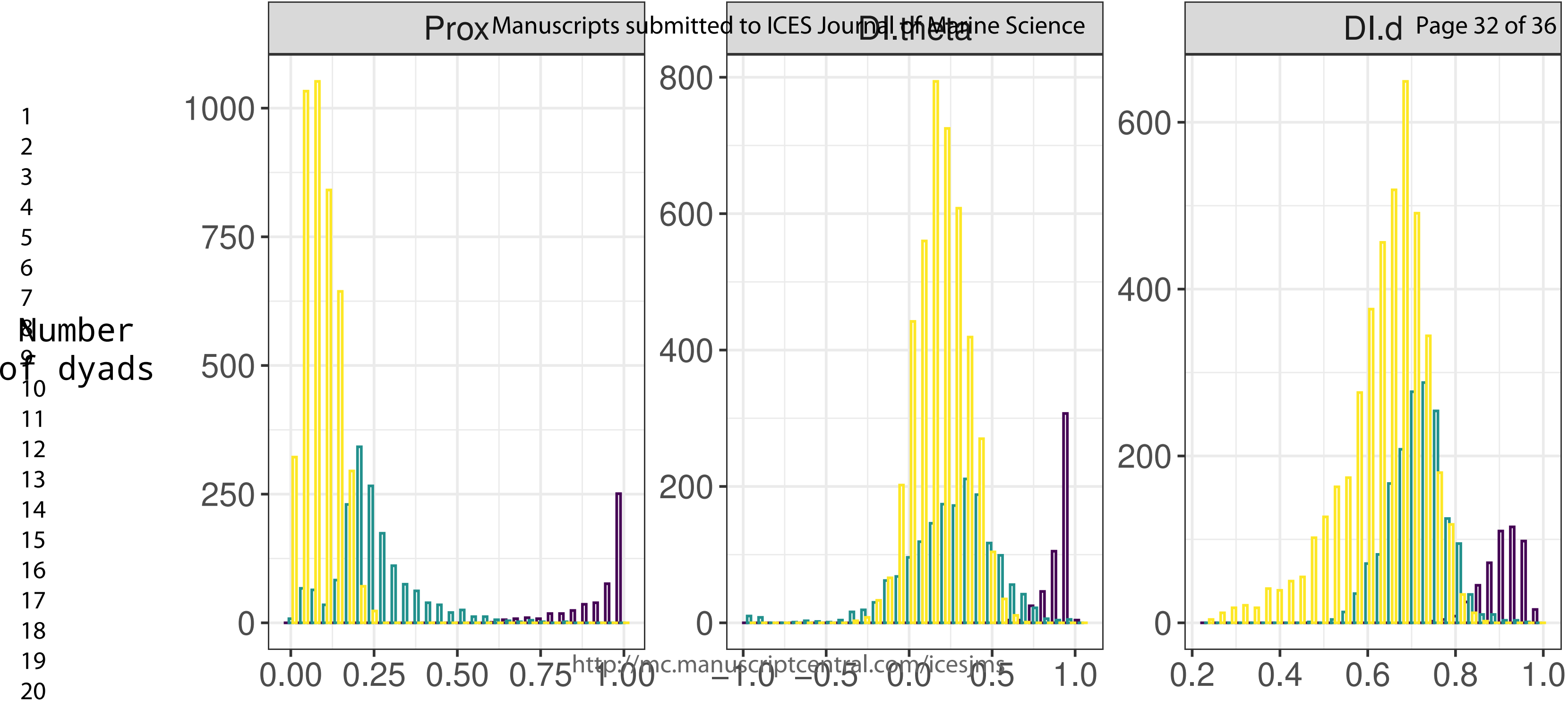
Fig. 2. The most representative dyadic example of each cluster for the pelagic pair trawler fleet, with the values of the metrics. The coordinates were transformed to avoid disclosing information about the vessels, whose identifiers are not shown either. a: Dyad from cluster 1. Prox = 1; $DI_\theta = 1$; $DI_d = 0.98$. b: Dyad from cluster 2. Prox =

0.57; $DI_\theta = 0$; $DI_d = 0.69$. c: Dyad from cluster 3. Prox = 0.06; $DI_\theta = -0.07$; DI_d = 0.24

Fig. 3. Boxplots of the posterior probabilities $P(Z_i = g|X_i = x_i)$ of each dyad i classified in each group. a: Pelagic pair trawlers. b: Large bottom otter trawlers. c: Small bottom otter trawlers. d: Mid-water otter trawlers. e: Tuna purse-seiners. f: Anchovy purse-seiners.

Fig. 4. Histograms of the joint movement metrics (Prox, DI_θ, and DI_d, in the left, centre and right columns, respectively) for the first group or partners at sea, comparing the pelagic pair trawlers (blue) with each of the other fleets (mustard). The other fleets are, in row order from top to bottom: large bottom otter trawlers, small bottom otter trawlers and anchovy purse-seiners. Tuna purse-seiners and mid-water otter trawlers are not shown as no dyad and only three dyads, respectively, were associated with partnership.

Fig. 5. Network representation of partnership for the pelagic pair trawlers (a), small bottom otter trawlers (b), large bottom otter trawlers (c) and anchovy purse-seiners (d). Tuna purse-seiners and mid-water otter trawlers are not shown as no dyad and only three dyads, respectively, were associated with partnership. Within each network, only vessels that engaged in partnership at sea at least once were represented. The size of the nodes (vessels) are proportional to the number of times they were involved in partnership. The thickness of the lines between nodes are proportional to the number of partnerships between both nodes.


Prox
DI.theta
DI.d
Number of dyads
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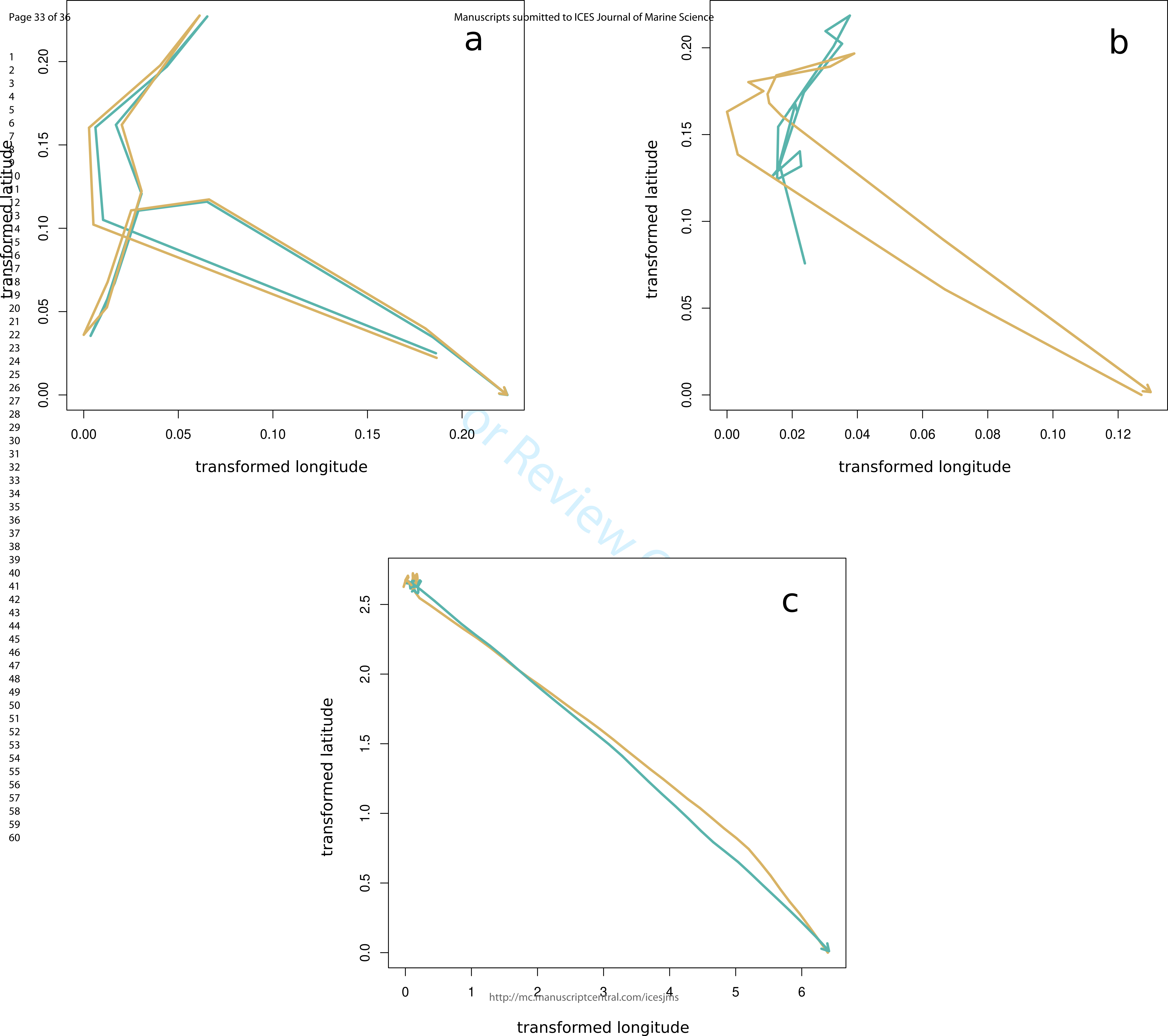
500
250
0
0.00
0.25
0.50
0.75
1.00
800
600
400
200
0
−1.0
−0.5
0.0
0.5
1.0
600
400
200
0
0.2
0.4
0.6
0.8
1.0


a
transformed latitude
transformed longitude
0.00
0.05
0.10
0.15
0.20
b
transformed latitude
transformed longitude
0.00
0.02
0.04
0.06
0.08
0.10
0.12
c
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2.0
2.5
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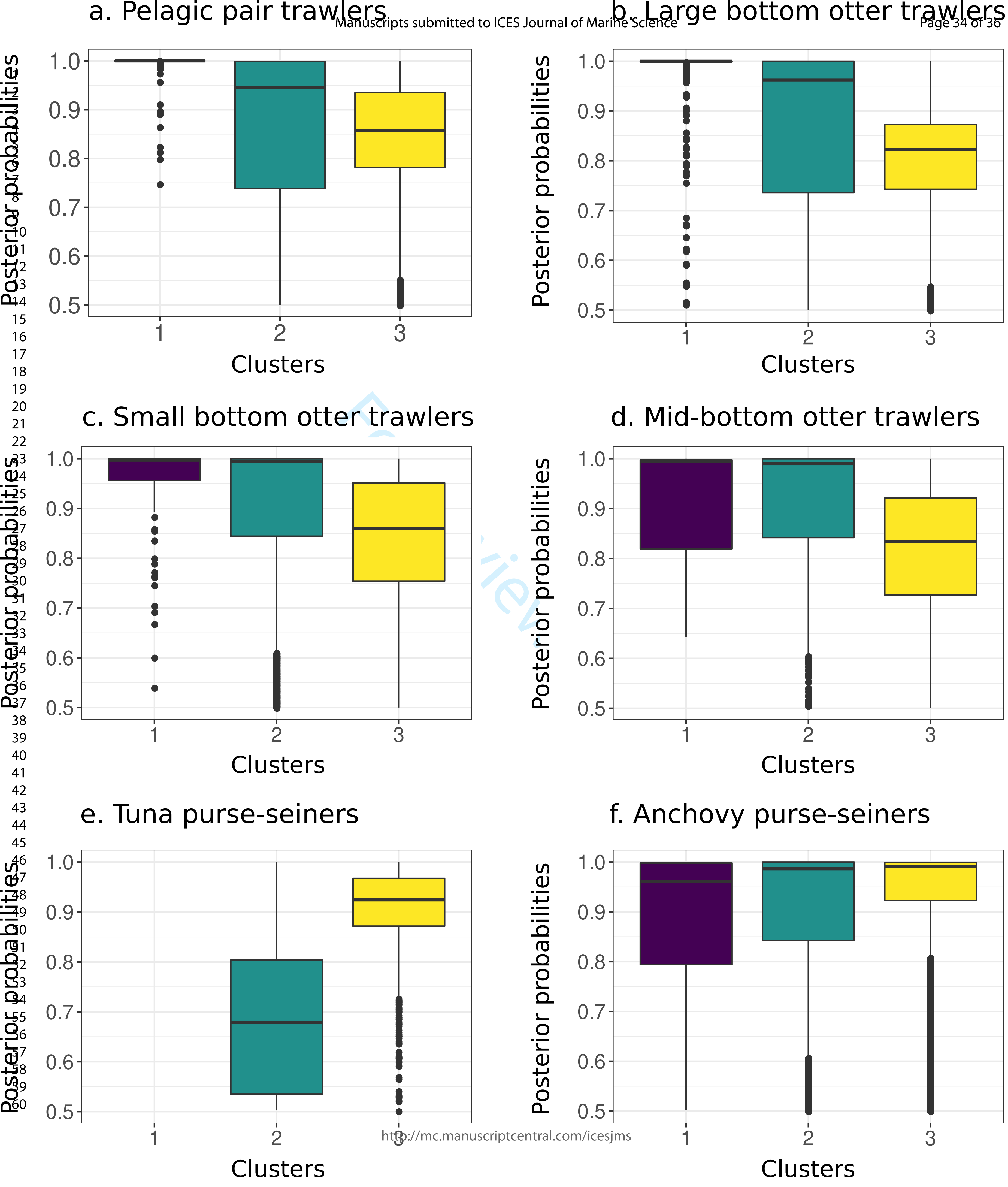
3
4
5
6


a. Pelagic pair trawlers
b. Large bottom otter trawlers
c. Small bottom otter trawlers
d. Mid-bottom otter trawlers
e. Tuna purse-seiners
f. Anchovy purse-seiners
Posterior probabilities
Clusters
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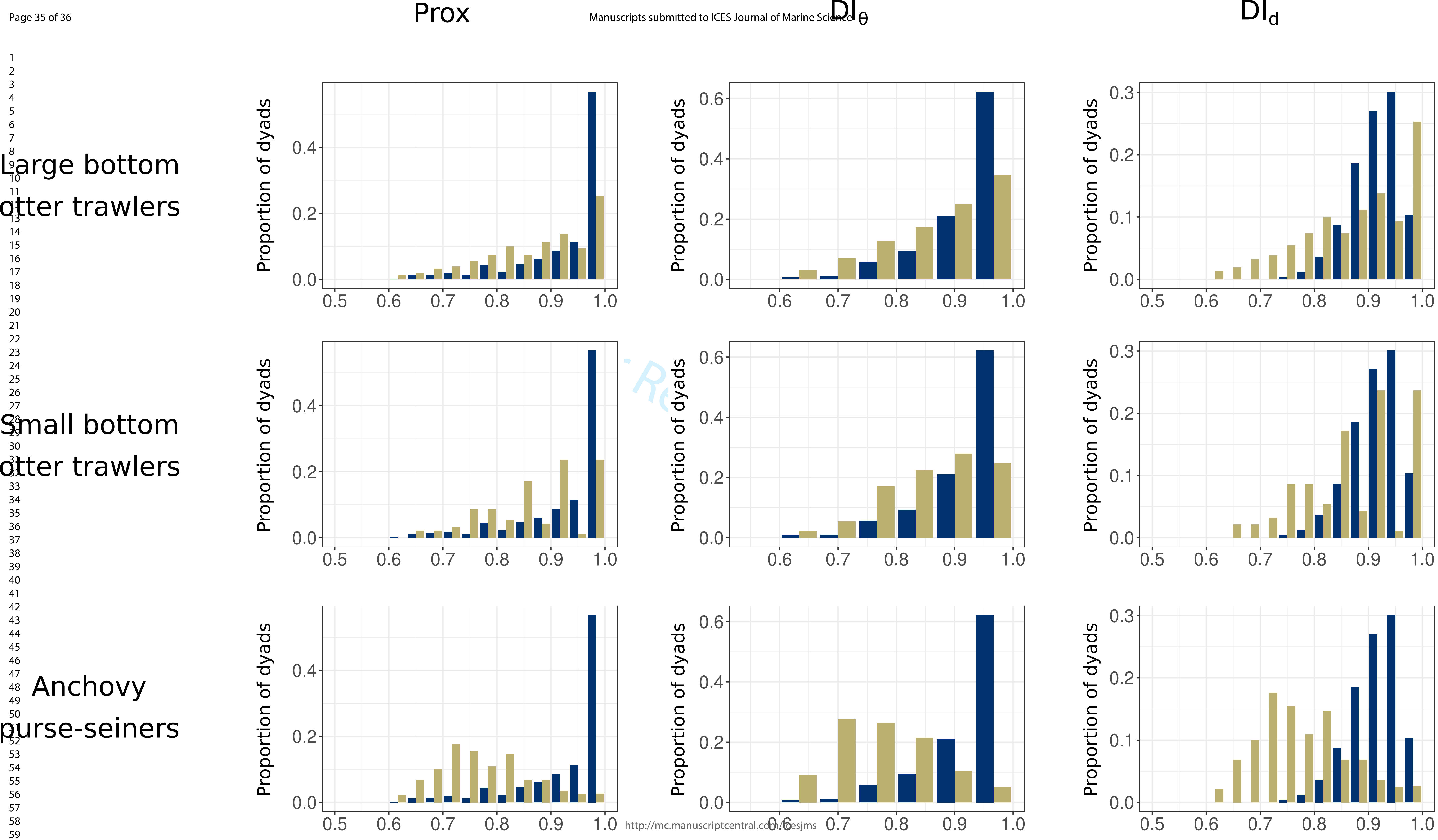
0.9
0.8
0.7
0.6
0.5
1
2
3


Prox
DI$_\theta$
DI$_d$
Large bottom otter trawlers
Small bottom otter trawlers
Anchovy purse-seiners
Proportion of dyads
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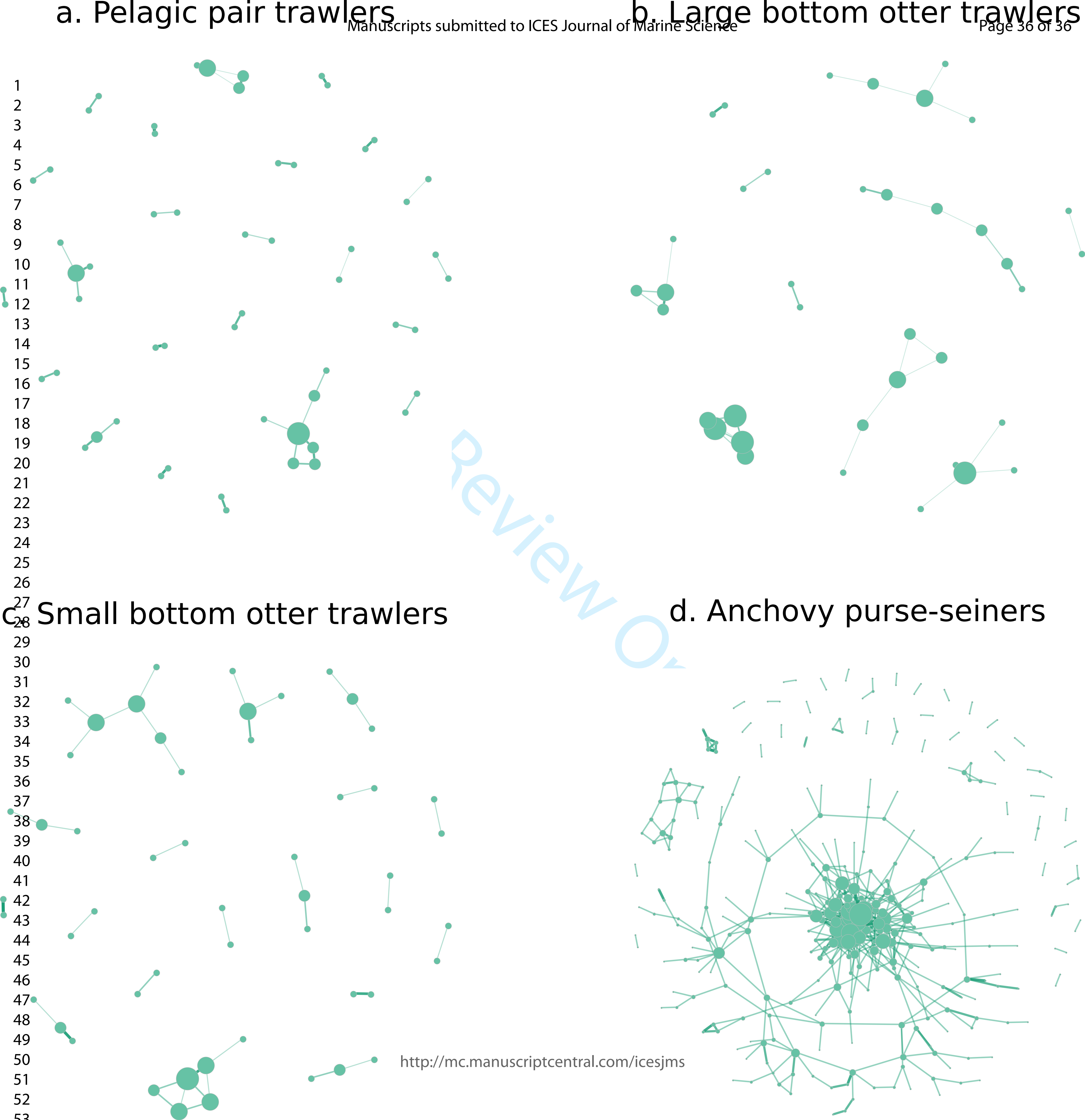
0.4
0.6
0.1
0.3
0.5
0.6
0.7
0.8
0.9
1.0


a. Pelagic pair trawlers
b. Large bottom otter trawlers
c. Small bottom otter trawlers
d. Anchovy purse-seiners