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Defining fishing spatial strategies from VMS data: Insights from the world's largest monospecific fishery

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ABSTRACT

Understanding the spatiotemporal behavior of fishermen at the fleet scale is key for defining effective strategies for fisheries management. Here we classify the spatial patterns exhibited by fishing trip trajectories in the world's largest monospecific fishery, the Peruvian anchovy fishery. Our goal is to identify spatial strategies and their possible changes over 2000–2009. The data comprise more than 350,000 fishing trips, recorded using a vessel monitoring system. On-board observers monitored a small fraction of those trips (>2000), providing data for inferring the type of activity (fishing, searching, and cruising) from the position records, for use in a state-space model. Each fishing trip was characterized by its duration, maximum distance to the coast, geographical extension, and time spent fishing, searching and cruising. Using clustering techniques, we identified four types of fishing trips, associated with differences in management among regions, fleet segments, and skippers' behavior. The methodology could be used to investigate fishing spatial strategies using VMS trajectories in other fisheries.

1. Introduction

Understanding fishermen's spatial behavior and fishing effort is essential to the design of fisheries management systems (Salas and Gaertner, 2004; Wilen, 2004; Babcock et al., 2005; Garcia and Cochrane, 2005). Fishermen's spatial behavior results from external stresses (*e.g.*, biotic and abiotic conditions, management rules, economic incentives) and 'internal' factors (*e.g.*, skippers' skill and personality, characteristics of the vessels), which are reflected to some extent in the geometry of the fishing trip track. The characterization of fishermen's movement patterns at the scale of a fishing trip has been made easier by the implementation of vessel monitoring systems (VMS). However, to date this technology has only been used for discriminating métiers[1] (Russo et al., 2011).

The Peruvian anchovy (*Engraulis ringens*) fishery provides an opportunity to compare fishing strategies and tactics, as defined in Salas and Gaertner (2004), which for simplicity will be called strategies. This very large fishery (4–9 million tons landed each year over the last decade, Fréon et al., 2008; SOFIA, 2014) involves a single purse seine métier, subject to the intense environmental variability of the Northern Humboldt Current System (NHCS) over multidecadal to intraseasonal timescales (Chavez et al., 2008). This environmental variability determines the extent of the tridimensional anchovy habitat (Bertrand et al., 2004, 2011), which in turn affects fish availability for fishermen (Bertrand et al., 2008; Joo et al., 2014) and leads to adaptations in fishing strategies.

In addition, neo-liberal economic policies during 1990–2000 and the recovery of the stock after the 1982–1983 El Niño provided an opportunity for a rapid expansion of fishing capacity: reduced

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[1] A group of fishing operations targeting a specific assemblage of species, using a specific gear, during a precise period of the year and/or within a particular area (*e.g.* Deporte et al., 2012).

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tariffs and import restrictions, relaxed domestic price controls and fewer constraints on foreign investment encouraged investment in vessels and plant modernization and construction (Aguilar Ibarra et al., 2000; Aranda, 2009). Moreover, in 1998, the Peruvian government promulgated a law authorizing owners of wooden vessels larger than 30 m^3 of fish-hold capacity to join the pelagic industrial fleet. Since then, the industrial fleet has been composed of two segments: a steel fleet (vessels made of steel and with at least 120 m^3 of fish-hold capacity; Aranda, 2009) and a wooden fleet (wooden-hulled and between 30 m^3 and 119 m^3 of fish-hold capacity). During the last decade, the number of vessels operating in the fishery increased substantially, reaching a peak of ∼1200 active vessels by day in 2006 (Fréon et al., 2008). Overcapacity, together with an open-access management regime, made the race for fish more intense, increasing the pressure on anchovy and leading to a reduction in the length of the fishing season (the total allowable catch was attained in fewer days each year; Fréon et al., 2008). Starting in 2009, individual vessel quota allocations (IVQs) were implemented in the anchovy fishery, with the aim of stopping the race for fish. They had an immediate effect, lengthening the annual fishing season and reducing the total number of active vessels (Tveteras et al., 2011).

The management of the anchovy fishery is adaptive on short time scales to cope with environmental, biological and fishing effort variation. For instance, when juveniles account for more than 10% of the catches in a given port, landings may be prohibited in that area within two days (Arias Schreiber et al., 2011). Decisions on opening and closure dates for fishing seasons (usually there are two fishing seasons per year) are also made on short time scales. Moreover, there are distinct management policies for the north-center (from 3° S to 16° S) and south regions (from 16° S to the frontier with Chile). Catch shares are established independently for each region; the fishing season is longer in the south than in the north-center; and, during the last decade, the ban on fishing within the first few nautical miles from the coastline was set to 5 nm in the north-center region, while it varied between 1.5 nm and 3 nm in the south.

The spatial behavior of Peruvian anchovy fishermen might be shaped by all these elements. Patterns of fishermen's trajectories can be investigated from VMS data. From time series of vessel positions, it is possible to derive fishing trip descriptors such as duration, distance traveled, maximum distance to the coast and time spent fishing, among others. In Peru, VMS has been mandatory for the industrial pelagic fleet since 2000. In practice, while the steel fleet was almost entirely covered with VMS by 2000, the coverage of the wooden fleet was much more gradual. Here we analyzed 352,711 fishing trips monitored by VMS during the period from 2000 to 2009, from which a set of descriptors were computed. By means of a hierarchical cluster analysis, we study how the trips associate into groups without establishing *a priori* the number of clusters. We then examine which factors determined those clusters of contrasted spatial strategies.

2. Materials and methods

2.1. Data and pre-processing

We used VMS positioning records from the Peruvian anchovy industrial fleet corresponding to the decade 2000–2009 (∼100 m of accuracy; ∼1 record per hour; Table 1 and Fig. 1). Pre-processing of raw VMS data was performed based on the criteria and algorithms described in Bertrand et al. (2005, 2007) and Joo et al. (2011). For each fishing trip, we first computed the following seven global metrics: duration (Dur), total distance traveled (Dist), maximum distance from the coast (Max.DC), maximum and minimum latitudes reached during the trip (Lat.Max and Lat.Min, respectively), and maximum and minimum longitudes reached during the trip (Lon.Max and Lon.Min, respectively).

A complimentary source of information on ∼1% of the fishing trips was provided by an on-board observer program run by the Peruvian Marine Research Institute (IMARPE). Observers record the location and time of three main activities occurring during the trips: fishing, searching and cruising. In order to infer the activities for the remaining 99% of the VMS-tracked fishing trips, a supervised hidden semi-Markov model was trained and validated using the on-board observer dataset (Joo et al., 2013). This model used speed and speed variation between VMS records to infer the activities. The sample size used for training and validating the model consisted of 2070 fishing trips (only a subsample of 242 was used for Joo et al., 2013). The model reached a mean accuracy of 79% in the determination of the activities from the VMS data. From the reconstructed sequences of activities performed during the fishing trips, we computed seven additional metrics: the time spent searching (Time.Searching), fishing (Time.Fishing) and cruising (Time.Cruising), the proportion of time spent on each of those activities with respect to the duration of the trip (Prop.Searching, Prop.Fishing and Prop.Cruising, respectively) and the time spent from the beginning of the trip until the first fishing set (Bef.Fishing). Hence, we had a total of 14 metrics describing fishing trips.

2.2. Classification analyses

The 14 metrics describing fishing trips were standardized (Z-scores). As a first step, we carried out a principal component analysis (PCA) (Pearson, 1901; Jolliffe, 2002). Variables with strong correlations among them (Pearson correlation coefficient $r > 0.7$) and singular matrix problems were not used for PCA computation and rather used as supplementary variables, having no effect on the loadings of the active variables. We used PCA for (i) removing the noise in the data by eliminating the last dimensions; (ii) retaining only the components that we are able to interpret; and (iii) learning more about the interaction between variables (Husson et al., 2010; Deporte et al., 2012). Raîche et al. (2013) performed a comparison of nongraphical solutions for determining the number of components to retain *via* simulations. They found that Zoski and *Jur's b* coefficient of regression index (Mreg) and Cattell–Nelson–Gorsuch CNG indices (Cng) led to the smallest biases and variability when choosing the number of components. We used both criteria. A hierarchical clustering was then carried out over the first principal components (Husson et al., 2010). This method organizes partitions in a dendrogram (*i.e.*, a tree structure) and partitions can be seen at different levels of granularities (*i.e.*, refine/coarsen clusters) using different numbers of clusters, which provides a better understanding of the data. The dendrogram was constructed using Ward's minimum variance method (Johnson and Wichern, 2007) and the Euclidean distance function.

Statistical analyses were performed with R software (R Core Team, 2014). FactoMineR package (Husson et al., 2014) was used for PCA, nFactors (Raîche, 2010) for choosing the number of components and Rclusterpp (Linderman, 2013) for the hierarchical clustering.

3. Results

For the PCA, not all variables were used as active variables. Dist, Lat. Max and Lon. Min were only used as supplementary variables since they were highly correlated to other active variables: Dur ($r = 0.89$), Bef.Fishing ($r = 0.74$) and Time.Cruising ($r = 0.73$), Lat.Min ($r = 0.97$) and Lon.Max ($r = 0.96$), respectively. Moreover, when comparing absolute times and proportions in each activity as active variables, absolute times were more closely correlated

Table 1
Statistics of fishing trips per year: absolute frequency (number of trips), relative frequency (percentage of trips) and percentage of trips corresponding to wooden-made vessels.

	Number of trips	Percentage of trips (from the total of trips in the dataset)	Percentage of wooden-vessel trips (from the trips occurred in each year)
2000	28,807	8.2	0.5
2001	26,176	7.4	1.1
2002	44,429	12.6	0.7
2003	30,764	8.7	1.6
2004	43,648	12.4	8.9
2005	41,518	11.8	27.7
2006	31,018	8.8	37.6
2007	30,606	8.7	42.0
2008	36,143	10.2	42.5
2009	39,602	11.2	53.2
Total	352,711	100.0	22.0

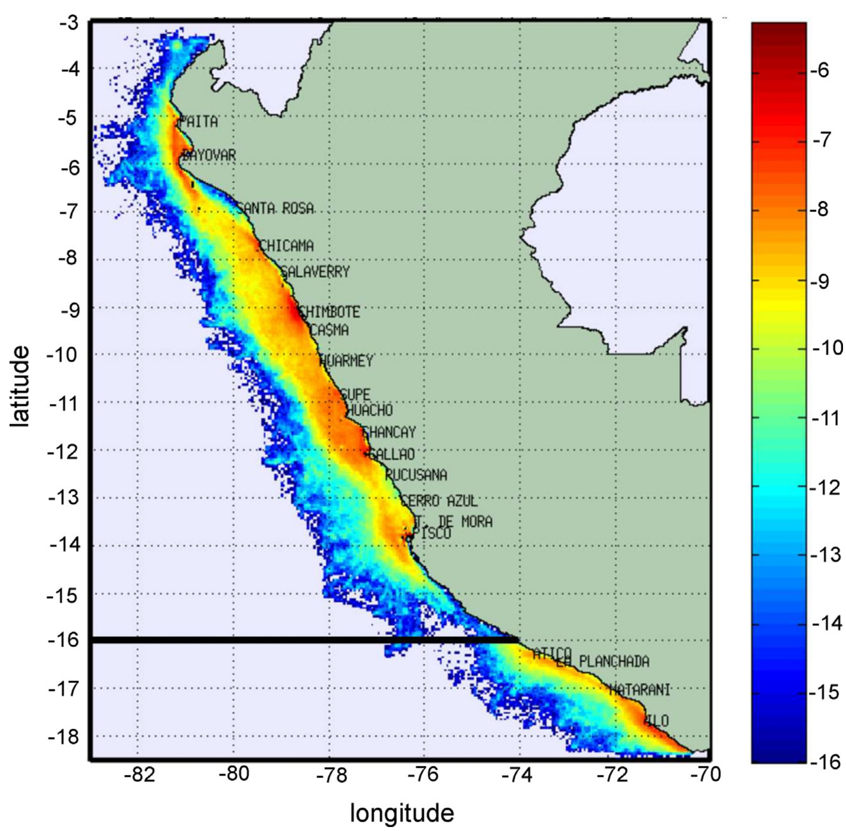

Fig. 1. VMS positioning records from 2000 to 2009. The colors correspond to the values of the log-transformed spatial density of the VMS records. The thick black line represents the division between the north-center (above the line) and the south management regions (below the line).

to the principal components, so we used absolute times as active variables. In addition, the sum of Time.Cruising, Time.Fishing and Time.Searching for each trip is equal to Dur, and no variable should be expressed as a linear combination of others. For that reason, we discarded Time.Searching, since searching was the most difficult activity to infer with the hidden semi-Markov model (67% accuracy; Joo et al., 2013). Overall, Dur, Lat.Min, Lon.Max, Max.DC, Time.Fishing, Time.Cruising and Bef.Fishing were retained as active variables and the other variables were used as supplementary variables and projected into the PCA space (Fig. A.1 in Appendix A). The Mreg and the Cng criteria determined different numbers of components, 4 and 3, respectively. We retained the first three components since they were the ones we could interpret. The first component, which accounted for 45% of the variance, was strongly correlated with Dur, Dist, Time.Cruising, Bef.Fishing and Max.DC (Table 2). It separated long and offshore trips from short and inshore trips. The second component, accounting for 28% of the variance, explained

Table 2
Significant correlations between the variables and the principal components ($p < 0.05$). Supplementary variables are in italic. Correlations above 0.70 are in bold.

	PC1 (45%)	PC2 (28%)	PC3 (14%)
Dur	**0.94**	−0.07	0.26
Dist	**0.93**	−0.18	−0.10
Time.Cruising	**0.87**	−0.19	−0.23
Bef.Fishing	**0.74**	−0.20	−0.41
Max.DC	**0.73**	0.01	−0.23
Time.Fishing	0.59	0.10	**0.78**
Time.Searching	0.39	0.02	0.29
Prop.Cruising	0.35	−0.25	−0.55
Lat.Max	0.27	**0.94**	−0.11
Lat.Min	0.14	**0.98**	−0.08
Lon.Max	−0.19	**−0.97**	0.11
Prop.Fishing	−0.19	0.26	**0.72**
Prop.Searching	−0.22	0.08	0.12
Lon.Min	−0.33	**−0.93**	0.14

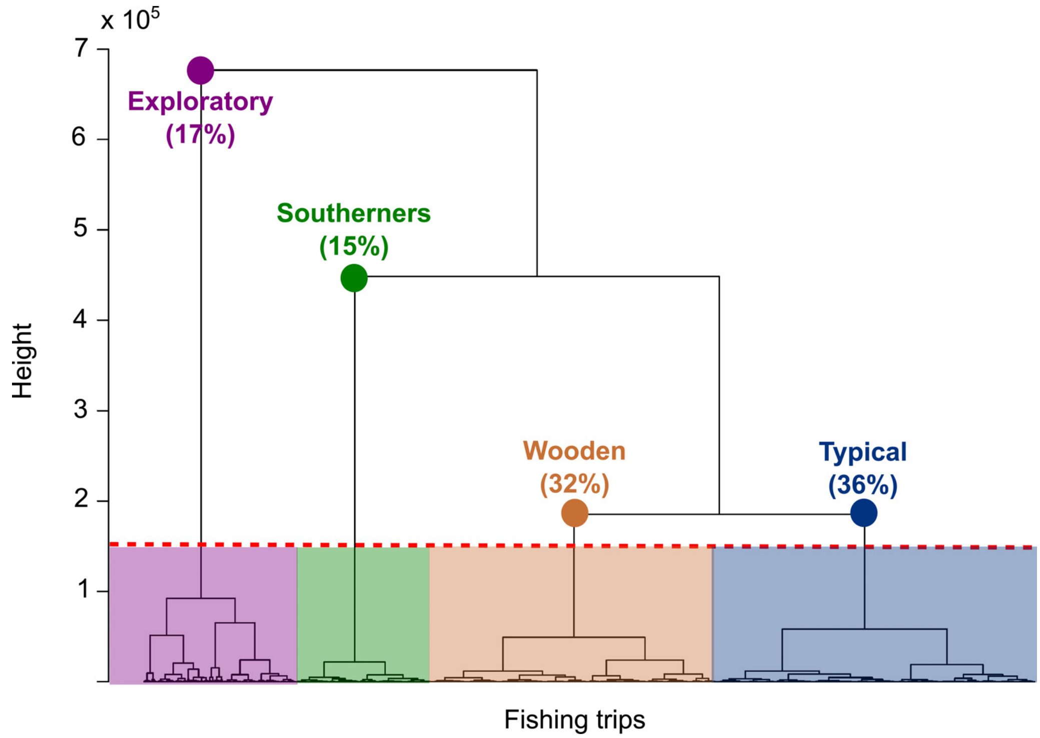

Fig. 2. Dendrogram from the hierarchical cluster analysis. The dotted line represents the pruning level. For each cluster, an associated label and percentage of fishing trips are shown. The height corresponds to the increase within-cluster computed in Ward's method (Husson et al., 2010).

the geographical location. High values on this axis corresponded to northern fishing trips. The third component, which accounted for 14% of the variance, could be interpreted as a fishing effort proxy. High values in this axis were associated with long time spent fishing (in absolute time and in proportion to the duration of the trip). Overall, the three components explained 87% of the variance.

HCA was then performed over the scores corresponding to the three components. The Hartigan index (Hartigan, 1975) gave six as the optimal number of clusters, but not all of them had a clear interpretation for fisheries. Thus, based on this argument and on the computed dendrogram (Fig. 2), the 4-cluster structure was kept; it represented 61% of the explained variance (*i.e.*, the percentage of total variance represented by the between-cluster variance; Husson et al., 2010;Fig. 3). Each cluster contained fishing trips from all years (Table A.1 in Appendix A). Boxplots of each descriptor display the differences among clusters (Fig. 4).

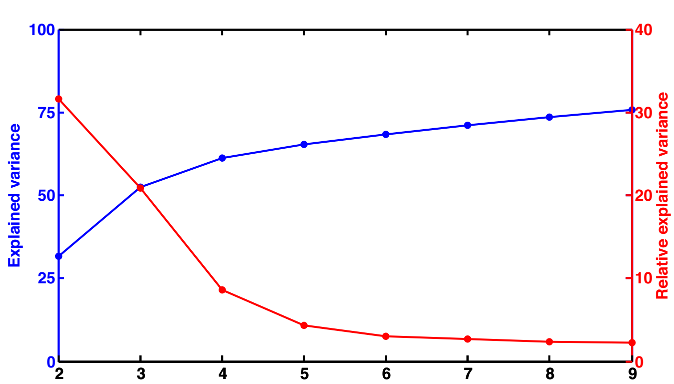

Fig. 3. Variance plot from hierarchical cluster analysis. For each number of clusters (x-axis), the left y-axis represents the percentage of explained variance, and the right y-axis represents the increase in the percentage of explained variance in relation to the preceding number of clusters.

The largest cluster was composed of 36% of the fishing trips. Trips associated with this cluster had average distance traveled, duration and maximum distance from the coast. Most of those fishing trips operated between latitudes of 9° S and 13° S. This cluster contained higher proportions of fishing trips from the 2000–2005 period than the other clusters (between 38% and 45% of trips of those years belonged to this cluster; Table A.2 in Appendix A).

A second cluster was composed of 32% of the fishing trips, and was mostly related to short and relatively inshore trips. Those trips had the highest proportions of time spent fishing and searching and the lowest in cruising. They mostly operated at northern latitudes (between 7° S and 9° S). 75% of the fishing trips corresponding to wooden vessels were included in this cluster (Table A.2 in Appendix A). Besides, this cluster contained the highest proportions of fishing trips from the years 2006–2009 (between 40% and 49% of the trips of those years belonged to this cluster; Table A.2 in Appendix A). Those 2006–2009 fishing trips constituted 56% of the total trips in the cluster (Table A.1 in Appendix A).

A third cluster comprised 17% of the fishing trips. It contained the longest trips with the largest distances to the coast. The highest fishing, searching and cruising absolute duration were also associated with this cluster (Fig. 4). This cluster mostly involved trips concentrated at the central latitudes (between 8° S and 12° S), though some trips also operated in all the other latitudinal zones off Peru. From the 1264 fishing vessels under study, 29% had at least 20% of their trips associated with this cluster, and 70% of the vessels had at least 5% of their trips in this cluster.

A fourth cluster was composed of 15% of the fishing trips. It was mostly associated with fishing trips from the south region (almost 100% of southern trips; see Table A.1 in Appendix A), operated in fishing grounds quite close to the coast.

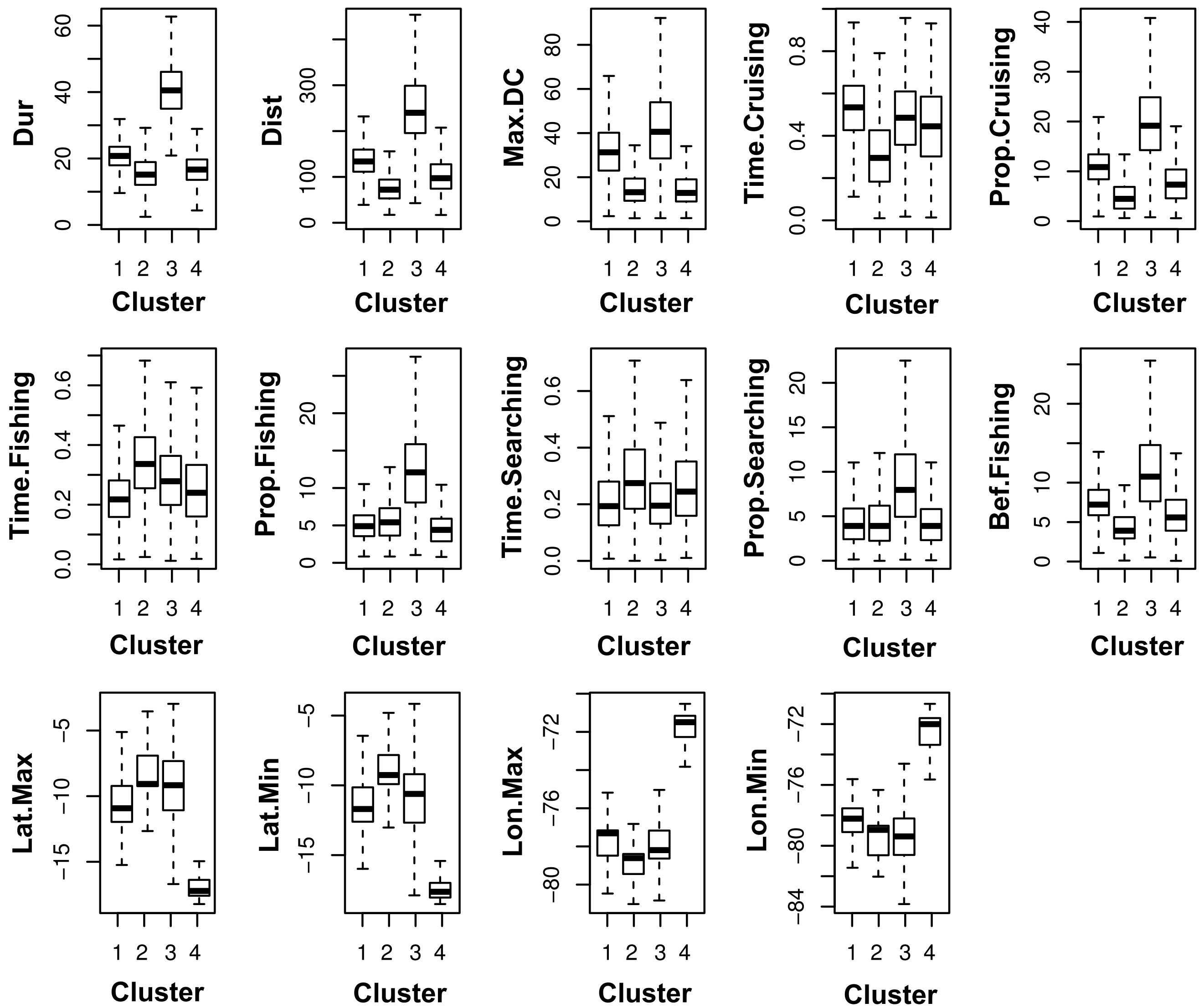

Fig. 4. Boxplots for each fishing trip descriptor and each cluster (*x*-axis).

4. Discussion

From the classification of the 352,711 fishing trip tracks, four clusters emerged (Fig. 5). They were mostly explained by fleet characteristics, skipper behavior and regional management rules.

The first and largest cluster, labeled ‘typical’, presented the most common features of the Peruvian anchovy fishing industry: the trips were made by vessels with steel hulls in the north-center region, without outstanding duration or distances.

The second cluster comprised more than 75% of the trips performed by vessels with wooden hulls and was therefore labeled ‘wooden’. This cluster comprises mostly short coastal trips and a high percentage of trips from 2006 to 2009. From 2005, both the number of wooden vessels in the fishing industry (IMARPE, 2013) and their coverage rate by VMS increased. The concentration of fishing trips of this cluster between 7° S and 9° S matches the spatial distribution of wooden vessels in the most recent years. This clustering identification supports the evidence shown by random walk modeling (Bertrand, pers. comm.) that wooden and steel vessels present different spatial strategies: steel vessels tend to exhibit more diffusive behavior and explore wider areas than their wooden counterparts. Since wooden vessels are smaller, they are more limited in fish-hold capacity, gear size, fuel consumption and fish detection technology. Thus, they are expected to stay inshore, and they spent most of their time at sea fishing and searching rather than cruising. Some steel vessels were included in this cluster. This demonstrates that there were steel vessels that tried to optimize their effort by making short coastal trips and spending most of their time in the fishing grounds, *i.e.*, ‘wooden-like’ behavior.

The third cluster gathered the most exploratory trips, mainly performed by the steel vessels that were better equipped than wooden vessels for long trips at sea. The habitat of anchovy is restricted to the cold coastal waters, which generally do not extend beyond 20–35 nm from the coast (Swartzman et al., 2008). The potential fishing grounds are thus restricted to a relatively narrow coastal fringe, limiting the need for far offshore exploration. Yet, anchovy is both pelagic (*i.e.*, constantly moving, *e.g.*, Peraltilla and Bertrand, 2014) and gregarious (the probability of finding a school close to another school is higher than anywhere else, *e.g.*, Fréon and Misund, 1999). The challenge for the fleet thus consists in locating clusters of schools within the cold coastal water domain. Once a cluster is located, information transfer among vessels (either between friends or by spying competitors during the race for fish) allows a quick and efficient exploitation of this gregarious fish, greatly limiting the need for exploratory behavior at the fleet scale. This functioning is similar to the ‘scrounger’ or ‘exploiter’

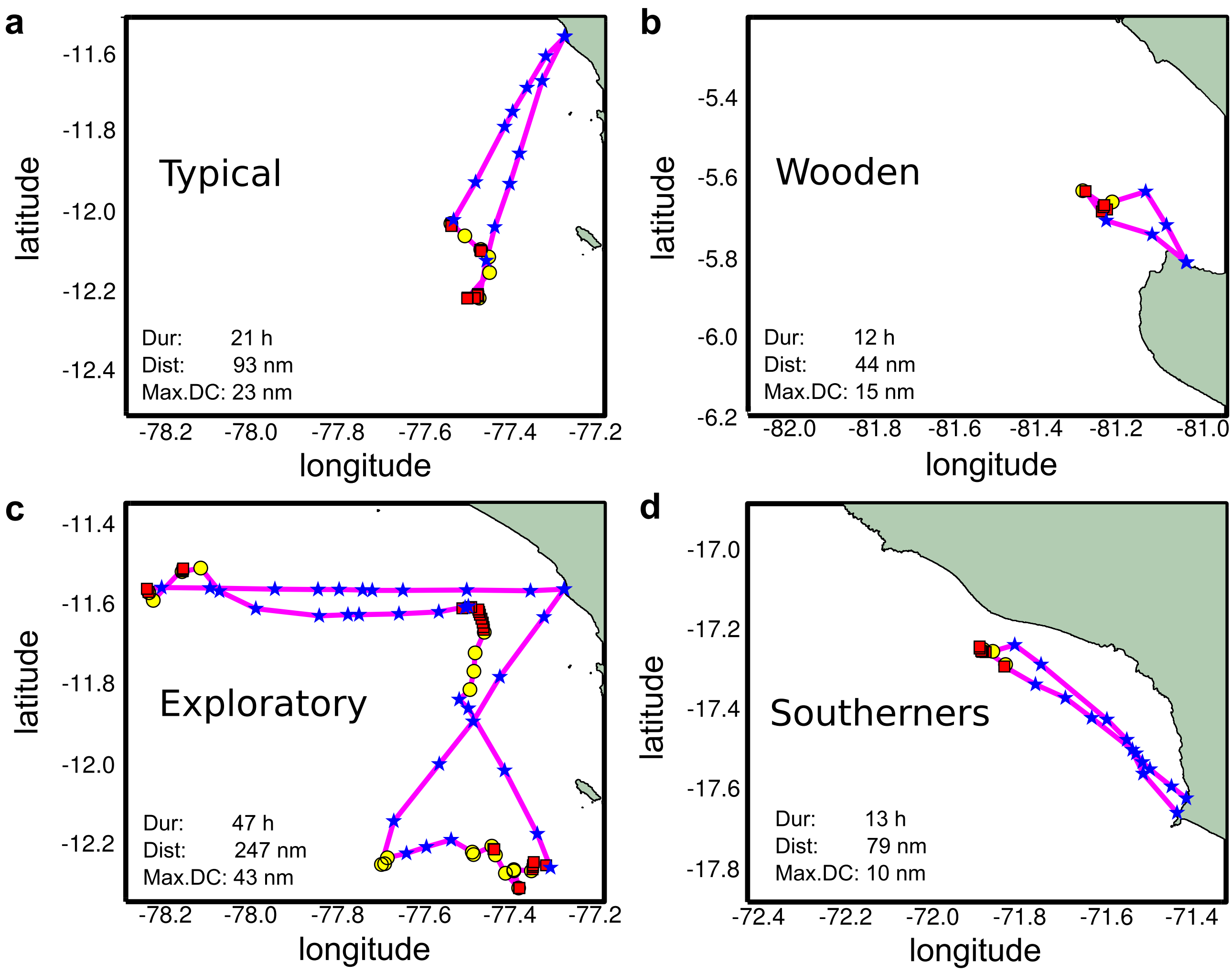

Fig. 5. A fishing trip example associated with the first cluster (a), the second cluster (b), the third cluster (c) and the fourth cluster (d). Red squares, yellow circles and blue stars represent fishing, searching and cruising positioning records, respectively. Dur: duration of the trip; Dist: distance traveled; Max.DC: maximum distance to the coast. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

behavior that has been described in animal populations where foragers use other foragers to make decisions instead of searching for prey on their own (Tania et al., 2012). Yet, anchovy accessibility near the coast could be reduced due to either environmental conditions, such as strong upwelling extending the cold coastal waters domain to >100 nm (Swartzman et al., 2008), or local and temporary depletions due to fishing removals in the less distant coastal zones (Bertrand et al., 2012). In those cases, some fishermen may need to explore the domain more widely to locate farther or more dispersed anchovy clusters. A small proportion of the 'exploratory' trips was performed by wooden vessels. While most of the steel vessels are owned by fishing companies, favoring the risk-adverse and collective exploitation strategies described above, wooden vessels are mostly owned by small entrepreneurs, so their strategies are more individually than company based. Most of the adopted strategies are scrounger-like to cope with their infrastructure and technological disadvantages, placing their trips in cluster 2. However, some of them may adopt risk-taking strategies (Allen and McGlade, 1986), which are poorly sustained by existing information.

The fact that almost half of the vessels performed a few exploratory trips shows that exploratory behavior may strongly respond to environmental/management conditions. On the other hand, a few vessels performed exploratory trips more systematically than others, which could indicate skipper behavior as a strong driver for fishing strategies. In synthesis, while the first and second clusters may include exploiter-like strategies (conservative collective or individual strategies), this third cluster may provide evidence for exploratory behavior, which should be explicitly studied in future work.

The fourth cluster, labeled 'Southerners', emerged as a direct consequence of the specific management policy implemented in the south region: very short fishing closures and lesser coastal fishing restrictions (until 2009, between 1.5 nm and 3 nm instead of 5 nm in the north-center). With anchovy usually distributed close to the coast and with fewer coastal restrictions for fishing, fishermen tend to stay near the coast to minimize effort (less fuel consumption and fewer hours per trip). For these reasons, fishing trips in this region were typically inshore and lasted less time than in the north-center region. The percentage of fishing trips associated with this cluster, 15%, matched the average percentage of fishing trips performed in the south region between 2000 and 2008 (also 15%), computed from landing data (Bouchon, pers.comm.).

Finally, individual quotas were implemented in the fishery in 2009 in order to control the race for fish. We expected the 2009 trips to possibly emerge as a specific cluster. Those trips were actually distributed into two clusters ('wooden' and 'typical'), suggesting that there were no great changes, at least immediately, in fishermen's movement patterns and strategies when this management rule was introduced. Interviews with fishermen and fleet managers support the idea that they have been adapting progressively to the regulation context.

In this work, we explored fishing trip heterogeneity in the world's largest monospecific fishery. Previous studies involving statistical classification methods for fishing strategies and behavior (*e.g.*, Pelletier and Ferraris, 2000; Palmer et al., 2009; Andersen et al., 2012; Deporte et al., 2012; Winker et al., 2013) were applied on multispecific fisheries, and mostly aimed at the identification of métiers. Here, we were able to study fishing strategies from vessels targeting a single species, *i.e.*, without a métier effect. For the Peruvian anchovy fishery, we found that skipper behavior, fleet segmentation and management regulations conditioned four main fishing trip strategies. The classification of spatial strategies for such a volume of fishing trips was only possible through the analysis of VMS data. They provided rich and spatially explicit information on fishing trips (*e.g.*, location, duration, distances, among others). The use of a hidden semi-Markov model trained on observers' data for inferring the activities made within the trips, was also key for the analysis. The differences in time spent fishing, searching and cruising contributed to disentangling fishing strategies, particularly for the 'wooden' cluster.

Activities at sea and their related duration were also used in Bez et al. (2011) to analyze fishing strategies (though at a vessel level) in an effort to define an effective fishing effort. Effort is commonly used for assessing fish abundance and mortality. Catch-per-unit-effort (CPUE) needs to be standardized in order to be used as an abundance index in stock assessment models (Maunder and Punt, 2004). A common approach is to use a statistical model (*e.g.*, generalized linear model or generalized additive model) to quantify the effects of the relationships between CPUE and covariates representing possible sources of variations in targeted efforts, such as space and time components, gear, fishing power, fishing behavior and strategies (Marchal et al., 2006; Winker et al., 2013, 2014). Indeed, variation in fishing strategies influence catchability (*i.e.*, the fraction of biomass caught per unit effort; Pelletier and Ferraris, 2000; Winker et al., 2013). The strategies may be introduced in the model in the form of a categorical variable representing the fishing strategy obtained by the clustering procedure or in the form of the principal component scores (Winker et al., 2013). Once the effort is standardized, its correlation with fish mortality should also increase (Marchal et al., 2006).

The incorporation of the environmental, biological and management contexts – in the form of covariates or as factors whose effect could be tested *via* design of experiments – could provide new insights for fisheries management in future studies. Understanding fishermen's behavior and strategies in different ecological conditions is a major step toward predicting how changes in management regulations may cause changes in effort dynamics, which itself may lead to changes in fishing mortality and the dynamics of individual stocks (Andersen et al., 2012).

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.fishres.2014.12.004.

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