

1 *Fine-scale fronts as hotspots of fish aggregation*
2 *in the open ocean*

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15 **Abstract.** Oceanic Lagrangian Coherent Structures have been shown to
16 deeply influence the distribution of primary producers and, at the other
17 extreme of the trophic chain, top predators. However, the relationship be-
18 tween these structures and intermediate trophic levels is much more ob-
19 scure. In this paper we address this knowledge gap by comparing acous-
20 tic measurements of mesopelagic fish concentrations to satellite-derived
21 fine-scale Lagrangian Coherent Structures in the open ocean. The results
22 demonstrate unambiguously that higher fish concentrations are signifi-
23 cantly associated with stronger Lagrangian Coherent Structures, and we
24 observe that these features represent a limiting condition for high fish
25 concentrations. A model, specifically built for mid trophic levels with
26 realistic parameters, provides a possible mechanism of fish aggregation,
27 and is coherent with the observations. These results may help to inte-
28 grate intermediate trophic levels in trophic models, which can ultimately
29 support management and conservation policies.

30 **Introduction**

31 Marine biomass distribution is highly patchy and variable in time across the
32 entire trophic web Bertrand et al. (2014); McManus and Woodson (2012). Dis-
33 cerning the factors underpinning ocean patchiness is fundamental to understand
34 how they influence biogeochemical reactions and ecosystem stability Martin
35 (2003); Lévy and Martin (2013). These issues are pivotal for conservation pur-
36 poses Gaines et al. (2010) and for assessing the impact of climate change on the
37 marine environment Hoegh-Guldberg and Bruno (2010).

38 One of the origins of the heterogeneity of the biotic fields is the dynamic nature
39 of the ocean environments, which transforms the water masses on a large range

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40 of temporal scales, including those of ecological relevance. In this regard, a special
41 role is fulfilled by the mesoscale and submesoscale McGillicuddy (2016), now
42 commonly referred to together as “fine-scales”, which span a spatial range from
43 a few to hundreds of kilometers.

44 One fruitful approach for capturing the structuring effect of fine-scale dynamics
45 is the extraction of so-called Lagrangian Coherent Structures, and in particular
46 Lagrangian fronts Haller (2015); Lehahn et al. (2018). Lagrangian Coherent
47 Structures (LCSs) provide several types of information regarding flow properties,
48 such as the location of fronts, barriers to transport Boffetta et al. (2001),
49 or retentive and coherent regions d’Ovidio et al. (2013). One of the most common
50 Lagrangian diagnostics used to determine LCSs is the Finite-size Lyapunov
51 Exponent (FSLE, d’Ovidio et al., 2004). This measures the exponential rate of
52 water parcel deformation and has maximal values over frontal regions.

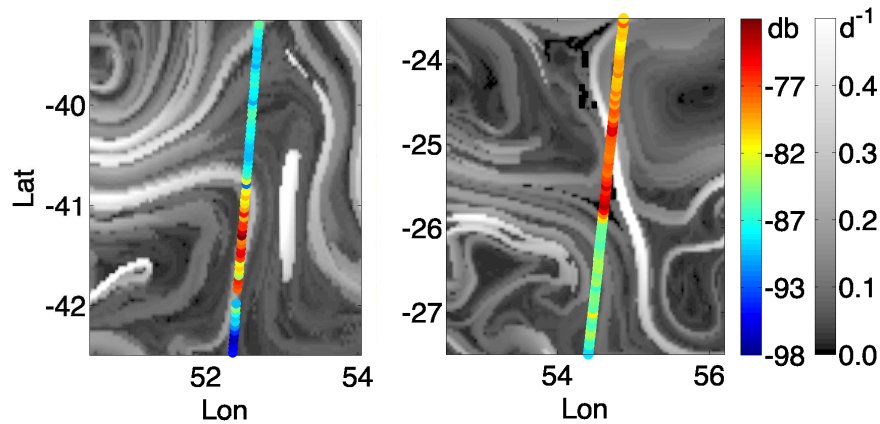
53 By shaping and elongating water patches, Lagrangian Coherent Structures have
54 been demonstrated to set the frontiers of phytoplanktonic patches in terms
55 of chlorophyll concentration Lehahn et al. (2018), and even functional type
56 d’Ovidio et al. (2010). This in turn enhances contacts between different communities,
57 regulating plankton diversity De Monte et al. (2013).

58 More recently, advances in biologging programs provided evidence on the impact
59 of fine-scale structures on top predators behavior. The concentration of predators
60 foraging efforts has been observed in the neighbourhoods of Lagrangian
61 fronts Kai et al. (2009); Scales et al. (2018). Furthermore, fronts detected by
62 Lagrangian Coherent Structures (which in the following we will call Lagrangian
63 fronts) have been observed to influence predators movements Della Penna et al.
64 (2015). This could enhance energy transfer and gain Abrahms et al. (2018).

65 However, while the influence of Lagrangian fronts has been observed on both extremes
66 of the trophic chain, much less is known about mid-trophic levels. Prants
67 et al. (see in particular Prants et al., 2014) demonstrated a correlation between
68 Pacific saury catches and Lyapunov exponents, and Watson et al. (2018) found
69 that several fishery vessels track LCSs when targeting fishery spots. However,
70 these results leave some concerns about possible biases because commercial fisheries
71 provides only punctual observations, and because they are even known to
72 use satellite images. Therefore, fishing vessels may target intentionally frontal
73 systems. Unbiased fish measurements have been instead recently used by Sato
74 et al. (2018) to analyse the relationship between a frontal system and acoustic
75 measurements in a coastal upwelling system. This allowed the authors to highlight
76 the different role played by in-shore and off-shore waters. In terms of the
77 mechanisms which can explain how fine-scale structures influence mid-trophic
78 biomass distribution, even less is known. Classical explanations are based primarily
79 on bottom-up mechanisms along fronts with intense upwelling Yoder et al.
80 (1994); Woodson and Litvin (2015). However, these hypothesis do not take into
81 account the necessity of a maturation time, which in the case of fish is consistently
82 longer than both the growth response of lower trophic levels and the lifetime of
83 the front. Neither the fish behavior is considered, despite the fact
84 that fish possess efficient sensorial and swimming capacities along the horizontal

85 (Kasumyan (2004) and Supporting Information SI.2).
86 The objective of the present study is to analyze the relationship between fine-
87 scale structures in the open ocean and mid-trophic organisms with unbiased,
88 direct observations of fish concentrations, and to propose a mechanism by which
89 fine-scales organize mid-trophic biomass.
90 This study was conducted in the subantarctic area of the southern Indian ocean.
91 The functioning of this region is mainly regulated by the Kerguelen plateau, a
92 major topographic barrier for the Antarctic Circumpolar Current (ACC). The
93 plateau enriches in iron, a limiting nutrient, the high-nutrients-low-chlorophyll
94 waters advected by the ACC. Depending on seasonal light conditions and stratifi-
95 cation of the water column, this provokes a large annual phytoplanktonic bloom,
96 which supports a rich trophic chain. This is one of the reasons for which the Ker-
97 guelen archipelago and its surrounding waters are part of one of the ten largest
98 marine protected areas in the world (<http://www.mpatlas.org/>).
99 In this region, the myctophids, also known as lantern fish, are one of the most
100 abundant groups of mesopelagic fish. They are also present in other oceans world-
101 wide and are thought to constitute one of the largest portions of world fish biomass
102 Irigoien et al. (2014). They also represent important prey items for numerous
103 predators Chérel et al. (2010). Myctophids are reported to play a central role in
104 the carbon export to deep sea depths, and are suspected to affect the climate
105 Kwon et al. (2009). Constituting a potentially massive harvestable resource, they
106 are threatened to be exploited in the near future St. John et al. (2016). A bet-
107 ter understanding of the mechanisms regulating their biomass is thus urgently
108 needed.
109 In this paper, we relate acoustic measurements of fish concentrations and satel-
110 lite derived diagnostics. These diagnostics allow us to identify the intensity of
111 several fine scale fronts. The aim is to explore the degree to which fish distribu-
112 tion is shaped by these fine-scale features, and in particular Lagrangian fronts.
113 Our results indicate that stronger Lagrangian fronts aggregate larger quantities
114 of fish, although not all these structures are aggregation sites. We then propose
115 a simple aggregating mechanism specifically designed for fish, based on a cue
116 pursuing dynamic along the horizontal dimension. Myctophids are supposed to
117 be able to orientate and to actively swim to search for food (hypothesis discussed
118 in SI.2). They follow a gradient of a passive tracer, which is considered a proxy
119 for heterogeneously-distributed zooplankton. All the parameters values of this
120 model are set using observational data (SI.5) and none of them has been opti-
121 mized nor fitted. The predictions of such model are consistent with the observed
122 concentrations. In addition, the model provides also theoretical estimations of
123 the dominant spatio-temporal scales of aggregation.

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127 Fig. 1: Illustrative examples of two transects of the boat trajectory. The color of each
128 dot is proportional to the Acoustic Fish Concentration (in decibels, right colorbar
129 for scale). The transects are superimposed on a simultaneous field of Finite-size Lyapunov
130 Exponents. These identify fine-scale frontal structures. They are computed with
131 altimetry derived velocities (days^{-1} , left colorbar for the scale). Left panel: August,
132 29th, 2014. Right panel: August, 31st, 2013.

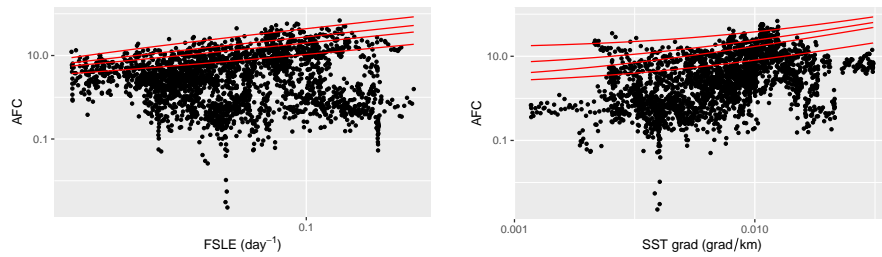
124 Results

125 Relationships between acoustic fish concentration and 126 satellite-derived diagnostics

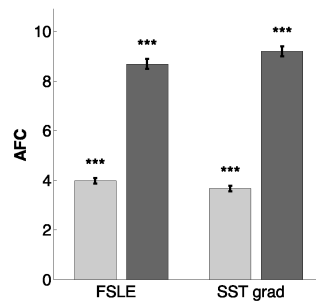
149 We used ship acoustic measurements acquired along 6 transects of 2860 linear
150 kilometers. For each point of the boat trajectory, we computed a value of Acoustic
151 Fish Concentration (AFC). This is representative of the fish concentration in
152 the water column. Alongside this, we calculate two satellite derived diagnostics:
153 the Finite-size Lyapunov Exponent (FSLE) and the Sea Surface Temperature
154 (SST) gradient. These two metrics are typically associated with front intensity
155 (see Materials and Methods for further details). Other diagnostics are reported
156 in SI.1. In-situ temperature measurement were available only on a part of the
157 transects, and were therefore not considered in the analysis.

158 Fig. 1 depicts two illustrative examples of the boat trajectory on August 29th,
159 2014 and August 31st, 2013 respectively. They are superposed on a field of Finite-
160 size Lyapunov exponents. The latter are associated with frontal features. Each
161 dot of the boat trajectory is colored proportionally to the AFC in that point. On
162 both the panels, AFC values indicate a qualitative agreement with the FSLE,
163 increasing in correspondence of the frontal features identified by high values of
164 the Lyapunov exponents.

165 Fig. 2 depicts the scatter plots of the AFC against the two diagnostics, with both
166 the axes in logarithmic scale. To determine whether the AFC values present sig-
167 nificant differences in proximity of fine-scale features, a bootstrap analysis was
168 conducted. Details of the methodology are provided in Materials and Methods



135 Fig. 2: Scatter plot of AFC against FSLE (left panel) and SST gradient (right panel).
136 The lines, from the bottom to the top, indicate the linear quantile regressions at 75th,
137 90th, 95th and 99th percentiles. The analysis is used to investigate the relationship
138 between the front intensity and just the higher values of fish concentration. Both axes
139 are in logarithmic scale (values equal to zero are therefore not depicted). Values of the
140 quantile regression coefficients are reported in Table S.1.



143 Fig. 3: Bootstrap method results. Left columns refer to FSLE analysis, right columns
144 to SST gradient. Light gray columns represent the mean AFC under the respective
145 threshold, and the dark gray columns represent the mean AFC over the threshold.
146 Error bars indicate the standard deviation, while black stars indicate the significance
148 of the bootstrap test.

169 section. The results are reported in Fig. 3. Significantly higher AFC values are
170 detected over the thresholds (p -value < 0.001) for both FSLE and SST gradient.

171 Finally, linear quantile regression method was employed Koenker (2005). This
172 analysis was used to investigate the relationship between the higher values of
173 AFC and the front intensity. Results of the regression are displayed in Fig. 2 as
174 red lines. All the quantile slopes are statistically different from zero. This sug-
175 gests the presence of a positive relationship between the higher values of AFC
176 and FSLE and SST gradient (Table S.1).

177 **A fine-scale mechanism of fish aggregation**

178 Why do fish aggregate along frontal features? We addressed this question by
179 proposing a simple mathematical model. The model assumes a gradient climb-

180 ing capacity, which is one of the most widespread movement mechanisms used in
181 other biological contexts (e.g., chemotaxis, Adler (1975)). This gradient climbing
182 capacity is specifically tuned for mid-trophic organisms and myctophids and is
183 based on a cue pursuing dynamic. Fish try to climb a gradient of tracer. We
184 considered this tracer a proxy of zooplankton concentration, prey of several fish
185 species, and in particular of myctophids Pakhomov et al. (1996). At the scales
186 considered in this study (10s of kilometers) zooplankton swimming capacities are
187 restricted to the vertical axis Genin et al. (2005). They can thus be considered,
188 along the horizontal axis, passive tracers. Along this dimension, zooplankton ag-
189 gregation and growth is usually driven by a relatively fast response to nutrients
190 presence, of the order of days to weeks Vidal (1980). In particular, this is valid
191 also for zooplankton species present in our study region Alonzo et al. (2003);
192 Labat et al. (2005). Conversely, fish have growth rates consistently slower: in
193 particular, pelagic fishes and myctophids are considered as “slow-growing fish”,
194 with lifetimes spanning few years Greely et al. (1999). Therefore, their aggre-
195 gation can not be explained by the same dynamics affecting the zooplankton.
196 Alongside this, fish have extremely developed sensorial capacities and, differ-
197 ently from zooplankton, they can actively swim, with both capacities involved
198 in many functional activities, including feeding Kasumyan (2004). These argu-
199 ments support our approach of modelling zooplankton as a passive tracer and
200 fish as active swimmers (we invite the reader to refer to SI.2 for further details).
201 To include ocean patchiness, we perturbed the ability of the fish to properly iden-
202 tify the spots of zooplankton with a noise term. However, we assumed that fish
203 are able to orientate without problems over a given threshold of the zooplank-
204 ton gradient. This threshold was estimated from the zooplankton concentrations
205 (SI.5).
206 Making these assumptions, the average velocity of a group of fish $U_F(x)$ can
207 be found applying simple algebra to a standard gradient climbing model (see
208 Materials and Methods, subsection “Gradient climbing model”):

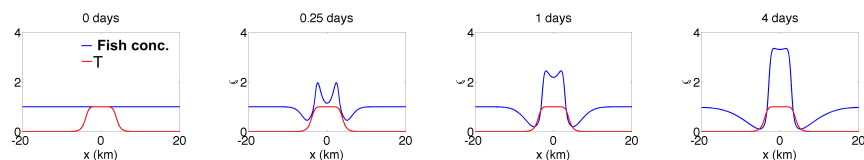
$$U_F(x) = V \frac{\frac{\partial T}{\partial x}}{\frac{\partial T}{\partial x} MAX} \left(2 - \frac{\left| \frac{\partial T}{\partial x} \right|}{\frac{\partial T}{\partial x} MAX} \right) \quad (1)$$

217 in which T is the zooplankton concentration, $\frac{\partial T}{\partial x} MAX$ is the threshold of the
218 zooplankton gradient, and V is the cruising speed of the myctophids.
219 Similarly, the evolution of the fish concentration over time can be easily obtained
220 from the one-dimensional continuity equation, by imposing the conservation of
221 fish total biomass, and by using Expr. 4 (see Materials and Methods for fur-
222 ther details). The tracer shape used describes a sigmoid function, which models
223 a generic local gradient in the zooplankton concentration. At the limits of the
224 plateau, the tracer decreases along a distance of ~ 5 km, a typical fine-scale
225 range.
226 Four different snapshots (at 0, 6 hours, 1 day and 4 days) of the fish modelled
227 concentration are illustrated in Fig. 4. Intuitively, having chosen a gradient-
228 climbing behavior, one can expect that fish concentration will evolve quickly in
229 the regions in which the tracer gradient is larger. Indeed, after only 6 hours,

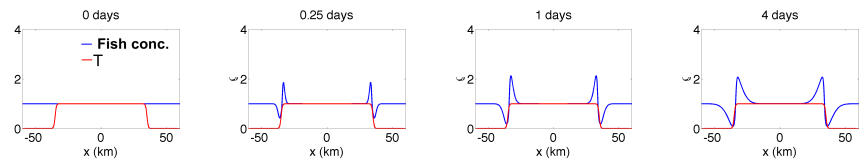
230 two peaks of doubled concentration are present in correspondence with the margins
231 of the tracer plateau. In the following days, the two peaks decreased their
232 growth rate, while the concentration between them increases until they merged
233 together. The fish concentration is thus homogeneous over the plateau, present-
234 ing values between 2.5 and 3.5 times higher than the initial concentration. In
235 case of a larger plateau (Fig. 5), the model predicts a similar behavior, but the
236 merging between the peaks occurs over longer timescales. In that case, the peaks
237 reach their maximum value after the first day, with the creation of two regions
238 of increased concentration at the margins of the plateau. Changing the type of
239 fish behavior leads to similar results (see SI.3).

240 We note that this mechanism does not explicitly take into account fronts. How-
241 ever, in the oceanic environment, frontal regions represent areas of convergence
242 of water masses with different properties. This is why regions of strong gradients
243 are often associated to frontal features Yoder et al. (1994).

244 However, at the same time during which this mechanism occurs, the tracer can
245 evolve. As a sensitivity test, we numerically analyzed a scenario in which the
246 tracer, subjected to a typical frontal dynamics, is stretched in a filament and
247 eroded by diffusion (SI.4). Using realistic bio-physical parameters representative
248 of the study area, we found that these tracer dynamics do not compromise the
249 aggregation mechanism presented above, but may even facilitate the aggrega-
250 tion of fish along frontal zones. Indeed, the model developed predicts several
251 quantitative information, such as an estimate of the fish aggregation over time.
252 The latter highlighted a final concentration, on average, an order of magnitude
253 stronger than the initial one. In addition, it was possible to obtain the “school
254 life time”. This quantity indicates the amount of time during which a group of
255 fish is able to follow a patch of interest before it vanishes due to the frontal



209 Fig. 4: Time evolution of the fish concentration (blue line, adimensional) according to
210 the continuity equation. The tracer (red line, adimensional) describes a plateau of 8
211 km in width. At its limits, its values range from 1 to 0 in about 5 km. Each panel
212 represents a different snapshot at 0, 6 hours, 1 day, and 4 days.



214 Fig. 5: Time evolution of the fish concentration as reported in Fig. 4. This time, the
215 plateau width has been set to 70 km.

256 dynamics. The school life times we obtained ranged between 7 to 25 days, with
257 an average value of around 2 weeks. Remarkably, this amount of time matches
258 with that of fine-scale processes.

259 Discussion

260 In the oceans, patchiness characterizes biomass distribution, which regulates
261 ecosystem stability and biogeochemical processes Bertrand et al. (2014); Mar-
262 tin (2003); Lévy and Martin (2013). In the open ocean, biomass distribution is
263 largely driven by processes at the fine-scale (between 1 and hundreds of kilo-
264 meters or a few days to several weeks, such as lateral advection and horizontal
265 stirring Martin (2003); Lévy et al. (2018).

266 One approach to studying the structuring processing occurring at this scale is
267 provided by Lagrangian methods. In the past, Lagrangian tools like the com-
268 putation of Lagrangian Coherent Structures have revealed the structuring role
269 of fine-scale dynamics on primary levels of the trophic chain (see a review in
270 Lehahn et al. (2018)). On the other hand, they have highlighted their influence
271 on apex predators behaviors as well Kai et al. (2009); Scales et al. (2018).

272 However, less information is available on intermediate trophic levels. In the
273 present study (i) we correlate the intensity of acoustic fish concentrations and
274 fine-scale fronts, and (ii) we propose a mechanism of fish aggregation along fronts.

275 We analyze the Kerguelen region in the Southern Ocean, one of the ten largest
276 protected areas in the world, and an oasis for several threatened species (IUCN,
277 <https://www.iucn.org/>). The reference fish of this study are the myctophids,
278 which are highly diffused in that region and one of the most abundant group of
279 mesopelagic fish in the world Irigoien et al. (2014).

280 Our results reveal a significant difference in fish concentration between frontal
281 and non-frontal features. These are difficult to explain with traditional mecha-
282 nisms usually prescribed to lower trophic levels, such as rapid growth associated
283 to a presence of nutrient, because fish have slower growth rates. Therefore, start-
284 ing from a homogeneous fish distribution and applying simple ecological rules,
285 we propose a gradient-climbing model specifically calibrated for the study of
286 mid-trophic organisms. Once parameterized with values typical for the study
287 region, the model demonstrates a quick response to gradient structures. Two
288 peaks of doubled concentration appear after just 6 hours, and then merge after
289 4 days. Fish thus tend to be homogeneously distributed over the entire patch of
290 interest. This is in coherence with on-going studies on myctophids' response to
291 food concentration. These presuppose that myctophids have a Holling type III
292 functional response, in that they ingest always the same quantity of food over a
293 certain prey density (A. Hulley, personal communication).

294 Tracer patchiness is known to be associated with frontal features Yoder et al.
295 (1994); Lehahn et al. (2018). However, patchiness evolves, and under the double
296 effect of stretching and diffusion, local gradients can be eroded. Thus, we tested
297 the robustness of our model to this feature in SI.4. As in the former case, none
298 of the parameters employed has been optimized nor fitted, but they all represent

299 rigorous estimations of Southern Ocean physical and biological conditions, such
300 as stretching and mixing rates or fish cruising speed. Results allowed us to esti-
301 mate a typical lifetime for a fine-scale patch of around two weeks, much longer
302 than the peak doubling time (~ 6 hours). This robustness analysis is consistent
303 with the hypothesis of a fixed tracer assumed in the gradient climbing scenario.
304 Furthermore, we demonstrated that the stretching and diffusion dynamics can
305 potentially enhance fish aggregations.

306 The patch of interest is considered as a proxy of zooplankton concentration.
307 However, being parameterized as a passive tracer, it can be considered, more
308 simply, as a physical water property. Indeed, physical characteristics, such as
309 temperature, have been proven to be used by predators to find favorable condi-
310 tions where concentrated food occurs Snyder et al. (2017).

311 The proposed mechanism of aggregation needs two obvious initial conditions: the
312 presence of fish, and the presence of a zooplankton patch. It is presumable that
313 fine-scale fronts, lacking one or both these conditions, cannot act as aggregating
314 spots. Furthermore, while we assumed that the aggregation occurs after a certain
315 amount of time, the environment studied is dynamic. Thus, it is likely that the
316 aggregation mechanism was observed during different stages. The statistically
317 significant positive relationships between the high values of acoustic fish concen-
318 tration with the front intensity diagnostics confirms the previous considerations.
319 Not all of the strong fronts detected indicate high acoustic fish concentrations.
320 On the contrary, strong fish aggregation is preconditioned by the intensity of a
321 frontal feature. Our results suggest that fronts represent in this regard a limit-
322 ing condition for high fish concentrations. Model predictions are in accordance
323 with the observations. Furthermore, the model provided estimations of other
324 aggregation dynamics, such as the dimensions of the aggregation patterns or its
325 intensity, with timescales comparable with those of fine scale processes. Specific
326 experiments are necessary to validate these outputs, which however look promis-
327 ing.

328 Within the ACC, little information available on mid-trophic levels reported that
329 the large circumpolar fronts are known to host (i) large densities of zooplankton
330 and myctophids and (ii) that these organisms are patchily distributed Pakhomov
331 and Froneman (2000). We identified in this study, at least partly, the potential
332 mechanisms driving the patchiness observed at fine-scale. Assessing the precon-
333 ditions and the other dynamics necessary for front aggregation is a new, open
334 challenge emerging from the present work.

335 Note that in our work we focus only on open ocean Lagrangian fronts, that
336 is, fine-scale frontal features induced by the mesoscale open ocean activity. In
337 particular, we intentionally exclude coastal fronts as well as large scale fronts,
338 whose dynamics and ecological role may be different (e.g., Lara-Lopez et al.
339 (2012); Netburn and Koslow (2018); Sato et al. (2018)). Finally, the limitations
340 of our analysis must be discussed. No vertical dynamics has been included in
341 the model presented. However, these play an important role in the organization
342 of marine biota Lévy et al. (2018), and, typically, stronger gradients are present
343 along the vertical Ohman (1988). This assumption is due to the fact that, while

344 knowledge on horizontal dynamics is more advanced, 3D Lagrangian analyses,
345 while appealing Sulman et al. (2013), are not currently possible, due to a lack
346 of quantitative information on the vertical velocities of the ocean. Future satel-
347 lite missions (such as SWOT: <https://swot.cnes.fr>) will possibly help to mitigate
348 this problem, by helping the assimilation scheme to better reconstruct the three
349 dimensional dynamics Morrow et al. (2019). At the same time, they will also im-
350 prove satellite resolution, providing a more precise location of fine-scale fronts.
351 The model studied does not consider the diel vertical migration of myctophids
352 either. This choice is driven by the difficulty in parameterizing such a non linear
353 behavior and in assimilating different migratory diel patterns. However, we note
354 that many zooplankton species exhibit a diel cycle as well. Finally, zooplankton
355 consumption due to fish foraging is considered to be negligible, or compensated
356 by source terms (like blooms). The limitations presented can open the way for
357 future investigations. Thus, the present study sheds some light on a largely un-
358 explored topic.

359 The results presented here may be useful for improving the representation of
360 intermediate trophic levels to coupled ecological and physical models Robinson
361 et al. (2011), habitat models PC et al. (2018), targeting the mesopelagic com-
362 partment in particular. At the same time, the possibility of using Lagrangian
363 Coherent Structures as a proxy of higher fish concentrations may further improve
364 the integration of satellite-derived Lagrangian tools in conservation planning
365 Penna et al. (2017).

366 **Materials and Methods**

367 **Acoustic measurements**

368 Two subsets of data were used for the analysis. Both of them were collected
369 within the Mycto-3D-MAP program. The first subset (named MYCTO) was
370 collected during 6 campaigns in 2013 and 2014, both in summer and in winter
371 (see Tab. 1 for more details), using split-beam echo sounders at 38 and 120kHz.
372 The data were then treated with a bi-frequency algorithm, applied to the 38 and
373 120 kHz frequencies (details of data collection and processing are provided in
374 Béhagle et al. (2017)). This provides a quantitative estimation of the concentra-
375 tion of gas-bearing organisms, mostly attributed to fish containing a gas-filled
376 swimbladder in the water column Kloser et al. (2009). Most mesopelagic fish
377 present swimbladders and several works pointed out that myctophids are the
378 dominant mesopelagic fish in the region Duhamel et al. (2014). Therefore, we
379 considered the acoustic signal as mainly representative of myctophids concentra-
380 tion. Data were organized in acoustic units, averaging acoustic data over 1.1 km
381 along the boat trajectory on average. Myctophid school length is in the order
382 of tens of meters Saunders et al. (2013). For this reason, acoustic units were
383 considered as not autocorrelated. Every acoustic unit is composed of 30 layers,
384 ranging from from 10 to 300 meters (30 layers in total).

385 The second subset of data (named ZOO) was collected between January the
386 22nd and February the 5th, 2014. It was processed in the same manner as the

387 other dataset, but this time the bifrequency algorithm was used to infer the
388 zooplankton biomass. This second subset possesses a higher resolution with an
389 acoustic unit every 206 m of the boat trajectory on average.
390 The two datasets were used to infer the Acoustic Fish Concentration (AFC) and
391 the Acoustic Zooplankton Concentration (AZC) in the water column, respec-
392 tively. We considered as AFC (or AZC) of the point (x_i, y_i) the average of the
393 bifrequency acoustic backscattering on the whole column, with the exclusion of
394 the first layer. The latter was not considered due to surface noise.
395 The AZC was used to compute the zooplankton gradient. The zooplankton gra-
396 dient of a point i of the boat transect is computed as:

$$\frac{\partial Z}{\partial x}(i) = \frac{1}{2} \left(\frac{Z_i - Z_{i-1}}{d_{i-1}} + \frac{Z_{i+1} - Z_i}{d_i} \right)$$

397 in which d_i indicates the kilometeric distance between the point $i + 1$ and i , and
398 Z_i is the cubic spline interpolation (to smooth the noise effects), in an around of
399 2 km, of the zooplankton concentrations. This type of interpolation, in contrast
400 with the moving average, preserves the trend of the data, and thus a possible
401 front.

Acoustic campaigns details

Cruise	Season	St. Date	End Date	Distance (km)
LOGIPEV193.RUNKER	Summer	09/02/2013	17/02/2013	2752
LOGIPEV193.KERMAU	Summer	04/03/2013	10/03/2013	3781
OP2013-2.RUNKER	Winter	30/08/2013	10/09/2013	3310
LOGIPEV197.RUNKER	Summer	06/01/2014	13/01/2014	2800
LOGIPEV197.KERMAU	Summer	06/02/2014	18/02/2014	2045
OP2014-2.RUNKER	Winter	24/08/2014	04/09/2014	3677

406 Table 1: Details of the acoustic transects analyzed.

407 Regional data selection

408 The geographic area of interest of the present study is the Southern Ocean. To
409 select the boat trajectory points belonging to this region, we used the ecopar-
410 tition of Sutton et al. Sutton et al. (2017). Only points falling in the *Antarctic*
411 *Southern Ocean* region were considered. We highlight that this choice is con-
412 sistent with the ecopartition of Koubbi et al. Koubbi et al. (2011) (group 5),
413 which is specifically designed for the myctophids, the reference fish of this study.
414 Furthermore, this choice allowed us to exclude major fronts which have been the
415 subject of different research works Lara-Lopez et al. (2012); Netburn and Koslow
416 (2018). In this way our analysis is focused specifically on fine scale fronts.

417 **Day-night data separation**

418 Several species of myctophids present a diel vertical migration. They live at great
419 depths during the day (between 500 and 1000 m), ascending at dawn in the upper
420 euphotic layer, where they spend the night. Since the maximal depth reached
421 by our equipment is 300 m, in the analysis reported in Fig. 2 and 3 we excluded
422 data collected during the day. However, their analysis is reported in SI.1. This is
423 also consistent with the use of the Lagrangian and Eulerian diagnostics. These
424 quantities, obtained from geostrophic velocity fields, are representative of the
425 first part of the water column (~ 50 m).

426 **Satellite data**

427 *Velocity current data and processing.* Velocity currents are obtained from the Sea
428 Surface Height (SSH), which is measured by satellite, through the geostrophic
429 approximation. Data, which were downloaded from E.U. Copernicus Marine En-
430 vironment Monitoring Service (CMEMS, <http://marine.copernicus.eu/>), were
431 obtained from DUACS (Data Unification and Altimeter Combination System)
432 delayed-time multi-mission altimeter, and displaced over a regular grid with spa-
433 tial resolution of $\frac{1}{4} \times \frac{1}{4}^\circ$ and a temporal resolution of 1 day.

434 Trajectories were computed with a Runge-Kutta scheme of the 4th order with an
435 integration time of 3 hours. Finite-size Lyapunov Exponents (FSLE) were com-
436 puted following the methods in d'Ovidio et al. (2004), with initial and final sep-
437 aration of 0.04° and 0.4° respectively. This Lagrangian diagnostic is commonly
438 used to identify Lagrangian Coherent Structures. This method determines the
439 location of barriers to transport, and it is usually associated with oceanic fronts
440 Haller (2015).

441 *Temperature field.* The Sea Surface Temperature (SST) field was downloaded
442 from the OSTIA global foundation Sea Surface Temperature product (SST_GLO_SST_L4_NRT_OBSERVAT
443 The data are represented over a regular grid with spatial resolution of $0.05 \times 0.05^\circ$
444 and daily-mean maps.

445 *Satellite data extrapolation.* For each point of the boat trajectory, we considered
446 as value of the diagnostic the average value over a disc of radius σ . Different
447 σ were tested, and the best results were obtained with the $\sigma = 0.2^\circ$, reference
448 value reported in the present work. This value is consistent with the uncertainty
449 of the satellite velocity field.

450 **Statistical processing**

451 *Bootstrap method.* In this section, we describe the analysis necessary for the
452 bootstrap test. To identify the frontal features, the following diagnostic values
453 were chosen as thresholds for representing the front: for the FSLEs, we used 0.08
454 days^{-1} , a threshold value consistent with those chosen in De Monte et al. (2012)
455 and obtained from Kai et al. (2009). For the SST gradient, we considered repre-
456 sentative of thermal front values greater than $0.9^\circ\text{C}/100$ km, which is about the
457 half of the value chosen in De Monte et al. (2012). However, in that work, the

458 SST gradient was obtained from the advection of the SST field with satellite-
459 derived currents for the previous 3 days, which structures it in high resolution
460 features that therefore present higher gradient values.

461 The threshold value splits the AFC into two groups: over and under the thresh-
462 old. Their independency was tested using a Mann-Whitney or U test. Finally,
463 bootstrap analysis is applied following the methodologies used in De Monte et al.
464 (2012).

465 *Linear quantile regression.* Linear quantile regression method Koenker (2005)
466 is employed to estimate the effect of FSLE and SST gradient on the upper
467 limit of the AFC, as in Sankaran et al. (2005). The percentiles values used are
468 75th, 90th, 95th, and 99th. The analysis is performed using the statistical pack-
469 age QUANTREG in R (<https://CRAN.R-project.org/package=quantreg>, v.5.38,
470 Koenker (2005)), using the default settings.

471 Gradient climbing model

472 The fish searching dynamic is considered a one dimensional, individual-based,
473 Markovian process. Time is discretized in timesteps of length $\Delta\tau$. We presuppose
474 that, at each timestep, the fish chooses between swimming in one of the two
475 directions. This decision depends on the comparison between the quantity of
476 tracer at its actual position and the one perceived at a distance f_W from it,
477 where f_W is the field view of the fish. We consider the fish immersed in a tracer
478 whose concentration is described by the function $T(x)$.

479 An expression for the average velocity of the fish, $U_F(x)$, can now be derived.
480 We assume that the fish is able to observe simultaneously the tracer to its right
481 and its left. Fish sensorial capacities are discussed in SI.2. The tracer observed
482 is affected by a noise. Noise distribution is considered uniform, with $-\xi_{MAX} <$
483 $\xi < \xi_{MAX}$, $\xi_{MAX} > 0$. The effective values perceived by the fish, at its left and
484 its right, will be, respectively:

$$\begin{aligned}\tilde{T}(x_0 - \Delta x) &= T(x_0 - \Delta x) + \xi_1 \\ \tilde{T}(x_0 + \Delta x) &= T(x_0 + \Delta x) + \xi_2 .\end{aligned}$$

485 We assume that, if $\tilde{T}(x_0 + \Delta x) > \tilde{T}(x_0 - \Delta x)$, the fish will move to the right,
486 and, vice versa, to the left. We hypothesize that the observational range is small
487 enough to consider the tracer variation as linear, as illustrated in Fig. S.6 (SI.3).
488 In this way:

$$\begin{aligned}\tilde{T}(x_0 + \Delta x) &= T(x_0) + f_W \frac{\partial T}{\partial x} + \xi_1 \\ \tilde{T}(x_0 - \Delta x) &= T(x_0) - f_W \frac{\partial T}{\partial x} + \xi_2 .\end{aligned}$$

489 In case of absence of noise, or with $\xi_{MAX} < f_W \frac{\partial T}{\partial x}$, the fish will always move
490 in the correct direction, in that it will climb the gradient. Assuming V as the

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491 cruising swimming velocity of the fish, this means $U_F(x) = V$.
492 Let's now assume $\xi_{MAX} > f_W \frac{\partial T}{\partial x}$. If $T(x_0 + \Delta x) > T(x_0 - \Delta x)$ (as in Fig. S.6),
493 and the fish will swim leftward if

$$\xi_1 - \xi_2 > 2f_W \frac{\partial T}{\partial x}.$$

494 Since ξ_1 and ξ_2 range both between $-\xi_{MAX}$ and ξ_{MAX} , we can obtain the prob-
495 ability of leftward moving $P(L)$. This will be the probability that the difference
496 between ξ_1 and ξ_2 is greater than $2f_W \frac{\partial T}{\partial x}$

$$\begin{aligned} P(L) &= \frac{1}{8\xi_{MAX}^2} \left(2\xi_{MAX} - 2f_W \frac{\partial T}{\partial x} \right)^2 \\ &= \frac{1}{2} \left(1 - \frac{f_W}{\xi_{MAX}} \frac{\partial T}{\partial x} \right)^2 \end{aligned}$$

497 The probability of moving right will be

$$P(R) = 1 - P(L)$$

498 and their difference gives the frequency of rightward moving

$$\begin{aligned} P(R) - P(L) &= 1 - 2P(L) = 1 - \left(1 - \frac{f_W}{\xi_{MAX}} \frac{\partial T}{\partial x} \right)^2 \\ &= \frac{f_W}{\xi_{MAX}} \frac{\partial T}{\partial x} \left(2 - \frac{f_W}{\xi_{MAX}} \left| \frac{\partial T}{\partial x} \right| \right), \end{aligned}$$

499 where the absolute value of $\frac{\partial T}{\partial x}$ has been added to preserve the correct climbing
500 direction in case of negative gradient. The above expression leads to:

$$U_F(x) = \frac{V f_W}{\xi_{MAX}} \frac{\partial T}{\partial x} \left(2 - \frac{f_W}{\xi_{MAX}} \left| \frac{\partial T}{\partial x} \right| \right). \quad (2)$$

501 We then assume that, over a certain value of tracer gradient $\frac{\partial T}{\partial x}_{MAX}$, the fish are
502 able to climb the gradient without being affected by the noise. This assumption,
503 from a biological perspective, means that the fish does not live in a completely
504 noisy environment, but that under favorable circumstances it is able to correctly
505 identify the swimming direction. This means that

$$f_W * \frac{\partial T}{\partial x}_{MAX} = \xi_{MAX}. \quad (3)$$

506 Substituting then (3) into (2) gives:

$$U_F(x) = V \frac{\frac{\partial T}{\partial x}}{\frac{\partial T}{\partial x}_{MAX}} \left(2 - \frac{\left| \frac{\partial T}{\partial x} \right|}{\frac{\partial T}{\partial x}_{MAX}} \right). \quad (4)$$

507 Finally, we can include an eventual effect of currents speed, considering that
508 the tracer is transported passively by them, simply adding the current speed U_C
509 to Expr. (4).

510 The representations provided are individual based, with each individual repre-
511 senting a single fish. However, we note that all the considerations done are also
512 valid if we consider an individual representing a fish school. U_F will then simply
513 represent the average velocity of the fish schools. This aspect should be stressed
514 since many fish species live and feed in groups (see SI.2 for further details).

515 **Continuity equation in one dimension.** The solution of this model will now
516 be discussed. The continuity equation is first considered in one dimension. The
517 starting scenario is simply an initially homogeneous distribution of fish, that are
518 moving in a one dimensional space with a velocity given by $U_F(x)$.

519 We assume that in the time scales considered (few days to some weeks), the
520 fish biomass is conserved, so for instance fishing mortality or growing rates are
521 neglected. In that case, we can express the evolution of the concentration of the
522 fish ρ by the continuity equation

$$\frac{\partial \rho}{\partial t} + \nabla \cdot \mathbf{j} = 0 \quad (5)$$

523 in which $\mathbf{j} = \rho U_F(x)$, so that Eq. (5) becomes

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho U_F(x)) = 0. \quad (6)$$

524 In one dimension, the divergence is simply the partial derivate along the x -axis.
525 Eq. (6) becomes

$$\frac{\partial \rho}{\partial t} = -\frac{\partial}{\partial x} (\rho U_F) \quad (7)$$

526 Now, we decompose the fish concentration ρ in two parts, a constant one and a
527 variable one $\rho = \rho_0 + \tilde{\rho}$. Eq. (7) will then become

$$\frac{\partial \rho}{\partial t} = -U_F \frac{\partial \tilde{\rho}}{\partial x} - \rho \frac{\partial U_F}{\partial x}. \quad (8)$$

528 Using Expr. (4), Eq. (8) is numerically simulated with the Lax method. In
529 Expr. (4) we impose that $U_F(x) = V$ when $U_F(x) > V$. This biological assump-
530 tion means that fish maximal velocity is limited by a physiological constraint
531 rather than by gradient steepness. Details of the physical and biological param-
532 eters are provided in SI.5.

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543 **Authors contribution**

544 A.B., E.S.G. and F.d.O designed the research with assistance from X.C. A.B.
545 performed the research. A.B. and D.d.O. analyzed the data. C.C. and Y.C.
546 provided the data. A.B. wrote the paper, with assistance from F.d.O., E.S.G.,
547 D.d.O, X.C., and C.C.

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