

Spatial separation of catches in highly mixed fisheries

Paul J. Dolder^{1,2} & James T. Thorson³ & Cóilín Minto¹

¹*Marine and Freshwater Research Centre, Galway-Mayo Institute of Technology (GMIT), Dublin Road, Galway, H91 T8NW, Ireland*

²*Centre for Environment, Fisheries and Aquaculture Science (Cefas), Pakefield Road, Lowestoft, Suffolk, NR33 0HT, UK*

³*North West Fisheries Science Center, NOAA, 2725 Montlake Blvd E, Seattle, Washington, 98112, USA*

- 1 Mixed fisheries capture a mix of species at the same time and are the dominant type of
2 fishery worldwide. Overexploitation in mixed fisheries occurs when catches continue for
3 available quota species while low quota species are discarded¹. As EU fisheries manage-
4 ment moves to count all fish caught against quota (the ‘landings obligation’), the challenge
5 is to catch available quota within new constraints, else lose productivity. A mechanism for
6 decoupling exploitation of species caught together is spatial targeting, but this remains
7 challenging due to complex fishery and population dynamics in space and time^{2,3}. How
8 far spatial targeting can go to practically separate species is often unknown and anec-
9 dotal. Here we develop a dimension-reduction framework based on joint species distri-
10 bution modelling (spatial dynamic factor analysis) to understand how spatial community
11 and fishery dynamics interact to determine species and size composition. In the example
12 application to the highly mixed fisheries of the Celtic Sea, clear common spatial patterns
13 emerge for three distinct species-groups and, while distribution varies inter-annually, the
14 same species-groups are consistently found in higher densities together, with more subtle

15 **differences within species-groups - where spatial separation may not be practically possi-**
16 **ble. We highlight the importance of dimension reduction techniques to focus management**
17 **discussion on axes of maximal separation in space and time. We propose that spatiotem-**
18 **poral modelling of available data is a scientific necessity to address the pervasive and**
19 **nuanced challenges of managing mixed fisheries.**

20

21 **Mixed fisheries and the EU landings obligation** Efforts to reduce exploitation rates in commer-
22 cial fisheries have begun the process of rebuilding depleted fish populations⁴. Improved fisheries
23 management can increase population sizes and allow increased sustainable catches, yet fish-
24 eries catch globally remains stagnant⁵. With future increased demand for fish protein there is an
25 important role for well managed fisheries in supporting future food security⁶ necessitating fisheries
26 are managed efficiently to maximise productivity.

27 A challenge in realising increased catches from rebuilt populations is maximising yields from
28 mixed fisheries^{2,7,8}. In mixed fisheries managed by individual quotas, if catches do not match
29 available stock quotas, either a vessel must stop fishing when the first quota is reached (the 'choke'
30 species) or overexploitation of the weaker species occurs while fishers catch more healthy species
31 and throw back ('discard') the fish for which they have no quota¹. There is a pressing need for
32 scientific tools which simplify the complexities of mixed fisheries to help avoid discarding.

33 Sustainability of European fisheries has been hampered by this 'mixed fishery problem' for decades
34 with large-scale discarding⁹. Under the EU Common Fisheries Policy (CFP) reform of 2012, by
35 2019 all fish that are caught are due to be counted against the respective stock quota. Unless

36 fishers can avoid catch of unwanted species they will have to stop fishing when reaching their first
37 restrictive quota introducing a significant cost to under-utilised quota⁸ and strong incentive to
38 mitigate such losses¹⁰. The ability to align catch with available quota depends on being able to
39 exploit target species while avoiding unwanted catch, either by switching fishing method, changing
40 technical gear characteristics, or the timing and location of fishing activity¹¹.

41 Spatiotemporal measures have been applied to reduce unwanted catch with varying degrees of
42 success^{3,12}, partly because they have been targeted at individual species without considering as-
43 sociations among several species. Highly mixed fisheries are complex with spatial, technological
44 and community interactions; our goal is to develop a framework for understanding these complex-
45 ities. We do so by implementing a spatio-temporal dimension reduction method and use results to
46 draw inference on the fishery-community dynamics, creating a framework to identify trends com-
47 mon among species and describe the potential for and limitations of spatial measures to mitigate
48 unwanted catches in highly mixed fisheries.

49 **Framework for analysing spatio-temporal mixed fisheries interactions** We characterise the
50 spatiotemporal dynamics of key components of a fish community by implementing a factor anal-
51 ysis decomposition to describe trends in spatiotemporal dynamics of the different species as a
52 function of latent variables¹³ representing spatial variation (9 factors; 'average' spatial variation)
53 and spatio-temporal variation (9 factors) for encounter probability and positive catch rates ('pos-
54 itive density') separately¹⁴. This allows us to take account of how the factors contribute to affect
55 catches of the species in mixed fisheries. Gaussian Markov Random Fields (GMRFs) capture spa-
56 tial and temporal dependence within and among species groups for both encounter probability and
57 positive density¹⁵. Fixed effects account for systematic differences driving encounter and catches
58 such as differences in sampling efficiency (a.k.a. catchability), while random effects capture the

59 spatio-temporal dynamics of the fish community.

60 **Dynamics of Celtic Sea fisheries** The Celtic Sea is a temperate sea where fisheries are spatially
61 and temporally complex^{16,17}. Close to 150 species have been identified in the commercial catches
62 of the Celtic Sea, with approximately 30 species dominating the catch¹⁸. We parametrise our
63 model using catch data from seven fisheries-independent surveys undertaken over the period
64 1990 - 2015 (Table S1) and include nine of the main commercial species (see Table S2, Figure 2)
65 which make up >60 % of landings by towed fishing gears for the area (average 2011 - 2015;¹⁹).
66 Each species was separated into juvenile and adult size classes based on their legal minimum
67 conservation reference size (Table S2).

68 **Common average spatial patterns driving species associations** A spatial dynamic factor anal-
69 ysis decomposes the dominant spatial patterns driving differences in encounter probability and
70 positive density. The first three factors account for 83.7% of the between species variance in av-
71 erage encounter probability and 69% of the between species variance in average positive density.
72 A clear spatial pattern can be seen both for encounter probability and positive density, with a
73 positive value associated with the first factor in the inshore north easterly part of the Celtic Sea
74 into the Bristol Channel and Western English Channel, moving to a negative value offshore in the
75 south-westerly waters (Figure 1). The species loadings coefficients show plaice, sole and whiting
76 to be positively associated with the first factor for encounter probability while the other species
77 are negatively associated. For average positive density, positive associations are also found for
78 haddock and juvenile cod.

79 On the second spatial factor for encounter probability a north / south split can be seen at approxi-
80 mately 49° N while positive density is more driven by a positive value in the deeper westerly waters

81 as well as some inshore areas. Species values for the second factor indicate there are positive
82 associations for juvenile monkfish (*L. piscatorius*), juvenile hake, juvenile megrim, plaice and ju-
83 venile whiting with average positive density, which may reflect two different spatial distributions in
84 the more offshore and in the inshore areas (Figure 1).

85 On the third factor, there is a positive association with the easterly waters for encounter probability
86 and negative with the westerly waters. This splits the roundfish species cod, haddock and whiting
87 which have a positive association with the third factor for average encounter probability from the
88 rest of the species . Positive density is driven by a north / south split (Figure 1), with positive values
89 in the northerly areas. Juvenile monkfish (*L. budgessa* and *L. piscatorius*), cod, juvenile haddock,
90 hake, adult plaice and whiting are also positively associated with the third factor in the north while
91 adult monkfish (*L. budgessa* and *L. piscatorius*), adult haddock, megrims, juvenile plaice and sole
92 are negatively associated (Figure 1).

93 **Time varying species distributions, but stability within species groups** Inter-annual differ-
94 ences in factor coefficients show less structure (Figures S5, S6). These inter-annual differences
95 are important as they reflect the ability of fishers to predict where they can target species from
96 one year to the next. Common patterns in spatiotemporal factor coefficients among species drive
97 spatiotemporal distributions of megrim, anglerfish species and hake (the deeper water species,
98 species-group negatively associated with the second axes of Figure 2a) and the roundfish and
99 flatfish (species-group more positively associated with the second axes of Figure 2a). For spatio-
100 temporal positive density (Figure 2b) cod, haddock and whiting (the roundfish species) are sepa-
101 rated from plaice, sole (the flatfish) and deeper water species.

102 **Three clusters of species show similar spatial patterns** To gain greater insight into the com-
103 munity dynamics we considered how species covary in space and time through among species
104 correlations. Pearson correlation coefficients for the modelled average spatial encounter proba-
105 bility (Figure 3a) show clear strong associations between adult and juvenile size classes for all
106 species (>0.75 for all species except hake, 0.56). Hierarchical clustering identified the same three
107 common groups with roundfish (cod, haddock, whiting), flatfish (plaice and sole) and species found
108 in the deeper waters (hake, megrim and both anglerfish species) showing strong intra-group cor-
109 relations indicating similar spatial distributions. Correlation coefficients for the average positive
110 density also have strong associations among roundfish (Figure 3b).

111 **Subtle differences in distributions may be important to separate catches within groups** If
112 production from mixed fisheries is to be maximised, decoupling catches of species between and
113 within the groups will be key. For example, asking where the maximal separation in the densities
114 of two coupled species is likely to occur? We map the difference in spatial distribution for each
115 pair of species within a species-group for a single year (2015; Figure 4) to facilitate discussion
116 on maximal separation, for example, between difficult to separate species such as haddock and
117 whiting (Figure 4c).

118 Predicted catch distribution from a “typical” otter trawl gear and beam trawl fishing at three differ-
119 ent locations highlights the differences fishing gear and location makes on catches (Figure 4h).
120 In the inshore area (location ‘A’) plaice and sole are the two main species caught reflecting their
121 distribution and abundance, though the otter trawl gear catches a greater proportion of plaice to
122 sole than the beam trawl. The area between Britain and Ireland (location ‘B’) has a greater contri-
123 bution of whiting, haddock, cod, hake and anglerfishes in the catch with the otter trawl catching a
124 greater proportion of the roundfish, haddock, whiting and cod while the beam trawl catches more

125 anglerfishes and megrims. The offshore area has a higher contribution of megrim, anglerfishes
126 and hake with the otter trawl catching a greater share of hake and the beam trawl a greater pro-
127 portion of megrim. Megrim dominates the catch for both gears in location 'C', reflecting its relative
128 abundance in the area.

129 **Addressing the scientific challenges of the landing obligation in mixed fisheries** We have
130 identified spatial separation of three distinct species-groups (roundfish, flatfish and deeper water
131 species) while showing that only subtle differences exist in distributions within species-groups.
132 The differences in catch compositions between gears at the same location (Figure 4h) show that
133 changing fishing methods can go some way to affecting catch, yet that differences in catches
134 between locations are likely to be more important. This highlights that changes in spatial fishing
135 patterns are likely to play an important role in supporting implementation of the landings obligation.

136 More challenging is within-group spatial separation due to overlaps in spatial distributions for the
137 species, driven by common environmental factors. Subtle changes in location fished may yield
138 some benefit in changing catch composition, yet the outcome is likely to be much more difficult to
139 predict. Subtle differences in the distribution of cod, haddock and whiting can be seen in Figures
140 4a-c, showing spatial separation of catches is likely to need to be supported by other measures
141 such as changes to the selectivity characteristics of gear²⁰.

142 A role that science can play in supporting effectiveness of spatiotemporal avoidance could be in
143 providing probabilistic advice on hotspots for species which can inform fishing decisions. Previ-
144 ous modelling studies have shown how spatiotemporal models could improve predictions of high
145 ratios of bycatch species to target species²¹⁻²³, and geostatistical models are well suited as they
146 incorporate spatial dependency while providing for probabilities to be drawn from posterior distri-

¹⁴⁷ butions of the parameter estimates. We posit such advice could be enhanced by integrating data
¹⁴⁸ obtained directly from commercial fishing vessels at a higher temporal resolution, providing real-
¹⁴⁹ time forecasts to inform fishing choices that also captures seasonal differences in distributions.
¹⁵⁰ Such advice could inform optimal policies for time-area closures, move-on rules or even as infor-
¹⁵¹ mal information utilised by fishers directly without being reliant on costly continuous data collection
¹⁵² on environmental parameters.

¹⁵³ An important question for the implementation of the EU's landing obligation is how far spatial
¹⁵⁴ avoidance can go to achieve catch balancing in fisheries. Our model captures differences be-
¹⁵⁵ tween location fished for two gear types and broad scale effect on catch composition. Empirical
¹⁵⁶ studies^{2,7} suggest limits to the effectiveness of spatial avoidance. Differences in ability to change
¹⁵⁷ catch composition have also been observed for different fleets²⁴. This analysis likely reflects a
¹⁵⁸ lower bound on avoidance as fine-scale behavioural decisions such as time-of-day, gear configu-
¹⁵⁹ ration and location choices can also be used to affect catch^{25,26}.

¹⁶⁰ Complex environmental, fishery and community drivers of distribution for species highlights the
¹⁶¹ scale of the challenge in separating catches using spatial management measures. This has im-
¹⁶² portant implications for management of the mixed fisheries under the EU landings obligation. Our
¹⁶³ analysis identifies where it may be easier to separate catches of species (among groups) and
¹⁶⁴ where it is more challenging (within groups). We propose that the framework presented in Figures
¹⁶⁵ 1-4 provides a viable route to reducing the complexity of highly mixed systems. This can allow
¹⁶⁶ informed management discussion over more traditional anecdotal knowledge of single-species
¹⁶⁷ distribution in space and time.

168 **Methods**

169 **Model structure:** We use a geostatistical Vector Autoregressive Spatiotemporal model (VAST)¹
170 to implement a delta-generalised linear mixed modelling (GLMM) framework that takes account
171 of spatio-temporal correlations among species through implementation of a spatial dynamic factor
172 analysis (SDFA). Spatial variation is captured through a Gaussian Markov Random Field, while we
173 model random variation among species and years. Covariates affecting catchability (to account for
174 differences between fishing surveys) and density (to account for environmental preferences) can
175 be incorporated for predictions of presence and positive density. The following briefly summarises
176 the key methods implemented in the VAST framework. For full details of the model the reader is
177 invited directed to Thorson *et al* 2017²⁷.

SDFA: A spatial dynamic factor analysis incorporates advances in joint dynamic species models²⁷ to take account of associations among species by modelling response variables as a multivariate process. This is achieved through implementing a factor analysis decomposition where common latent trends are estimated so that the number of common trends is less than the number of species modelled. The factor coefficients are then associated through a function for each factor that returns a positive or negative association of one or more species with any location. Log-density of any species is then described as a linear combination of factors and loadings:

$$\theta_c(s, t) = \sum_{j=1}^{n_j} L_{c,j} \psi_j(s, t) + \sum_{k=1}^{n_k} \gamma_{k,c} \chi_k(s, t) \quad (1)$$

178 Where $\theta_c(s, t)$ represents log-density for species c at site s at time t , ψ_j is the coefficient for factor
179 j , $L_{c,j}$ the loading matrix representing association of species c with factor j and $\gamma_{k,c} \chi_k(s, t)$ the
180 linear effect of covariates at each site and time²⁸.

¹Software in the R statistical programming language can be found here: www.github.com/james-thorson/VAST

181 The factor analysis can identify community dynamics and where species have similar spatio-
 182 temporal patterns, allowing inference of species distributions and abundance of poorly sampled
 183 species through association with other species and allows for computation of spatio-temporal cor-
 184 relations among species²⁸.

185 We use the resultant factor analysis is used to identify community dynamics and drivers common
 186 among 18 species and results presented through transformation of the loading matrices using
 187 PCA rotation.

Estimation of abundances: Spatio-temporal encounter probability and positive catch rates are modelled separately with spatio-temporal encounter probability modelled using a logit-link linear predictor;

$$\text{logit}[p(s_i, c_i, t_i)] = \beta_p(c_i, t_i) + \sum_{f=1}^{n_\omega} L_\omega(c_i, f) \omega_p(s_i, f) + \sum_{f=1}^{n_\varepsilon} L_\varepsilon(c_i, f) \varepsilon_p(s_i, f, t_i) + \sum_{v=1}^{n_v} \delta_p(v) Q_p(c_i, v_i) \quad (2)$$

and positive catch rates modelling using a gamma- distribution¹⁴.

$$\text{log}[r(s_i, c_i, t_i)] = \beta_r(c_i, t_i) + \sum_{f=1}^{n_\omega} L_\omega(c_i, f) \omega_r(s_i, f) + \sum_{f=1}^{n_\varepsilon} L_\varepsilon(c_i, f) \varepsilon_r(s_i, f, t_i) + \sum_{v=1}^{n_v} \delta_r(v) Q_r(c_i, v_i) \quad (3)$$

188 where $p(s_i, c_i, t_i)$ is the predictor for encounter probability for observation i , at location s for species
 189 c and time t and $r(s_i, c_i, t_i)$ is similarly the predictor for the positive density. $\beta_*(c_i, t_i)$ is the inter-
 190 cept, $\omega_*(s_i, c_i)$ the spatial variation at location s for factor f , with $L_\omega(c_i, f)$ the loading matrix for
 191 spatial covariation among species. $\varepsilon_*(s_i, c_i, t_i)$ is the linear predictor for spatio-temporal variation,
 192 with $L_\varepsilon(c_i, f)$ the loading matrix for spatio-temporal covariance among species and $\delta_*(c_i, v_i)$ the

193 contribution of catchability covariates for the linear predictor with Q_{c_i, v_i} the catchability covariates
 194 for species c and vessel v ; * can be either p for probability of encounter or r for positive density.

The Delta-Gamma formulation is then:

$$\begin{aligned}
 Pr(C = 0) &= 1 - p \\
 Pr(C = c | c > 0) &= p \cdot \frac{\lambda^k c^{k-1} \cdot \exp(-\lambda c)}{\Gamma_k}
 \end{aligned} \tag{4}$$

195 for the probability p of a non-zero catch C given a gamma distribution for the positive catch with
 196 a rate parameter λ and shape parameter k .

197 **Spatio-temporal variation:** The spatiotemporal variation is modelled using Gaussian Markov
 198 Random Fields (GMRF) where data is associated to nearby locations through a Matérn covariance
 199 function with the parameters estimated within the model. Here, the correlation decays smoothly
 200 over space the further from the location and includes geometric anisotropy to reflect the fact that
 201 correlations may decline in one direction faster than another (e.g. moving offshore)¹⁵. The best
 202 fit estimated an anisotropic covariance where the correlations were stronger in a north-east -
 203 south-west direction, extending approximately 97 km and 140 km before correlations for encounter
 204 probability and positive density reduced to <10 %, respectively (Figure S9). Incorporating the
 205 spatiotemporal correlations among and within species provides more efficient use of the data as
 206 inference can be made about poorly sampled locations from the covariance structure.

A probability distribution for spatio-temporal variation in both encounter probability and positive catch rate was specified, $\varepsilon_*(s, p, t)$, with a three-dimensional multivariate normal distribution so that:

$$vec[\mathbf{E}_*(t)] \sim MVN(0, \mathbf{R}_* \otimes \mathbf{V}_{\varepsilon*}) \tag{5}$$

207 Here, $\text{vec}[\mathbf{E}_*(t)]$ is the stacked columns of the matrices describing $\varepsilon^*(s, p, t)$ at every location,
208 species and time, \mathbf{R}_* is a correlation matrix for encounter probability or positive catch rates
209 among locations and \mathbf{V}_* a covariance matrix for encounter probability or positive catch rate among
210 species (modelled within the factor analysis). \otimes represents the Kronecker product so that the cor-
211 relation among any location and species can be computed²⁷.

212 **Incorporating covariates** Survey catchability (the relative efficiency of a gear catching a species)
213 was estimated as a fixed effect in the model, $\delta_s(v)$, to account for differences in spatial fishing
214 patterns and gear characteristics which affect encounter and capture probability of the sampling
215 gear²⁹. Parameter estimates (Figure S10) showed clear differential effects of surveys using otter
216 trawl gears (more effective for round fish species) and beam trawl gears (more effective for flatfish
217 species).

218 No fixed covariates for habitat quality or other predictors of encounter probability or positive density
219 were included. While incorporation may improve the spatial predictive performance²⁷, it was not
220 found to be the case here based on model selection with Akaike Information Criterion (AIC) and
221 Bayesian Information Criterion (BIC).

222 **Parameter estimation** Parameter estimation was undertaken through Laplace approximation of
223 the marginal likelihood for fixed effects while integrating the joint likelihood (which includes the
224 probability of the random effects) with respect to random effects. This was implemented using
225 Template Model Builder (TMB;³⁰) with computation through support by the Irish Centre for High
226 End Computing (ICHEC; <https://www.ichec.ie>) facility.

227 **Data** The model integrates data from seven fisheries independent surveys taking account of cor-
228 relations among species spatio-temporal distributions and abundances to predict spatial density
229 estimates consistent with the resolution of the data.

230 The model was been fit to nine species separated into adult and juvenile size classes (Table S2)
231 to seven survey series (Table S1) in the Celtic Sea bound by 48° N to 52 ° N latitude and 12 ° W
232 to 2° W longitude (Figure S8) for the years 1990 - 2015 inclusive.

233 The following steps were undertaken for data processing: i) data for survey stations and catches
234 were downloaded from ICES Datras ([www.ices.dk/marine-data/data-portals/Pages/
235 DATRAS.aspx](http://www.ices.dk/marine-data/data-portals/Pages/DATRAS.aspx)) or obtained directly from the Cefas Fishing Survey System (FSS); ii) data were
236 checked and any tows with missing or erroneously recorded station information (e.g. tow duration
237 or distance infeasible) removed; iii) swept area for each of the survey tows was estimated based
238 on fitting a GAM to gear variables so that Doorspread = s(Depth) + DoorWt + WarpLength +
239 WarpDiameter + SweepLength and a gear specific correction factor taken from the literature³¹; iii)
240 fish lengths were converted to biomass (Kg) through estimating a von bertalanffy length weight
241 relationship, $Wt = a \cdot L^b$, fit to sampled length and weight of fish obtained in the EVHOE survey
242 and aggregated within size classes (adult and juvenile).

243 The final dataset comprised of estimates of catches (including zeros) for each station and species
244 and estimated swept area for the tow.

245 **Model setup** The spatial domain was setup to include 250 knots representing the Gaussian Ran-
246 dom Fields. The model was configured to estimate nine factors each to describe the spatial and
247 spatiotemporal encounter probability and positive density parameters, with a logit-link for the linear

248 predictor for encounter probability and log-link for the linear predictor for positive density, with an
249 assumed gamma distribution.

250 Three candidate models were identified, i) a base model where the vessel interaction was a ran-
251 dom effect, ii) the base but where the vessel x species effect was estimated as a fixed covariate, iii)
252 with vessel x species effect estimated, but with the addition of estimating fixed density covariates
253 for both predominant habitat type at a knot and depth. AIC and BIC model selection favoured the
254 second model (Table S3). The final model included estimating 130,950 coefficients (1,674 fixed
255 parameters and 129,276 random effect values).

256 **Model validation** Q-Q plots show good fit between the derived estimates and the data for positive
257 catch rates and between the predicted and observed encounter probability (S11, S12). Further,
258 model outputs are consistent with stock-level trends abundances over time from international as-
259 sessments (S13), yet also provide detailed insight into species co-occurrence and the strength of
260 associations in space and time.

1. Batsleer, J., Hamon, K. G., Overzee, H. M. J., Rijnsdorp, A. D. & Poos, J. J. High-grading and over-quota discarding in mixed fisheries. *Reviews in Fish Biology and Fisheries* **25**, 715–736 (2015). URL ["http://dx.doi.org/10.1007/s11160-015-9403-0.](http://dx.doi.org/10.1007/s11160-015-9403-0)
2. Branch, T. & Hilborn, R. Matching catches to quotas in a multispecies trawl fishery: targeting and avoidance behavior under individual transferable quotas. *Canadian Journal of Fisheries and Aquatic Sciences* **65**, 1435–1446 (2008). URL [http://article.pubs.nrc-cnrc.gc.ca/ppv/RPViewDoc?issn=1205-7533{\&}volume=65{\&}issue=7{\&}startPage=1435{\&}ab=y.](http://article.pubs.nrc-cnrc.gc.ca/ppv/RPViewDoc?issn=1205-7533&volume=65&issue=7&startPage=1435&ab=y)
3. Dunn, D. C. *et al.* Empirical move-on rules to inform fishing strategies: A New England case study. *Fish and Fisheries* **15**, 359–375 (2014). URL [http://doi.wiley.com/10.1111/faf.12019.](http://doi.wiley.com/10.1111/faf.12019)
4. Worm, B. *et al.* Rebuilding Global Fisheries. *Science* **325**, 578–585 (2009). URL [http://www.sciencemag.org/cgi/doi/10.1126/science.1173146.](http://www.sciencemag.org/cgi/doi/10.1126/science.1173146)
5. FAO. The state of world fisheries and aquaculture. *Food and Agriculture Organization of the United Nations* **2014**, 218 (2014). URL [http://scholar.google.com/scholar?hl=en{\&}btnG=Search{\&}q=intitle:THE+STATE+OF+WORLD+FISHERIES+AND+AQUACULTURE{\#\#}0.978-92-5-106675-1.](http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:THE+STATE+OF+WORLD+FISHERIES+AND+AQUACULTURE{#\#}0.978-92-5-106675-1)
6. Mcclanahan, T., Allison, E. H. & Cinner, J. E. Managing fisheries for human and food security. *Fish and Fisheries* **16**, 78–103 (2015).
7. Kuriyama, P. T., Branch, T. A., Bellman, M. A. & Rutherford, K. Catch shares have not led to catch-quota balancing in two North American multispecies trawl fisheries. *Marine Policy* **71**, 60–70 (2016). URL [http://dx.doi.org/10.1016/j.marpol.2016.05.010.](http://dx.doi.org/10.1016/j.marpol.2016.05.010)
8. Ulrich, C. *et al.* Achieving maximum sustainable yield in mixed fisheries: A management approach for the North Sea demersal fisheries. *ICES Journal of Marine Science* **74**, 566–575 (2017). URL [https://academic.oup.com/icesjms/article-lookup/doi/10.1093/icesjms/fsw126.](https://academic.oup.com/icesjms/article-lookup/doi/10.1093/icesjms/fsw126)
9. Uhlmann, S. S. *et al.* Discarded fish in European waters: General patterns and contrasts. *ICES Journal of Marine Science* **71**, 1235–1245 (2014).

10. Condie, H. M., Grant, A. & Catchpole, T. L. Incentivising selective fishing under a policy to ban discards; lessons from European and global fisheries. *Marine Policy* **45**, 287–292 (2014). URL <http://linkinghub.elsevier.com/retrieve/pii/S0308597X1300198X>.
11. Van Putten, I. E. *et al.* Theories and behavioural drivers underlying fleet dynamics models. *Fish and Fisheries* **13**, 216–235 (2012). URL <http://doi.wiley.com/10.1111/j.1467-2979.2011.00430.x>.
12. Needle, C. L. & Catarino, R. Evaluating the effect of real-time closures on cod targeting. *ICES Journal of Marine Science* **68**, 1647–1655 (2011). URL <http://icesjms.oxfordjournals.org/cgi/doi/10.1093/icesjms/fsr092>.
13. Thorson, J. T. *et al.* Spatial factor analysis: A new tool for estimating joint species distributions and correlations in species range. *Methods in Ecology and Evolution* **6**, 627–637 (2015).
14. Thorson, J. T., Shelton, A. O., Ward, E. J. & Skaug, H. J. Geostatistical delta-generalized linear mixed models improve precision for estimated abundance indices for West Coast groundfishes. *ICES Journal of Marine Science* **72**, 1297–1310 (2015).
15. Thorson, J. T. & Ward, E. J. Accounting for space-time interactions in index standardization models. *Fisheries Research* **147**, 426–433 (2013).
16. Ellis, J. R., Rogers, S. I. & Freeman, S. M. Demersal Assemblages in the Irish Sea, St George's Channel and Bristol Channel. *Estuarine, Coastal and Shelf Science* **51**, 299–315 (2000). URL <http://www.sciencedirect.com/science/article/pii/S0272771400906772>.
17. Gerritsen, H. D., Lordan, C., Minto, C. & Kraak, S. B. M. Spatial patterns in the retained catch composition of Irish demersal otter trawlers: High-resolution fisheries data as a management tool. *Fisheries Research* **129-130**, 127–136 (2012).
18. Mateo, M., Pawłowski, L. & Robert, M. Highly mixed fisheries: fine-scale spatial patterns in retained catches of French fisheries in the Celtic Sea. *ICES Journal of Marine Science: Journal du Conseil fsw129* (2016). URL <http://icesjms.oxfordjournals.org/lookup/doi/10.1093/icesjms/fsw129>.

19. STECF. EU's Scientific, Technical and Economic Committee on Fisheries (STECF): Fisheries Dependent Information Database (2017). URL <https://stecf.jrc.ec.europa.eu/dd/effort/graphs-annex>.
20. Santos, J. *et al.* Reducing flatfish bycatch in roundfish fisheries. *Fisheries Research* **184**, 64–73 (2016).
21. Ward, E. J. *et al.* Using spatiotemporal species distribution models to identify temporally evolving hotspots of species co-occurrence. *Ecological Applications* **25**, 2198–2209 (2015).
22. Cosandey-Godin, A., Krainski, E. T., Worm, B. & Flemming, J. M. Applying Bayesian spatiotemporal models to fisheries bycatch in the Canadian Arctic. *Canadian Journal of Fisheries and Aquatic Sciences* **72**, 186–197 (2015). URL <http://www.nrcresearchpress.com/doi/abs/10.1139/cjfas-2014-0159>.
23. Breivik, O. N., Storvik, G. & Nedreaas, K. Latent Gaussian models to decide on spatial closures for bycatch management in the Barents Sea shrimp fishery. *Canadian Journal of Fisheries and Aquatic Sciences* **73**, 1271–1280 (2016). URL <http://www.nrcresearchpress.com/doi/10.1139/cjfas-2015-0322>.
24. Pascoe, S., Koundouri, P. & Bjørndal, T. Estimating targeting ability in multi-species fisheries: a primal multi-output distance function approach. *Land Economics* **83**, 382–397 (2007). URL <http://le.uwpress.org/content/83/3/382.short>.
25. Abbott, J. K., Haynie, A. C. & Reimer, M. N. Hidden Flexibility: Institutions, Incentives, and the Margins of Selectivity in Fishing. *Land Economics* **91**, 169–195 (2015).
26. Thorson, J. T. & Kristensen, K. Implementing a generic method for bias correction in statistical models using random effects, with spatial and population dynamics examples. *Fisheries Research* **175**, 66–74 (2016). URL <http://dx.doi.org/10.1016/j.fishres.2015.11.016>.
27. Thorson, J. T. & Barnett, L. A. K. Comparing estimates of abundance trends and distribution shifts using single- and multispecies models of fishes and biogenic habitat. *ICES Journal of Marine Science: Journal du Conseil* fsw193 (2017). URL <http://icesjms.oxfordjournals.org/lookup/doi/10.1093/icesjms/fsw193>.

28. Thorson, J. T. *et al.* Joint dynamic species distribution models: a tool for community ordination and spatio-temporal monitoring. *Global Ecology and Biogeography* **25**, 1144–1158 (2016).
29. Thorson, J. T. *et al.* The importance of spatial models for estimating the strength of density dependence. *Ecology* **96**, 1202–1212 (2015). URL [http://dx.doi.org/10.1890/14-0739.1\\$\\backslash\\$http://www.esajournals.org/doi/pdf/10.1890/14-0739.1](http://dx.doi.org/10.1890/14-0739.1$\\backslash$http://www.esajournals.org/doi/pdf/10.1890/14-0739.1).
30. Kristensen, K., Nielsen, A., Berg, C. W., Skaug, H. & Bell, B. TMB: Automatic Differentiation and Laplace Approximation. *Journal of Statistical Software* **70**, 1–21 (2016). URL <http://arxiv.org/abs/1509.00660>.
31. Piet, G. J., Van Hal, R. & Greenstreet, S. P. R. Modelling the direct impact of bottom trawling on the North Sea fish community to derive estimates of fishing mortality for non-target fish species. *ICES Journal of Marine Science* **66**, 1985–1998 (2009).

Acknowledgements Paul J Dolder gratefully acknowledges funding support from the MARES joint doctoral research programme (MARES_14_15) and Cefas seedcorn (DP227AC) and logistical support, desk space and enlightening discussions with Trevor Branch, Peter Kuriyama, Cole Monnahan and John Trochta at the School of Aquatic and Fisheries Science (SAFS) at the University of Washington during a study visit. The authors gratefully acknowledge the hard-work of many scientists and crew in collecting and storing data during the numerous scientific surveys used in this study without which it would not have been possible. The manuscript benefited greatly from discussions with David Stokes, Colm Lordan, Claire Moore and Hans Gerritsen (Marine Institute, Ireland), Lisa Ready, Chris Darby, Ian Holmes, Stephen Shaw and Tim Earl (Cefas). The authors are very grateful to Lisa Ready for provision of the Cefas datasets.

Author contributions P.J.D., C.M and J.T.T. designed the study. P.J.D. conducted the analysis. All authors contributed to writing the manuscript.

Competing Interests The authors declare that they have no competing financial interests.

Correspondence Correspondence and requests for materials should be addressed to Paul Dolder (email: paul.dolder@gmit.ie).

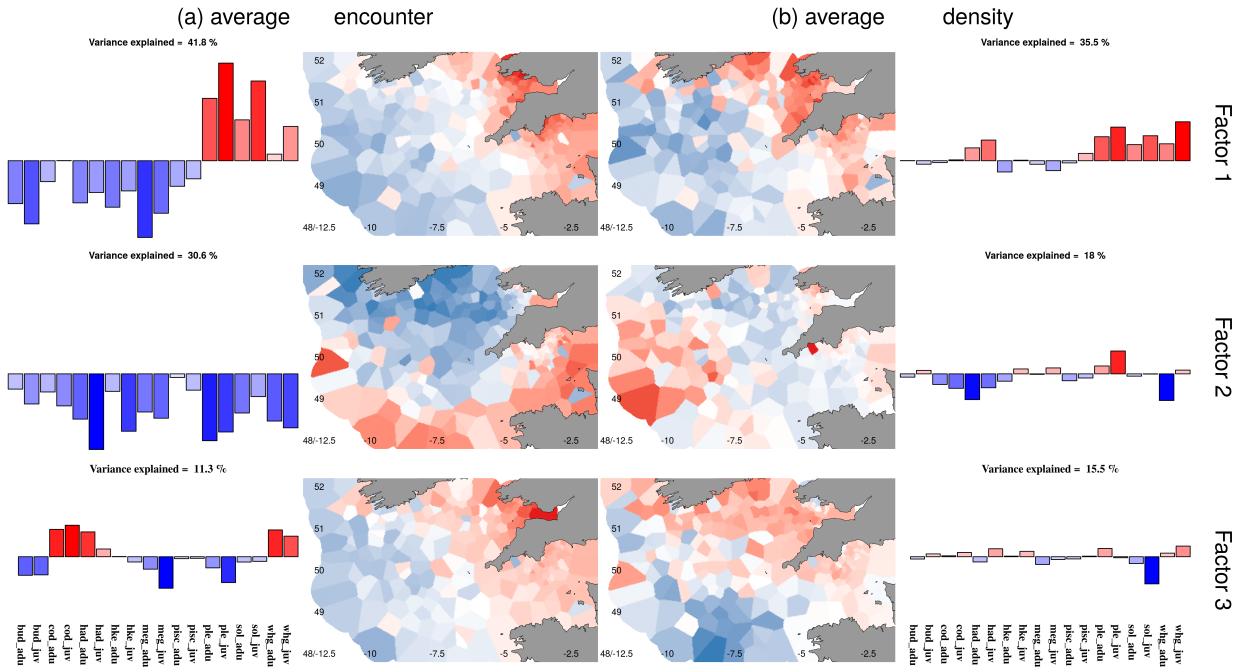


Figure 1: Factor values for the first three factors for (a) Average encounter probability and (b) Average positive density for the species (outer figures) and spatially (inner figures). Red: positive association to the factor, Blue: negative association

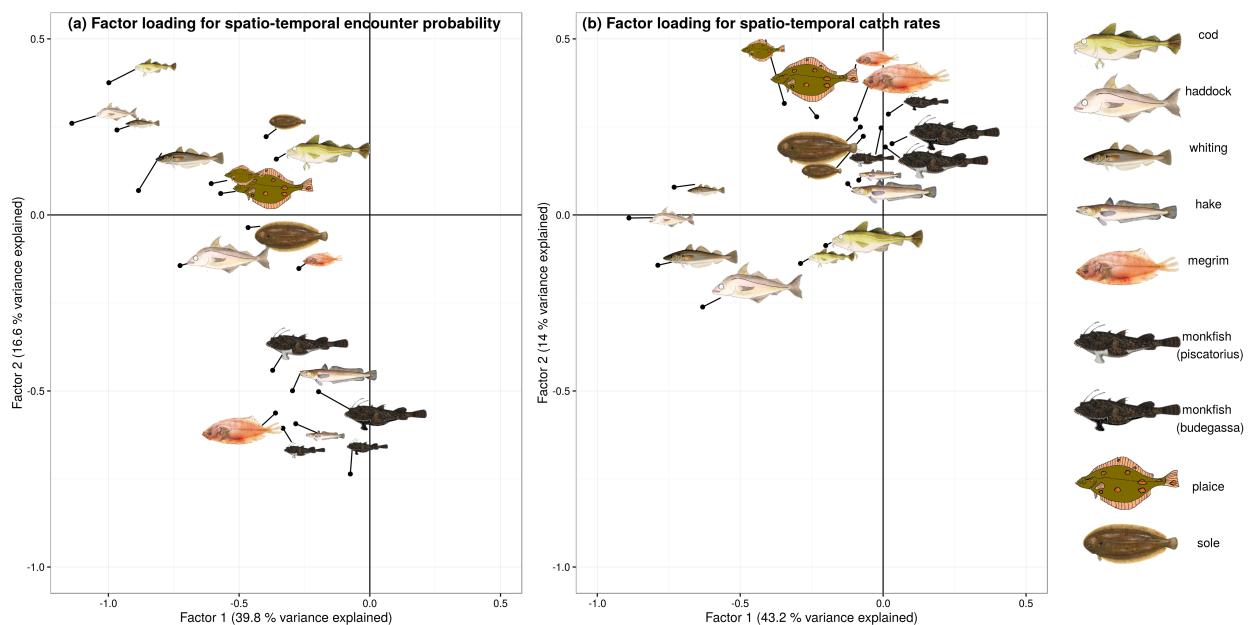


Figure 2: Position of each species on the first two axes from the factor analysis for (a) spatio-temporal encounter probability and (b) spatio-temporal positive density.

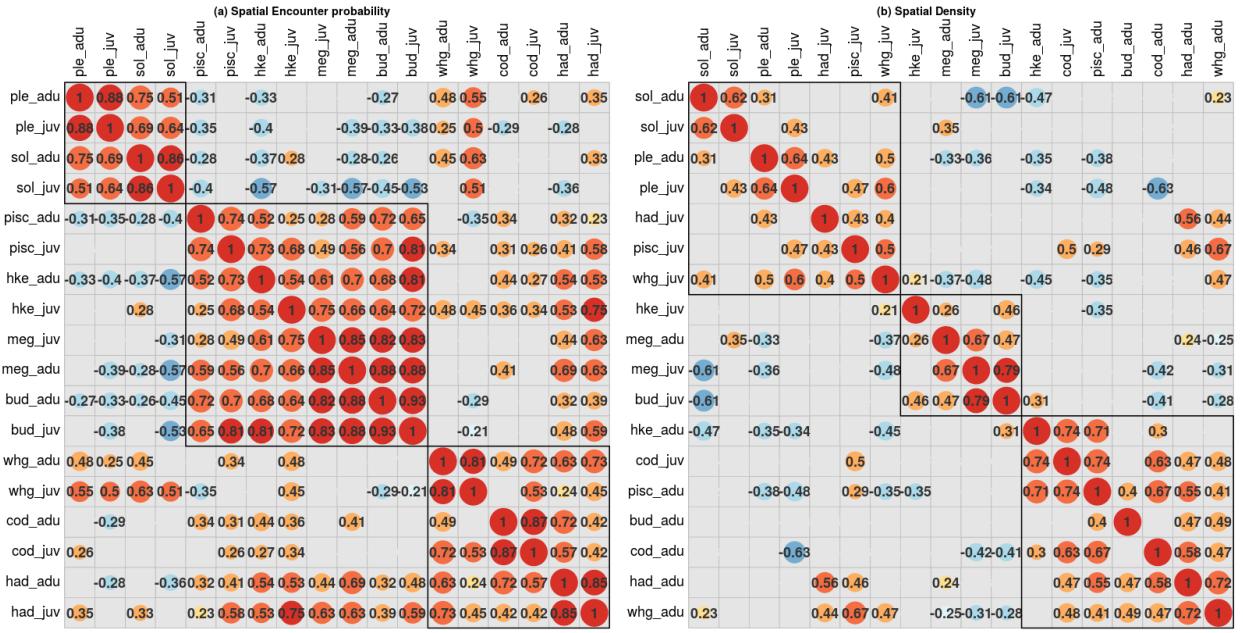


Figure 3: Inter-species correlations for (a) spatial encounter probability over all years and (b) spatial positive density. Species are clustered into three groups based on a hierarchical clustering method with non-significant correlations (the Confidence Interval $[+/- 1.96 * \text{SEs}]$ spanned zero) left blank.

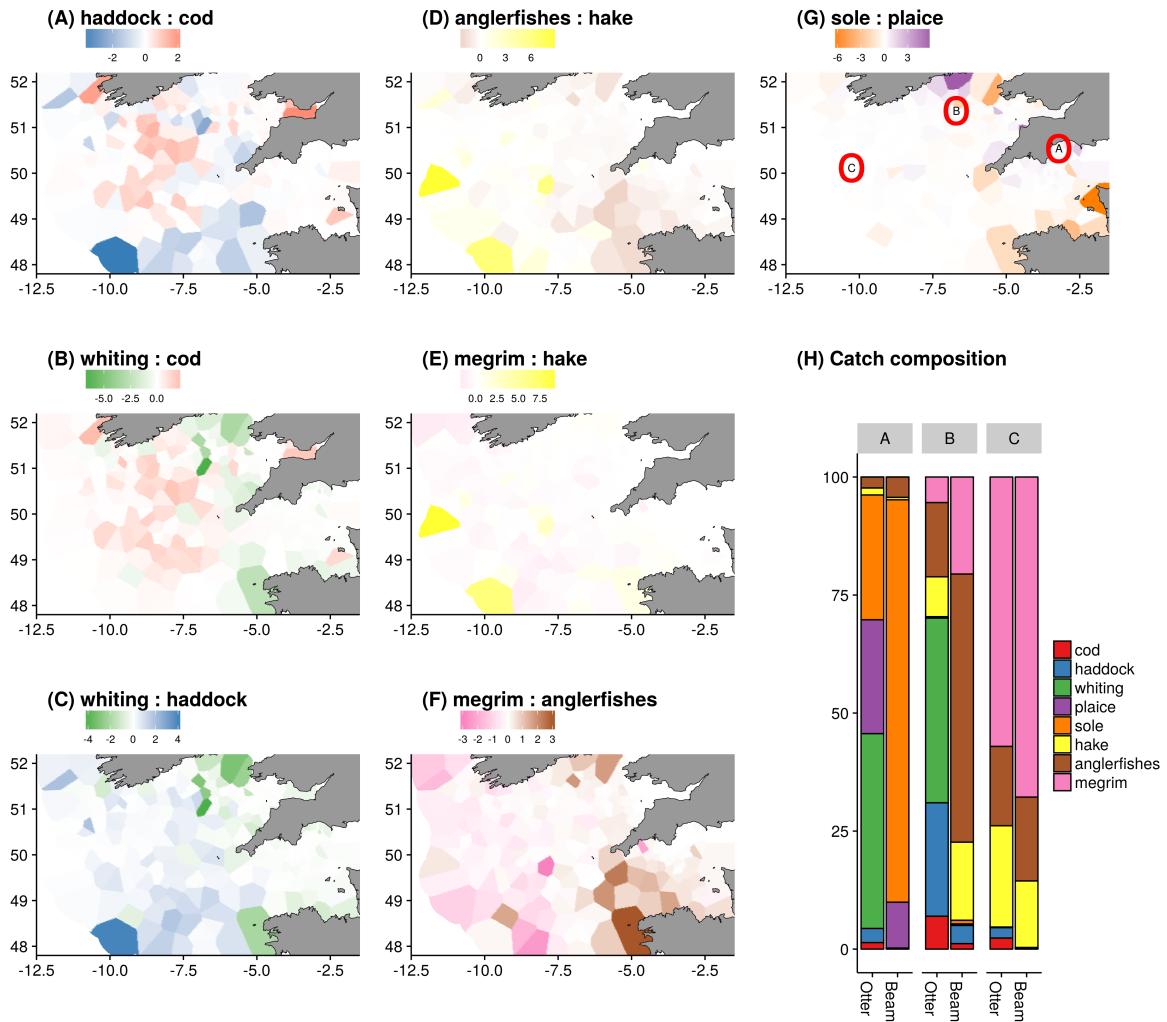


Figure 4: Differences in the standardised spatial density for pairs of species and expected catch rates for two different gears at three different locations in 2015.