Working title: Spatial separation of catches in highly mixed fisheries

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Mixed fisheries have resulted in overexploitation of weaker stocks as over-quota catches continue in fisheries pursuing available quota of healthy stocks. As EU fisheries management moves to a system where all fish caught are counted against the quota (the 'Landings obligation'), from 2019 the challenge will be to maximise catches within the new constraints. Failure to achieve this will result in lower productivity as quota for healthier stocks remains uncaught in order to protect the weaker stocks. Consequently decoupling exploitation of species caught together in mixed fisheries has become an important goal for fisheries sustainability. A potential mechanism for decoupling exploitation is spatial targeting (driven by spatial management or rights-based incentives), but this remains technically challenging due to complex fishery dynamics, the co-occurrence of species at fine spatial and temporal scales and a lack of understanding of how this is driven by community dynamics. We set out a framework to understand how spatial community and fishery dynamics interact to determine species composition in catch. We do so by applying a spatio-temporal joint species distribution model, VAST, to characterise the highly mixed fisheries of the Celtic Sea where numerous target and bycatch species are landed as part of a diverse catch.

Clear common drivers for spatial distribution patterns emerge for three species groups commonly targeted (roundfish flatfish and shelf species) and, while abundance varies from year to year, the same species groups are commonly found in higher densities together. More subtle differences in distribution can be found within a species group, which can be used to adjust catch to species composition, where practical. This indicates common drivers of distribution for groups of species and highlights the scale of the challenge in separating catches within the species-groups using spatial management measures, having important implications for management of the mixed fisheries under the EU landings obligation.

[304 words]

Mixed fisheries and the EU landings obligation Recent decades have seen efforts to reduce exploitation rates in fisheries and rebuild depleted fish populations start to bear fruit [1]. Improved management of fisheries has the potential to increase population sizes and allow increased catches, yet fisheries catch globally remains stagnant [2]. In light of projected increased demand for fish protein [3] there is an important role for well managed fisheries to play in supporting future food security [4] and so there remains a need to ensure fisheries are managed efficiently to maximise productivity.

A particular challenge in realising increased catches from rebuilt populations is maximising yields from mixed fisheries [5–7]. This is because in mixed fisheries, the predominant type of fishery worldwide, several fish species are caught together in the same net or fishing operation (known as 'technical interaction'). If managed by individual quotas and catches do not match available species quotas for a fishing vessel, either the vessel must stop fishing when the first quota is reached (the 'choke' species) or there is overexploitation of the weaker species while fishers continue to catch more healthy species and throw back ('discard') the fish for which they have no quota.

The sustainability of European fisheries have been hampered by this 'mixed fishery problem' for decades with large-scale discarding [8, 9]. However, a paradigm shift is being introduced under the EU Common Fisheries Policy (CFP) reform of 2012 through two significant management changes. First, by 2019 all fish that are caught are due to be counted against the respective stock quota; second, by 2020 all fish stocks must be fished so as to be able to produce their Maximum Sustainable Yield (MSY) [10]. The changes are expected to contribute to attainment of Good Environmental Status (GES) under the European Marine Strategy Framework Directive (MSFD; [11]) and move Europe towards an ecosystem based approach to fisheries management [12]. Unless fishers can avoid catch of unwanted species they will have to stop fishing when reaching their first restrictive quota. This introduces a potential significant cost to fishers of under-utilised quota [7, 13] and provides a strong incentive to mitigate such losses [14, 15]. The ability of fishers to align their catch with available quota depends on being able to exploit target species while avoiding unwanted catch. Methods by which fishers can alter their fishing patterns include by switching fishing method (e.g. trawling to netting), changing technical gear characteristics (e.g. introducing escapement panels in nets), or the timing and location of fishing activity [16, 17].

Spatio-temporal management measures (such as time-limited fishery closures) have been applied in the past to reduce unwanted catch through changes in spatial fishing patterns with varying degrees of success (e.g. [18–21]) while move-on rules have also been proposed or implemented to influence catch rates of particular vulnerable species in order to reduce or eliminate discards (e.g. [22–24]). However, such measures have generally been targeted at individual species without considering associations and interactions among several species. Highly mixed fisheries are complex with spatial, technological and community interactions combining. The design of spatio-temporal management measures which aim to allow exploitation of healthy stocks while protecting weaker stocks requires understanding of these interactions on a meaningful scale to managers and fishers. Here, we set out a framework for understanding these complexities. We do this by implementing a spatio-temporal dimension reduction method and use the results to draw inference and create a framework to identify trends common among species groups to describe where spatial measures can contribute to mitigating unwanted catches in the Celtic Sea mixed fisheries.

[589 words]

Framework for analysing spatio-temporal mixed fisheries interactions We present a framework for analysing how far spatio-temporal avoidance can go towards mitigating imbalances in quota in mixed fisheries. We use fisheries independent survey data to characterise the spatio-temporal dynamics of key components of a fish community by employing a geostatistical Vector Autoregressive Spatio-temporal model (VAST). VAST includes i) a factor analysis decomposition to describe trends in spatio-temporal dynamics of the different species as a function of *n* latent variables [25] to identify community dynamics and drivers common among species groups. This allows for inference of the distribution and density of poorly sampled species through association with the modelled factors. In addition, VAST ii) separately models spatio-temporal encounter probability and catch rates to allow identification of differences in associations for distribution of the species groups and densities upon encounter [26], employs iii) Gaussian Markov Random Fields (GMRFs) to capture spatial and temporal correlations within and among species groups for both encounter probability and catch rates [27], and iv) is set in a mixed modelling framework to allow estimation of fixed effects to account for systematic differences driving encounter and catches, such as survey catch rate differences, while integrating across random effects which capture the spatio-temporal properties of the fish community.

[200 words]

Dynamics of Celtic Sea fisheries We use the fisheries in the Celtic Sea as a case study. The Celtic Sea is a temperate sea where a large number of species make up the commercial catches. Fisheries are spatially and temporally complex with mixed fisheries undertaken by several nations using different gear types [28, 29]. (MORE SPECIFIC - details of number of species in typical landings, key species).

We parametrise our spatio-temporal model using catch data from seven fisheries independent surveys undertaken over the period 1990 - 2015 (Table S1) and include nine of the main commercial species: Atlantic cod (*Gadus morhua*), Atlantic haddock (*Melanogrammus aeglefinus*), Atlantic whiting (*Merlangius merlangus*), European Hake (*Merluccius merluccius*), white-bellied anglerfish (*Lophius piscatorius*), black-bellied anglerfish (*Lophius budegassa*), megrim (*Lepidorhombus whiffiagonis*), European Plaice (*Pleuronectes platessa*) and Common Sole (*Solea solea*). These species make up $>$60 % of landings by towed fishing gears for the area (average 2011 - 2015, STECF data). Each species was separated into juvenile and adult size classes based on their legal minimum conservation reference size (Table S2).

We analyse the data to understand how the different associations among species-groups (combination of species and size class) and their potential drivers affect catch compositions in mixed fisheries. We consider how these have changed over time, and the implications for mixed fisheries in managing catches of quota species under the EU's landings obligation.

[223 words]

Common spatial patterns driving species associations A spatial dynamic factor analysis decomposes the dominant spatial patterns driving differences in encounter probability and abundance. Figure 1 shows the first three factors for (a) average spatial encounter probability and (b) average density. The first three factors account of 83.7 % of the variance in encounter probability and 69 % of the variance in density, respectively. A clear spatial pattern can been seen both for encounter probability and density, with a positive association with the first factor in the inshore North Easterly part of the Celtic Sea into the Bristol Channel and Western English Channel, moving to a negative association offshore in the south-westerly waters. On the second factor a North / South split can be seen for encounter probability at approximately the 49° N while density is more driven by a positive association in the deeper westerly waters. The opposite is evident on the third factor, with a positive association with the Easterly waters for encounter probability and negative with the westerly waters, while density is driven by a North / South split.

The first factor was highly correlated with log(depth) for both encounter probability (-0.85, CI = -0.88 to -0.81; Figure S1) and density (-0.71, CI = -0.77 to -0.65; Figure S2). A random forest classification tree assigned 80 % of the variance in the first factor for encounter probability to depth and predominant substrate type, with the majority (86 %) of the variance explained by depth. The variance explained by these variables dropped to 25 % on the second factor with a more even split between depth and substrate, while explaining 60 % of the variance on the third factor. For density, the variables explained less of the variance with 62 %, 35 %, and 31 % for each of the factors, respectively.

It is clear that depth and to a lesser extent substrate are important predictors for the main driver of similarities and differences in distributions and abundances for the different species groups. The first factor correlates strongly with these variables, despite them not explicitly being incorporated in the model. The utility of these variables as predictors of species distributions has been identified in other marine species distribution models [30]; the advantage to the approach taken here is that, where such data is unavailable at appropriate spatial resolution, the spatial factor analysis can adequately characterise these influences.

[397 words]

Changes in spatial patterns over time, but stability in species dynamics While there are clear spatial patterns in the factors describing average encounter probability and density, there are inter-annual differences in factor coefficients which show less structure (Figures S4, S5). While temperature is often included as a covariate in species distribution models it was found not to contribute to the variance in the factor coefficients (Figure S6, correlations for both encounter probability and density ~ 0).

While spatio-temporal factor coefficients did not show common trends, among species groups there were common dynamics. Figure 2a shows that the same factors appear to drive spatio-temporal distributions of megrim, anglerfish species and hake (the deeper water species, species grouping negatively associated with the second axes) on the one hand and the roundfish and flatfish on the other. For spatio-temporal density (Figure 2b) cod, haddock and whiting (the roundfish species) are separated from plaice, sole (the flatfish) and deeper water species. As such, higher catches the other roundfish species group would be expected when catching one species group. This suggests that a common environmental driver is influencing the distributions of the species groups.

[178 words]

Correlations show three distinct species-group associations Pearson correlation coefficients for the modelled average spatial encounter probability (Figure 3a) show clear strong associations between adult and juvenile size classes for all species (>0.75 for all species except Hake, 0.56). Among species groups, hierarchical clustering identified three common groups; Roundfish (cod, haddock, whiting) are found closely associated, with correlations for adult cod with adult haddock and adult whiting of 0.73 and 0.5 respectively, while adult haddock with adult whiting was 0.63. Flatfish (plaice and sole) are also strongly correlated with adult plaice and sole having a coefficient of 0.75. The final group are principally species found in the deeper waters (hake, megrim and both anglerfish species) with the megrim strongly associated with the budegassa anglerfish species (0.88). Negative relationships were found between plaice and sole and the monkfish species (-0.27, -0.26 for the adult size class with budegassa adults respectively) and hake (-0.33, -0.37) indicating spatial separation in distributions.

Correlation coefficients for the average density (Figure 3b) show less significant relationships then for encounter probability, but still evident are the strong association among the roundfish with higher catches of cod are associated with higher catches of haddock (0.58) and whiting (0.47), as well as the two anglerfish species (0.71 for piscatorius and 0.44 for budegassa) and hake (0.73). Similarly, plaice and sole are closely associated (0.31) and higher catches of one would expect to see higher catches of the other, but also higher catches of some juvenile size classes of roundfish (whiting and haddock) and anglerfish species. Negative association of juvenile megrim, anglerfish (budegassa) and hake with adult sole (-0.61, -0.61 and -0.47 respectively), plaice (-0.36 and -0.35 for megrim and hake only) indicate generally high abundance of one can predict low abundance of the other successfully.

[[In addition to the average correlation, we also estimate how correlations change from one year to the next. The spatial correlations (representing the average correlations across all years) from the population correlations show reasonable alignment with the spatio-temporal population correlations (representing how correlations change from year to year) indicating generally predictable relationships between species groups from one year to the next (0.59 (0.52 - 0.66) and 0.47 (0.38 - 0.55) for encounter probability and density respectively). However, a linear regression between the spatial correlations and the spatio-temporal correlations shows high variance (R^2 = 0.36 and 0.22 respectively), indicating that the scale of these relationships do change from one-year to the next. This would have implications for the predictability of the relationship between catches of one species group and another. It can also be seen in the spatial factor scores that there are subtle differences in spatial patterns in factor coefficients from one year to the next (Figures S5 and S6) indicating changes being driven by temporally changing environmental factors.]]

[459 words]

Subtle differences in distributions may be important to separate catches within groups under the landing obligation The analysis shows the interdependence within species groups (roundfish, flatfish and deeper water species) which has important implications for how spatial avoidance can be used to support implementation of the EU's landings obligation. If mixed fisheries are to maximise productivity, decoupling catches of species between and among the groups will be key. Methods to do this include changes to the selectivity characteristics of gear (e.g. [31]) and spatio-temporal avoidance. Both are likely to play a role but the extent to which they can contribute to fisheries sustainability is unknown. While here we demonstrate the separation of three distinct species groupings (roundfish, flatfish and deeper water species) separating catches within groups is likely to be equally as important. Figure 4 shows the difference in spatial distribution within a group for each of the species groupings for a single year (2015).

Figure 4a indicates that cod had a more North-westerly distribution than haddock while cod had more westerly distribution than whiting roughly delineated by the 7° W line. Whiting appeared particularly concentrated in an area between 51 and 52 ° N and 5 and 7 ° W, which can be seen by comparing the whiting distribution with both cod (Figure 4b) and haddock (Figure 4c). For the deeper water species Figures 4d and 4e indicate that hake are particularly concentrated in two areas compared to anglerfishes[1] and megrim (though for megrim, a fairly even relative distribution elsewhere is indicated by the large amount of white space). For anglerfishes and megrim (Figure 4f), anglerfishes have a more easterly distribution than megrim. For the flatfish species plaice and sole (Figure 4g), sole appear to be more concentrated along the coastal areas of Ireland and the UK, while Plaice are more concentrated in the Southern part of the English Channel along the coast of

[1] two species combined as they are managed as one

France.

These nuanced differences in distribution can have important implications for fishers seeking to fish in areas which match their quota holdings. Figure 4h shows the predicted catch distribution from a ”typical” Otter trawl gear and Beam trawl gear fishing at three different locations. As can be seen, both the gear selectivity and area fished play important contributions to the catch compositions; in the inshore area (66) plaice and sole are the two main species in catch reflecting their distribution and abundance, though the Otter trawl gear catches a greater proportion of plaice than the Beam trawl. The area between the UK and Ireland (79) has a greater contribution of whiting, haddock, cod, hake and anglerfishes in the catch with the Otter trawl catching a greater proportion of the roundfish, haddock, whiting and cod. The offshore area has a higher contribution of megrim, anglerfishes and hake with the Otter trawl catching a greater share of hake and the Beam trawl a greater proportion of megrim. Megrim dominates the catch for both gears in area 216, reflecting its relative abundance in the area.

[[Figure 5 shows the joint production function for the entire spatial domain, giving the global production sets for the years 2011 - 2015. It gives the space in which vessels have to operate where they can change the relative composition of each species in the catch as a function of changing location fished only. The convex hull of the space is the flexibility vessels have in order to adapt to the changing fishing opportunities given the association of species with each other [32]. As can be seen from Figure 5a which shows the trade-off between cod and haddock for an Otter trawler....

Figure 5b shows the same for plaice and sole for a Beam trawler... STRUGGLING TO DEFINE WHAT IS ’LOTS’ AND WHAT IS ’LITTLE’ SPACE OBJECTIVELY...?]]

[489 words]

Application of framework to support implementation landing obligation in mixed fisheries

The framework described and applied here to the Celtic Sea identifies three species groups that show spatial separation. Within groups spatial separation is more challenging which has important implications for how the EU's landings obligation is implemented.

Real time? Commercial data ? Hotspots & Notspots ??

How far can spatial changes in targeting bring you towards achieving the right balance of catch in mixed fisheries to maintain productivity. FOOD SECURITY!!

Methods

Model structure: VAST[2] implements a delta-generalised linear mixed modelling (GLMM) framework that takes account of spatio-temporal correlations among species-groups through implementation of a spatial dynamic factor analysis (SDFA). In the model, spatio-temporal variation is represented through three-dimensional Gaussian Random Fields while covariates affecting catchability (to account for differences between fishing surveys) and density (to account for environmental preferences) can be incorporated for predictions of presence and density. The following briefly summarises the key methods implemented in the VAST framework. For full details of the model the reader is invited directed to Thorson *et al* 2017 [33].

[2] software in the R statistical programming language can be found here: `www.github.com/james-thorson/VAST`

SDFA: A spatial dynamic factor analysis incorporates developments in joint dynamic species models [33] to take account of associations among species / species-groups 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 (M) is less than the number of species-groups (N) modelled ($1 \leq N \leq M$). The species group trends 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 be described as a linear combination of factors:

$$\theta_p(s,t) = \sum_{j=1}^{n_j} L_{p,j}\psi_j(s,t) + \sum_{k=1}^{n_k} \gamma_{k,p}\chi_k(s,t) \tag{1}$$

Where $\theta_p(s,t)$ represents log-density for species p at site s at time t, ψ_j is the coefficient for factor j, $L_{p,j}$ the loading matrix representing association of species p with factor j and $\gamma_{k,p}\chi_k(s,t)$ the linear effect of covariates at each site and time [34].

The factor analysis can identify community dynamics and where species have similar spatio-temporal patterns, allowing inference of species distributions and abundance of poorly sampled species through association with other species and allows for computation of spatio-temporal correlations among species-groups [34].

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;

$$logit[p(s_i,p_i,t_i)] = \gamma_p(p_i,t_i) + \varepsilon_p(s_i,p_i,t_i) + \delta_p(p_i,v_i) \tag{2}$$

and positive catch rates modelling using a gamma- distribution [26].

$$gamma[r(s_i, p_i, t_i)] = \gamma_p(p_i, t_i) + \varepsilon_p(s_i, p_i, t_i) + \delta_p(p_i, v_i) \tag{3}$$

With $\gamma_*(p_i, t_i)$, $\varepsilon_*(s_i, p_i, t_i)$ and $\delta_*(p_i, v_i)$ representing an intercept, spatio-temporal variation and a vessel effect (v) respectively for for either probability of encounter, p or density r.

Spatio-temporal variation: The spatio-temporal variation is modelled using Gaussian Markov Random Fields (GMRF) where data is associated to nearby locations through a Matérn covariance function with the parameters estimated within the model. Here, the correlation decays smoothly over space/time the further from the location and includes geometric anisotropy to reflect the fact that correlations may decline in one direction faster than another (e.g. moving offshore) [27]. The best fit estimated an anisotropic covariance where the correlations were stronger in a North-East - South-West direction, extending approximately 97 km and 140 km before correlations for encounter probability and density reduced to $<$10 %, respectively (Figure S10). Incorporating the spatio-temporal correlations among and within species provides more efficient use of the data as 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:

$$vec[\mathbf{E}_*(t)] \sim MVN(0, \mathbf{R}_* \otimes \mathbf{V}_{\varepsilon *}) \tag{4}$$

Here, $vec[\mathbf{E}_*(t)]$ is the stacked columns of the matrices describing $\varepsilon*(s, p, t)$ at every location, species and time, $\mathbf{R}_*$ is a correlation matrix for encounter probability or positive catch rates among locations and $\mathbf{V}_*$ a correlation matrix for encounter probability or positive catch rate among species (modelled within the factor analysis). $\otimes$ represents the Kronecker product so that the correlation among any location and species can be computed [33].

Incorporating covariates Survey catchability (the relative efficiency of a gear catching a species-group) was estimated as a fixed effect in the model, $\delta_s(v)$, to account for differences in spatial fishing patterns and gear characteristics which affect encounter and capture probability of the sampling gear [35]. Parameter estimates (Figure S11) showed clear differential effects of surveys using otter trawl gears (more effective for round fish species) and beam trawl gears (more effective for flatfish species).

No fixed covariates for habitat quality or other predictors of encounter probability or density were include. While incorporation may improve the spatial predictive performance [33], it was not found to be the case here based on model selection with Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Parameter estimation Parameter estimation was undertaken through Laplace approximation of the marginal likelihood for fixed effects while integrating the joint likelihood (which includes the probability of the random effects) with respect to random effects. This was implemented using Template Model Builder (TMB; [36]) with computation through support by the Irish Centre for High End Computing (ICHEC; `https://www.ichec.ie`) facility.

Data The model integrates data from seven fisheries independent surveys taking account of correlations among species-group spatio-temporal distributions and abundances to predict spatial density estimates consistent with the resolution of the data.

The model was been fit to nine species separated into adult and juvenile size classes (Table S2) to seven survey series (Table S1) in the Celtic Sea bound by 48° N to 52 ° N latitude and 12 ° W to 2° W longitude (Figure S9) for the years 1990 - 2015 inclusive.

The following steps were undertaken for data processing: i) data for survey stations and catches were downloaded from ICES Datras (`www.ices.dk/marine-data/data-portals/Pages/DATRAS.aspx`) or obtained directly from the Cefas Fishing Survey System (FSS); ii) data were checked and any tows with missing or erroneously recorded station information (e.g. tow duration or distance infeasible) removed; iii) swept area for each of the survey tows was estimated based on fitting a GAM to gear variables so that Doorspread = s(Depth) + DoorWt + WarpLength + Warp-Diameter + SweepLength and a gear specific correction factor taken from the literature [37]; iii) fish lengths were converted to biomass (Kg) through estimating a von bertalanffy length weight relationship, $Wt = a \cdot L^b$, fit to sampled length and weight of fish obtained in the EVHOE survey and aggregated within size classes (adult and juvenile).

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

[1019 words]

Model setup The spatial domain was setup to include 250 knots representing the Gaussian Random Fields. The model was configured to estimate nine factors to describe the spatial and spatio-temporal encounter probability and density parameters, with a log-link between the logit encounter probability and assumed gamma distribution on positive catches.

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

Model validation Q-Q plots show good fit between the derived estimates and the data for positive catch rates and between the predicted and observed encounter probability. Further, model outputs are consistent with stock-level trends abundances over time from international assessments, yet also provide detailed insight into species co-occurrence and the strength of associations in space and time.

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Figure 1 Spatial Factor coefficients for (a) the average spatial encounter probability and (b) the average density, on the first 3 factors. Red: positive association to the factor, Blue: negative association

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

Figure 3 Inter-species correlations for (a) spatial encounter probability over all years and (b) spatial density. Species-groups are clustered into three groups based on a hierarchical clustering method with non-significant correlations (those where the Confidence Interval spanned zero) left blank

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

Figure 5 Example of technical efficiency space