Title: A feeding guild indicator to assess environmental change impacts on marine ecosystem structure and functioning

Authors: Murray S. A. Thompson[1], Hugo Pontalier[1], Michael A. Spence[1], John K. Pinnegar[1], Simon Greenstreet[2], Meadhbh Moriarty[2,3], Pierre Hélaouët[4] and Christopher P. Lynam[1]

[1] Centre for Environment, Fisheries and Aquaculture Science (Cefas), Lowestoft Laboratory, Pakefield Road, Lowestoft, Suffolk, NR33 0HT, UK

[2] Marine Scotland Science, UK

[3] Environmental Sciences Research Institute, Ulster University, Cromore Road, Coleraine, BT52 1SA, UK

[4] Marine Biological Association, UK

Correspondence: murray.thompson@cefas.co.uk

Abstract

1. Integrating food web indicators into ecological status assessments is central to developing effective management measures that can improve degraded ecosystems. This is because they can reveal how ecosystems respond to environmental change that cannot be inferred from studying habitat, species or assemblages alone. However, the substantial investment required to monitor food webs (e.g. via stomach contents analysis) and the lack of internationally agreed approaches to assessing them has hampered their development.

2. Inventories of trophic interactions have been collated worldwide and across biomes, and can be applied to infer food web structure and energy flow. Here, we compile a new marine dataset containing 8092 unique predator-prey interactions from 415,294 fish stomachs. We demonstrate how feeding guilds (i.e. groupings based on diet and life stage) could be defined systematically and in a way that is conducive to their application internationally across ecosystems; and apply them to the North Sea fish assemblage to demonstrate their responsiveness to anthropogenic pressures.
3. We found evidence for seven distinct feeding guilds. Differences between guilds were related to predator size, which positively correlated with piscivory, phylogeny, with multiple size-classes of a species often in the same guild, and habitat, as pelagic, benthic and shallow-coastal foraging was apparent.
4. Guild biomasses were largely consistent through time at the North Sea-level and spatially aggregated at the regional level with change relating to changes in resource availability, temperature, fishing, and the biomass of other guilds. This suggests that fish biomass was partitioned across broad feeding and environmental niches, and changes over time were governed partly by guild carrying capacities, but also by a combination of covariates with contrasting patterns of change. Management of the North Sea ecosystem could therefore be adaptive and focused towards specific guilds and pressures in a given area.
5. *Synthesis and applications*. We propose a food web indicator which has been explicitly called for to inform policy via food web status assessment as part of the European Union's Marine Strategy Framework Directive and the indicator

toolkit supporting The Convention for the Protection of the Marine Environment of the North-East Atlantic (the 'OSPAR Convention').

Keywords: feeding guilds, food web indicator, marine ecosystem, ecosystem structure and function, environmental change, fishing impacts, good environmental status, ecological status assessment

French translation of Title, Abstract and Keywords:

Titre: Un indicateur de guilde, basé sur la spécialisation alimentaire, pour appréhender l'impact des changement environnementaux sur la structure et le fonctionnement des écosystèmes marins

Résumé

1. L'intégration des indicateurs de réseaux trophiques dans les évaluations des statuts écologiques est essentielle pour développer des mesures de gestions efficaces des écosystèmes dégradés. De par leur nature intégrative, ces indicateurs peuvent dévoiler la façon dont les écosystèmes répondent aux changements environnementaux même lorsque ces réponses ne peuvent être déduites des études d'habitats, d'espèces ou d'assemblages effectuées séparément. Cependant l'investissement considérable nécessaire à la surveillance des réseaux trophiques (par ex. les analyses de contenus stomacaux) et l'absence d'une approche internationalement acceptée pour les évaluer a freiné leur développement.

2. Les interactions trophiques ont été inventoriées à travers le monde et les biomes et peuvent être utilisés pour en déduire la structure des réseaux trophiques et les flux d'énergie. Nous avons compilé un nouveau jeu de données marines contenant 8 092 interactions uniques proie-prédateur à partir de 415 294 estomacs de poissons. Nous décrivons une manière de caractériser systématiquement les guildes alimentaires (ie. regroupement basé sur le régime alimentaire et le moment de la vie) et de manière propice à leur application dans tous les écosystèmes à l'échelle internationale; et nous les mettons en œuvre dans les assemblages des espèces de poissons de la Mer du Nord pour décrire leur réactivité aux pressions anthropogéniques.

3. Nous avons mis en évidence sept guildes alimentaires distinctes. Les différences entre guildes sont liées à la taille des prédateurs (positivement corrélée avec la piscivorie), la phylogénie (plusieurs classes de taille d'une espèce sont souvent dans la même guilde), et l'habitat (les habitats pélagiques, benthiques et côtier peu profond sont mis en évidence).

4. Les biomasses des guildes sont essentiellement constantes à travers le temps à l'échelle de la Mer du Nord et agrégées spatialement à l'échelle régionale. Les fluctuations des biomasses sont dictées par la variation de la disponibilité alimentaire, la température, la pêche et la biomasse des autres guildes. Cela suggère que la biomasse des poissons est divisée entre de larges niches alimentaires et environnementales et que les changements temporels sont en partie contrôlés par la capacité de charge des guildes mais

aussi par une combinaison de covariables aux fluctuations opposées. La gestion des écosystèmes dans la Mer du Nord pourrait ainsi être adaptatif et se concentrer sur des pressions et guildes spécifiques dans une région donnée.

5. *Synthèse et applications.* Dans le cadre de la Directive Cadre Stratégie pour le Milieu Marin de l'Union Européenne, nous proposons un indicateur des réseaux trophiques, ouvertement réclamé pour éclairer les pratiques, via l'évaluation des statuts des réseaux trophiques, ainsi que la boite à outils de l'indicateur en appui à la Convention pour la protection du milieu marin de l'Atlantique du Nord-Est (Convention OSPAR).

Mot-clés: guildes alimentaires, indicateur de réseaux trophiques, écosystème marin, structure et fonction écosystémique, changement environnementale, impact de la pêche, bon état écologique, évaluation de l'état écologique

Introduction

Determining how anthropogenic and environmental stressors affect ecosystems is critical in ecological status assessment. Analysis of food webs is seen as a key component in evaluating ecosystem status because they reveal system-level phenomena that cannot be detected by studying focal species or assemblages alone (Cohen, Schittler, Raffaelli, & Reuman, 2009; Rombouts et al., 2013; Tam et al., 2017). For instance, studies have shown that effects mediated via the food web can

include changes to resources ('bottom-up' effects), to predation pressure ('top-down' effects), lead to secondary extinctions, and these responses, among others, may interact (Brose et al., 2016; Dunne, Williams, & Martinez, 2002; Lynam et al., 2017; Wang & Brose, 2018). In the marine environment, an area we focus on here, impacts from overfishing and warming associated with climate change have been widely reported to manifest at the food web-level (Ciannelli et al., 2007; Heath, 2005; Planque et al., 2010; Scheffer, Carpenter, & De Young, 2005). Hence, marine food web indicator development has received much recent attention (e.g. Greenstreet et al., 2011; Rombouts et al., 2013; Queirós, Fernandes, Genevier, & Lynam, 2018).

Organismal body size has been described as a 'super trait' since it determines many other traits which can affect food web structure and energy flux, such as trophic level, access to resources, vulnerability to predation and sensitivity to perturbation (Brose et al., 2006; Cohen et al. 2009; Hirt et al., 2018; Petchey et al. 2008; Woodward et al., 2005). This has led to the use of body size distributions (e.g. Jennings et al. 2001; Kerr & Dickie, 2001), such as proportion of large individuals (e.g. the large fish indicator; LFI; Engelhard et al., 2015; Greenstreet et al., 2011; Modica et al., 2014; Shephard et al., 2011), and the inclusion of species life-stages to interpret changes to food webs (Clegg, Ali, & Beckerman, 2018). Research conducted by The European Science Foundation Research Network (SIZEMIC) indicated that further synthesis of taxonomic information with body size distribution data could help to develop a universal indicator of ecological status (Petchey & Belgrano, 2010). Despite this, and specific calls for the development of food web indicators within regulatory frameworks such as OSPAR and the Marine Strategy Framework Directive (MSFD), a more synthetic approach that encapsulates body

size, taxonomy and feeding interactions has not yet been accepted into any indicator framework.

Using functionally distinct ‘guilds’ or ‘groups’ that encapsulate taxonomic and trait information relevant to food web assessment has been widely advocated (e.g. EC, 2010; ICES, 2014, 2018; Rombouts et al., 2013; Shephard et al., 2015). Yet, the process of defining such groups has received less attention, often relying on either feeding ecology, habitat preference, taxon-based morphological information, or some expert judgement of a combination of these (e.g. Greenstreet et al. 1997; Heath, 2005; Reecht et al. 2013; Shephard et al., 2014; but see Garrison & Link, 2000). This makes comparisons across systems challenging because any difference could have a methodological basis. Another approach would be to comprehensively survey feeding interactions. However, this would be prohibitively expensive (Gray et al., 2015; Ings et al., 2009), especially given the dearth of feeding information for the lower tropic levels in marine food webs (Rombouts et al., 2013), and this is before more complex spatial and/ or temporal changes in communities (e.g. via seasonal migrations) or interactions between small and large individuals are considered. Thus, despite the many potential advantages of food web assessment, and further integration of taxonomic and body size data into this, defining guilds and gathering feeding interaction data remains a significant challenge.

Inventories of trophic interactions with predator-prey body sizes have been collated worldwide and across biomes (e.g. Brose et al., 2005; Gray et al., 2015; Pinnegar, 2014). Information from these can be applied to assess within- and cross-system changes in food web structure and energy flow in a repeatable, standardised way. For instance, based on species lists collated during long-term UK-wide

monitoring of running waters, Gray *et al.* (2016) used a feeding link inventory to infer food web structure and thereby asses biotic recovery following widespread improvements in water quality. Feeding inventories such as the 'Integrated Database and Portal for Fish Stomach Records' (DAPSTOM; Pinnegar, 2014) and ICES 'Year of the Stomach' database (ICES, 1997; www.ices.dk/marine-data/data-portals/Pages/Fish-stomach.aspx) exist for marine ecosystems but have not yet been applied to develop food web indicators. We combine these databases to produce the most comprehensive dataset of trophic interactions for the North East Atlantic (NEA) and its marginal seas. These data are then used to establish 'feeding guilds' (henceforth guilds, defined here as predators that have many prey taxa in common; Garrison & Link, 2000) for a range of juvenile and adult size classes per species using an approach that could be reproduced where taxonomic, feeding interaction and ontogenetic trait data exist. We then use these guilds to assess changes in fish populations in the North Sea as a case study. In doing so, our aim was to assess the applicability of guilds as the basis of an indicator for food webs to support OSPAR Quality Status Assessments (and fulfil the candidate indicator requirement 'biomass and abundance of functional groups') and Good Environmental Status (GES) assessments to meet the needs of the European MSFD and national reporting (e.g. UK Marine Strategy).

Specifically, we test for distinct guilds and partitioning of fish biomass across them, how this varies in space and time, and relate these to anthropogenic and environmental stressors. Because guilds integrate biomass structure with the processes that cause it, such as predation (e.g. variation in piscivore biomass), energy flux and resource limitation (e.g. via dynamic relations between guilds),

recruitment and ontogeny (i.e. taxa occur across multiple guilds because their diet changes through ontogeny), we use the distribution and dynamics of guild biomasses as a measure of ecosystem structure and functioning. Hence, we assess whether change in the biomass of guilds in the North Sea was indicative of changes in ecosystem structure and functioning between 1985-2014, and whether adaptive management over that period (i.e. reductions in fishing activity) were detectable. We test the following hypotheses: i) there are distinct guilds in the trophic interaction dataset; ii) guild biomasses, and thus food web structure and ecosystem functioning, vary in space; iii) spatiotemporal change in guild biomasses are related to changes in resource availability (bottom-up), temperature (which can be a combination of direct and indirect effects impacting both bottom-up and top-down processes, e.g. see Lynam et al., 2017), inter-guild predation and fishing (top-down effects). Our aim was two-fold: firstly, to develop a reproducible method for defining guilds and, secondly, to assess whether they could be applied to reveal ecosystem-level responses to stressors and thus offer potential as a food web indicator.

Materials and Methods

Feeding guild classification

DAPSTOM is an ongoing initiative digitizing fish stomach records. The database contains information collected between 1836-2013 on 187 predator species (most occurring in northern European groundfish surveys). ICES Year of The Stomach Dataset contains records from 35 fish species between 1980-1991 sampled in the North Sea. Both datasets have information on predator-prey

interactions for given sea areas and years. The new trophic interaction dataset spans the NEA (Fig. S1), contains 8092 unique predator-prey interactions from 415,294 fish stomachs, representing 155 predatory fish taxa and 1643 prey taxa.

Guilds are defined here as a group of predators that have many prey taxa in common, and whose prey differentiate it from other predator guilds. We pooled all observed feeding links for five size classes of each predator taxa (usually predator species; predator groupings are thus referred to as taxa-by-size-classes) across both space and time to produce an aggregated diet for each. We pooled in this way because stomach contents analysis captures only a snapshot of a predator's diet, predators are typically gape-limited (i.e. body size is an important determinant of what prey are available to a predator), the developmental stage of fish is important for stock assessment, and fishing is known to disproportionately remove large fish from high trophic levels (Greenstreet et al., 2011; Shephard et al., 2012; Shin et al., 2005). Taxa-by-size-class categories were defined as: <3 cm considered larvae (Lv); small juvenile fish (Js) of 3 cm to half of length at maturity; juvenile-medium fish (Jm) from half of length at maturity to length at maturity; medium fish (M) from length at maturity to half-length at infinity; and large fish (L) above half-length at infinity. Length at maturity and length at infinity were estimated for fish taxa using the R package *Fishlife* (Thorson, Munch, Cope, & Gao, 2017).

Any rarefaction to test for the number of stomachs required to reach a dietary asymptote would be confounded here by the differences in spatial and temporal distribution of sampling effort. For example, the number of samples required to classify the diet of a predator one year may be different from another year, or other predator species in the same year, simply because samples varied in their spatial

distribution. Our aim therefore was to group fish into guilds based on their having similar predatory roles given the broadest understanding of predator-prey interactions and in a way that was insensitive to variation in sampling effort across predators. Hence, we selected only taxa-by-size-classes with 30+ stomach samples in the trophic interaction dataset to avoid inaccurate representation of diets. In addition, we use the presence of prey taxonomic 'family' to account for changes in predator-prey interactions through space and/or time, which will be strongly influenced by prey availability and sampling effort (e.g. Pinnegar, Trenkel, Tidd, et al., 2003; Woodward et al., 2010). Using prey species identity (e.g. rather than family) or a quantity (e.g. % occurrence) could mean we interpret predators to be selecting different prey and/ or at different rates when in fact they are feeding on similar taxa at quantities driven by their relative abundance in the environment. An additional concern was that the diet width of predators with more stomach data could be broader due to sampling bias (e.g. Table S1). We attempt to standardise the data by using the median number of prey families exploited (n = 21) as a threshold for maximum diet width thereby excluding rarely consumed prey for highly-sampled predators (i.e. to make sampling across predators more consistent, we use all data for the majority of predators, but remove rare prey from the minority of predators with the most data). We also distinguish fish larvae (<=3 cm) as prey from other fish (>3 cm), as feeding on larvae is analogous to zooplanktivory as opposed to piscivory, and use the lower taxonomic classification of 'order' for larvae due to the difficulty in resolving their taxonomy. Guilds were assigned in R using the *stats* package (R Development Core Team, 2018) and based on cluster analysis using the 'ward D2' agglomeration method on Sørensen dissimilarities on binary data. The optimum

number of feeding guilds (i.e. clusters) was assessed using the average silhouette width (Kaufman & Rousseeuw, 2009), gap statistic (Tibshirani, Walther, & Hastie, 2001) and elbow method.

We explore differences between guilds by relating covariates to non-metric multidimensional scaling (nMDS) dimensions and generate *p*-values based on *n* = 999 permutation tests using the *envfit* function in the R package *vegan* (Oksanen et al., 2015). Specifically, we assess whether variation in predator size, the occurrence of different prey functional groups (e.g. benthic, planktonic; using World Register of Marine Species classifications), prey types (after Pinnegar, 2014), prey phyla and variation in sampling effort across predators (i.e. number of stomachs) were significant explanatory variables in our ordination.

Data and statistical modelling to assess changes in guild biomass and correlations with covariates

We investigate changes in biomass of guilds based on processed survey data (Moriarty, Greenstreet, & Rasmussen, 2017) and make use of the Greater North Sea otter trawl data in quarter 1 (i.e. the International Bottom Trawl Survey, henceforth trawl data; Moriarty & Greenstreet, 2017). We adjusted for the area swept to estimate the absolute biomass of each species and length category at the ICES statistical rectangle-scale. Feeding guilds were allocated based on taxa and size category to estimate the annual biomass of each guild in each grid cell.

To estimate annual fishing pressure at the same scale, beam and otter trawl effort (fishing hours) was compiled for the period 1985-2014 after Couce, Schratzberger, & Engelhard (2019). Pelagic trawling impacts were estimated using

landings reported by the Scientific, Technical and Economic Committee for Fisheries (2017). Annual estimates for pelagic landings for the complete guild biomass time-series was not possible so only mean pelagic landings were assessed. As an estimate of resource availability, annual averages of zooplankton density were calculated for hydrodynamic regions (after Capuzzo et al., 2017; see also Van Leeuwen, Tett, Mills, & Van Der Molen, 2015) between 1985-2014 from the Continuous Plankton Recorder (CPR, https://www.cprsurvey.org/data/our-data/; Batten et al., 2003; SAHFOS, 2018). Mean annual sea bed temperature data were calculated using the data product published by the Copernicus Marine Environment Monitoring Service (http://marine.copernicus.eu) for the MyOcean project (see Wakelin et al., 2015).

We modelled annual estimates of fish biomass for the guilds at location s and time t (from 1985, $t = 1$, to 2014, $t = 30$), $\boldsymbol{G}_{s,t}$ (a 7 dimensional vector), as a function of top-down effects (beam trawl effort, $V_{beam,s,t}$, and otter trawl effort, $V_{otter,s,t}$), bottom-up effects (zooplankton abundance, $V_{zoo,s,t}$, and pelagic fish landings, $V_{pel,s,t}$) and temperature, $V_{temp,s,t}$. To account for temporal and spatial correlation in the data, we used a mixed effect model (Fig. 1).

For each location s, we calculated the mean value of the covariates across all 30 years,

$$\overline{\boldsymbol{V}_{\boldsymbol{s}}} = \frac{1}{30}\sum_{t=1}^{30}\boldsymbol{V}_{s,t}, \qquad (1)$$

where $\boldsymbol{V}_{s,t} = (V_{temp,s,t}, V_{otter,s,t}, V_{beam,s,t}, V_{pel,s,t}, V_{zoo,s,t})'$. For some of the covariates there was evidence of quadratic effects, $\overline{\boldsymbol{U}}_s = \left(\overline{V}_{temp,s}{}^2, \overline{V}_{otter,s}{}^2, \overline{V}_{beam,s}{}^2\right)'$. We defined the expected guild biomass at location *s* as

$$\boldsymbol{\mu}_s = \boldsymbol{\theta} + B_\mu \overline{\boldsymbol{V}}_{\boldsymbol{s}} + B_{p\mu} \overline{\boldsymbol{U}}_s, \quad (2)$$

where $\boldsymbol{\theta}$ is a 7-dimensional vector, B_μ is a 7×5 matrix and $B_{p\mu}$ is a 7×3 matrix. The dynamics of the covariates, $\boldsymbol{V}_{s,t}$, at location s and time t were described by

$$\boldsymbol{V}_{s,t} = \overline{\boldsymbol{V}}_s + t\boldsymbol{\beta}_{v,s} + \boldsymbol{\epsilon}_{s.t} \quad (3)$$

where $\boldsymbol{\beta}_{v,s}$ is a 7-dimensional vector and $\boldsymbol{\epsilon}_{s.t}$ follows an independent auto regressive model of order 1 (Chib, Omori, & Asai, 2009), i.e.,

$$\boldsymbol{\epsilon}_{s,t} \sim N(P_\epsilon \boldsymbol{\epsilon}_{s,t-1}, \Sigma_\epsilon), \quad (4)$$

where the diagonal elements of P_ϵ and Σ_ϵ are $\boldsymbol{\rho}_\epsilon$ and $\boldsymbol{\sigma}_\epsilon^2$ respectively, and the off-diagonal elements are 0. The rate of change in the guild biomass at location s was vector defined as

$$\boldsymbol{\beta}_s = \boldsymbol{\mu}_\beta + B_\alpha \boldsymbol{\beta}_{v,s} + \boldsymbol{\eta}_s + \boldsymbol{\omega}_s \quad (5)$$

where $\boldsymbol{\mu}_\beta$ is a 7-dimensional vector, B_α is a 7×5 matrix, $\boldsymbol{\eta}_s$ is sampled from a spatial auto-regressive model with correlation parameter $\boldsymbol{\rho}_\eta$ and variance $\boldsymbol{\sigma}_\eta^2$ (Ver Hoef, Peterson, Hooten, Hanks, & Fortin, 2018), and $\boldsymbol{\omega}_s \sim N(\mathbf{0}, \Omega)$. Ω describes the covariance of the rate of change between guilds. The guild biomass at location s and time t was

$$\boldsymbol{G}_{s,t} = \boldsymbol{\mu}_s + t\boldsymbol{\beta}_s + \boldsymbol{\zeta}_{s,t} \quad (6)$$

where $\boldsymbol{\mu}_s$ is the expected guild biomass at location s, defined in Equation 2, $\boldsymbol{\beta}_s$, defined in Equation 5 and $\boldsymbol{\zeta}_{s,t}$ follows an independent auto-regressive model of order 1 with parameters $\boldsymbol{\rho}_\zeta$ and $\boldsymbol{\sigma}_\zeta^2$. Due to the dimensionality and correlation of the uncertain parameter space, we fitted the model using No U-turn Hamiltonian Monte Carlo (Hoffman & Gelman, 2011) in the R package *Stan* (Gelman, Lee, & Guo, 2015).

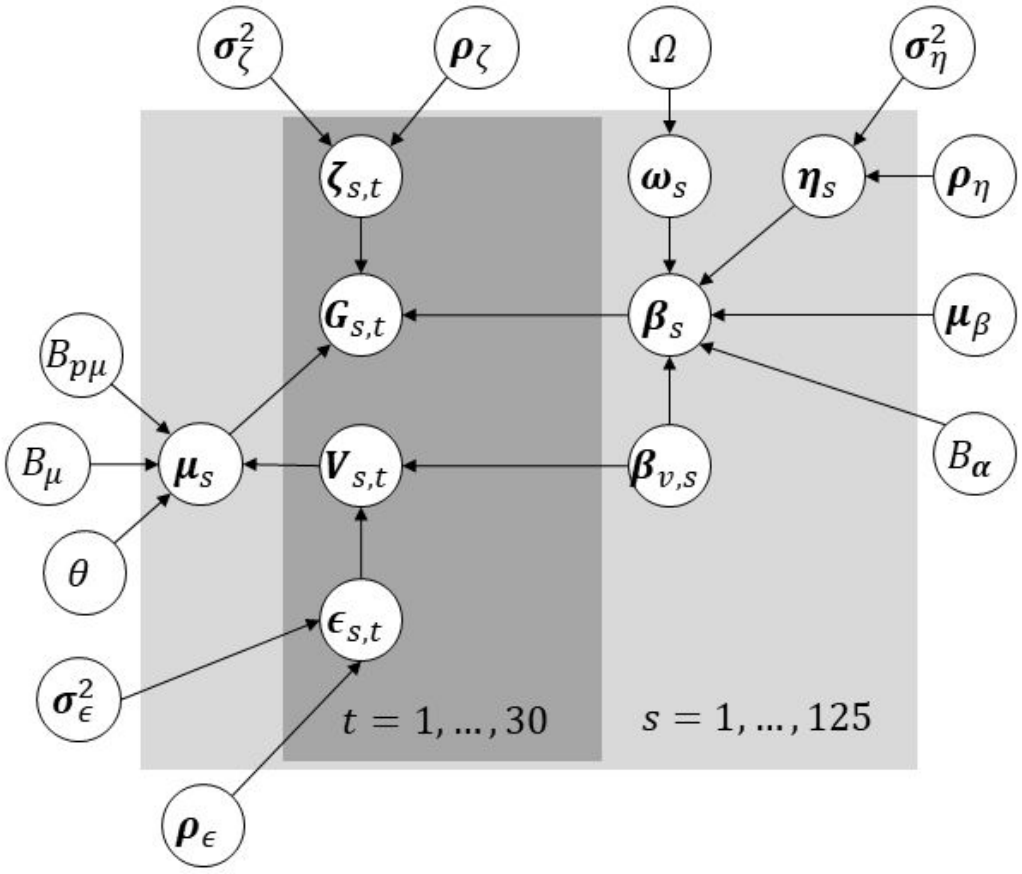


Fig. 1. A directed acyclic graph (DAG) of the model.

Using Bayes factors (ratios of the likelihood probability) we can evidence the relationship between the biomass of guilds and covariates in space and over time.

We focus primarily on results which surpass the more stringent thresholds suggested by Gelman & Robert (2014; Bayes factors <=0.04 and >=25 indicate strong to compelling evidence for a negative or positive relationship, respectively) but note less compelling relationships following Kass & Raftery (1995) which could correspond with *p* values of 0.05 (Bayes factors between >0.04 to 0.333 and 3 to <25 indicate evidence for a negative and positive relationship, respectively).

We complement this finer spatial scale approach using structural change analysis (Zeileis, Kleiber, Walter, & Hornik, 2003; Zeileis, Leisch, Hornik, & Kleiber, 2015) to test for significant sustained temporal change in guild biomass at the whole system level. Further details of data generation and statistical modelling are given in Supporting Materials and Methods.

Results

Feeding guild classification

There were diet data for 220 taxa-by-size-classes (73 predator taxa) and multiple distinct guilds were evident (nMDS axes 1-2; r^2 = 0.68, p = 0.001; we selected seven as an optimum based on Fig. S2), supporting our first hypothesis that multiple guilds are identifiable (Fig. 2; S3; S4; Tables S1-S3). Omnivory was ubiquitous, with fish, benthic and planktonic prey occurring in the diet of all guilds, albeit to quite different levels. Arthropoda, specifically crustaceans, were the most frequently encountered prey phylum across all but a piscivorous guild (Table S2). Differences in the diet of guilds were related to the size of predators, which positively correlated with piscivory, and negatively correlated with % Annelida, Mollusca and Arthropoda, among other prey (Fig. 2; S4; Table S3). Differences between guilds

were also related to habitat as, for example, planktonic and benthic foraging guilds were apparent, and these correlated with planktivory and benthivory gradients (i.e. predator clustering based on prey presence data was supported by the relative occurrence of prey functional groups to predator diets). The number of stomachs processed and the number of observations for each taxa-by-size-class were not significant explanatory variables for discriminating between guilds (Table S3), indicating that differences in sample size were not driving guild differences. The following seven guilds were identified: 1) ‘Generalist planktivore’; 2) ‘Zooplanktivore’; 3) ‘Coastal benthivore’; 4) ‘Generalist benthivore’; 5) ‘Specialist benthivore’; 6) ‘Zoobenthivore’; and 7) ‘Piscivore’. Guilds are described in detail in Supporting Results.

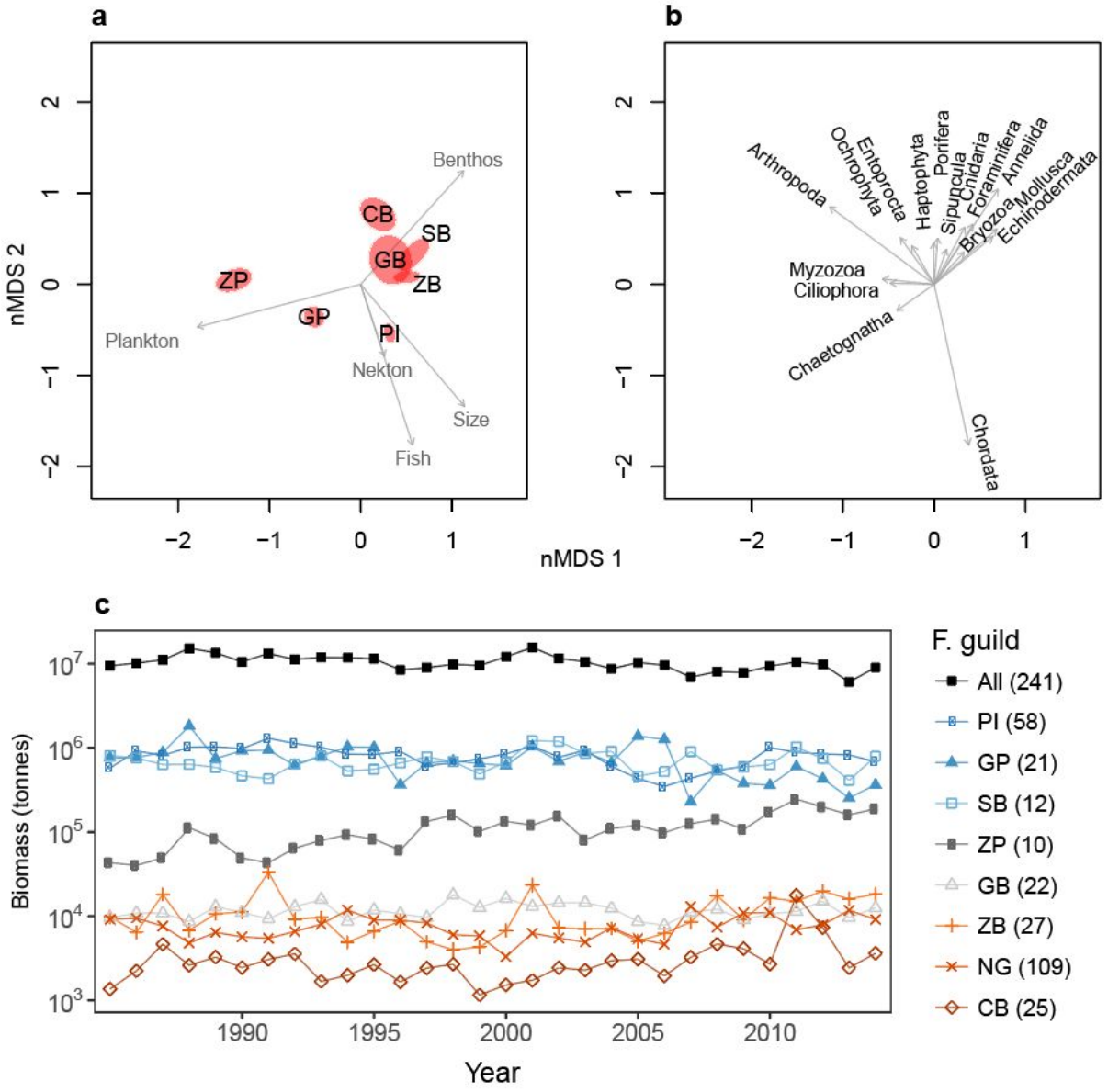


Fig. 2. a) Differences between guilds in nMDS represented by standard error ellipses with % occurrence of prey functional groups and predator length in cm (Size); b) significant % occurrence of prey phyla recorded in predator stomach contents. c) Variation in guild biomasses on a Log_{10} scale over the study period in the North Sea. GP = ‘Generalist planktivore'; ZP = ‘Zooplanktivore’; CB = 'Coastal benthivore’; GB = ‘Generalist benthivore '; SB = 'Specialist benthivore'; ZB= 'Zoobenthivore'; PI = 'Piscivore'; NG = ‘No guild’. The respective number of taxa-by-size-classes are represented in brackets.

Guild-level assessment of North Sea Otter trawl data

All guilds identified in the NEA stomach contents data were present in the trawl data, with corresponding information for 175 taxa-by-size-classes representing 99.7% of the biomass (Fig. 2; Table S1; S4). Three guilds made up 93.9% of the biomass: the Piscivore guild (33.6%) which was dominated by a range of whiting (*Merlangius merlangus*), grey gurnard (*Eutrigla gurnardus*) and cod (*Gadus morhua*) size classes; the Generalist planktivore guild (31.1%) was dominated by juvenile herring (*Clupea harengus*), followed by adult herring and a range of size classes of Norway pout (*Trisopterus esmarkii*) and mackerel (*Scomber scombrus*; i.e. forage fish); and the Specialist benthivore guild (29.2%) contained a range of size classes of haddock (*Melanogrammus aeglefinus*), dab (*Limanda limanda*), plaice (*Pleuronectes platessa*) and sole *(Soleo soleo*). The Zooplanktivore (4.7%), Generalist benthivore (0.5%), Zoobenthivore (0.5%), Coastal benthivore (0.1%), guilds represented a tiny fraction of the surveyed biomass (see also Supporting Results; Table S4; Fig. S5, S6).

Guilds were widely distributed but their biomass was spatially aggregated within the North Sea, confirming our second hypothesis that ecosystem structure and function vary in space (Fig. 3). The Piscivore and Zoobenthivore guilds aggregated in the west, Specialist and Generalist benthivore guilds in the north, the Coastal benthivore and Zooplanktivore guilds in the south, and Generalist planktivores were more patchy aggregating around Dogger bank and in the north, among other areas.

Guild biomasses related to environmental and anthropogenic covariates in space and over time, supporting our third hypothesis that resource availability,

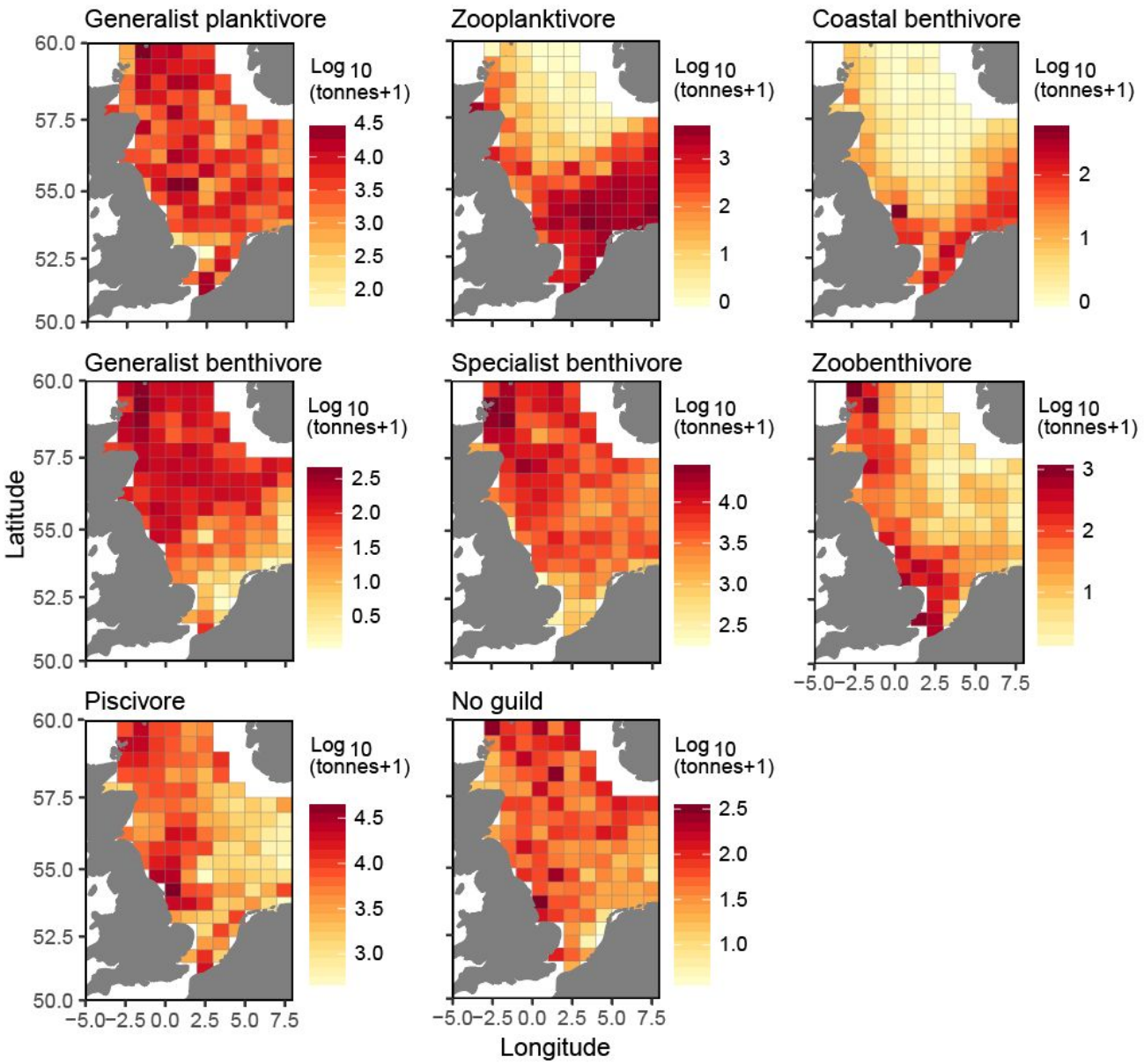
temperature and fishing effects are important drivers of change in ecosystem structure and function (Table 1; S5). The majority of guild and covariate spatial correlations were strong to compelling. For example, Piscivore guild biomass correlated positively with otter trawling, but negatively with pelagic landings, temperature and zooplankton density, and was not related to beam trawling; and otter trawling correlated negatively with Coastal benthivore biomass, with no relationship to Zooplanktivore biomass, and positively with all other guild biomasses (Figs. 3-4).

Temporal correlations between guilds and between guilds and covariates were all weak. Temperature correlated dynamically and positively with Zooplanktivore biomass, and negatively with Generalist benthivore and Piscivore biomass. Zooplankton density correlated dynamically and positively with Zoobenthivore biomass. Negative dynamical relationships existed between beam trawling and Zoobenthivore and Piscivore biomasses highlighting potential negative impacts from fishing and recovery from it on these guilds. However, weak positive dynamical correlations were also evident between beam trawling and Zooplanktivore, Generalist benthivore and Specialist benthivore biomasses (Figs. 5-6). There was no evidence for negative dynamical correlations between guilds (i.e. top-down inter-guild control; Fig. 5), but only weak positive correlations. Despite marked regional changes in guild biomasses (Fig. 5) and large within-guild variation in the distribution of biomass between taxa-by-size-classes (Fig. S6), sustained changes at the North Sea-scale were less apparent. Change in Zooplanktivore and Generalist planktivore guilds was driven by changes in the surveyed biomass of individual species within them, namely increasing juvenile sprat (*Sprattus sprattus*) and decreasing herring,

respectively (Fig. 2c; S6; S7), with shorter-term fluctuations evident in the Piscivore and Coastal benthivore guilds.

Table 1. Positive and negative relationships based on Bayes factors evident following mixed effect modelling for spatial (denoted by *) and dynamic correlations between guild biomasses and covariates. Columns represent guilds: GP = ‘Generalist planktivore'; ZP = ‘Zooplanktivore’; CB = 'Coastal benthivore’; GB = ‘Generalist benthivore '; SB = 'Specialist benthivore'; ZB= 'Zoobenthivore'; PI = 'Piscivore'; related to covariates (rows). Compelling evidence for a negative (<0.01 = ---) or positive (>100 = +++) relationship; strong evidence for a negative (>0.01 to 0.04 = --) or positive (25 to <100 = ++) relationship; evidence of a negative (>0.04 to 0.333 = -) or positive (3 to <25 = +) relationship (see Table S5 for Bayes factors).

	GP	ZP	CB	GB	SB	ZB	PI
Temperature*	---	+++	+++	---	---	+++	---
Otter trawling*	+++		---	+++	+++	+++	+++
Beam trawling*	+++	+++	+	-	---	--	
Pelagic landings*	---		+	---	---	-	---
Zooplankton*	+++	+++	+++	---		---	---
Temperature		+		-			-
Otter trawling							
Beam trawling		+		+	+	-	-
Zooplankton						+	
ZP	+						
CB							
GB	+						
SB			+	+			
ZB				+	+		
PI	+		+	+	+	+	



1

2 Fig. 3. Mean feeding guild biomass distribution between 1985 and 2014 across ICES

3 statistical rectangles in the North Sea.

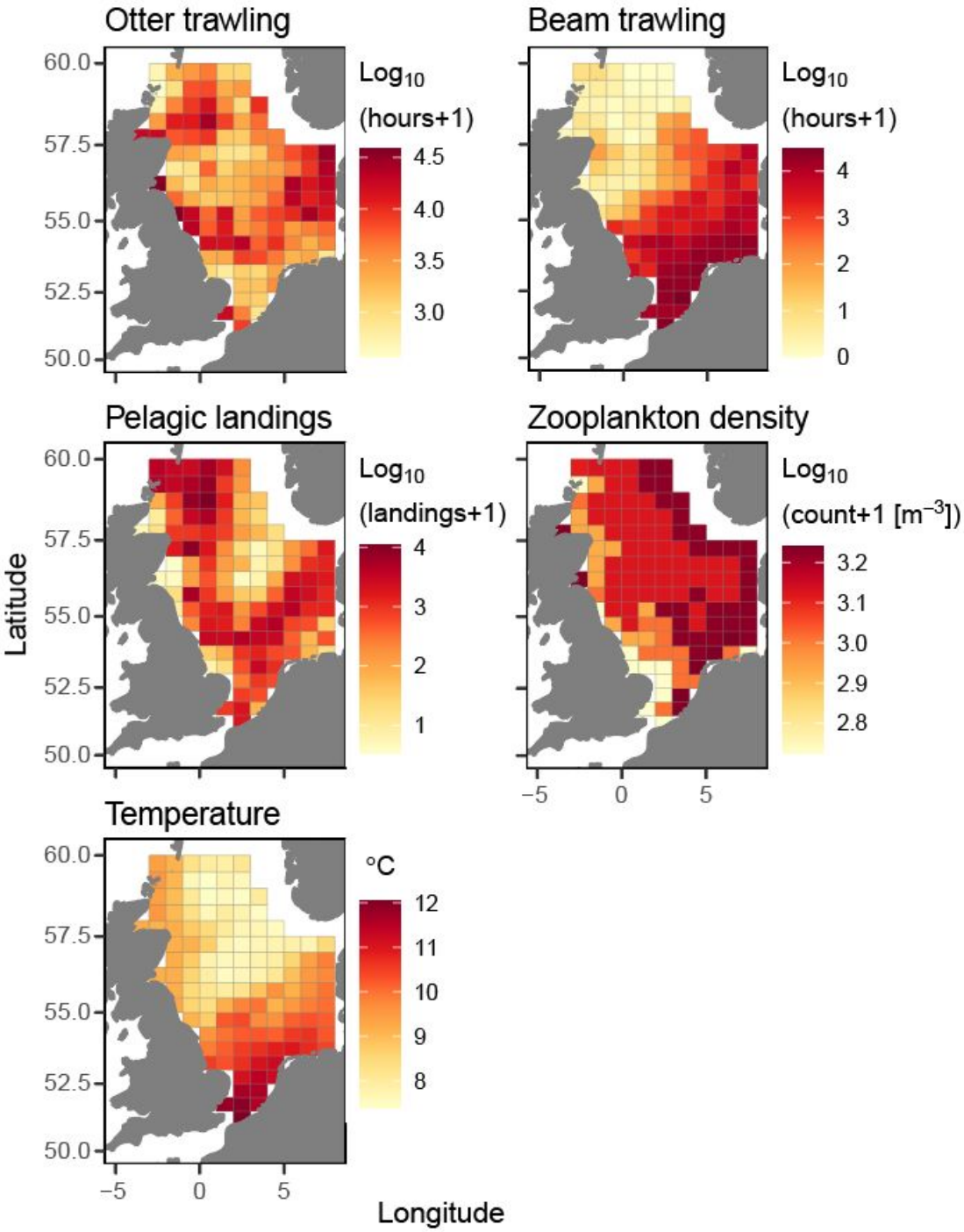


Fig. 4. Mean covariate distributions between 1985 and 2014 across ICES statistical rectangles in the North Sea. Zooplankton density per m^3 has been calculated for hydraulic zones following Capuzzo *et al.*, (2017).

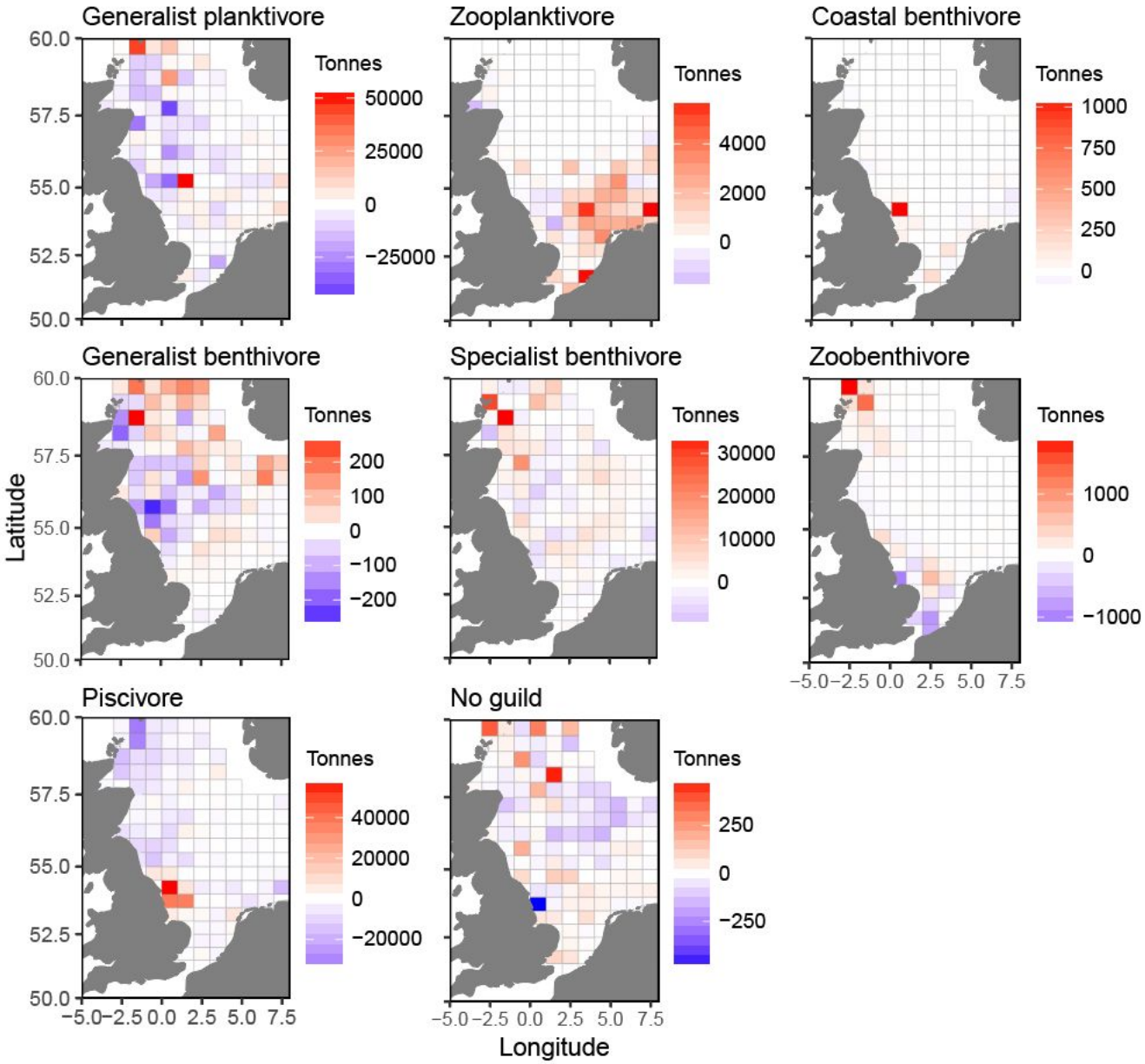


Fig. 5. Feeding guild biomass change over time between 1985 to 1999 and 2000 to 2014 across ICES statistical rectangles in the North Sea.

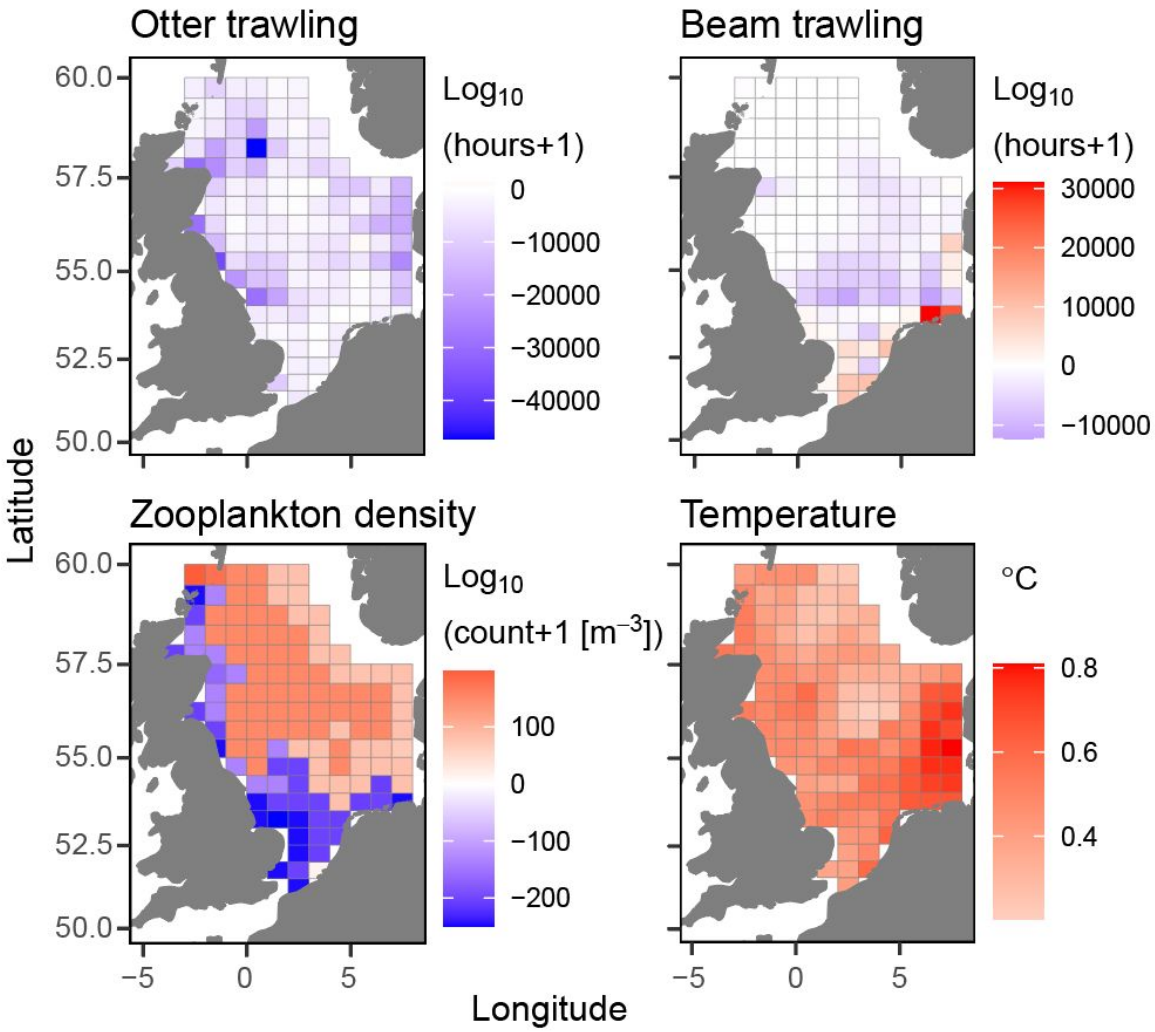


Fig. 6. Change in mean annual fishing effort, zooplankton density and sea bed temperature (℃) between 1985-1999 and 2000-2014 across ICES statistical rectangles in the North Sea. Zooplankton density has been calculated for hydrodynamic zones following Capuzzo et al. (2017).

Discussion

Guild assessment represents a synthesis of taxonomic- and size-based approaches, supplemented with dietary information, that can reveal higher-level phenomena undetectable to its component parts if considered independently. For instance, temporal variation in Generalist benthivore and Piscivore guilds (Fig. 5)

were less apparent at the North Sea scale (Fig. 2c) because of contrasting regional responses. Sustained changes were most apparent in guilds dominated in the survey by individual species. This highlights regional changes in food web structure and functioning but also points to guild carrying capacities. In studies of the fish community in the western Atlantic, Garrison & Link (2000) and Auster & Link (2009) found guild biomasses to be remarkably consistent through time despite fishery-induced perturbations on species within guilds. Given guild composition may change dramatically through time (Fig. S6; see also Auster & Link, 2009; Garrison & Link, 2000) and in response to multiple drivers, guild biomasses were likely sustained via high functional redundancy analogous to the insurance hypothesis (Yachi & Loreau, 1999): whereby change in a species biomass is offset by contrasting change in another within the same guild such that guild biomass, which reflects the contribution of particular energy pathways to fish biomass, is relatively stable over time. Guild biomass is therefore likely constrained by the amount of available energy, the number of species able to exploit it, and changes to it highlight where pressures manifest at the system-level. This, in turn, provides critical new insights into whether changes are caused by energetic constraints and/ or environmental change, for instance, which is valuable information within the ecosystem approach to fisheries that could help to develop a more holistic understanding of anthropogenic impacts on ecosystems.

Our findings complement the powerful size-structuring widely reported to belie food web taxonomic structure (Brose et al., 2006; Clegg et al., 2018; Jennings, 2005; Jennings et al., 2001). For instance, fish with markedly different foraging strategies and evolutionary histories, e.g. dab, herring and saithe, grouped together as larvae

and juveniles in the Zooplanktivore guild, but larger size classes of those species were grouped in different guilds suggesting divergence in foraging through ontogeny related to taxonomy and size, with many large apex predators in the Piscivorous guild. Moreover, the unique spatial distributions and unique correlations between each guild and the covariates suggests even apparently similar guilds, e.g. benthivores (Table 1; Fig. 3), provide useful information about how foraging behaviour changes in space and over time. This highlights the complex interactions between species, size classes and diet embedded in the guild classifications which would not be considered if based on one or two of those components.

Our results show that the optimal number of guilds was between four to nine, with no clear threshold of change using the elbow method (Fig. S2). We based our case study assessment on the North Sea using seven as an intermediate value but recognise a simpler or more complex approach could be justified and depends on the question. If the need was to understand relative changes in planktivory in its most simple form, the first split between planktivores and those more benthivorous and/or piscivorous in the dendrogram could be used (Fig. S3). To get a more nuanced understanding of change with distinctions in the type of planktivory (e.g. specialist planktivores versus zooplanktivores, the former of which preys on the latter) and benthivory (e.g. coastal versus generalist) then more complex solutions would be justifiable. We see this as a strength of our approach because feeding guilds are hierarchically structured much like how taxonomic or other trait information has been organised. We provide a table in the Supporting Material which details the branches for up to nine feeding guilds so future assessments can choose which level of complexity suits their need (Table S6). And, because it is a data-driven,

reproducible approach, new information can be systematically integrated to 1) further resolve the number of feeding guilds that can be confidently characterised, 2) their composition and 3) test if seasonal to annual changes in feeding behaviour provides evidence for dynamical classifications. Feeding interactions could, for example, be further spatiotemporally resolved by future targeted stomach content sampling (e.g. under-sampled taxa-size-class feeding interactions, Table S1) using conventional and emerging molecular techniques (e.g. see Pompanon et al., 2012), inferring from similar predators where species-level data are sparse (e.g. following Gray et al., 2015) and also via predictive modelling (Link, 2004; O'Gorman et al., 2019; Petchey et al. 2008).

Our mixed effect model and structural change analysis provide a 30-year overview of change at the ICES statistical rectangle scale with annual ecosystem-scale temporal dynamics, respectively. Stronger spatial rather than temporal effects were evident in the mixed effect model largely due to the level of change in space relative to change over time in both responses and covariates (Figs. 3-6). For example, the spatial difference in mean annual temperature is ~4 ℃, whereas the largest change over time was ~0.8 ℃. By comparing findings across analyses we were able to better understand both the spatiotemporal scale and potential causes of change. For instance, Zooplanktivores showed a consistent increasing trend at the North Sea scale (Fig. S7). Coupled with the results from the finer-scale assessment that shows a positive dynamical correlation with temperature (Table 1 and Figs. 5-6), this suggests Zooplanktivores (mostly juveniles of sprat and herring) were prospering where waters warmed most. Piscivores and Generalist benthivores did not show sustained declines over time despite having negative dynamical correlations with

temperature. This is likely because of contrasting patterns of change in their biomasses with increases where warming was relatively low and decreases in coastal areas where warming was higher (Figs. 5-6). Using the temperature-guild relationships evidenced here, future simulations could build on species-based approaches (e.g. Cheung et al., 2009), to make predictions about how ecosystem structure and function could be affected as warming becomes more pronounced.

The positive temporal correlations between guilds reported here could be caused by several factors potentially acting simultaneously: one guild received recruits from another, their resources and responses to environmental change were correlated, and one or both consume the other without exerting top-down forcing. Since fishing fleets target adult size classes and can quickly adapt to spatiotemporal changes in target species biomass, the relationship between guild biomasses and fishing are also likely to be complex. For instance, positive spatial correlations between otter trawling and Specialist benthivore and Piscivore biomass were in line with our expectations. However, the negative spatial correlation between the Genralist planktivore guild and pelagic landings (used here as a proxy for fishing pressure on planktivorous fish; Engelhard et al., 2014), was not, possibly because juvenile biomass dominated this guild and the fishery targets adult fish across the Zooplanktivore and Genralist planktivore guilds which have contrasting distributions. Moreover, despite overall reductions in demersal fishing effort occurred during the study period (Fig. 6; Couce et al. 2019), there was only weak evidence of negative impacts from fishing and recovery from it at the guild-level, possibly due to dynamic fleet behaviour and/ or the long lag time expected for the recovery of fish communities (Fung et al., 2013; Shephard et al., 2013). There were also likely

indirect or spurious (i.e. coincidental) positive dynamical correlations between beam trawling and Zooplanktivore guild biomass. Given that we include juvenile and adult life stages across many fish taxa, there is potential for more complex guild-covariate spatiotemporal lags than was explored here. Future work could consider developing an approach to test for these more subtle but important lagged relationships and thereby further refine our understanding of responses to more heterogeneous and dynamic pressures such as fishing and resource availability (Fountalis, Dovrolis, Bracco, Dilkina, & Keilholz, 2018; Probst, Stelzenmüller, & Fock, 2012).To further understand how between-guild and guild-covariate correlations determine fish biomass distribution and their relative importance, future refinements could integrate acoustic survey data to better capture variation in pelagic fish populations and beam trawl survey data for benthic fish via Bayesian spatial multispecies modelling (e.g. Juntunen, Vanhatalo, Peltonen, & Mäntyniemi, 2012), for instance. Catchability corrections were not implemented here, but future research could estimate undersampling of some species due to behavioural responses (e.g. schooling, net avoidance) and/ or limitations of the gear to catch particular size classes. Intra-guild indicators and synthesis with existing indicators would be another logical future development. A guild's size structure could be used to assess impacts from fishing via the Typical Length indicator (OSPAR 2017a) or the 95% percentile of the length frequency distribution (Probst et al., 2012)-and through change in species composition via the Mean Maximum Length Indicator (Fisher, Frank, & Leggett, 2010; OSPAR 2017b). Measures such as intra-guild evenness and species richness could help to reveal key energetic pathways and the level of intra-guild redundancy. For example, we expect functional redundancy to be more constrained in guilds and

areas dominated by a single species, hence where food web structure and ecosystem function are likely to vary most and be least resilient to change. And changes in total fish biomass, such as the decline ~2006 in the North Sea largely driven by the decrease in Generalist planktivore biomass, highlight the importance of particular guilds to system-wide structure and functioning (Figs. S6-S7). Developments such as these could therefore enable a more synthetic approach to understanding changes in ecosystem structure and functioning than has yet been achieved within the indicator framework.

Effective ecosystem management will need to consider how large-scale pressures, such as nutrient availability and temperature, and more localised and heterogeneous human activities, such as fishing, may interact (e.g. Capuzzo et al., 2017). In combination with a suite of indicators relating to species composition and size structure of communities, guild assessment could enable targeted advice for fishing-levels to offset impacts of increasing temperature and/ or decreasing primary production, for instance, which cannot be managed directly in the short-term or locally. Comparable guild assessment could be applied in other marine systems (e.g. Garrison & Link, 2000) making the approach potentially applicable as part of a global-scale Integrated Ecosystem Assessment (DePiper et al., 2017). This will be informative to gauge how larger contrasts in environmental drivers, such as fishing and temperature, act on ecosystem structure and function, and thus enable a more predictive approach than was possible here. Moreover, the notion that, by supplementing organismal size with taxonomic information and feeding behavior, the potential for a universal indicator of ecological status could be more rigorously tested.

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Authors’ contributions

MT, HP, MS, CL conceived the ideas and designed methodology; MT, HP, JP, MM, SG, PH collected the data; MT, HP, MS, PH, CL analysed the data; MT led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

Data availability statement

Processed interaction data are available from the Cefas datahub https://doi.org/10.14466/CefasDataHub.102 (Thompson et al., 2020). All other data used are cited and published

References

Auster, P. J., & Link, J. S. (2009). Compensation and recovery of feeding guilds in a northwest Atlantic shelf fish community. *Marine Ecology Progress Series*, *382*, 163–172. doi:10.3354/meps07962

Batten, S. D., Clark, R., Flinkman, J., Hays, G., John, E., John, A. W. ., … Walne, A. (2003). CPR sampling: the technical background, materials and methods, consistency and comparability. *Progress in Oceanography*, *58*(2–4), 193–215. doi:10.1016/J.POCEAN.2003.08.004

Brose, U., Blanchard, J. L., Eklöf, A., Galiana, N., Hartvig, M., Hirt, M. R., … Jacob, U. (2017). Predicting the consequences of species loss using size-structured biodiversity approaches. *Biological Reviews*, *92*(2), 684–697. doi:10.1111/brv.12250

Brose, U., Cushing, L., Berlow, E. L., Jonsson, T., Banasek-Richter, C., Bersier, L.-F., … Martinez, N. D. (2005). Body sizes of consumers and their resources. *Ecology*, *86*(9), 2545–2545. doi:10.1890/05-0379

Brose, U., Jonsson, T., Berlow, E. L., Warren, P., Banasek-Richter, C., Bersier, L.-F., … Blandenier, M.-F. C. (2006). Consumer–resource body-size relationships in natural food webs. *Ecology*, *87*(10), 2411–2417.

Capuzzo, E., Lynam, C. P., Barry, J., Stephens, D., Forster, R. M., Greenwood, N., … Engelhard, G. H. (2017). A decline in primary production in the North Sea over 25 years, associated with reductions in zooplankton abundance and fish stock recruitment. *Global Change Biology*, *24*(1), e352–e364. doi:10.1111/gcb.13916

Cheung, W. W. L., Lam, V. W. Y., Sarmiento, J. L., Kearney, K., Watson, R., & Pauly, D. (2009). Projecting global marine biodiversity impacts under climate change scenarios. *Fish and Fisheries*. doi:10.1111/j.1467-2979.2008.00315.x

Chib, S., Omori, Y., & Asai, M. (2009). Multivariate stochastic volatility. In *Handbook of Financial Time Series* (pp. 365–400). Springer.

1 Ciannelli, L., Hjermann, D. O., Lehodey, P., Ottersen, G., Duffy-Anderson, J. T., &
2 Stenseth, N. C. (2007). Climate forcing, food web structure, and community
3 dynamics in pelagic marine ecosystems. *Aquatic Food Webs: An Ecosystem*
4 *Approach*, 143–169. doi:10.1093/acprof:oso/9780198564836.003.0013
5 Clegg, T., Ali, M., & Beckerman, A. P. (2018). The impact of intraspecific variation on
6 food web structure. *Ecology*, *99*(12), 2712–2720. doi:10.1002/ecy.2523
7 Cohen, J. E., Schittler, D. N., Raffaelli, D. G., & Reuman, D. C. (2009). Food webs
8 are more than the sum of their tritrophic parts. *Proceedings of the National*
9 *Academy of Sciences of the United States of America*, *106*(52), 22335–22340.
10 doi:10.1073/pnas.0910582106
11 Commission, E. (2010). Commission Decision of 1 September 2010 on criteria and
12 methodological standards on good environmental status of marine waters.
13 *Official Journal of the European Union*, *232*, 14–24.
14 doi:10.1080/00207540110058331
15 Couce, E., Schratzberger, M., & Engelhard, G. H. (2019). Reconstructing three
16 decades of total international trawling effort in the North Sea. *Earth System*
17 *Science Data Discussions*. doi:10.5194/essd-2019-90
18 DePiper, G. S., Gaichas, S. K., Lucey, S. M., Da Silva, P. P., Anderson, M. R.,
19 Breeze, H., … Wildermuth, R. P. (2017). Operationalizing integrated ecosystem
20 assessments within a multidisciplinary team: Lessons learned from a worked
21 example. *ICES Journal of Marine Science*, *74*(8), 2076–2086.
22 doi:10.1093/icesjms/fsx038
23 Dunne, J. A., Williams, R. J., & Martinez, N. D. (2002). Food-web structure and
24 network theory: The role of connectance and size. *Proceedings of the National*

Academy of Sciences, *99*(20), 12917–12922. doi:10.1073/pnas.192407699

Engelhard, G. H., Lynam, C. P., García-Carreras, B., Dolder, P. J., & Mackinson, S. (2015). Effort reduction and the large fish indicator: Spatial trends reveal positive impacts of recent European fleet reduction schemes. *Environmental Conservation*, *42*(3), 227–236. doi:10.1017/S0376892915000077

Engelhard, G. H., Peck, M. A., Rindorf, A., C. Smout, S., Van Deurs, M., Raab, K., … Dickey-Collas, M. (2014). Forage fish, their fisheries, and their predators: Who drives whom? *ICES Journal of Marine Science*, *71*(1), 90–104. doi:10.1093/icesjms/fst087

Fisher, J. A. D., Frank, K. T., & Leggett, W. C. (2010). Global variation in marine fish body size and its role in biodiversity-ecosystem functioning. *Marine Ecology Progress Series*, *405*, 1–13. doi:10.3354/meps08601

Fountalis, I., Dovrolis, C., Bracco, A., Dilkina, B., & Keilholz, S. (2018). δ-MAPS: from spatio-temporal data to a weighted and lagged network between functional domains. *Applied Network Science*. doi:10.1007/s41109-018-0078-z

Fung, T., Farnsworth, K. D., Shephard, S., Reid, D. G., & Rossberg, A. G. (2013). Why the size structure of marine communities can require decades to recover from fishing. *Marine Ecology Progress Series*, *484*, 155–171. doi:10.3354/meps10305

Garrison, L., & Link, J. (2000). Dietary and guild structure in the fish community of the United States northern continental shelf ecosystem. *Marine Ecology Progress Series*, *202*, 231–240. doi:10.3354/meps202231

Garrison, L. P., & Link, J. S. (2000). Fishing effects on spatial distribution and trophic guild structure of the fish community in the Georges Bank region. *ICES Journal*

of Marine Science, *57*(3), 723–730. doi:10.1006/jmsc.2000.0713

Gelman, A., Lee, D., & Guo, J. (2015). Stan: A Probabilistic Programming Language for Bayesian Inference and Optimization. *Journal of Educational and Behavioral Statistics*, *40*(5), 530–543. doi:10.3102/1076998615606113

Gelman, A., & Robert, C. P. (2014). Revised evidence for statistical standards. *Proceedings of the National Academy of Sciences*, *111*(19), E1933–E1933. doi:10.1073/pnas.1322995111

Gray, C., Hildrew, A. G., Lu, X., Ma, A., McElroy, D., Monteith, D., … Woodward, G. (2016). Recovery and Nonrecovery of Freshwater Food Webs from the Effects of Acidification. *Advances in Ecological Research*, *55*, 475–534. doi:10.1016/bs.aecr.2016.08.009

Gray, Clare, Figueroa, D. H., Hudson, L. N., Ma, A., Perkins, D., & Woodward, G. (2015). Joining the dots: An automated method for constructing food webs from compendia of published interactions. *Food Webs*, *5*, 11–20. doi:10.1016/j.fooweb.2015.09.001

Greenstreet, S. P. R., Bryant, A. D., Broekhuizen, N., Hall, S. J., & Heath, M. R. (1997). Seasonal variation in the consumption of food by fish in the North Sea and implications for food web dynamics. *ICES Journal of Marine Science*, *54*(2), 243–266. doi:10.1006/jmsc.1996.0183

Greenstreet, S. P. R., Rogers, S. I., Rice, J. C., Piet, G. J., Guirey, E. J., Fraser, H. M., & Fryer, R. J. (2011). Development of the EcoQO for the North Sea fish community. *ICES Journal of Marine Science*. *68(1)*, 1-11. doi:10.1093/icesjms/fsq156

Heath, M. R. (2005). Changes in the structure and function of the North Sea fish

foodweb, 1973-2000, and the impacts of fishing and climate. *ICES Journal of Marine Science*, *62*(5), 847–868. doi:10.1016/j.icesjms.2005.01.023

Hirt, M. R., Li, Y., Rall, B. C., Rosenbaum, B., Brose, U., & Grimm, V. (2018). Bridging Scales: Allometric Random Walks Link Movement and Biodiversity Research. *Trends in Ecology and Evolution*, *33*(9), 701–712. doi:10.1016/j.tree.2018.07.003

Hoffman, M. D., & Gelman, A. (2011). The No-U-Turn Sampler: Adaptively Setting Path Lengths in Hamiltonian Monte Carlo. *Journal of Machine Learning Research*, *15*(1), 1593–1623. doi:10.1190/1.3627885

ICES, (2014). Report of the Workshop to Develop Recommendations for Potentially Useful FoodWeb Indicators (WKFooWI). 31 March to 3 April 2014, ICES CM/ACOM: 48, Copenhagen, Denmark. 75 pp.

ICES, (1997). Database Report of the Stomach Sampling Project 1991. pp. 422.

ICES, (2018). Report of the Working Group on Ecosystem Effects of Fishing Activities (WGECO), 12–19 April 2018, San Pedro del Pinatar, Spain. ICES CM 2018/ACOM:27. 69 pp.

Ings, T. C., Montoya, J. M., Bascompte, J., Blüthgen, N., Brown, L., Dormann, C. F., … Woodward, G. (2009). Ecological networks - Beyond food webs. *Journal of Animal Ecology*. 78(1), 253-269. doi:10.1111/j.1365-2656.2008.01460.x

Jennings, S. (2005). Size-based analyses of aquatic food webs. In A. Belgrano, U. M. Scharler, J. Dunne, & R. E. Ulanowicz (Eds.), *Aquatic Food Webs: An ecosystem approach*. Oxford, UK: Oxford University Press. doi:10.1093/acprof:oso/9780198564836.003.0009

Jennings, S., Pinnegar, J. K., Polunin, N. V. C., & Boon, T. W. (2001). Weak cross-

species relationships between body size and trophic level belie powerful size-based trophic structuring in fish communities. *Journal of Animal Ecology*, *70*(6), 934–944. doi:10.1046/j.0021-8790.2001.00552.x

Juntunen, T., Vanhatalo, J., Peltonen, H., & Mäntyniemi, S. (2012). Bayesian spatial multispecies modelling to assess pelagic fish stocks from acoustic- and trawl-survey data. *ICES Journal of Marine Science*. doi:10.1093/icesjms/fsr183

Kass, R. E., & Raftery, A. E. (1995). Bayes factors. *Journal of the American Statistical Association*, *90*(430), 773–795. doi:10.1080/01621459.1995.10476572

Kaufman, L., & Rousseeuw, P. J. (2009). *Finding groups in data: an introduction to cluster analysis* (Vol. 344). John Wiley & Sons. New Jersey, USA.

Kerr, S. R., & Dickie, L. M. (2001). *The Biomass Spectrum: A Predator-Prey Theory of Aquatic Production*. New York, USA: Columbia University Press. doi:10.1016/S0022-0981(02)00053-9

Link, J. S. (2004). A General Model of Selectivity for Fish Feeding: A Rank Proportion Algorithm. *Transactions of the American Fisheries Society*, *133*(3), 655–673. doi:10.1577/T02-142.1

Linnane, A., McGarvey, R., Gardner, C., Walker, T. I., Matthews, J., Green, B., & Punt, A. E. (2014). Large-scale patterns in puerulus settlement and links to fishery recruitment in the southern rock lobster (Jasus edwardsii), across south-eastern Australia. *ICES Journal of Marine Science*, *71*(3), 528–536. doi:10.1093/icesjms/fst176

Lynam, C. P., Llope, M., Möllmann, C., Helaouët, P., Bayliss-Brown, G. A., & Stenseth, N. C. (2017). Interaction between top-down and bottom-up control in

marine food webs. *Proceedings of the National Academy of Sciences*, *114*(8), 1952–1957. doi:10.1073/pnas.1621037114

Modica, L., Velasco, F., Preciado, I., Soto, M., & Greenstreet, S. P. R. (2014). Development of the large fish indicator and associated target for a Northeast Atlantic fish community. *ICES Journal of Marine Science*, *71*(9), 2403–2415. doi:10.1093/icesjms/fsu101

Moriarty, M., & Greenstreet, S. (2017). Greater North Sea International Otter Trawl Quarter 1 Groundfish Survey Monitoring and Assessment Data Products. doi:10.7489/1922-1

Moriarty, M., Greenstreet, S. P. ., & Rasmussen, J. (2017). Derivation of Groundfish Survey Monitoring and Assessment Data Products for the Northeast Atlantic Area. Scottish Marine and Freshwater Science Report. *Scottish Marine and Freshwater Science*, *8*(16). doi:10.7489/1984-1

O'Gorman, E. J., Petchey, O. L., Faulkner, K. J., Gallo, B., Gordon, T. A. C., Neto-Cerejeira, J., … Woodward, G. (2019). A simple model predicts how warming simplifies wild food webs. *Nature Climate Change*. doi:10.1038/s41558-019-0513-x

Oksanen, J., Blanchet, F. G., Kindt, R., Legendre, P., Minchin, P. R., O'Hara, R. B., … Wagner, H. (2015). vegan: Community Ecology Package. R package version 2.3-0. http://CRAN.R-project.org/package=vegan.

OSPAR (2017a). Size Composition in Fish Communities. Intermediate Assessment 2017. Available at: https://oap.ospar.org/en/ospar-assessments/intermediate-assessment-2017/biodiversity-status/fish-and-food-webs/size-fish-composition/

OSPAR (2017b). Pilot Assessment of Mean Maximum Length of Fish. Intermediate

Assessment 2017. Available at: https://oap.ospar.org/en/ospar-assessments/intermediate-assessment-2017/biodiversity-status/fish-and-food-webs/mean-maximum-length/

Petchey, O. L., Beckerman, A. P., Riede, J. O., & Warren, P. H. (2008). Size, foraging, and food web structure. *Proceedings of the National Academy of Sciences*. doi:10.1073/pnas.0710672105

Petchey, Owen L., & Belgrano, A. (2010). Body-size distributions and size-spectra: Universal indicators of ecological status? *Biology Letters*, *6*(4), 434–437. doi:10.1098/rsbl.2010.0240

Petchey, Owen L, Beckerman, A. P., Riede, J. O., & Warren, P. H. (2008). Size, foraging, and food web structure. *Proceedings of the National Academy of Sciences of the United States of America*, *105*(11), 4191–4196. doi:10.1073/pnas.0710672105

Pinnegar, J. K. (2014). *DAPSTOM - An Integrated Database & Portal for Fish Stomach Records* (Vol. Version 4.). Centre for Environment, Fisheries & Aquaculture Science, Lowestoft, UK.

Planque, B., Fromentin, J. M., Cury, P., Drinkwater, K. F., Jennings, S., Perry, R. I., & Kifani, S. (2010). How does fishing alter marine populations and ecosystems sensitivity to climate? *Journal of Marine Systems, 79(3-4)*, 403-417. doi:10.1016/j.jmarsys.2008.12.018

Pompanon, F., Deagle, B. E., Symondson, W. O. C., Brown, D. S., Jarman, S. N., & Taberlet, P. (2012). Who is eating what: Diet assessment using next generation sequencing. *Molecular Ecology, 21(8)*, 1931-1950. doi:10.1111/j.1365-294X.2011.05403.x

Probst, W. N., Stelzenmüller, V., & Fock, H. O. (2012). Using cross-correlations to assess the relationship between time-lagged pressure and state indicators: An exemplary analysis of North Sea fish population indicators. *ICES Journal of Marine Science*. doi:10.1093/icesjms/fss015

Queirós, A. M., Fernandes, J., Genevier, L., & Lynam, C. P. (2018). Climate change alters fish community size-structure, requiring adaptive policy targets. *Fish and Fisheries*, *19*(4), 613–621. doi:10.1111/faf.12278

R Development Core Team. (2018). R: A language and environment for statistical computing. *Vienna, Austria*. doi:R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org.

Reecht, Y., Rochet, M. J., Trenkel, V. M., Jennings, S., & Pinnegar, J. K. (2013). Use of morphological characteristics to define functional groups of predatory fishes in the celtic sea. *Journal of Fish Biology*, *83*(2), 355–377. doi:10.1111/jfb.12177

Rombouts, I., Beaugrand, G., Fizzala, X., Gaill, F., Greenstreet, S. P. R., Lamare, S., … Féral, J. P. (2013). Food web indicators under the Marine Strategy Framework Directive: From complexity to simplicity? *Ecological Indicators*, *29*, 246–254. doi:10.1016/j.ecolind.2012.12.021

SAHFOS (2018) "*Murray Thompson*." SAHFOS. doi: 10.7487/2018.309.1.1150.

Scheffer, M., Carpenter, S., & De Young, B. (2005). Cascading effects of overfishing marine systems. *Trends in Ecology and Evolution,* 20(11), 579-581. doi:10.1016/j.tree.2005.08.018

Scientific, Technical and Economic Committee for Fisheries (2017) - *Fisheries Dependent Information – Classic (STECF-17-09) ADDENDUM*. doi:/10.2760/561459

Shephard, S., Fung, T., Houle, J. E., Farnsworth, K. D., Reid, D. G., & Rossberg, A. G. (2012). Size-selective fishing drives species composition in the Celtic Sea. *ICES Journal of Marine Science*, *69*(2), 223–234. doi:10.1093/icesjms/fsr200

Shephard, S., Fung, T., Rossberg, A. G., Farnsworth, K. D., Reid, D. G., Greenstreet, S. P. R., & Warnes, S. (2013). Modelling recovery of Celtic Sea demersal fish community size-structure. *Fisheries Research*, *140*, 91–95. doi:10.1016/j.fishres.2012.12.010

Shephard, S., Reid, D. G., & Greenstreet, S. P. R. (2011). Interpreting the large fish indicator for the Celtic Sea. *ICES Journal of Marine Science*, *68*(9), 1963–1972. doi:10.1093/icesjms/fsr114

Shephard, S., Rindorf, A., Dickey-Collas, M., Hintzen, N. T., Farnsworth, K., & Reid, D. G. (2014). Assessing the state of pelagic fish communities within an ecosystem approach and the European Marine Strategy Framework Directive. *ICES Journal of Marine Science*, *71*(7), 1572–1585. doi:10.1093/icesjms/fsu005

Shin, Y. J., Rochet, M. J., Jennings, S., Field, J. G., & Gislason, H. (2005). Using size-based indicators to evaluate the ecosystem effects of fishing. *ICES Journal of Marine Science*, *62*(3), 384–396. doi:10.1016/j.icesjms.2005.01.004

Tam, J. C., Link, J. S., Rossberg, A. G., Rogers, S. I., Levin, P. S., Rochet, M. J., … Rindorf, A. (2017). Towards ecosystem-based management: Identifying operational food-web indicators for marine ecosystems. In *ICES Journal of Marine Science* (Vol. 74, pp. 2040–2052). doi:10.1093/icesjms/fsw230

Thompson, M. S. A., Pontalier, H., Spence, M. A., Pinnegar, J. K., Greenstreet, S., Moriaty, M., Hélaouët, P., & Lynam, C. P. (2020). Trophic interaction data and taxonomic information for fish predators and their prey spanning the North East

Atlantic and its marginal seas between 1836-2013. Cefas, UK. V1. doi: https://doi.org/10.14466/CefasDataHub.102

Thorson, J. T., Munch, S. B., Cope, J. M., & Gao, J. (2017). Predicting life history parameters for all fishes worldwide. *Ecological Applications*, *27*(8), 2262–2276. doi:10.1002/eap.1606

Tibshirani, R., Walther, G., & Hastie, T. (2001). Estimating the number of clusters in a data set via the gap statistic. *Journal of the Royal Statistical Society. Series B: Statistical Methodology*. doi:10.1111/1467-9868.00293

Van Leeuwen, S., Tett, P., Mills, D., & Van Der Molen, J. (2015). Stratified and nonstratified areas in the North Sea: Long-term variability and biological and policy implications. *Journal of Geophysical Research C: Oceans*, *120*(7), 4670–4686. doi:10.1002/2014JC010485

Ver Hoef, J. M., Peterson, E. E., Hooten, M. B., Hanks, E. M., & Fortin, M. J. (2018). Spatial autoregressive models for statistical inference from ecological data. *Ecological Monographs*, *88*(1), 36–59. doi:10.1002/ecm.1283

Wakelin, S., While, J., King, R., O'Dea, E., Holt, J., Furner, R., … Blockley, E. (2015). Quality Information Document: North West European Shelf Reanalysis–NORTHWESTSHELF_REANALYSIS_PHYS_004_009 and NORTHWESTSHELF_REANALYSIS_BIO_004_011, EU Copernicus Marine Environment Monitoring Service. *EU Copernicus Marine Service*.

Wang, S., & Brose, U. (2018). Biodiversity and ecosystem functioning in food webs: the vertical diversity hypothesis. *Ecology Letters*, *21*(1), 9–20. doi:10.1111/ele.12865

Woodward, G., Blanchard, J., Lauridsen, R. B., Edwards, F. K., Jones, J. I.,

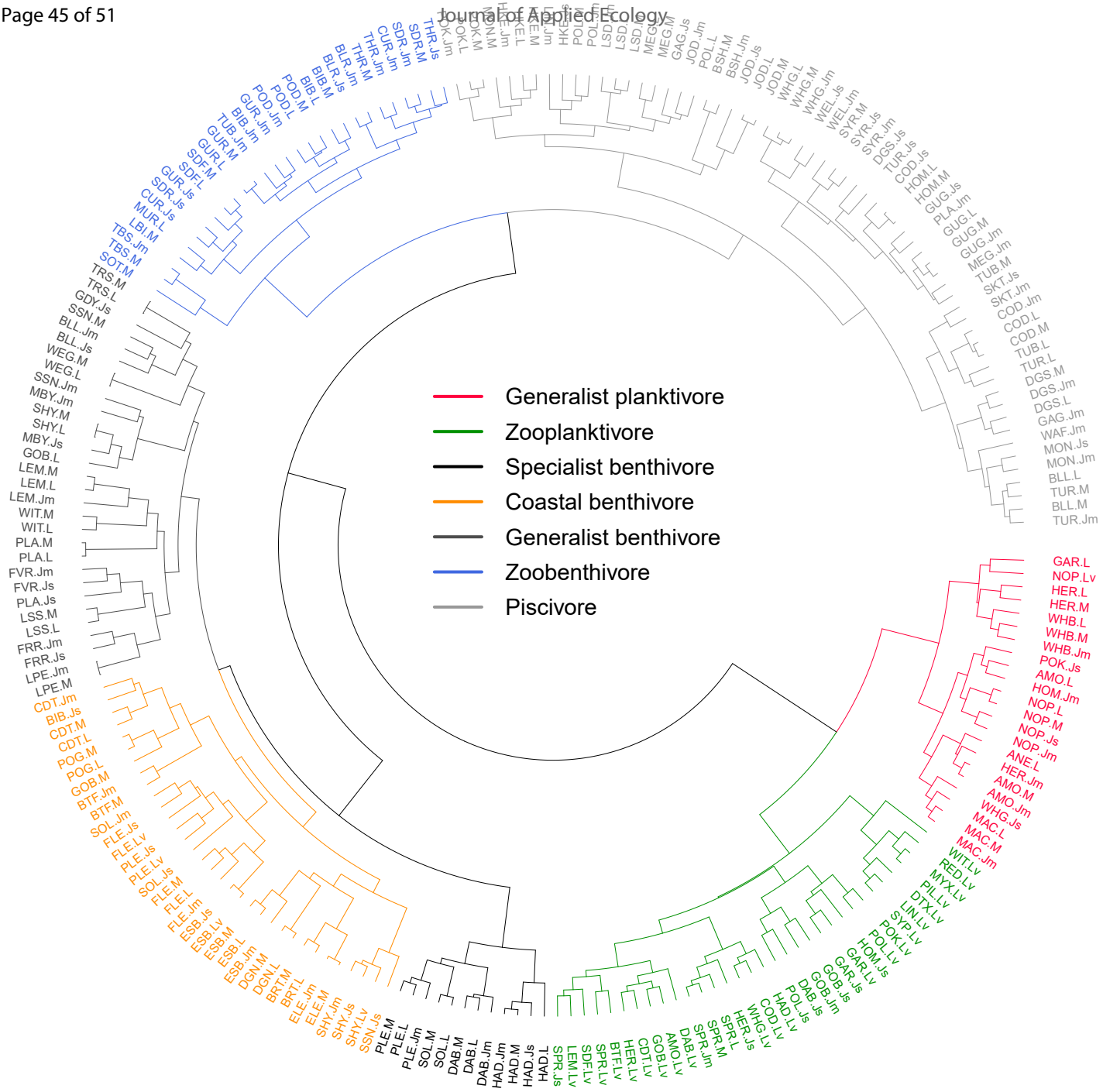
Figueroa, D., … Petchey, O. L. (2010). Individual-based food webs. Species identity, body size and sampling effects. *Advances in Ecological Research*, *43*, 211–266. doi:10.1016/B978-0-12-385005-8.00006-X

Woodward, G., Emmerson, M. C., Ebenman, B., Emmerson, M., Montoya, J. M., Montoya, J. M., … Warren, P. H. (2005). Body size in ecological networks. *Trends in Ecology and Evolution*, *20*(7), 402–9. doi:10.1016/j.tree.2005.04.005

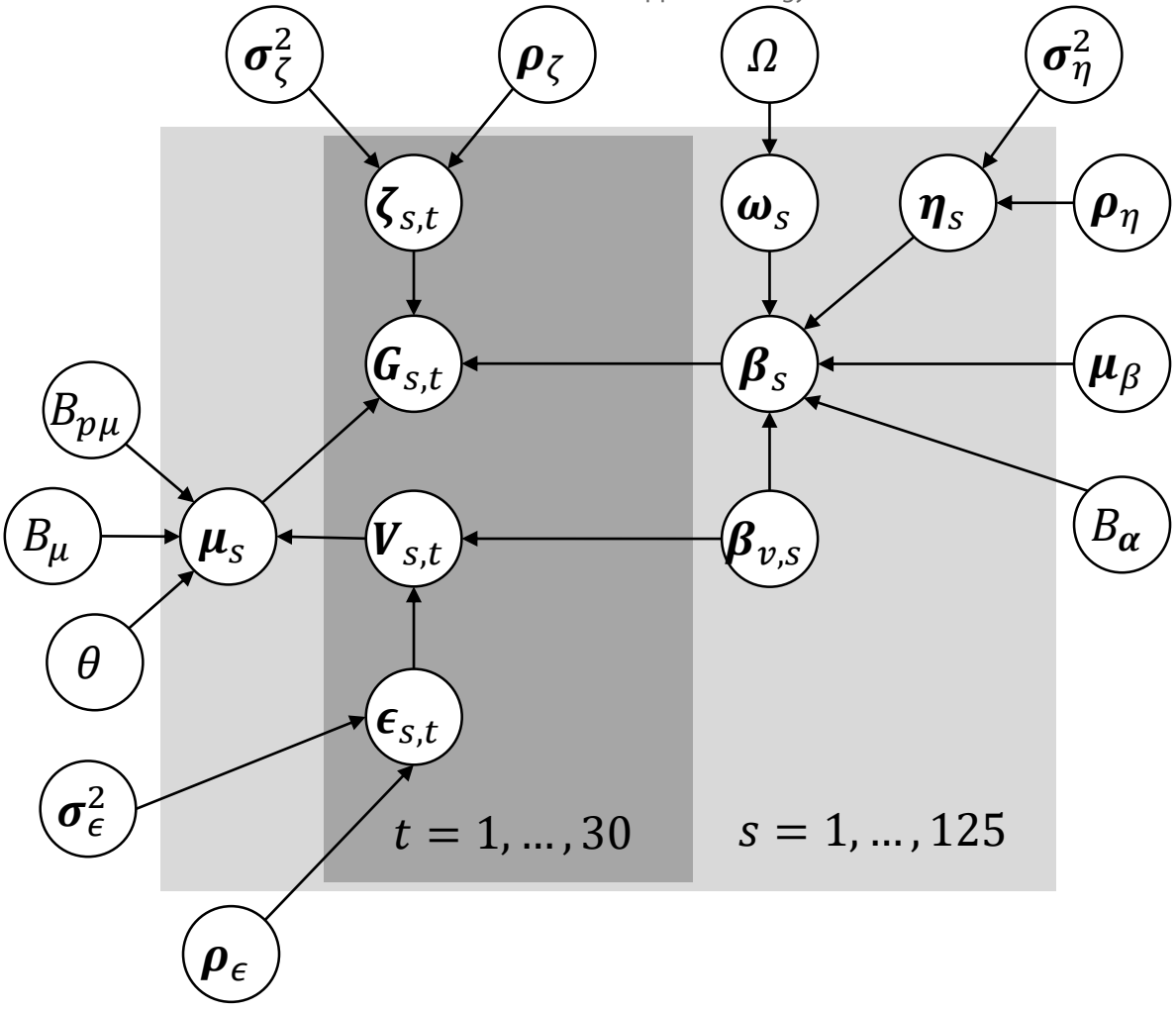
Yachi, S., & Loreau, M. (1999). Biodiversity and ecosystem productivity in a fluctuating environment: the insurance hypothesis. *Proceedings of the National Academy of Sciences of the United States of America*, *96*(4), 1463–1468.

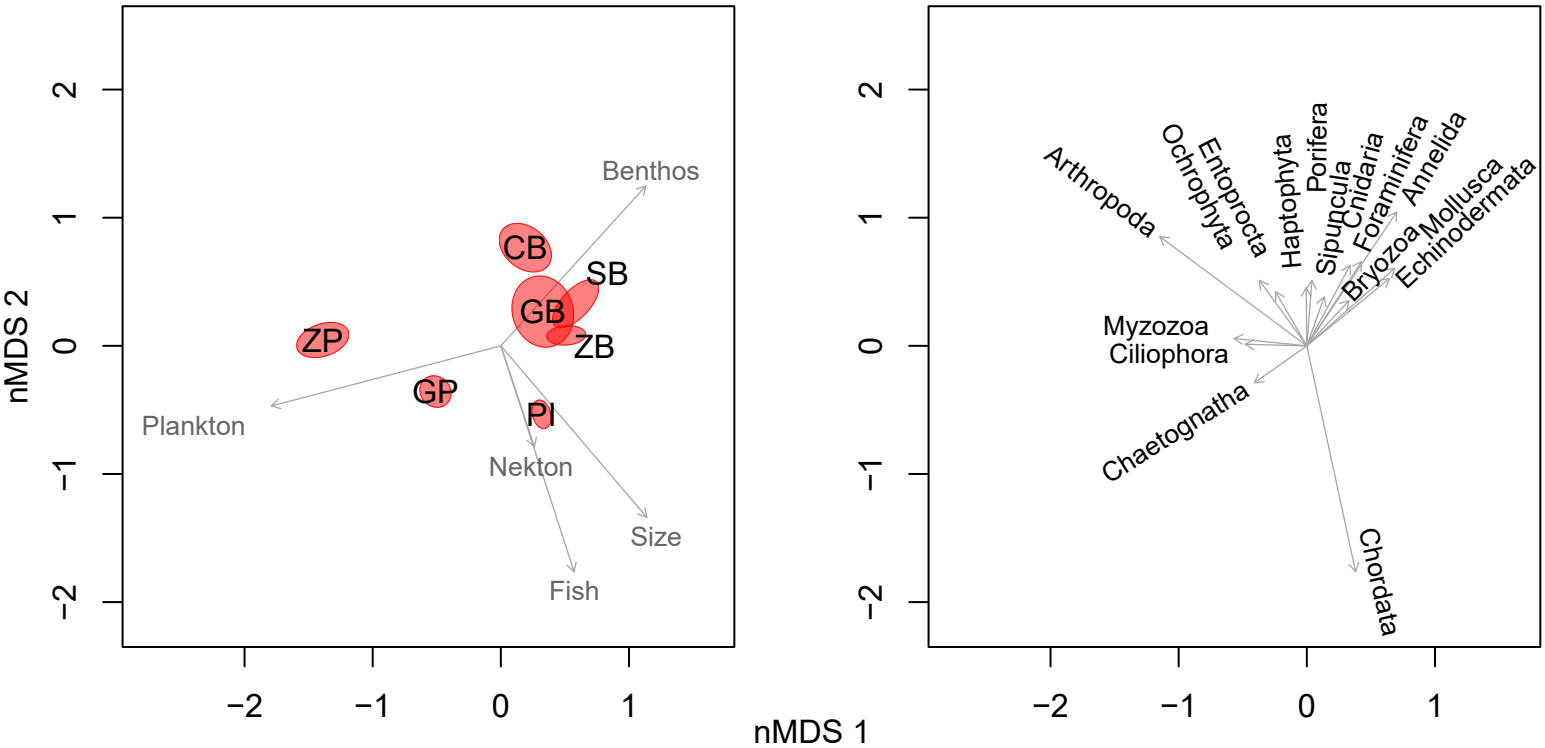
Zeileis, A., Kleiber, C., Walter, K., & Hornik, K. (2003). Testing and dating of structural changes in practice. *Computational Statistics and Data Analysis*. doi:10.1016/S0167-9473(03)00030-6

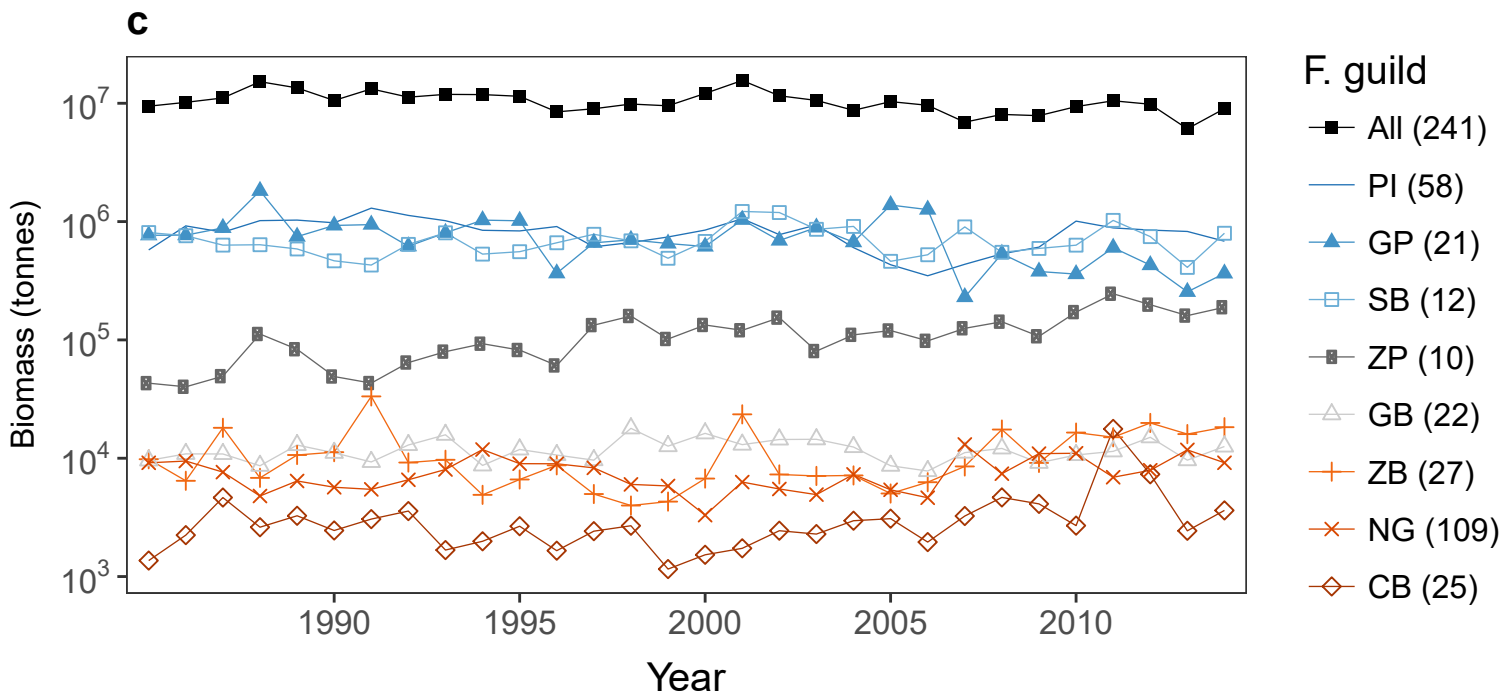
Zeileis, A., Leisch, F., Hornik, K., & Kleiber, C. (2015). strucchange : An R Package for Testing for Structural Change in Linear Regression Models . *Journal of Statistical Software*. doi:10.18637/jss.v007.i02

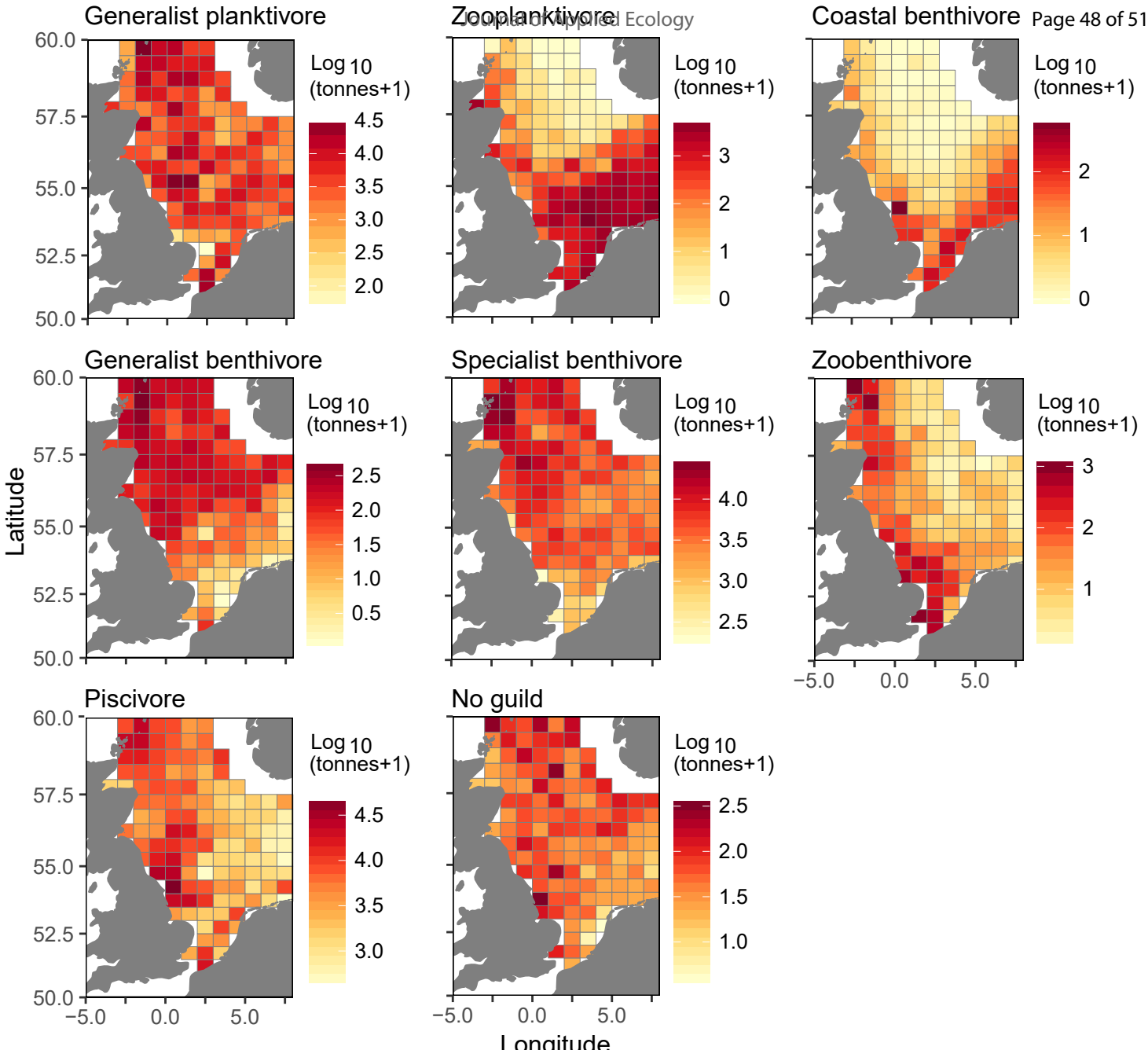


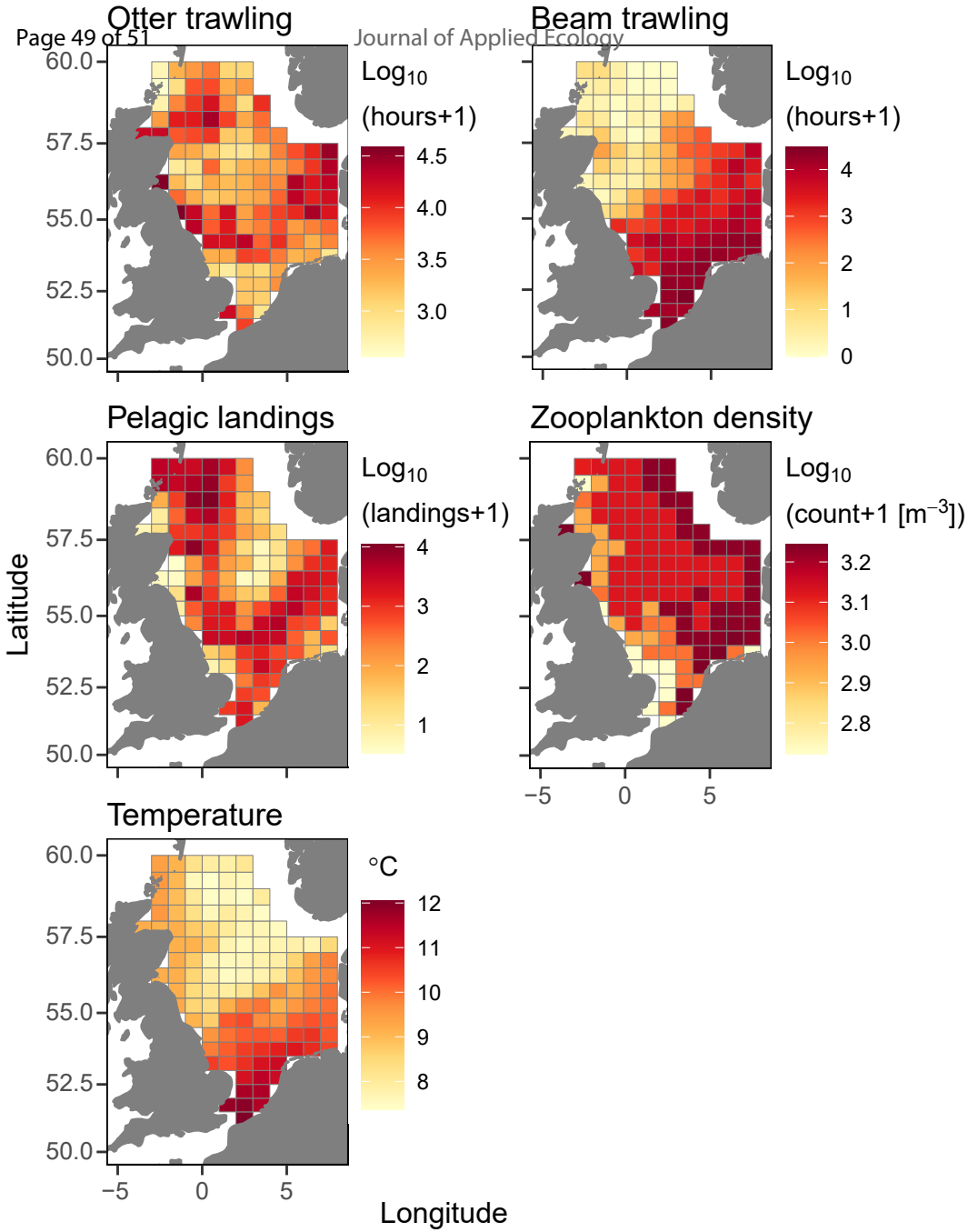
We propose fish feeding guilds (i.e. groupings based on diet and life stage) as a food web indicator to inform policy via food web status assessment as part of the European Union's Marine Strategy Framework Directive and the indicator toolkit supporting The Convention for the Protection of the Marine Environment of the North-East Atlantic (the 'OSPAR Convention'; letter codes represent taxa and size category, e.g. COD.L = large cod, see Table S1)

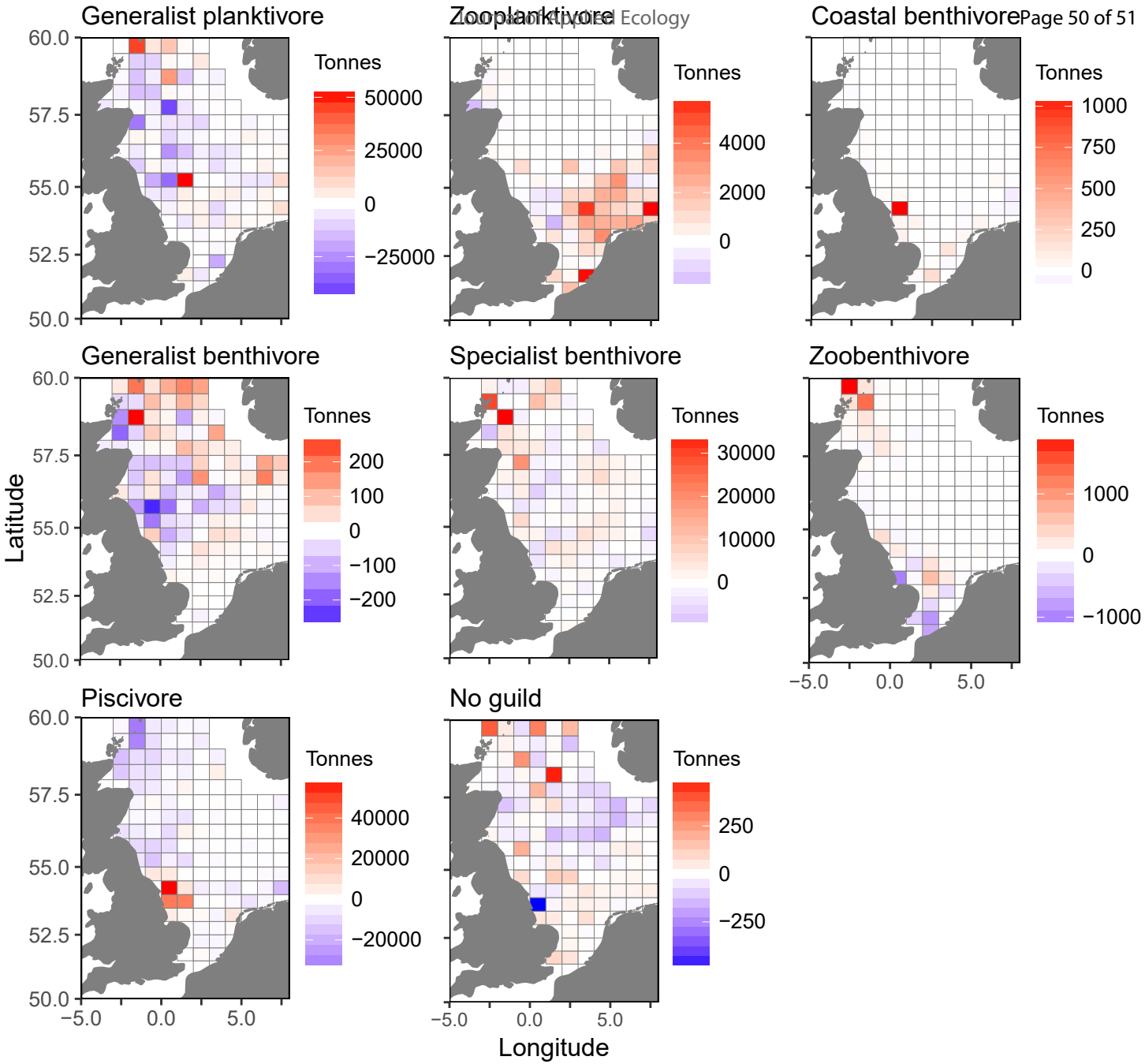

σ_ζ^2
ρ_ζ
Ω
σ_η^2
$\zeta_{s,t}$
ω_s
η_s
ρ_η
$G_{s,t}$
β_s
μ_β
$B_{p\mu}$
B_μ
μ_s
$V_{s,t}$
$\beta_{v,s}$
B_α
θ
$\epsilon_{s,t}$
σ_ϵ^2
$t = 1, \ldots, 30$
$s = 1, \ldots, 125$
ρ_ϵ

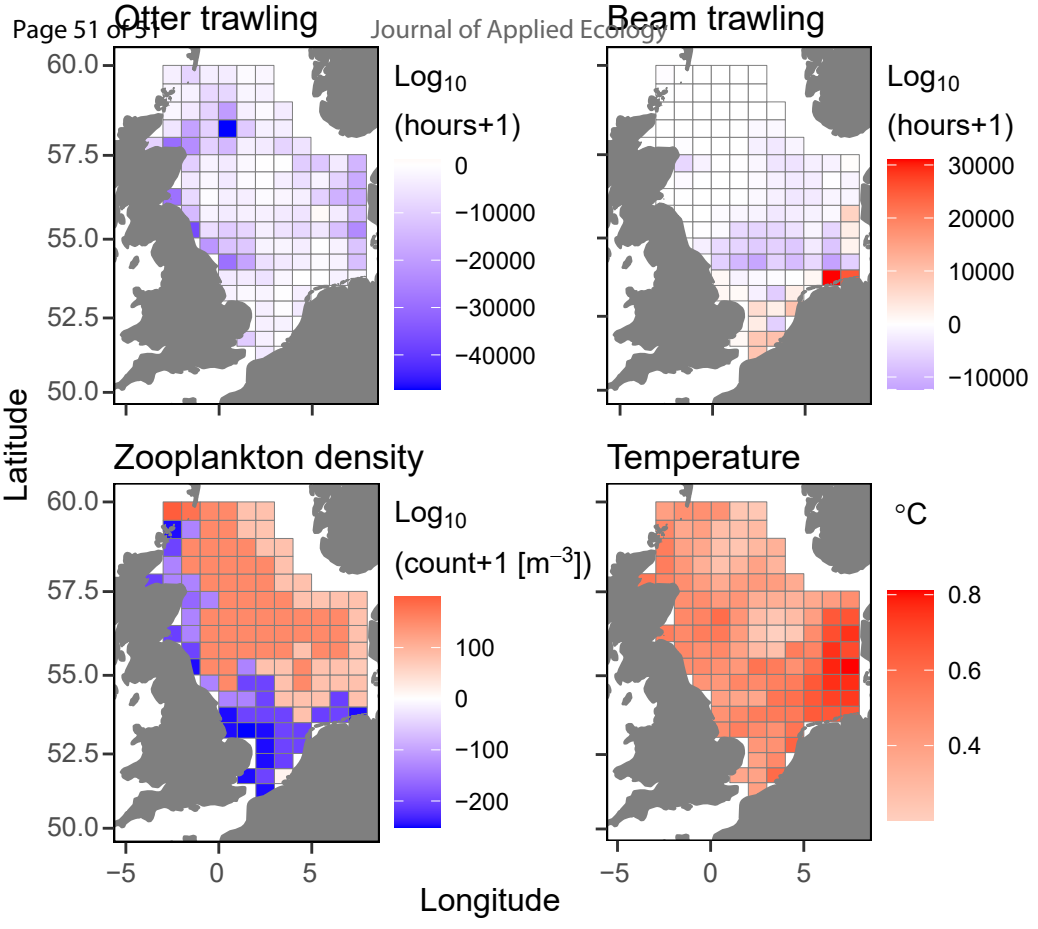

a
b
nMDS 2
nMDS 1
Benthos
Plankton
Nekton
Size
Fish
CB
SB
GB
ZB
ZP
GP
PI
Arthropoda
Ochrophyta
Entoprocta
Haptophyta
Porifera
Sipuncula
Chidaria
Foraminifera
Annelida
Bryozoa
Mollusca
Echinodermata
Myzozoa
Ciliophora
Chaetognatha
Chordata


c
Biomass (tonnes)
Year
F. guild
All (241)
PI (58)
GP (21)
SB (12)
ZP (10)
GB (22)
ZB (27)
NG (109)
CB (25)


Generalist planktivore
Zooplanktivore
Coastal benthivore
Generalist benthivore
Specialist benthivore
Zoobenthivore
Piscivore
No guild
Log 10 (tonnes+1)
Latitude
Longitude
60.0
57.5
55.0
52.5
50.0
−5.0
0.0
5.0


Otter trawling
Log10
(hours+1)
4.5
4.0
3.5
3.0
Beam trawling
Log10
(hours+1)
4
3
2
1
0
Pelagic landings
Log10
(landings+1)
4
3
2
1
Zooplankton density
Log10
(count+1 [m−3])
3.2
3.1
3.0
2.9
2.8
Temperature
°C
12
11
10
9
8
60.0
57.5
55.0
52.5
50.0
−5
0
5
Latitude
Longitude


Generalist planktivore
Zooplanktivore
Coastal benthivore
Generalist benthivore
Specialist benthivore
Zoobenthivore
Piscivore
No guild
Tonnes
50000
25000
0
−25000
4000
2000
1000
750
500
250
200
100
−100
−200
30000
20000
10000
−1000
40000
−20000
−250
60.0
57.5
55.0
52.5
50.0
−5.0
0.0
5.0
Latitude
Longitude


Otter trawling
Beam trawling
Zooplankton density
Temperature
Log10
(hours+1)
0
−10000
−20000
−30000
−40000
30000
20000
10000
0
−10000
Log10
(count+1 [m−3])
100
0
−100
−200
°C
0.8
0.6
0.4
60.0
57.5
55.0
52.5
50.0
−5
0
5
Latitude
Longitude