ICES Journal of Marine Science, 2022, **00**, 1–19
DOI: 10.1093/icesjms/fsac207
Original Article

Gaussian mixture models reveal highly diverse targeting tactics in a coastal fishing fleet

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Fishermen make repeated choices with respect to when, where, and how to catch their target species. While these targeting tactics—and the factors shaping them—are known to fishers and some experts, knowledge about them is largely informal and not well utilized for management purposes. To formalize information on targeting tactics, we propose a set of methods combining model-based classification of target species with generalized linear models. We apply these methods to Norwegian coastal fishing vessels that caught Atlantic **c**od (*Gadus morhua*) as a part of their catch portfolio in 2019. The data contains nearly 32000 fishing trips by 761 vessels. Gaussian mixture models identify eight latent targeting tactics. Cod contributes significantly to three of the tactics. The Herfindahl–Hirschman Index, a measure of vessel-level diversity of tactics, shows that one quarter of the vessels had a specialized strategy (targeting cod plus at most one additional tactic). While cod is often studied as a single-species fishery, we show that cod-catching vessels can be engaged in relatively pure fisheries during some fishing trips but switch to different, often more mixed targets during other trips. We term this as "sequential mixed fisheries". This is both a challenge and an opportunity for the fisheries management.

Keywords: cluster analysis, finite mixture model, fisher behaviour, fishing tactics, generalized linear model, métier choices, mixed fisheries management.

Introduction

Fish resource assessments and quota allocations are often made at a high level of spatial aggregation, on a yearly basis, and separately for each main target species. Fishing pressure and fishing impacts, however, have more granular distributions across space and seasons but are affecting many target and bycatch species simultaneously. Thus, there are mismatches between fisheries management and fishing operations in the degrees of spatial, temporal, and taxonomic resolution that could hamper the efficient implementation of fishing regulations and policies. The implications of a lack of oversight on fleet dynamics and fishers' behaviour could even be more severe than a lack of knowledge on biological resources (Hilborn, 1985, 2007).

From a management perspective, the incorporation of fisher's behaviour may reduce enforcement uncertainty (Little *et al.*, 2004) and improve the assessment of fisheries policy (Andrews *et al.*, 2021). For instance, models of marine reserves often assume that fishing effort is spatially uniform and unresponsive to economic incentives. Studies allowing a more realistic depiction of fishers behaviour found that the effect of marine reserves may be overstated by simplifying assumptions that ignore economic behaviour (Smith and Wilen, 2003). Fish stock assessment may also benefit from integrating fishers' knowledge. As fishers make repeated choices with respect to when and where to catch which species, they learn from their experiences and are likely to possess more knowledge about local stock abundance than what is typically available to researchers and managers. Information on fishers' landings, effort, and prices encountered has been used to assist resource assessment in data-poor fisheries (Pilling *et al.*, 2009).

It is common in ecosystem studies to treat fishers as a fixed element, with fishing effort being exogenous to the operational conditions and regulatory constraints they are in (Salas and Gaertner, 2004). In practice, however, fishers constantly adjust their fishing strategies and tactics (e.g. in a given fishing trip, which species to target and where and how to catch them) to cope with natural and market variability and the management itself (Smith and McKelvey, 1986; Hilborn and Walters, 1992). Scientists have called for modelling fishers' responses to regulations in order to understand their species and location choices and the underlying behavioural drivers (Branch *et al.*, 2006; Fulton *et al.*, 2011). Accordingly, there is a growing emphasis on the collection of fishing footprint data through logbooks, sales slips, the Vessel Monitoring System (VMS), and Automatic Identification System (AIS) data (Kroodsma *et al.*, 2018). This development provides researchers with new opportunities to analyse fishing patterns and behavioural drivers in detail. However, analysing highly detailed fishing footprint data is often hampered by serial and spatial dependence between the observations (Elhorst, 2008; Thorson *et al.*, 2016).

This study aims to develop a tool to reveal targeting tactics and their dynamics from a mixed-species perspective. We achieve this by combining Gaussian mixture models (GMM) for clustering analysis with generalized linear models (GLMs) to reveal heterogeneous vessel effects. The specific objectives of this study are threefold: (i) to identify latent species

Received: May 10, 2022. **Revised:** September 30, 2022. **Accepted:** October 27, 2022

targeting patterns using trip-level fishing revenue, which we interpret as targeting tactics; (ii) to reveal fishers' species diversification strategy at the fleet level; (iii) to understand how the identified tactics vary across vessel groups. Trip-level targeting tactics may be known to fishermen and some experts, but such knowledge remains largely informal and has not been well utilized for management purposes.

Fishing patterns and tactics have previously been analysed using the métier choice framework (Pelletier and Ferraris, 2000; Andersen *et al.*, 2012). The approaches used in métier studies follow three broad categories: input-based models that rely on surveys or interviews of fishers, often in data-poor situations (Tzanatos *et al.*, 2006); output-based models that use catch statistics and catch profiles from logbooks (Ulrich and Andersen, 2004); or a combination of both (Marchal, 2008; Boonstra and Hentati-Sundberg, 2016). Our approach is more similar to the second approach but differs from the existing métier studies in several important ways. First, we identify trip-level targeting tactics independently from spatial or seasonal characteristics. Instead, these were inferred from a posteriori, after trip-class memberships and probabilities were determined purely based on catches. Second, we use revenue rather than catch composition as input for determining the targeting tactics. Fishers' behavioural choices are probably better predicted by expected revenues than catches. Indeed, fishers' decisions are typically modelled in the framework of profit maximization, not catch maximization (Clark, 1974), and fish supply by a coastal fleet has been found to be responsive to both short- and long-run price changes (Jensen, 2002; Liu *et al.*, 2021). Third, we use GMM, a model-based method for clustering analysis. Previous studies on métiers and fishing tactics are primarily based on distance-based clustering methods (Pelletier and Ferraris, 2000; Cambiè *et al.*, 2017), including principal component analysis (PCA), multiple correspondence analysis (MCA), *K*-means, and hierarchical clustering. Model-based clustering is a more flexible technique because (a) it gives "soft classification"—assigning the posterior probability of each observation belonging to a latent cluster—and (b) it allows different assumptions about variance and covariance structures. Mixture models have previously been used for predicting the bycatch rate (Roberson and Wilcox, 2022), the abundance index for the targeted species (Okamura *et al.*, 2018), and fish discard mortality (Morfin *et al.*, 2017).

We demonstrate our method using data from Norwegian coastal fishing vessels <28 m in length using conventional fishing gears. Specifically, we will focus on the total fishing activity of the vessels that landed Atlantic cod (*Gadus morhua*, hereafter simply referred to as cod) as the main species at least once in 2019. We term this fleet segment the CaPoP fleet ("cod as a part of the catch portfolio"). Cod is the single most important fishery species in terms of landed value in Norway and among the top fishery species globally. The Atlantic cod fishery has been extensively studied both by biologists and economists (e.g. Eide *et al.*, 2003; Opdal, 2010; Sogn-Grundvåg *et al.*, 2022). Reflecting its dominant position in Norwegian fisheries, it has often been treated as if it were a single-species fishery. Here, we take a mixed-species perspective by focusing on cod-catching vessels but studying their full catch profiles throughout one year. Our analysis suggests eight targeting tactics for the CaPoP fleet, three of which include significant contributions from Atlantic cod. Our findings illustrate the diversity of tactics employed by the Norwegian cod-catching fleet.

Background on the case study region

The CaPoP fleet studied here is mostly active along the Norwegian coast of the Barents and Norwegian Seas (Figure 1). The region is known for its strong seasonality. The seasonal cycle of secondary production is driven by the spring bloom of planktonic algae (Skjoldal, 2004), triggered by increasing solar irradiation and stratification of the water masses (Sverdrup, 1953). The spring bloom first starts in the southwest and gradually progresses towards the northeast of the Barents Sea with the retracting ice edge (Skjoldal *et al.*, 1992). The bloom in the Norwegian coastal waters takes place earlier than in the offshore waters due to shallow waters and permanent stratification (Fernö *et al.*, 1998). Zooplankton feed on the blooming phytoplankton and provide an important food base for large fish, including cod and herring (*Clupea harengus*), to thrive. Many fish populations have developed seasonal migration patterns coinciding with the spring bloom cycle, with fish concentrating in the southern and south-western areas of the Barents Sea in February–March to spawn and primary distribution in the northern and eastern areas in August–September (Nakken, 1998). Seasonal aggregations of fish along the Norwegian coast offer unique fishing opportunities for coastal fleets. The late winter–early spring fishery of spawning cod near the Lofoten Islands in Vestfjorden (site 00 in Figure 1) is one of the best known examples and has existed throughout recorded history (Fernö *et al.*, 1998).

Fisheries management in Norway includes total allowable catch (TAC) regulations and various measures to protect juveniles and vulnerable species. Major stocks include Atlantic cod, haddock (*Melanogrammus aeglefinus*), saithe (*Pollachius virens*), herring, and mackerel (*Scomber scombrus*), all of which are quota-regulated; however, there are many commercial species that are subject to, rather than quota regulations, seasonal or area closures, and minimum mesh size restrictions (see a summary in Table A1). One important socio-economic management goal is to maintain a diversified fleet in terms of size and geographical distribution (Standal and Hersoug, 2014). This is reflected in the quota allocation key known as the "trawler ladder", which protects less-efficient coastal fleets (<28 m using conventional gears) from being outcompeted by ocean-going trawlers (Standal and Hersoug, 2014). In 2019 (our study year), the coastal fleet received 64, 58, and 36% of the TAC for cod, haddock, and saithe, respectively (Norwegian Directorate of Fisheries. 2018. J-261-2018 https://www.fiskeridir.no/Yrkesfiske/Regelverk-og-reguleringer/J-meldinger/Utgaatte-J-meldinger/J-261-2018). Moreover, vessels >21 m are largely excluded from fishing inside the Norwegian territorial waters.

Material and methods

Study scope

We define a CaPoP fleet as coastal vessels with lengths between 11 and 28 m that caught cod (*Gadus morhua*) north of 62°N at least once in 2019. This parallel is used in the Norwegian fishery management to separate southern and northern components of many stocks and also corresponds to a natural boundary (Johansen *et al.*, 2020). In total, there were 761 such fishing vessels. Cod is treated as a focal species in this study due to its biological and economic importance for the region and for Norwegian coastal fisheries in particular (Aglen *et al.*, 2004). There are three types (stocks) of cod included in our

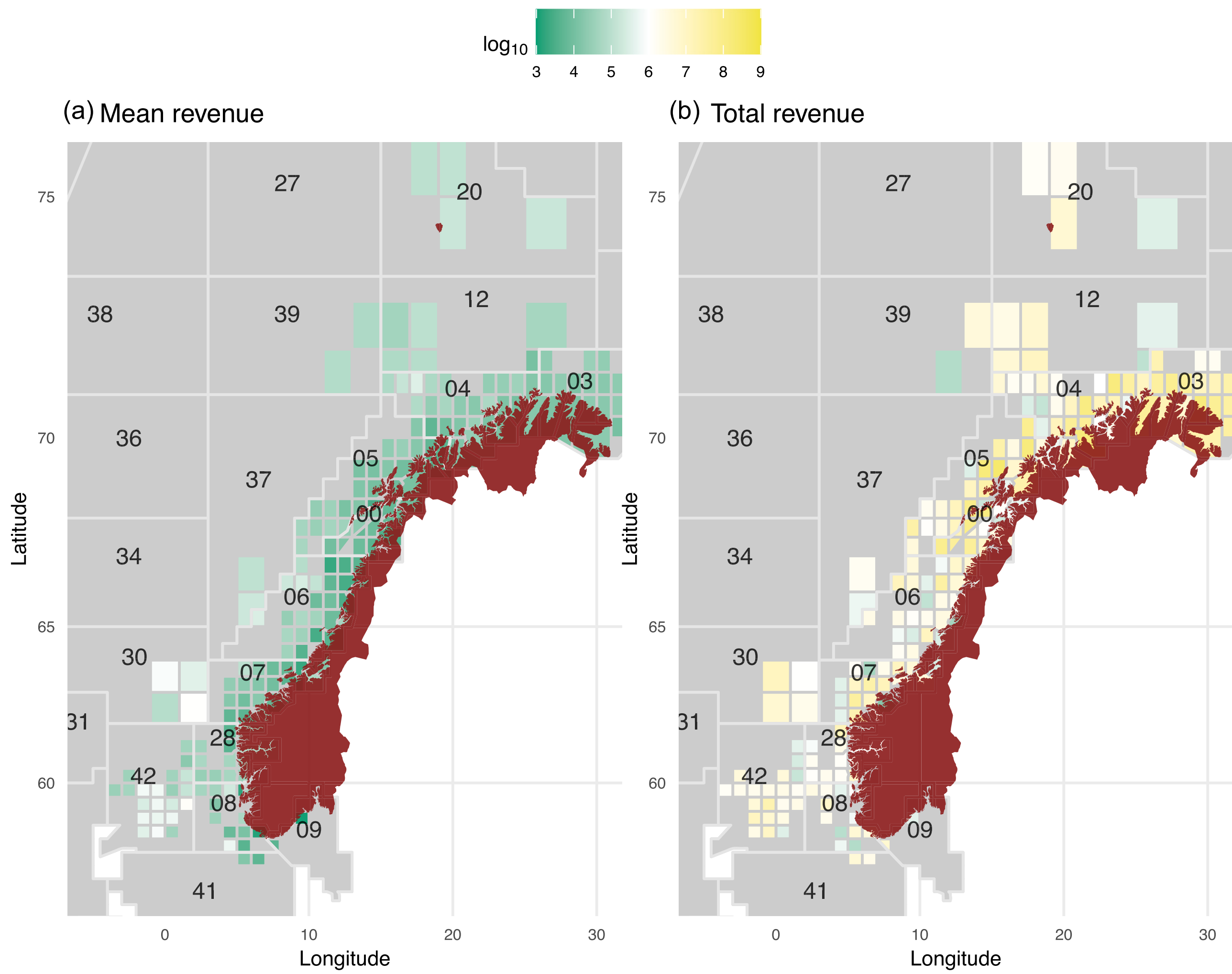

Figure 1. Activity map of the Norwegian CaPoP fleet. Colour indicates mean trip revenue (a) and total trip revenue (b) per statistical cell in the $\log_{10}$ scale in Norwegian kroner (NOK) in 2019. 1 NOK ≈ 0.1 Euro.

data set: northeast Arctic cod, North Sea cod, and coastal cod (potentially composed of several local sub-stocks). However, because of the inaccuracy of reporting, we aggregate all three types under the common name "cod".

To obtain a holistic picture of the fleet's behaviour, our analysis also covers the fishing activities of the selected vessels south of 62°N. An activity map (Figure 1) of the CaPoP fleet reveals that: (a) they are active not only in the fishing grounds along the coast but also further offshore; (b) fishing grounds along the coast of the northern counties (Troms and Finnmark) generated the highest revenues in 2019, but that (c) offshore fishing sites had higher mean revenues (note that fishing costs are not accounted for). Figure A1 shows the species caught by the CaPoP fleet in 2019. The list includes only the species that represent the highest or second-highest catch value per trip in no <50 fishing trips (aggregated over all vessels); it excludes "rare" species characterized by very low catch quantities (Norway introduced a full discard ban in 2009; Gullestad *et al.*, 2015). The exclusion affects some fisheries that are highly specialized, such as the wrasse (Labridae) or lumpsucker (*Cyclopterus lumpus*) fisheries. Our selection criteria led to 19 FAO species that were caught in over 31800 fishing trips.

Description of data

The main source of data for our case study is the 2019 sales slips compiled by the Norwegian Directorate of Fisheries. The data contains detailed landing information, including vessel characteristics, species-specific catches, revenues per landing, statistical fishing areas, and gears. The data set does not provide information on the length of fishing trips; however, trips can be identified using the reported last fishing day. The full descriptive statistics of the data are available in Table 1.

Inferring latent targeting tactics with Gaussian mixture models

We use GMM to identify latent targeting tactics because the species being targeted are not directly observable. This is particularly the case when the catches are mixed and contain several species. GMM is a model-based classification approach and is defined by the equation:

$$\log[P(X, Z|\mu, \sigma^2, \pi)] = \sum_{i=1}^{n} \log[\sum_{k=1}^{K} \pi_k N(x_i|\mu_k, \sigma_k^2)], \quad (1)$$

where P is the likelihood function of observed variables X and unobservable latent variables Z. GMM assumes that $X = (x_1,..., x_n)$ comes from K finite Gaussian (normal)

Table 1. Descriptive statistics on vessel and trip characteristics.

I. Vessel characteristics: N_{vessel}=761

Numeric variables

	Var. name	Description	Min	Max	Mean	SD
1.	Length	Vessel maximum length (m)	10.98	27.99	15.33	4.03
2.	logPower	$\log_e$ transformed engine power (hp)	4.62	7.09	5.81	0.51
3.	*C.V.*	Coefficient of variation in trip revenue	0.05	2.94	0.81	0.31

Categorical variables

4. Length group	Description	Freq	Prop
<15 m	10.98–14.99 m	581	0.76
>15 m	15–27.99 m	180	0.24

5. Registered county	Freq	Prop
Nordland	323	0.42
Troms and Finnmark	248	0.33
Trøndelag + south	190	0.25

II. Trip characteristics: N_{trip}=31800

Numeric variables

	Var. name	Description	Min	Max	Mean	SD
1.	Species price	Variation of price per vessel trip (NOK/kg)	0.00	850	17.2	25.6
2.	Species weight	Variation of weight per vessel trip in ton	0.00	394.8	1.62	8.82

Categorical variables

3. Main fishing areas* Levels	Freq	Prop
Røstbanken to Malangsgrunnen (05)	8 288	0.26
Vestfjorden (Lofoten) (00)	6 886	0.21
Vest-Finnmark (04)	5 047	0.16
Øst-Finnmark (03)	4 965	0.15
Storegga-Frøyabanken (07)	2 895	0.09
Helgelandsbanken (06)	2 723	0.08
Vikingbanken (28)	626	0.02
Eigersundbanken (08)	583	0.02
Skagerrak (09)	143	0.00
Shetland (42)	73	0.00
Nordkappbanken (12)	64	0.00
Central North Sea (41)	24	0.00
Southern Norwegian Sea (30)	18	0.00

4. Fishing month Month	Freq	Prop
Jan	3 390	0.10
Feb	4 346	0.13
Mar	5 937	0.18
Apr	2 968	0.09
May	2 186	0.07
Jun	1 813	0.06
Jul	1 258	0.04
Aug	2 233	0.07
Sep	1 850	0.06
Oct	2 344	0.07
Nov	3 143	0.10
Dec	898	0.03

5. Gears Levels	Freq	Prop
Set net	16 184	0.50
Danish seine	5 112	0.16
Oth. longlines	2 841	0.09
Autoline	1 493	0.05
Undefined gillnet	1 450	0.04
Shrimp trawl	1 148	0.04
Purse seine	1 027	0.03
Driftline	1 023	0.03
Lobster trap	985	0.03
Hand line/jig	749	0.02
Bottom trawl	104	0.00
Other	250	0.01

* Area IDs in parenthesis correspond to the statistical areas in Figure 1.

distributions and that each Gaussian in the mixture is determined by three parameters: the mean μ_k, variance σ_k^2, and the weight π_k. The weights account for the unequal number of samples from each distribution and sum up to one.

We assume fishers to be profit maximizers (Clark, 1974), and the revenue shares (x_i) per vessel trip of the 19 selected species (see Figure A1a) are used to infer Gaussian parameters $\Theta = (\mu, \sigma^2, \pi)$. Because species revenue shares are bounded between zero and one, we use the angular transformation $x_i' = 2\arcsin(\sqrt{x_i})$; the effect of this transformation is to pull out the ends of the distribution.

The goal of our GMM is to find a set of optimal parameters $\Theta = (\mu, \sigma^2, \pi)$ for K Gaussians that maximize the log-likelihood of the observations X. Latent targeting tactics (Z) are not observable but can be identified by the expectation–maximization (EM) algorithm (Redner and Walker, 1984). EM is the simplest and also most common algorithm for GMMs. Because EM is susceptible to local optima (Shireman *et al.*, 2017), multiple initial values are needed to get stable results. The maximum likelihood estimation determines the posterior probabilities of latent targeting tactics for each fishing trip.

Assumptions about the variance and covariance structures of the classes will affect class membership allocation. To avoid the situation where class numbers are too small or too large, we focus on configurations "ellipsoidal, equal volume, shape, and orientation" (EEE) and "diagonal, equal volume, shape and orientation" (EEI) as implemented in the *R* package *mclust* version 5.4.1 (Scrucca *et al.*, 2016). EEE means that variances and covariances are allowed to vary within classes but are fixed between classes. EEI is stricter and does not allow co-variances to vary within classes or between classes. These two configurations allow us to account for inter-species interactions, i.e. species that are caught together tend to be grouped in the same cluster. In the compositional data analysis literature, EEE is more preferred and considered less prone to local optima and non-convergence (Muthén, 2002; Ferrer-Rosell *et al.*, 2016). We apply the Bayesian Information Criterion (BIC) for model selection (Banfield and Raftery, 1993; Nylund *et al.*, 2007).

Model validation plays an important role in classification. In addition to BIC, we use multiple selection criterion for the best-fit model, including entropy and the level of uncertainty. However, since statistical criterion only provide a guideline (Nylund *et al.*, 2007), the interpretability and usefulness of the solutions are also important criteria to consider (Muthén, 2002; Weller *et al.*, 2020). We compared species profiles obtained by angular-transformed revenue shares with those based on posterior probabilities weighted by revenue shares, catch shares, and log-transformed revenues. The patterns of species compositions appear consistent across different measures (Figure A2). When membership ambiguity arises for clusters containing multiple species, we discuss reasonable allocations with the fisheries experts at the Norwegian Institute of Marine Research. The procedure leads to a selection of an eight-membership model, with the EEE configuration as the best model.

Diversity of vessel-level targeting tactics

We apply HHI to describe fishers' species diversification strategies. HHI, also known as the Simpson diversity index (Simpson, 1949), is often used to measure fishers' risk profiles (e.g. Kasperski and Holland, 2013). Here, HHI is vessel-specific and defined as follows:

$$\mathrm{HHI} = \sum_{k=1}^{8} \left(\frac{P_k N_k}{N_0}\right)^2, \tag{2}$$

where N_0 is the total fishing trips by the ith vessel in the year of 2019, and N_k is the fishing trips harvesting the kth species group. N_k are weighted by P_k, the posterior probability of a vessel trip belonging to the kth species class.

HHI takes a value between 0 and 1. Low values correspond to using many targeting tactics in relatively even proportions, whereas high values indicate domination of a few tactics. For example, if a vessel solely focuses on a single species class, HHI = 1; if trips are evenly distributed between two species classes, HHI = 0.5. We thus view HHI as a fishing diversification index. A simple fractional logit model is specified to investigate the variation of HHI with vessel characteristic variables. The best-fit model in Equation (3) includes the deviation of vessel length from group means (i.e. $len.deviation = len - \overline{len}_i$), length group (*lgroup*) and registered county (*county*):

$$\mathrm{HHI} = a + len.deviation + lgroup + county. \tag{3}$$

The model is analysed as a GLM, assuming a binomial error distribution. Robust standard errors are calculated using the *R* package *sandwich* (v3.0-2) (Zeileis *et al.*, 2020).

Correlates of targeting tactics

We construct a Poisson regression model to understand how targeting tactics vary with external variables such as vessel and fisher characteristics (e.g. risk perception). Specifically,

$$log(Y_{i,t,k}|X_1, X_2, mon) = \alpha + power_{i,k} + CV_i + mon_t \times (length_{i,k} + county_{i,k}). \tag{4}$$

We denote $Y_{i,\,t}$ as the probability-weighted total number of fishing trips in 2019 when vessel i caught species group k in month t. $Y_{i,t} = \sum^{N_t} p_i$, where p stands for the posterior probability of a vessel targeting species k and is assigned by the GMM; N_t refers to the total number of trips targeting a species group in month t. Because total trips Y is a non-integer expectation, and it must be a count (an integer), $Y_{i,\,t}$ is rounded up to the nearest integer. The model is run k times independently for each species cluster, all coefficients thus are cluster specific.

In addition to dummy variables for month (*mon*), Equation (4) includes two main types of variables, X_1 and X_2. X_1 captures vessel characteristics, including $\log_e$-transformed engine power (*power*), the length group it belongs to (*length*), and the county of registration (*county*). We allow month to interact with length group and county because fishing opportunities may differ by length group and county of registration: distance to a favourable fishing ground varies with vessels' home ports, and different quota allocation rules may apply to smaller and larger vessels (Standal and Hersoug, 2014). Moreover, the accessibility of fishing grounds depends on vessel size. The second variable type X_2 reflects fisher's risk perception, measured as the coefficient of variation (*C.V.*) in trip revenue experienced by each vessel (Kasperski and Holland, 2013; Anderson *et al.*, 2017). Intercept α captures unobserved variables that are common to all vessels (e.g. weather). We mean-centre two continuous variables, *power* and *C.V.*, so that estimates for intercepts can be directly interpreted as the expected

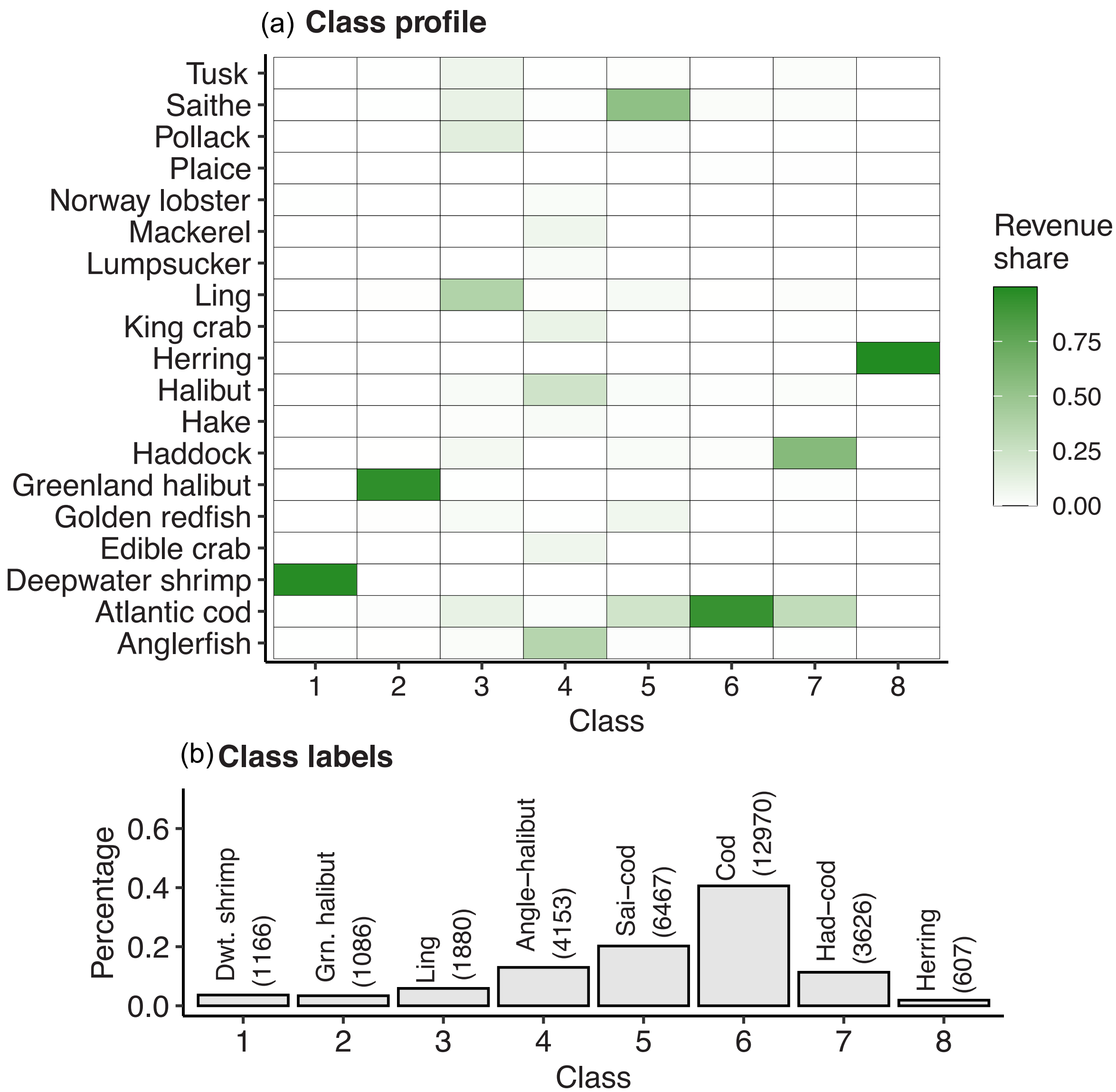

Figure 2. Eight species clusters were identified by the GMM to describe the targeting tactics of the Norwegian coastal fishing fleet. (a) Heat map indicating species compositions in probability (posterior) weighted revenue share for each class. (b) Barplot showing class distributions. Classes are labelled according to the dominating species indicated in panel A. The total number of trips per class are indicated in parenthesis.

number of trips for the reference cases (see intercepts in Table A3). The models are fitted as GLMs assuming Poisson distribution.

Results

Fishing patterns revealed by latent class analysis

The GMM suggests that eight species clusters can adequately summarize the fishing behaviour of the CaPoP fleet (Figure 2). Four of these clusters represent single-species targeting tactics; these are deep-water shrimp (class 1), Greenland halibut (class 2), Atlantic cod (class 6), and Norwegian spring-spawning herring (class 8). In addition to its own cluster, cod also significantly contributes to two mixed-species clusters, one dominated by saithe (class 5) and another by haddock (class 7). The two remaining mixed-species clusters are dominated by ling (*Molva molva*), a range of other gadids (class 3), and by anglerfish and Atlantic halibut (class 4).

Class proportions (Table in Figure 2) show that the single most important targeting tactic in terms of numbers of trips was pure cod fishing (class 6), accounting for over 40% of the total trips in 2019. If we also consider the cod caught together with haddock and saithe, cod-related tactics account for nearly three-quarters (72%) of all fishing trips in 2019. Also, the anglerfish–halibut tactic accounted for a sizeable fraction of trips (13%). The trips targeting ling, deepwater shrimp, Greenland halibut, and herring were fewer, making up 2–6% of each.

Harvest tactics by season, site, and gear

Figure 3 highlights variation in fishing behaviour by season, statistical area, and gear. These tactics can be viewed from

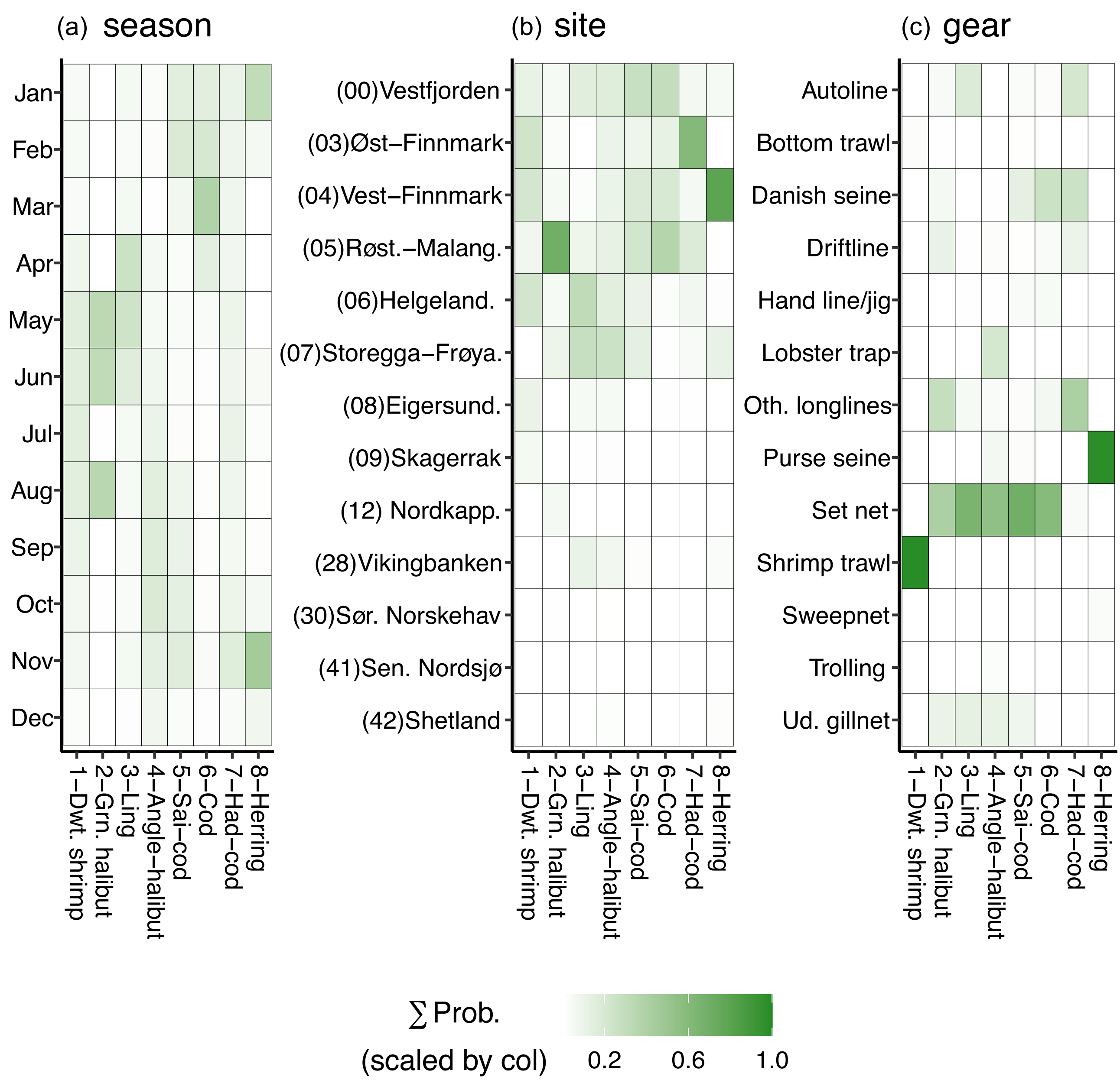

Figure 3. Probability (p) weighted trip frequency aggregated by season (a), site (b), and gear (c) for each species cluster (k). The summed trip probability is scaled by column categories (i), i.e. $\sum^{i} p_{k,\,i} = 1$. Infrequent categories (total occurrence $\leq$ 15 trips) are excluded. Site IDs in parenthesis in (b) correspond to the statistical areas in Figure 1 and run from northeast to southwest, with the exception of Vestfjorden (00), which is geographically adjacent to the areas 05 and 06 in Figure 1.

the perspective of species clusters (normalizing column-wise: Figure 3) or from the perspective of explanatory variables (normalizing row-wise: Figure A3).

Some targeting tactics are used almost year around with little seasonality, notably the haddock-cod tactic (class 7). Several other tactics exhibit strong seasonality that is related to both fishing opportunities (seasonal aggregation of fish) and constraints (fishery regulations). The best known seasonal aggregation is the spawning of the northeast Arctic stock of cod. In winter, these fish migrate from the Barents Sea to the coast of Norway for spawning in early spring (Hylen *et al.*, 2008; Olsen *et al.*, 2010). Figure 3a shows that pure cod fishing (class 6) takes place in January–April and peaks in March. The season for herring (class 8) is also short and occurs in the winter (November–January), coinciding with the overwintering aggregations in the innermost part of the fjords in northern Norway (Dragesund *et al.*, 2008). For deepwater shrimp, aggregation happens during the period of abundant daylight in late spring and summer (May–August), when the shrimp's light avoidance response (Ingólfsson *et al.*, 2021) causes them to aggregate close to the seafloor. These examples suggest that seasonal fisheries can be driven by periods of high catchability when the target species are close to the shore, in tight schools, and with low mobility, making them highly accessible for smaller vessels.

Regulations also play a role in shaping the seasonality of fishing. The abrupt stop of herring fishing in December (Figure 2a) may indicate that fishers have run out of annual

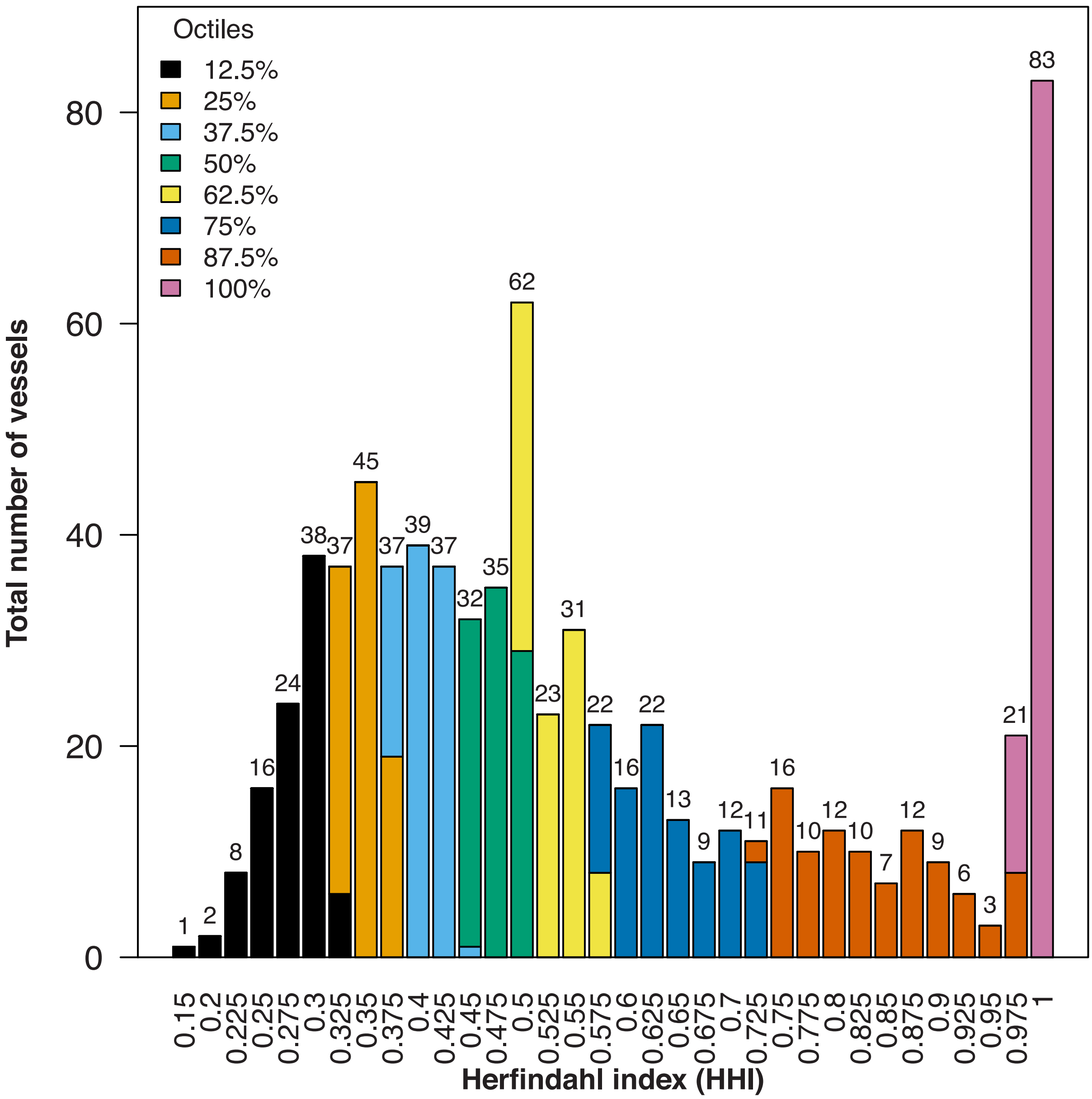

Figure 4. Herfindahl–Hirschman Index (HHI) octiles for all 761 vessels. In total, 83 vessels (i.e. HHI = 1) solely harvested the pure cod class in 2019.

quotas or that they allocate their effort in such a way that fishing close to the holiday period can be avoided. By contrast, the seasonality of fishing for Greenland halibut (class 2) appears to be driven by seasonal closures. The high season fell in May, June, and August of 2019 when fishing restrictions were lifted (see management overview in Table A1).

Most of the fishing activities take place off the coast of central and northern Norway (areas 00–07 of Figure 3b; see map in Figure 1); sites further south or away from the coast are less visited. Fishing in more offshore areas was typically associated with specific tactics (Figure A3b); for example, catching Greenland halibut in Nordkapp (area 12). Fishing grounds for pure cod fishing (class 6) spread into several areas in the north, from near Lofoten (areas 00 and 05) to Finnmark (areas 03 and 04), the northernmost county. In comparison, fishing grounds for the haddock-cod tactic appear to be concentrated in east Finnmark (area 03) and those for the herring cluster in west Finnmark (area 04).

Most targeting tactics are dominated by a single gear. Deep-water shrimp (class 1) and herring (class 8) are caught by specialized gears, shrimp trawl and purse seine, respectively. Other gears are less specialized, with set nets in particular being strongly associated with several tactics (Figure A3c).

Fishers' species diversification strategy

We computed the HHI for each vessel to describe the degree to which fishers changed their targeting tactics across fishing trips. The HHI octiles in Figure 4 show that about one-eighth (i.e. 83 vessels) of the CaPoP vessels were highly specialized and caught only one species cluster. This was always the pure cod cluster (class 6), representing fishing cod spawning in Lofoten in winter–early spring. Highly aggregated cod schools make fishing more cost-effective for smaller vessels, compensating for the lower prices fishers may face due to high landing volumes (Sogn-Grundvåg *et al.*, 2022). These vessel owners only went to sea during this specific time of the year, and their fishing quotas could be fulfilled just within a few days of fishing. Furthermore, about a quarter of the vessels had HHI indices over 0.75, which indicates a strong specialization in one to two species clusters (This is an approximation. HHI = 0.75 can be achieved by 85% of the trips target one species and 15% target the other, i.e. HHI = $0.85^2 + 0.15^2 \approx 0.75$. A more skewed distribution of effort across species groups would lead to HHI > 0.75). In practice, this means the pure cod cluster plus one additional cluster. The remaining three-quarters of the vessels engaged in more mixed harvest strategies by attending three or more species clusters. The fractional logit model of HHI (Table A2) suggests that bigger vessels within a length group and vessels from southern counties (e.g. Sogn og Fjordane, Vest-Agder) adopt a more diversified targeting strategy (i.e. a lower HHI).

Heterogeneous allocation of fishing effort

Poisson regression reveals that the fishing effort associated with each species cluster, measured by the number of fishing trips per vessel, depends on vessel characteristics and season (Table A3). Engine power is positively associated with the number of fishing trips for herring (class 8), haddock-cod (class 7), and saithe-cod clusters (class 5), but negatively with the trip frequency of catching ling, angler fish-halibut, Greenland halibut, and pure cod clusters. The sign of the regression coefficient associated with the coefficient of variation (*C.V.*) of trip revenue, which measures a fisher's risk altitude, also varies by species cluster. A more risk-seeking fisher (high *C.V.*) is expected to have more fishing trips for the anglerfish-halibut and saithe-cod clusters but fewer for the haddock-cod, pure cod, and ling clusters.

Seasonal effort allocation also appears to differ by vessels' county of registration and by length group. Figure 5 illustrates trip allocations of the three of the most prevalent species clusters, namely the pure cod, saithe-cod, and haddock-cod clusters. We can observe that (a) for vessels from Troms and Finnmark, the highest number of the pure cod fishing trips occurred in January, whereas the peak was delayed to March for the vessels from other counties (Figure 5a); (b) for vessels from more southerly counties (Nordland, Trøndelag, and south of Trøndelag), the peak saithe season was in February, in which smaller vessels (<15 m) took more frequent trips than the bigger ones (Figure 5b); (c) large vessels (≥15 m) registered in Troms–Finnmark and Nordland were more active in catching the haddock-cod cluster in July. Vessels from southerly counties (Trøndelag and southward), which are further away from the main haddock-cod fishing grounds in western Finnmark (Figure 3b), have fewer haddock-cod fishing trips. This may reflect the joint effects of economic, regulatory, and biological factors: because of the time and monetary costs, smaller vessels might avoid fishing grounds that are far away from home ports (Haynie and Layton, 2010), unless high catch rates compensate for the long travel (Sogn-Grundvåg *et al.*, 2022).

Discussion

Understanding fishers' dynamic responses to natural and market variability and to management itself is essential for designing effective management policies (Wijermans *et al.*, 2020). Here, we developed a technique based on GMM to study within-year dynamics of the CaPoP fleet—Norwegian coastal vessels catching cod as a part of their species portfolio. We conclude that the targeting tactics of the fleet can be described by eight latent species clusters. Although the fishery focuses on a single species, the CaPoP fleet reveals high variability both in terms of the number of species groups to target and the allocation of fishing effort across targeting tactics.

Our results highlight key factors shaping the vessel's targeting tactics. First, perhaps the most evident, biological drivers in the form of seasonal aggregations can boost catch rates of certain species. Second, management constraints can be influential. For example, quota exhaustion can partially explain the low level of fishing activities towards the end of the calendar year (e.g. herring) or beyond the biological fishing season (e.g. Greenland halibut). Finally, travel costs and expected prices, respectively, may explain that vessels from more southerly counties participated to a lower degree in fisheries associated with the northernmost part of Norway, while vessels from the northernmost counties follow a different timetable for catching spawning cod.

We note that biological, operational, and economic factors can be confounded, such that disentangling their individual effects can be difficult. For example, some TAC allocations follow seasonal patterns of aggregation (Table A1). There is a substantial price premium associated with coastal spawning stocks due to higher fat content and shorter transport distances (Zimmermann and Heino, 2013; Abe and Anderson, 2022). To improve the fish quality, fishers may adjust the harvest schedule according to intrinsic fish quality following biological aggregations (Larkin and Sylvia, 1999) or change gear types, haul sizes, trip lengths, and soaking times (Savina *et al.*, 2016; Sogn-Grundvåg *et al.*, 2020).

The findings from this study echo some earlier research on fishing tactics. Fishermen follow two generic behavioural patterns, specialist fishing and generalist fishing (McKelvey, 1983), as ways to cope with market and natural variability (Lloret *et al.*, 2000) and to improve their economic and financial resilience (Finkbeiner, 2015). Fishers target different species at different times of the year and at different locations so that the returns from the resources vary asynchronously (Kasperski and Holland, 2013; Birkenbach *et al.*, 2020). In mature fisheries, such as the cod fisheries being studied herein, fishing tactics are typically subject to regulations that restrict season length, vessel and gear types, fishing areas, and fleet size (Branch *et al.*, 2006). For cod-specialized fishers, Sogn-Grundvåg *et al.* (2022) suggest that this specialization results from a trade-off between quality and quantity: by engaging in swift and intense fishing during the spawning season, fishermen maximized fisheries output, minimized fishing costs, but had to endure lower quality of fish.

Targeting tactics identified by our method have some similarity to the "métiers" as recognized by the European Union's Common Fishery Policy—both are cluster of species in fisheries catches. However, the métier framework describes a hierarchical top–down structure of fishing activities, with métiers being subordinate to fleets and defined based on fishing gear, season, and area. The métier framework is sometimes challenged for being rigid, lacking clear quantitative guidance (Ulrich *et al.*, 2012), and not being able to reflect the reality of fishing (Jacobsen and Wilson, 2009). Our framework offers a bottom–up approach where clustering is driven by actual catches. The deployed methods are quantitative, combining model-based clustering analysis with GLMs, and can be replicated in other studies.

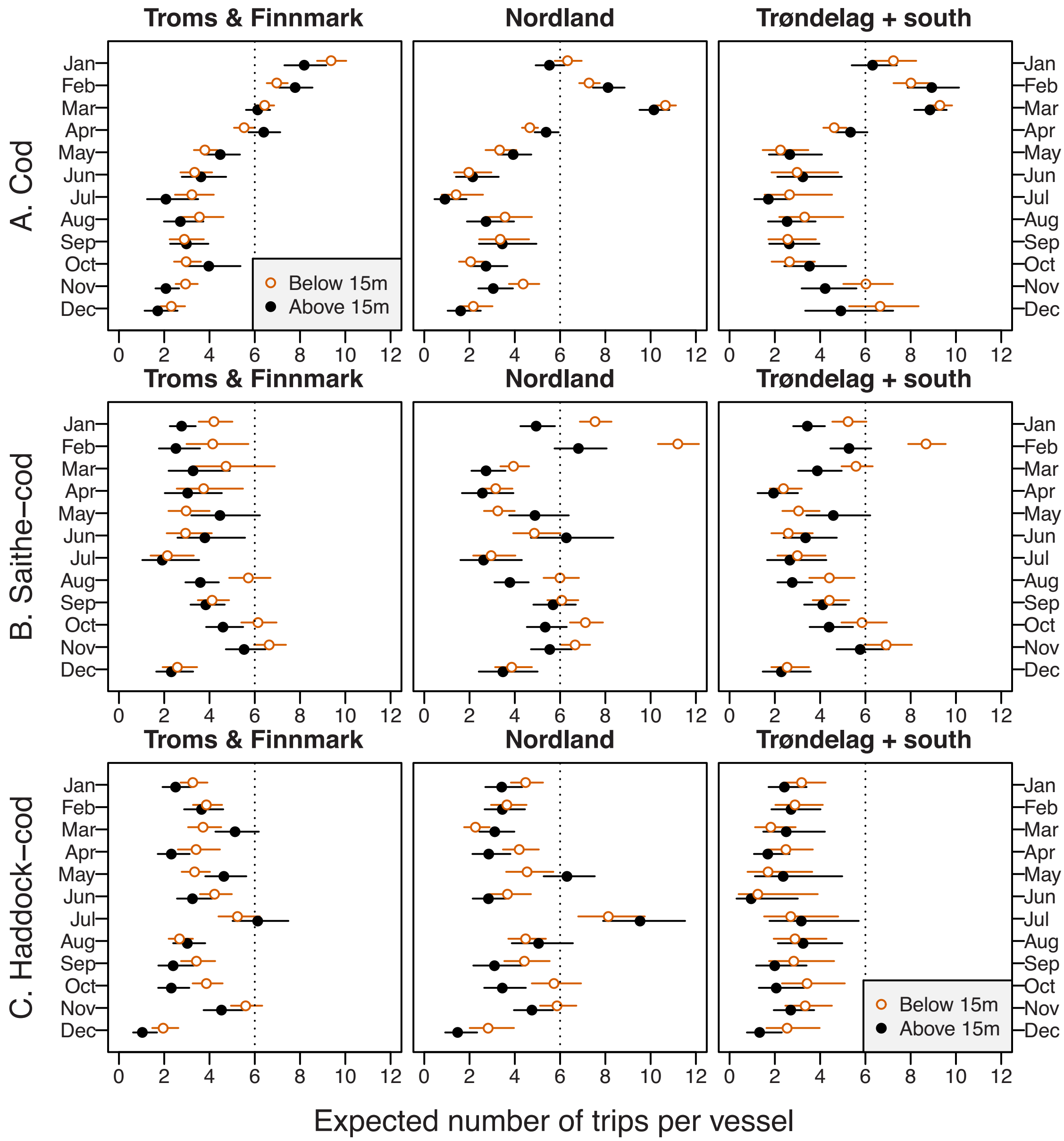

Figure 5. Predicted number of trips per vessel by main species clusters and county groups based on the model outputs in Table A3. Vessels are aggregated into two length groups: <15 m (vermilion circles) and between 15 and 28 m (black solid circles). Engine power and *C.V.* for revenue are fixed at the sample mean.

Métier studies typically rely on catch compositions. This raises the question of whether catch data serves better to determine target species than revenue or profit data. Our material suggests that the difference between catch- and revenue-based compositions is small (Figure A2c–d). However, these results might not hold for all fisheries. Two factors are critical: (i) how much prices vary across species, and (ii) how responsive are fishers to price changes? In our case, price variation across species is moderate (Figure A1b–c). Existing evidence supports the notion that short-run supply elasticity of fishers is small in optimally managed fisheries (see a review by Jensen, 2002), but greater in minimally controlled fisheries (Liu *et al.*, 2021). This provides some assurance for using trip-level catch compositions to describe targeting in managed fisheries. In lightly managed fisheries (e.g. semi-open access), when price variations are higher and catch data are highly aggregated over space and time, some caution in using catch compositions would be needed.

Our analysis is not without its caveats. First, the sales slip data includes the last fishing date but no information on trip duration. Missing trip duration is not critical when dealing with small vessels typically engaged in daily trips, but could confound a study where trip length can vary widely across vessels. Especially during longer trips, fishers could employ more than one tactic, but this would not be visible in data like ours. Second, while using revenue shares to classify targeting patterns likely is an improvement over catch-based approaches, using net revenue (i.e. profit) would arguably be even better. However, information on fishing operation costs is not easily obtained. Having trip-level information can partially mitigate this shortcoming because different species caught during the same trip share similar costs. The importance of including costs increases if using more aggregated data.

The study could be extended in several directions, such as cluster-level analysis to understand the factors that drive each fishing pattern, including environmental and biological factors. Cluster-specific factor analysis is particularly important for management policy evaluations; for instance, the haddock-cod cluster that emerged strongly from our analysis can be triggered by technical interactions (e.g. by-catch) or by a seasonal cod quota policy, a scheme that encourages catching cod beyond its main fishing season. Moreover, cluster analysis could be extended to multiple years, for example, in the framework of latent growth models. This would be particularly relevant when evaluating fishers' long-term responses to climate change.

Conclusions

We have demonstrated a new tool that can help fisheries managers and researchers gain a better overview of fleet dynamics. To our knowledge, this is the first study to quantitatively describe the targeting tactics of the cod-catching vessels from a multiple-species perspective. Cod is often studied as if it were a single-species fishery, reflecting the relatively pure catches obtained in the spawner fishery and its high economic yield. We show that the activities of the cod-catching vessels are much broader. Geographically, these vessels are active across multiple eco-regions; tactically, they target a number of species groups.

The importance of studying fishing tactics has primarily been emphasized for mixed fisheries (Tidd *et al.*, 2012), where many species are caught simultaneously. Our results show that cod-catching vessels can be engaged in relatively pure fisheries during some fishing trips and switch to different, possibly more mixed, targets during other trips—in other words, they can be engaged in sequential mixed fisheries. This diversity of behaviours has several management implications. First, knowledge of fishing tactics can allow developing more cost-effective monitoring programmes. Second, the diversity of fishing tactics makes it more difficult to predict the broader consequences of species-specific management measures. As the fishers have many tactics to choose from, such management measures can have unexpected spill-over effects on other species. On a positive note, this tactical flexibility gives resilience to the fishers themselves. Third, the managers can also take advantage of the known fishing tactics when designing new interventions. This would mean that the spill-over effects do not come as a surprise and could even be part of the desired outcome of the intervention.

Acknowledgements

We thank Holly Perryman for proofreading the manuscript and two reviewers for constructive comments.

Author contributions statement

Liu, Heino, and Hansen were responsible for the conceptualization and methodology of the manuscript and project funding acquisition. Liu performed formal analysis and wrote the original draft. Hansen and Heino supervised and administered the project. Nedreaas and Stockhausen provided data resources and contributed to result interpretations. All authors contributed to the writing—review and editing of the manuscript.

Funding

This work is supported by the Research Council of Norway through the projects SINORSEAS (288037), BESTfish (314248), and Barentsrisk (288192).

Conflict of interest

The authors have no conflicts of interest to declare.

Data availability statement

The datasets can be derived from the website of the Norwegian Directorate of Fisheries: https://www.fiskeridir.no/Tall-og-analyse/AApne-data/.

References

Abe, K., and Anderson, C. M. 2022. A dynamic model of endogenous fishing duration. Journal of the Association of Environmental and Resource Economists, 9: 425–454.

Aglen, A., Drevetnyak, K., and Sokolov, K. 2004. Cod in the Barents Sea (northeast Arctic cod): a review of the biology and history of the fishery and its management. *In* Proceedings of the 10th Norwegian–Russian Symposium. Norwegian Institute of Marine Research, Trondheim.

Andersen, B. S., Ulrich, C., Eigaard, O. R., and Christensen, A.-S. 2012. Short-term choice behaviour in a mixed fishery: investigating métier selection in the Danish gillnet fishery. ICES Journal of Marine Science, 69: 131–143.

Anderson, S. C., Ward, E. J., Shelton, A. O., Adkison, M. D., Beaudreau, A. H., Brenner, R. E., Haynie, A. C. *et al.*. 2017. Benefits and risks of diversification for individual fishers. Proceedings of the National Academy of Sciences, 114: 10797–10802.

Andrews, E. J., Pittman, J., and Armitage, D. R. 2021. Fisher behaviour in coastal and marine fisheries. Fish and Fisheries, 22: 489–502.

Banfield, J. D., and Raftery, A. E. 1993. Model-based Gaussian and non-Gaussian clustering. Biometrics, 49: 803–821.

Birkenbach, A. M., Cojocaru, A. L., Asche, F., Guttormsen, A. G., and Smith, M. D. 2020. Seasonal harvest patterns in multispecies fisheries. Environmental and Resource Economics, 75: 631–655.

Boonstra, W. J., and Hentati-Sundberg, J. 2016. Classifying fishers' behaviour. An invitation to fishing styles. Fish and Fisheries, 17: 78–100.

Branch, T. A., Hilborn, R., Haynie, A. C., Fay, G., Flynn, L., Griffiths, J., Marshall, K. N. *et al.*. 2006. Fleet dynamics and fishermen behavior: lessons for fisheries managers. Canadian Journal of Fisheries and Aquatic Sciences, 63: 1647–1668.

Cambiè, G., Pantin, J. R., Lincoln, H., Hiddink, J. G., Lambert, G. T., and Kaiser, M. J. 2017. Diversity of fishing métier use can affect incomes and costs in small-scale fisheries. Canadian Journal of Fisheries and Aquatic Sciences, 74: 2144–2152.

Clark, C. W. 1974. Mathematical bioeconomics. *In* Mathematical Problems in Biology. Springer, Berlin, Heidelberg. pp. 29–45.

Dragesund, O., Østvedt, O. J., and Toresen, R. 2008. Norwegian Spring-Spawning Herring and Northeast Arctic Cod, pp. 41–82. Ed. by Nakken O.. Tapir Academic Press, Trondheim.

Eide, A., Skjold, F., Olsen, F., and Flaaten, O. 2003. Harvest functions: the Norwegian bottom trawl cod fisheries. Marine Resource Economics, 18: 81–93.

Elhorst, J. P. 2008. Serial and spatial error correlation. Economics Letters, 100: 422–424.

Fernö, A., Pitcher, T. J., Melle, W., Nøttestad, L., Mackinson, S., Hollingworth, C., and Misund, O. A. 1998. The challenge of the herring in the Norwegian Sea: making optimal collective spatial decisions. Sarsia, 83: 149–167.

Ferrer-Rosell, B., Coenders, G., and Martínez-Garcia, E. 2016. Segmentation by tourist expenditure composition: an approach with compositional data analysis and latent classes. Tourism Analysis, 21: 589–602.

Finkbeiner, E. M. 2015. The role of diversification in dynamic small-scale fisheries: lessons from Baja California Sur, Mexico. Global Environmental Change, 32: 139–152.

Fulton, E. A., Smith, A. D., Smith, D. C., and van Putten, I. E. 2011. Human behaviour: the key source of uncertainty in fisheries management. Fish and Fisheries, 12: 2–17.

Gullestad, P., Blom, G., Bakke, G., and Bogstad, B. 2015. The "Discard Ban Package": experiences in efforts to improve the exploitation patterns in Norwegian fisheries. Marine Policy, 54: 1–9.

Haynie, A. C., and Layton, D. F. 2010. An expected profit model for monetizing fishing location choices. Journal of Environmental Economics and Management, 59: 165–176.

Hilborn, R. 1985. Fleet dynamics and individual variation: why some people catch more fish than others. Canadian Journal of Fisheries and Aquatic Sciences, 42: 2–13.

Hilborn, R. 2007. Managing fisheries is managing people: what has been learned? Fish and Fisheries, 8: 285–296.

Hilborn, R., and Walters, C. J. 1992. Quantitative Fisheries Stock Assessment: Choice, Dynamics and Uncertainty. Springer Science & Business Media, New York, NY.

Hylen, A., Nakken, O., and Nedreaas, K. 2008. Northeast Arctic cod: fisheries, life history, stock fluctuations and management. *In* Norwegian Spring-Spawning Herring and Northeast Arctic Cod, pp. 83–118. Ed. by Nakken O.. Tapir Academic Press, Trondheim.

Ingólfsson, Ó. A., Jørgensen, T., Sistiaga, M., and Kvalvik, L. 2021. Artificial light improves size selection for northern shrimp (*Pandalus borealis*) in trawls. Canadian Journal of Fisheries and Aquatic Sciences, 78: 1910–1917.

Jacobsen, R. B., and Wilson, D. C. 2009. Governance issues in mixed-fisheries management: an analysis of stakeholder views. Deliverable no. 6.3 to the EU 6th Framework Programme. Project no. 044168, AFRAME. IFM-Innovative Fisheries Management.

Jensen, C. L. 2002. Applications of dual theory in fisheries: a survey. Marine Resource Economics, 17: 309–334.

Johansen, T., Besnier, F., Quintela, M., Jorde, P. E., Glover, K. A., Westgaard, J.-I., Dahle, G. *et al.*. 2020. Genomic analysis reveals neutral and adaptive patterns that challenge the current management regime for East Atlantic cod *Gadus morhua* L. Evolutionary Applications, 13: 2673–2688.

Kasperski, S., and Holland, D. S. 2013. Income diversification and risk for fishermen. Proceedings of the National Academy of Sciences, 110: 2076–2081.

Kroodsma, D. A., Mayorga, J., Hochberg, T., Miller, N. A., Boerder, K., Ferretti, F., Wilson, A. *et al.*. 2018. Tracking the global footprint of fisheries. Science, 359: 904–908.

Larkin, S. L., and Sylvia, G. 1999. Intrinsic fish characteristics and intraseason production efficiency: a management-level bioeconomic analysis of a commercial fishery. American Journal of Agricultural Economics, 81: 29–43.

Little, L. R., Kuikka, S., Punt, A. E., Pantus, F., Davies, C. R., and Mapstone, B. D. 2004. Information flow among fishing vessels modelled using a Bayesian network. Environmental Modelling & Software, 19: 27–34.

Liu, X., Shaw, D., Bjørndal, T., and Heino, M. 2021. The day-to-day supply responses of a limited-entry mixed fishery. Marine Resource Economics, 36: 71–90.

Lloret, J., Lleonart, J., and Solé, I. 2000. Time series modelling of landings in northwest Mediterranean Sea. ICES Journal of Marine Science, 57: 171–184.

Marchal, P. 2008. A comparative analysis of métiers and catch profiles for some French demersal and pelagic fleets. ICES Journal of Marine Science, 65: 674–686.

McKelvey, R. 1983. The fishery in a fluctuating environment: coexistence of specialist and generalist fishing vessels in a multipurpose fleet. Journal of Environmental Economics and Management, 10: 287–309.

Morfin, M., Kopp, D., Benoît, H. P., Méhault, S., Randall, P., Foster, R., and Catchpole, T. 2017. Survival of European plaice discarded from coastal otter trawl fisheries in the English Channel. Journal of Environmental Management, 204: 404–412.

Muthén, B. O. 2002. Beyond SEM: general latent variable modeling. Behaviormetrika, 29: 81–117.

Nakken, O. 1998. Past, present and future exploitation and management of marine resources in the Barents Sea and adjacent areas. Fisheries Research, 37: 23–35.

Nylund, K. L., Asparouhov, T., and Muthén, B. O. 2007. Deciding on the number of classes in latent class analysis and growth mixture modeling: a Monte Carlo simulation study. Structural Equation Modeling A Multidisciplinary Journal, 14: 535–569.

Okamura, H., Morita, S. H., Funamoto, T., Ichinokawa, M., and Eguchi, S. 2018. Target-based catch-per-unit-effort standardization in multispecies fisheries. Canadian Journal of Fisheries and Aquatic Sciences, 75: 452–463.

Olsen, E., Aanes, S., Mehl, S., Holst, J. C., Aglen, A., and Gjøsæter, H. 2010. Cod, haddock, saithe, herring, and capelin in the Barents Sea and adjacent waters: a review of the biological value of the area. ICES Journal of Marine Science, 67: 87–101.

Opdal, A. F. 2010. Fisheries change spawning ground distribution of northeast Arctic cod. Biology Letters, 6: 261–264.

Pelletier, D., and Ferraris, J. 2000. A multivariate approach for defining fishing tactics from commercial catch and effort data. Canadian Journal of Fisheries and Aquatic Sciences, 57: 51–65.

Pilling, G. M., Apostolaki, P., Failler, P., Floros, C., Large, P. A., Morales-Nin, B., Reglero, P. *et al.*. 2009. Assessment and management of data-poor fisheries. Advances in Fisheries Science, 50: 280–305.

Redner, R. A., and Walker, H. F. 1984. Mixture densities, maximum likelihood and the EM algorithm. SIAM Review, 26: 195–239.

Roberson, L. A., and Wilcox, C. 2022. Bycatch rates in fisheries largely driven by variation in individual vessel behaviour. Nature Sustainability, 1–9. https://www.nature.com/articles/s41893-022-00865-0 (last accessed 16 November 2022).

Salas, S., and Gaertner, D. 2004. The behavioural dynamics of fishers: management implications. Fish and Fisheries, 5: 153–167.

Savina, E., Karlsen, J. D., Frandsen, R. P., Krag, L. A., Kristensen, K., and Madsen, N. 2016. Testing the effect of soak time on catch damage in a coastal gillnetter and the consequences on processed fish quality. Food Control, 70: 310–317.

Scrucca, L., Fop, M., Murphy, T. B., and Raftery, A. E. 2016. mclust 5: Clustering, classification and density estimation using Gaussian finite mixture models. The R Journal, 8: 289–317.

Shireman, E., Steinley, D., and Brusco, M. J. 2017. Examining the effect of initialization strategies on the performance of Gaussian mixture modeling. Behavior Research Methods, 49: 282–293.

Simpson, E. H. 1949. Measurement of diversity. Nature, 163: 688.

Skjoldal, H. R. 2004. An introduction to the Norwegian Sea ecosystem. *In* The Norwegian Sea Ecosystem. pp. 15–32. Ed. by Skjoldal H. R.. Tapir Academic Press, Trondheim.

Skjoldal, H. R., Gjøsæter, H., and Loeng, H. 1992. The Barents Sea ecosystem in the 1980s: ocean climate, plankton, and capelin growth. ICES Marine Science Symposia, 195: 278–290.

Smith, C. L., and McKelvey, R. 1986. Specialist and generalist: roles for coping with variability. North American Journal of Fisheries Management, 6: 88–99.

Smith, M. D., and Wilen, J. E. 2003. Economic impacts of marine reserves: the importance of spatial behavior. Journal of Environmental Economics and Management, 46: 183–206.

Sogn-Grundvåg, G., Zhang, D., and Dreyer, B. 2020. Fishing methods for Atlantic cod and haddock: quality and price versus costs. Fisheries Research, 230: 105672.

Sogn-Grundvåg, G., Zhang, D., Henriksen, E., Joensen, S., Bendiksen, B.-I., and Hermansen, Ø. 2022. Fishing tactics and fish quality: the case of the coastal fishery for Atlantic cod in Norway. Fisheries Research, 246: 106167.

Standal, D., and Hersoug, B. 2014. Back to square one? Fisheries allocation under pressure. Marine Policy, 43: 236–245.

Sverdrup, H. 1953. On conditions for the vernal blooming of phytoplankton. Journal du Conseil Permanent International pour l'Exploration de la Mer, 18: 287–295.

Thorson, J. T., Fonner, R., Haltuch, M. A., Ono, K., and Winker, H. 2016. Accounting for spatiotemporal variation and fisher targeting when estimating abundance from multispecies fishery data. Canadian Journal of Fisheries and Aquatic Sciences, 74: 1794–1807.

Tidd, A. N., Hutton, T., Kell, L. T., and Blanchard, J. L. 2012. Dynamic prediction of effort reallocation in mixed fisheries. Fisheries Research, 125: 243–253.

Tzanatos, E., Somarakis, S., Tserpes, G., and Koutsikopoulos, C. 2006. Identifying and classifying small-scale fisheries métiers in the Mediterranean: a case study in the Patraikos Gulf, Greece. Fisheries Research, 81: 158–168.

Ulrich, C., and Andersen, B. S. 2004. Dynamics of fisheries, and the flexibility of vessel activity in Denmark between 1989 and 2001. ICES Journal of Marine Science, 61: 308–322.

Ulrich, C., Wilson, D. C., Nielsen, J. R., Bastardie, F., Reeves, S. A., Andersen, B. S., and Eigaard, O. R. 2012. Challenges and opportunities for fleet-and métier-based approaches for fisheries management under the European common fishery policy. Ocean & Coastal Management, 70: 38–47.

Weller, B. E., Bowen, N. K., and Faubert, S. J. 2020. Latent class analysis: a guide to best practice. Journal of Black Psychology, 46: 287–311.

Wijermans, N., Boonstra, W. J., Orach, K., Hentati-Sundberg, J., and Schlüter, M. 2020. Behavioural diversity in fishing—towards a next generation of fishery models. Fish and Fisheries, 21: 872–890.

Zeileis, A., Köll, S., and Graham, N. 2020. Various versatile variances: an object-oriented implementation of clustered covariances in R. Journal of Statistical Software, 95: 1–36.

Zimmermann, F., and Heino, M. 2013. Is size-dependent pricing prevalent in fisheries? The case of Norwegian demersal and pelagic fisheries. ICES Journal of Marine Science, 70: 1389–1395.

Appendix

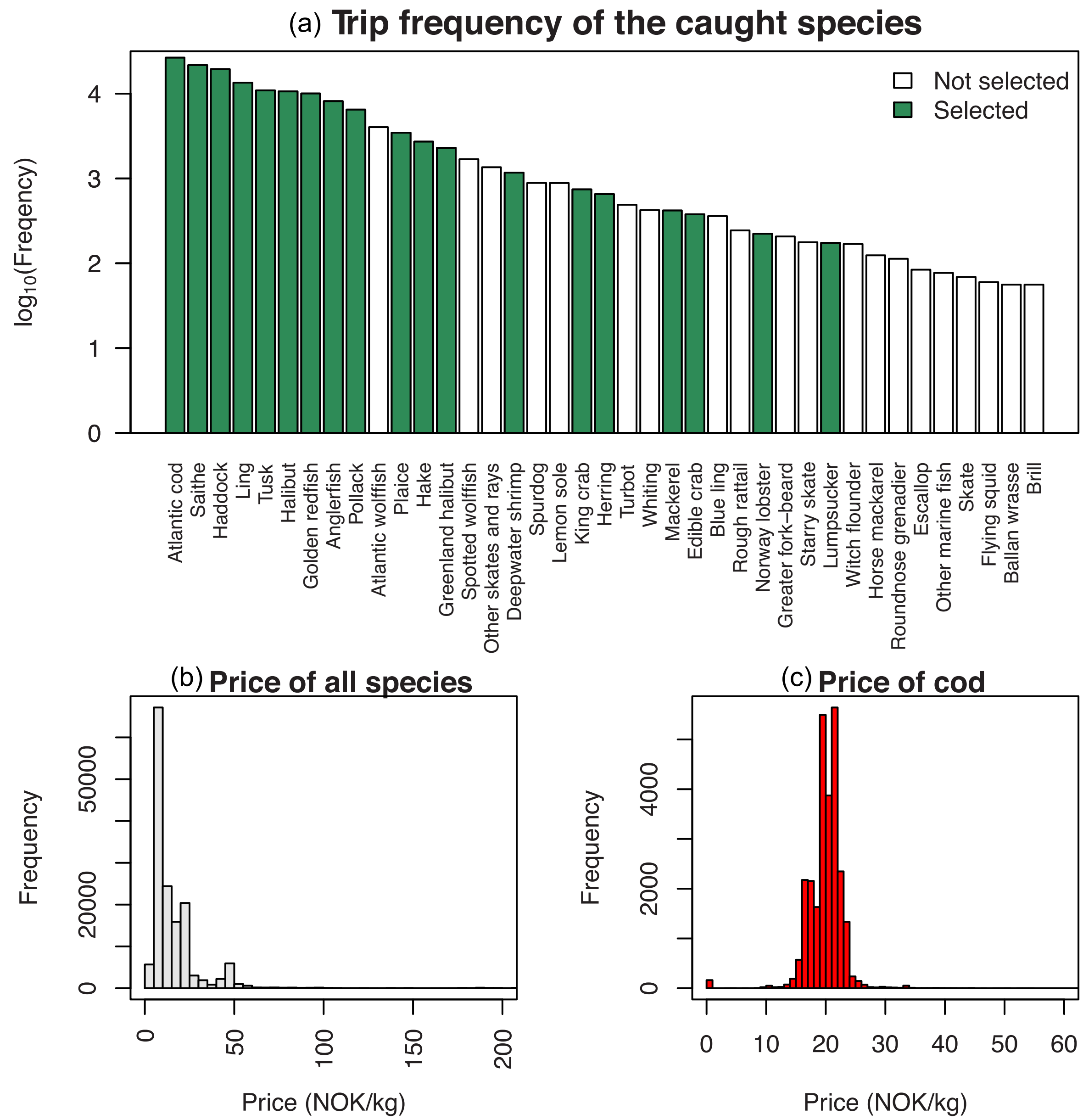

Figure A1. (a) Frequency (in logarithm scale) of occurrence of the main species in 2019 by the CaPoP fleet. We select 19 FAO species (in green) that were caught in at least 50 trips (out of 31,800 trips) as the main species (where species revenue share per vessel trip was the highest or second highest) for clustering analysis. (b) Price variability of all selected species; (c) Price variability of cod.

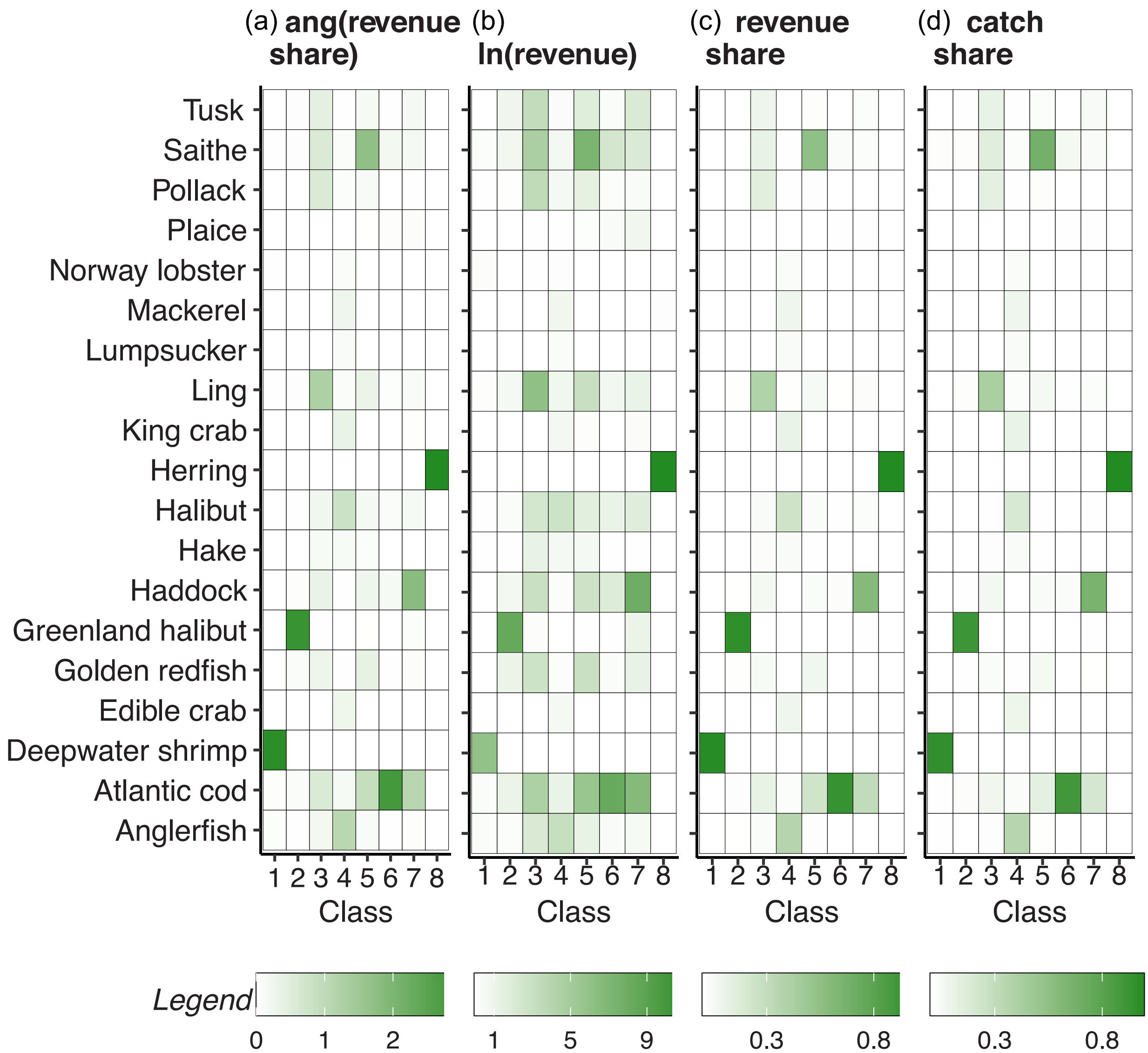

Figure A2. Verification of clusters according to species revenue and catch profiles. The classification is based on angularly transformed revenue shares (a). The posterior probabilities are then used to calculate probability-weighted species profiles measured in log-revenue (b), revenue share (c), and catch share (d). The results are used to assist cluster interpretation.

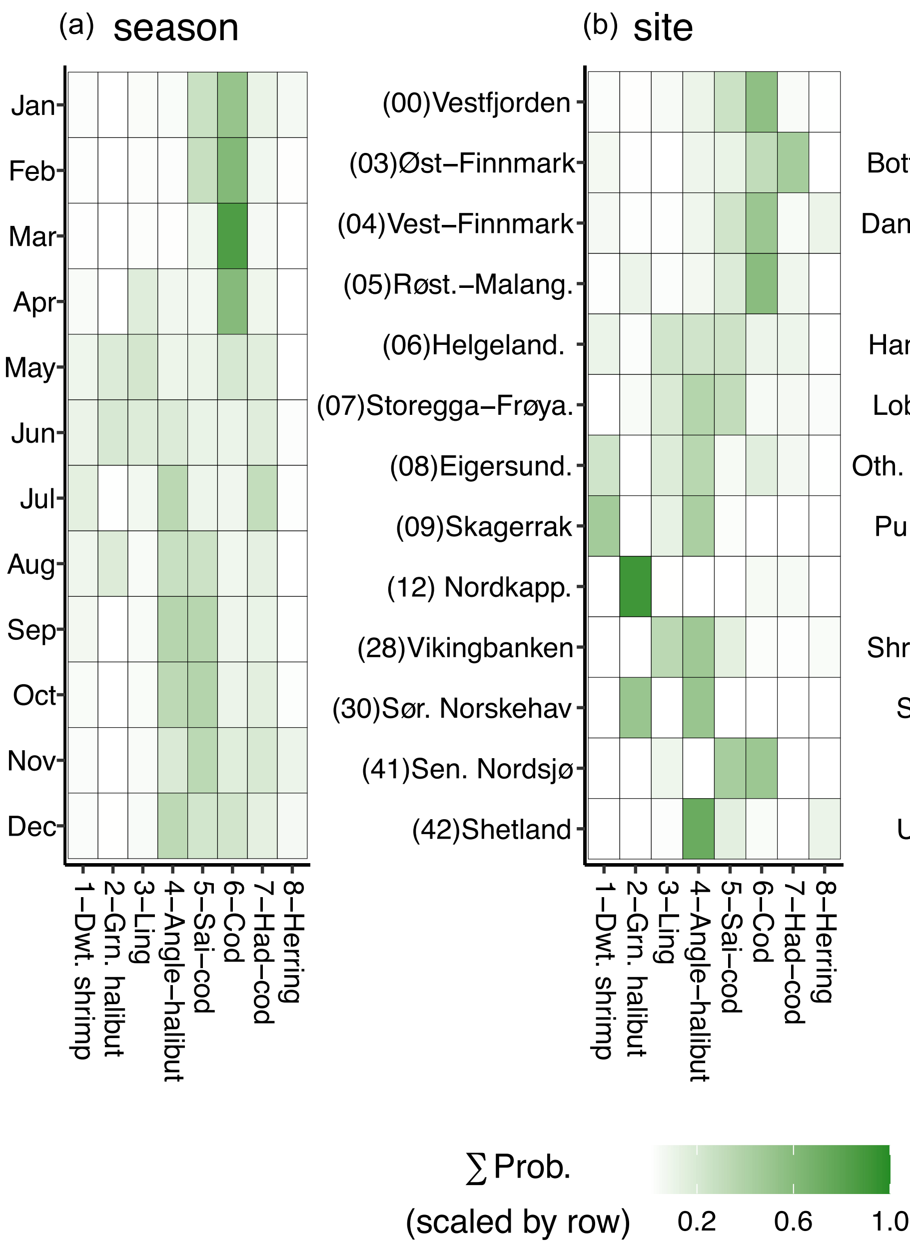

Figure A3. Probability (*p*) weighted trip frequency aggregated by season (a), site (b), and gear (c) for each species group (*k*). Infrequent categories (*i*) are excluded if a total occurrence ≤15 trips. The aggregated trip frequencies are scaled by species cluster, i.e. $\sum^k p_{k,i} = 1$. Site IDs in parenthesis in (b) correspond to the statistical area in Figure 1.

Table A1. An overview of fisheries regulation applied to coastal fleets.

Species	Regulation	Notes
Atlantic cod	TAC, area/gear/length restriction	Quota proportional to max length and length group
Haddock, saithe	TAC, by-catch quota	Quota proportional to max length and length group
Deepwater shrimp	Area closure, minimum mesh, period-specific TAC (south 62°N)	No TAC for stock north of 62°N
NSS herring	TAC	Quota proportional to max length and length group
Greenland halibut	Period-specific TAC	Periods (2019): 20 May–11 Jun, 5–17 Aug
Flounder species (Anglerfish, halibut)	No TAC	
Ling	No TAC	

Source: Norwegian Directorate of Fisheries.

Table A2. Fractional logit model of diversification index (HHI).

N=761[a]	Estimate	Std. Error	*z* value	Pr(>|z|)[b]
(Intercept)	0.346	0.076	4.540	0.000***
log(len.deviation)[c]	– 1.316	0.380	-3.466	0.000***
lgroup: under 11 m[d]	– 0.622	0.621	-1.000	0.317
lgroup: 15–20.99 m	0.158	0.105	1.506	0.132
lgroup: 21–27.99 m	– 0.131	0.113	– 1.163	0.245
county: Hordaland[d]	– 0.232	0.202	– 1.150	0.250
county: Møre og Romsdal	– 0.204	0.133	– 1.527	0.127
county: Nordland	– 0.017	0.093	– 0.182	0.855
county: Østfold	– 0.361	0.077	– 4.708	0.000***
county: Rogaland	– 0.375	0.168	– 2.225	0.026*
county: Sogn og Fjordane	– 0.502	0.182	– 2.754	0.006**
county: Troms	0.111	0.115	0.962	0.336
county: Trøndelag	– 0.066	0.178	– 0.373	0.709
county: Vest-Agder	– 0.784	0.213	– 3.677	0.000***

[a] Number of observations.
[b] ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.
[c] len.deviation measures the deviation of vessel length from the group (i) mean, i.e. len.deviation = length—$\overline{length}_i$.
[d] Reference groups are 11–14.99 m and Finnmark for length group (lgroup) and county respectively.

Table A3. Statistical models.

Class Ind. var.	1 D. shrimp	2 G. halibut	3 Ling	4 Ang-halibut	5 Sai-cod	6 Cod	7 Had-cod	8 Herring
(Intercept)	1.91***	0.63***	0.48	0.90***	1.44***	2.24***	1.18***	1.17***
	(0.38)	(0.10)	(1.05)	(0.17)	(0.09)	(0.04)	(0.09)	(0.23)
15m+	0.07	− 0.13	− 0.05	− 0.66	− 0.42***	− 0.14*	− 0.27*	− 0.02
	(0.53)	(0.14)	(0.61)	(0.45)	(0.09)	(0.06)	(0.12)	(0.18)
logPower.	− 0.06	− 0.16*	− 0.21***	− 0.17***	0.06*	− 0.04*	0.12**	0.40**
	(0.07)	(0.08)	(0.06)	(0.04)	(0.03)	(0.02)	(0.04)	(0.14)
C.V.	0.15	− 0.07	− 0.39***	0.17***	0.14**	− 0.11***	− 0.67***	− 0.22
	(0.09)	(0.11)	(0.08)	(0.05)	(0.04)	(0.03)	(0.08)	(0.18)
Feb	0.00		− 0.52	0.04	− 0.02	− 0.30***	0.17	− 0.60
	(0.53)		(1.45)	(0.26)	(0.19)	(0.05)	(0.12)	(0.47)
Mar	− 0.73		− 0.03	0.11	0.12	− 0.38***	0.13	− 1.29
	(0.47)		(0.23)	(0.27)	(0.21)	(0.05)	(0.13)	(1.01)
Apr	0.05		0.16	0.57**	− 0.12	− 0.53***	0.04	
	(0.41)		(1.16)	(0.19)	(0.21)	(0.05)	(0.16)	
May	0.28		0.69	0.25	− 0.35*	− 0.90***	0.02	
	(0.40)		(1.06)	(0.21)	(0.18)	(0.08)	(0.13)	
Jun	0.32	− 0.01	0.90	0.14	− 0.36	− 1.03***	0.26*	0.87**
	(0.40)	(0.15)	(1.08)	(0.21)	(0.19)	(0.11)	(0.12)	(0.29)
Jul	0.18	− 0.56	0.21	− 0.07	− 0.67**	− 1.07***	0.47***	0.22
	(0.41)	(1.01)	(1.16)	(0.23)	(0.24)	(0.14)	(0.13)	(0.40)
Aug	0.48	− 0.10	0.08	0.24	0.31*	− 0.97***	− 0.20	− 1.05
	(0.40)	(0.15)	(1.10)	(0.19)	(0.12)	(0.14)	(0.14)	(0.59)
Sep	− 0.04	− 0.42	0.64	0.32	− 0.02	− 1.17***	0.05	− 0.62
	(0.42)	(1.02)	(1.07)	(0.20)	(0.12)	(0.14)	(0.14)	(0.40)
Oct	− 0.67	− 0.68	0.82	0.34	0.38***	− 1.15***	0.17	− 1.04
	(0.47)	(1.01)	(1.10)	(0.19)	(0.11)	(0.11)	(0.13)	(0.85)
Nov	− 0.38	− 0.68	− 0.18	0.40*	0.46***	− 1.16***	0.54***	− 0.03
	(0.47)	(1.01)	(1.10)	(0.19)	(0.10)	(0.09)	(0.11)	(0.31)
Dec	− 0.41	0.27	− 0.65*	0.09	− 0.49**	− 1.40***	− 0.51**	− 0.07
	(0.40)	(0.73)	(0.30)	(0.20)	(0.17)	(0.12)	(0.17)	(0.44)
Nordland	− 0.60	0.07	0.45	− 0.15	0.58***	− 0.39***	0.32**	0.13
	(0.46)	(0.12)	(1.05)	(0.34)	(0.10)	(0.06)	(0.11)	(0.23)
Trøndelag s.	− 0.02	0.09	0.72	0.42	0.22	− 0.26***	− 0.03	− 0.18
	(0.44)	(0.18)	(1.03)	(0.22)	(0.11)	(0.07)	(0.17)	(0.24)
15m+: Feb			0.25		− 0.08	0.24***	0.21	0.14
			(0.85)		(0.12)	(0.07)	(0.18)	(0.51)
15m+: Mar			0.22	1.34	0.05	0.09	0.59***	
			(0.68)	(0.74)	(0.15)	(0.07)	(0.17)	
15m+: Apr	0.12		− 0.22	− 0.62	0.21	0.28***	− 0.12	
	(0.65)		(0.63)	(1.10)	(0.23)	(0.08)	(0.20)	
15m+: May	0.45		0.01	0.43	0.83***	0.30**	0.60***	
	(0.60)		(0.62)	(0.65)	(0.16)	(0.11)	(0.17)	
15m+: Jun	− 0.17	0.11	− 0.07	− 0.69	0.68***	0.22	0.01	− 1.40**
	(0.57)	(0.18)	(0.63)	(0.84)	(0.18)	(0.17)	(0.18)	(0.45)
15m+: Jul	− 0.12	0.80	0.51	0.19	0.30	− 0.30	0.43**	− 0.45
	(0.56)	(1.14)	(0.66)	(0.55)	(0.26)	(0.27)	(0.16)	(0.58)
15m+: Aug	− 0.89	0.17	0.19	0.32	− 0.04	− 0.13	0.39*	− 0.25
	(0.57)	(0.18)	(0.67)	(0.53)	(0.13)	(0.18)	(0.18)	(1.16)
15m+: Sep	− 0.04		0.00	0.12	0.35**	0.17	− 0.08	
	(0.58)		(0.75)	(0.49)	(0.12)	(0.17)	(0.21)	
15m+: Oct	0.65	1.36	− 0.46	0.10	0.13	0.42*	− 0.24	0.12
	(0.63)	(1.16)	(0.73)	(0.47)	(0.12)	(0.16)	(0.19)	(0.67)
15m+: Nov		1.36	0.34	0.40	0.24*	− 0.22	0.06	− 0.17
		(1.16)	(0.67)	(0.50)	(0.11)	(0.14)	(0.16)	(0.20)
15m+: Dec			0.71		0.32	− 0.17	− 0.38	− 0.13
			(0.75)		(0.20)	(0.21)	(0.27)	(0.38)
⋮								
Feb: Nordland	0.10		0.22	0.43	0.41*	0.44***	− 0.37*	− 1.30
	(0.64)		(1.48)	(0.53)	(0.19)	(0.07)	(0.17)	(1.03)
Mar: Nordland	1.17*		− 0.29	− 0.82	− 0.77***	0.90***	− 0.82***	
	(0.59)		(0.32)	(0.82)	(0.23)	(0.07)	(0.17)	
Apr: Nordland	− 0.46		0.46	0.01	− 0.75**	0.22**	− 0.11	
	(0.58)		(1.17)	(0.38)	(0.23)	(0.08)	(0.19)	
May: Nordland	0.34		0.14	0.20	− 0.49*	0.26*	− 0.01	
	(0.49)		(1.08)	(0.39)	(0.20)	(0.12)	(0.16)	

Table A3. Continued

Class Ind. var.	1 D. shrimp	2 G. halibut	3 Ling	4 Ang-halibut	5 Sai-cod	6 Cod	7 Had-cod	8 Herring
Jun: Nordland	− 0.15	0.05	− 0.12	0.40	− 0.08	− 0.13	− 0.46*	
	(0.50)	(0.17)	(1.09)	(0.39)	(0.21)	(0.22)	(0.18)	
Jul: Nordland	0.10		− 0.19	0.71	− 0.27	− 0.43	0.12	
	(0.50)		(1.19)	(0.39)	(0.28)	(0.33)	(0.16)	
Aug: Nordland	− 0.10	0.27	− 0.17	0.60	− 0.54***	0.40*	0.19	
	(0.49)	(0.18)	(1.12)	(0.37)	(0.14)	(0.19)	(0.17)	
Sep: Nordland	0.56	− 0.10	− 0.79	0.70	− 0.19	0.54**	− 0.06	
	(0.52)	(1.43)	(1.10)	(0.36)	(0.13)	(0.20)	(0.19)	
Oct: Nordland	1.06		− 1.09	0.64	− 0.43***	0.02	0.08	0.24
	(0.56)		(1.13)	(0.36)	(0.12)	(0.17)	(0.17)	(0.63)
Nov: Nordland	0.45		− 0.01	0.62	− 0.58***	0.78***	− 0.27	− 0.39
	(0.56)		(1.12)	(0.36)	(0.12)	(0.12)	(0.14)	(0.33)
Dec: Nordland	− 0.35		− 0.72	0.55	− 0.18	0.33	0.04	− 0.34
	(0.56)		(0.69)	(0.37)	(0.20)	(0.21)	(0.25)	(0.52)
Feb: Trøndelag s.	− 0.38		0.38	− 0.04	0.52*	0.40***	− 0.26	
	(0.62)		(1.44)	(0.34)	(0.21)	(0.09)	(0.26)	
Mar: Trøndelag s.	0.29			− 0.73	− 0.05	0.63***	− 0.69*	
	(0.62)			(0.44)	(0.23)	(0.08)	(0.31)	
Apr: Trøndelag s.	− 0.46		0.52	− 1.10**	− 0.67**	0.08	− 0.29	
	(0.52)		(1.15)	(0.35)	(0.26)	(0.10)	(0.29)	
May: Trøndelag s.	− 0.51		− 0.09	− 0.49	− 0.19	− 0.26	− 0.65	
	(0.52)		(1.05)	(0.28)	(0.22)	(0.23)	(0.42)	
Jun:Trøndelag s.	− 0.65	0.03	− 0.40	− 0.02	− 0.34	0.14	− 1.19*	
	(0.51)	(0.25)	(1.07)	(0.26)	(0.25)	(0.25)	(0.61)	
Jul: Trøndelag s.	− 1.00		− 0.22	0.27	0.11	0.06	− 0.63	
	(0.53)		(1.16)	(0.28)	(0.30)	(0.29)	(0.34)	
Aug: Trøndelag s.	− 0.78	0.13	0.03	0.24	− 0.48**	0.19	0.10	
	(0.51)	(0.25)	(1.10)	(0.25)	(0.18)	(0.24)	(0.27)	
Sep: Trøndelag s.	− 0.49		− 1.34	− 0.06	− 0.15	0.13	− 0.16	
	(0.56)		(1.10)	(0.25)	(0.17)	(0.23)	(0.31)	
Oct: Trøndelag s.	− 0.87		− 1.12	− 0.03	− 0.27	0.14	− 0.09	0.41
	(0.78)		(1.10)	(0.24)	(0.15)	(0.21)	(0.27)	(0.63)
Nov: Trøndelag s.	0.29		0.08	− 0.21	− 0.18	0.97***	− 0.49*	0.45
	(0.57)		(1.09)	(0.25)	(0.15)	(0.14)	(0.23)	(0.31)
Dec: Trøndelag s.				− 0.52	− 0.23	1.31***	0.29	− 0.46
				(0.29)	(0.24)	(0.18)	(0.31)	(0.47)
AIC	1 109	1 662	2 429	4 866	7 741	12 692	4 358	716
BIC	1 257	1 761	2 629	5 100	7 995	12 974	4 594	810
Log likelihood	−510	−808	−1166	−2385	−3820	−6296	−2129	−329
Deviance	346.00	270.32	938.53	1 823.40	3 848	5 695	1 714	115
Num. obs.	198	536	478	963	1 191	2 048	839	187

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Handling Editor: Pamela Woods