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Original Article

The value of commercial fish size distribution recorded at haul by haul compared to trip by trip

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Data from commercial fishing vessels may enhance the range of observations available for monitoring the marine environment. However, effort and catch data provide information on fish distribution with a bias due to spatial targeting and selectivity. Here, we measured the shortcomings of standard fishery-dependent data and advocate for the utilization of more precise datasets indirectly collected by the commercial fishery. Data from a Danish traceability system, which records size of commercial fish at the haul level, are held against the set-up of current eLog and sales slips' data collected for the Danish fisheries. We showed that the most accurate mapping of the spatial distribution of catches per size group is not only possible through size records collected at the haul level but also by high resolution on fishing effort data. In Europe, the regulation to land all catches with a quota or minimum size limit, including unwanted, has increased the focus on avoidance and discards; we show the potential of such data sources to inform on fish abundance and distribution, especially of importance where fishery-dependent data are the only source of information.

Keywords: electronic monitoring, sea-packing commercial fishery data, spatial analysis, spatial scale, species size distribution

Introduction

In many areas, commercial fishers are required to declare the landed amount of species in official logbooks. Since 2015, EU vessels must report landings in weight in the logbooks for each haul, or as a minimum once every 24 hr (EU, 2012). In addition, EU vessels above 12 m in length are required to carry a Vessel Monitoring System (VMS) (EU, 2011), which transmit time, position, speed, and course of the vessel at predefined time intervals. By coupling logbook and VMS data, it is possible to estimate the spatial and temporal distribution of landings by species (Bastardie *et al.*, 2010; Gerritsen and Lordan, 2011). However, the entry format of logbooks only provides knowledge on the species, not the body sizes of the fish (EU, 2011). Concurrently, along assessing the status of the marine fish species, scientific surveys conducted by research vessels do collect species and size information at a fine spatial scale. However, the temporal coverage and data quantity are much lower for survey data than commercial fisheries data that pose challenges in using them for widescale mapping of fish (Pennino *et al.*, 2016; Bourdaud *et al.*, 2017).

In a fisheries management context, the objective of the measures is to limit the fishery within predefined objectives (Hilborn, 2007). For such purpose, more detailed information on the catch composition including size of the fish at the actual fishing event ("haul" for active gears) may allow for better adaptations of management measures, at least in regions like the EU where the onboard observer coverage is closer to 1% than to 100% (Little *et al.*, 2015; James *et al.*, 2019). The full implementation of the European landing obligation in 2019 (EU, 2013; Salomon *et al.*, 2014) further increases the need for more detailed information as the fisheries adapt to the regulation, by increasing the fishing gear selectivity, e.g. with mesh size changes, grid panels or LED lights on gear (O'Neill *et al.*, 2019), or by avoiding the hotspots of unwanted fish spatially, which is also a way of making the fishing more selective (Little *et al.*, 2015; Reid *et al.*, 2019). Although certain species are always unwanted, some target species can also become unwanted, e.g. in the case where the allocated quota is close to being exhausted (Borges and Lado, 2019), or the encountered fish are undersized and therefore not marketable (Catchpole *et al.*, 2018; Villasante *et al.*, 2019), or simply because fishers have expectations on market preferences for certain species or sizes (Ono *et al.*, 2013; Batsleer *et al.*, 2015). Conversely, some bycatches may be wanted because they act as a bonus on top of the regular targeted species (Mortensen *et al.*, 2018). Therefore, being able to locate where the species population distribute and where its unwanted components are located, especially the undersized fish, is of importance to help achieve a more selective fishing (STECF, 2018) while maintaining the profitability of the fishery. Tailoring the avoidance of unwanted fish depends on the individual vessel, and the species and fishing grounds may at times translate into subtle tactical avoidance measures based on empirical experience at sea. For example, Mortensen *et al.* (2018) described some avoidance tactics used by individual fisher, some of which may appear counterintuitive: if large amount of saithe (*Pollachius virens*) are caught in a haul, the best approach might simply be to continue with a new haul at the same heading as the previous, on the basis that the previous haul had passed through the school of saithe, whereby a new haul in the same transect would likely be after the school.

Tools such as averaged species distribution maps can assist the fishermen in optimizing their fishing tactics at a larger scale (Little *et al.*, 2015; Reid *et al.*, 2019; Robert *et al.*, 2019), but at the scale of the individual fishing operation, better knowledge on the size distribution of target species may not only help spatial avoidance but could also increase the profit of fishing, in the situation of limited overall catch allowance, because of higher prices per kg fish landed.

The current data level in eLog reporting is at the haul level and sales slips' information from landings in port. This means that any size information is collected at the level of the full fishing trip (EU, 2011, 2016). This trip-level information can be redistributed back to the haul level by using the size composition of each species for the fishing trip, under the assumption that size composition at the trip level reflects the size composition at the haul level (Plet-Hansen *et al.*, 2018). Possible discrepancies when deducing spatial distribution from analysing commercial fishing data might not be an issue when using data from small-scale vessels, which perform only few hauls within short distance, but could be pronounced for large-scale vessels conducting several hauls per day and weeklong fishing trips, making a mismatch between trip and haul fish size composition highly likely. In this study, we investigated this possible mismatch using a recent commercial fisheries system collecting at-sea observations of species and their commercial size class from grading machines on-board vessels. We test whether a difference exists in terms of the false presence of certain size classes at the haul level, estimate the impact of the level of spatial resolution for data aggregation based on trip-level records, and investigate the potential bias that would arise from the chosen grid cell size and shape (Dark and Bram, 2007).

Material and methods

At-sea grading machine, "Sporbarhed I Fiskerisektoren" data

The Danish "Sporbarhed I Fiskerisektoren" (SIF) database contains information on haul positions and times derived from fishers entries in their electronic logbook (eLog) and landed amount in kg of each commercial size class by species derived from records by on-board grading machines on the vessel. It has been mandatory for Danish fishing vessels to fill in their eLog for each since 2015 (Fødevareministeriet, 2014). SIF therefore contains landings of species and their commercial size classes together with positional data at a haul-by-haul level. Commercial size classification follows the requirements of the EU (EU, 1996). Plet-Hansen *et al.* (2018) previously described the SIF dataset in details and investigated its usefulness for scientific purposes through comparison to logbook and sales slips data. The dataset was considered suitable for further scientific analyses, notwithstanding some variability in data quality across years, vessels, species, and size classes (Plet-Hansen *et al.*, 2018).

In the present study, we used SIF data from 10 092 hauls from six vessels over the period 2015–2017, for which the quality was deemed high for the following 12 species: cod (*Gadus morhua*), haddock (*Melanogrammus aeglefinus*), hake (*Merluccius merluccius*), lemon sole (*Microstomus kitt*), ling (*Molva molva*), monkfish (*Lophius* spp.), pollack (*Pollachius pollachius*), saithe (*P. virens*), turbot (*Scophthalmus maximus*), witch flounder (*Glyptocephalus cynoglossus*), wolffish (*Anarhichas* spp.), and whiting (*Merlangius merlangus*) (Table 1). These 12 species constituted 76.5% of the total landings in value and 67.1% of the total landings in weight for the 3 years for these six vessels. The final dataset after the validation according to Plet-Hansen *et al.* (2018) is the baseline for comparison as records of species and sizes are directly available at the individual haul level. The dataset is henceforth referred to as "SIF".

Trip-level reconstructed data

To estimate the gain of having size class recorded at the haul level, we calculated a second dataset from aggregating the SIF data to mimic the level of aggregation of standard logbooks data. In this second dataset, we aggregated the weight of the specific size classes for each of the 12 species in SIF to the trip level, as this is the stage at which size class information can be derived from vessels without on-board grading machines in Denmark. We calculated the full landing of each species for each haul, disregarding the size class information to mimic the entry format in the eLog. We then reallocated the average size composition aggregated at the trip level for each species back to the full landings of each species at

Table 1. Total degrees of freedom (DF), *r*-squared (r^2), and *r*-squared for data with log-transformation (log-transformed r^2) for the 12 species identified as being well in accordance with sales slips and logbook records for the six vessels in the years 2015–2017.

Species	DF	r^2	Log-trans r^2
Cod	3 510	0.871	0.841
Haddock	1 589	0.884	0.877
Hake	1 503	0.810	0.935
Lemon sole	1 549	0.916	0.944
Ling	1 058	0.974	0.937
Monkfish	2 382	0.944	0.944
Pollack	824	0.962	0.928
Saithe	1 617	0.879	0.916
Turbot	1 653	0.894	0.931
Witch flounder	1 653	0.908	0.931
Whiting	167	0.950	0.865
Wolffish	1 161	0.916	0.944

each haul. Thereby, this second dataset has the size class information as if it had been then the trip-level origin of size records (TOR). TOR thus represents the size class information that can be collected under the current limitation of size class information at the trip level, while full species composition information is available at the haul level from the eLog. Giving an example for illustration: two hauls recorded in SIF, one with 2 kg of size class 5 cod, and one with 8 kg of size class 1 cod will in TOR result in two hauls that both have size class 5 and size class 1 recorded. However, in TOR, the first haul will have 0.4 kg of size class 5 cod and 1.6 kg of size class 1 cod and the second haul will have 1.6 kg of size class 5 cod and 6.4 kg of size class 1 cod. The reason for this is that the TOR dataset is created under the assumption that the trip level size composition is the same as the haul level size composition. There, the percentage of size class 5 cod and the percentage for size class 1 cod for the full trip (20% for size class 5 and 80% for size class 1) will be redistributed back to the hauls as if the percentwise size composition for the trip also is the percentwise size composition for each haul.

Estimation of difference between SIF and TOR

For each haul, we calculated the difference between SIF and TOR by weight in landings of each species and size class and we aggregated size classes into two overall groups for each species ("small fish" and "large fish") to reduce the number of categories and amplify the potential differences between the datasets. Such a small/large fish division can be based on different factors, such as age and maturity. Here, we used the price difference as the main factor (Sjöberg, 2015; Hoff *et al.*, 2019). Because SIF data are commercial data and are influenced by the expected price of the sold fish, the separation was based on the economic value of the size classes for each species. The mean price per commercial size classes was calculated on SIF for the study period 2015–2017. The threshold under which size classes at the fish market are perceived as "small" was defined at the point where the value of the fish drops. In addition, we used literature indicating size class and economic effect on discarding practices as an extra indication to help validate this threshold (Table 2). Hence, for cod, haddock, hake, saithe, pollack, whiting, ling, and lemon sole these divisions coincide with 75–100% expected maturity of the fish (Silva *et al.*, 2013; ICES, 2014a, b, c, d; Macdonald *et al.*, 2017; FishBase, 2019a). For monkfish, turbot, wolffish and witch flounder, the maturity at division between "small" and "large" is uncertain but likely <50%, potentially as low as 0% (Bowering, 1976; Robinson *et al.*, 2010; Gunnarsson *et al.*, 2013; Silva *et al.*, 2013; Macdonald *et al.*, 2017; FishBase, 2019b, 2020.

When using fishery-dependent data from active fishing gear types, each haul can be viewed as a data sampling transect. Every haul containing a species and size class thereby becomes a record of presence. An analysis of fish presence/absence between SIF and TOR data set-up was made to estimate possible "false presence" samples (hauls) occurring when size class information from trip level is redistributed to the haul level. Haul locations were assigned to grid cells of 0.1° latitude by 0.2° longitude representing ca. 121 km^2 at the study area latitude (North Sea region). The grid cell size was decided based on two factors: (i) the average distance of hauls (~17 km N/S and ~16 km E/W), meaning that an average haul would not cross through more than two or three grid cells; and (ii) to comply with regulation protecting the confidentiality of individual vessels data on the fine-scale and infrequent fishing grounds. Each haul is thereby treated as a transect passing through a grid cell. Because only the total amount caught per haul in this dataset is known and therefore the exact timing of each caught fish within the haul is unknown, the landed amount from each haul is treated as equally likely to originate from any grid cell in which the haul passed through. The share of "false presence" samples was calculated for each species and size grouping as presence records in TOR where no presences occurred in SIF, divided by the total number of hauls passing through the grid cell.

To evaluate the degree of discrepancy between SIF and TOR when describing the spatial patterns of landed amounts of fish sizes, and the effect of the grid cell resolution, we used the SPAtial EFficiency metric (SPAEF) introduced in Koch *et al.* (2018). SPAEF is calculated as:

$$\text{SPAEF} = 1 - \sqrt{(\alpha-1)^2 + (\beta-1)^2 + (\gamma-1)^2},$$

where α is the Pearson correlation coefficient between SIF and TOR grid values, β is the coefficient of variation for SIF grid values divided by the coefficient of variation for TOR grid values, and γ is the histogram overlap between the grid patterns with SIF values and grid patterns with TOR values. SPAEF is thereby a multi-composite and statistical metric that summarizes the degree of matching of two spatial patterns in one single value (between $-\infty$ and 1 where 1 is full overlap) based on the balancing between multiple components from where the spatial comparison can be made, an approach that has been advocated for among geoscientists (Krause *et al.*, 2005; Gupta *et al.*, 2012; Koch *et al.*, 2018). While the topic for which this metric has been developed is not within the field of fisheries, the metric should be universal for spatial analysis and apply to any spatially distributed data such as delocalized recording of fish catches (Ciannelli *et al.*, 2008). Comparison of two by two spatial patterns results in many SPAEF outputs. Therefore, the visual SPAEF outputs are illustrated only for monkfish (Figures 2–5), which is a data-poor species in the study area (Poos *et al.*, 2018). SPAEF metrics of the remaining species are presented briefly, but detailed visual outcomes for each of the other species are available in the Supplementary material.

To illustrate the effect of chosen grain size, also known as the Modifiable Areal Unit Problem, which exists in spatial analysis including those directed at fisheries management (Jelinski and Wu, 1996; Dark and Bram, 2007; Guisan *et al.*, 2007; Salmivaara *et al.*, 2015), SPAEF was calculated at different raster grid cell sizes. In addition to the above-mentioned default cell size of 0.1 by 0.2°, we chose the coarser grids defined by The International Council for the Exploration of Sea (ICES), whereby statistical rectangles (0.5 by 1.0°) are officially used for landings declaration in fisher's logbooks (Hintzen *et al.*, 2019; ICES, 2019), and the finer grid resolution of 0.05 by 0.05°, which have been used for VMS analysis, including in the ICES Working Group on Spatial Fisheries Data (Hintzen *et al.*, 2012; ICES, 2018).

Results

False presence sampling estimation

Across all species, size groupings, and years, the average number of cells with a "false presence" recorded by TOR was 33 out of the total cell count of 883 when using a grid cell extend of 0.1° latitude by 0.2° longitude. The highest number of hauls recorded in

Table 2. Division by size class and kg between small and large grouping.

Species	Division small/large	Number of size classes in size group small	Number of size classes in size group large	Rationale
Cod	Size class 3 (≥2.00 kg)	2	4	Ulrich *et al.* (2013)
Haddock	Size class 2 (≥0.57 kg)	2	2	Stratoudakis *et al.* (1998) and Bergsson *et al.* (2017)
Hake	Size class 2 (≥1.20 kg)	2	3	Bergsson *et al.* (2017)
Lemon sole	Size class 2 (≥0.35 kg)	1	2	Prices 2015–2017
Ling	Size class 2 (≥3.00 kg)	1	2	Prices 2015–2017
Monkfish	Size class 4 (≥1.00 kg)	1	4	Prices 2015–2017
Pollack	Size class 2 (≥3.00 kg)	2	2	Prices 2015–2017
Saithe	Size class 3 (≥1.5 kg)	1	3	Bergsson *et al.* (2017)
Turbot	Size class 3 (≥1.00 kg)	1	3	Prices 2015–2017
Witch flounder	Size class 2 (≥0.3 kg)	1	2	Prices 2015–2017
Whiting	Size class 2 (≥0.35 kg)	2	2	Stratoudakis *et al.* (1998) and Bergsson *et al.* (2017)
Wolffish	Size class 3 (≥1.00 kg)	1	2	Prices 2015–2017

SIF passing through a grid cell during 2015–2017 was 31 while the lowest is 1. The "false presence" recorded hauls by TOR compared to SIF in the affected grid cells ranged from 3.22% (small hake) to 100% (Figure 1).

The amount of false presence samples (hauls) occurring in TOR differed between species and size class groupings (Figure 1). Large cod, haddock, lemon sole, large ling, monkfish, pollack, small saithe, small witch flounder, and wolffish all had a share of false presence hauls in TOR extending to 100%. Large saithe (up to 15 hauls), small haddock (up to 11 hauls), small hake (up to 12 hauls), small monkfish (up to 31 hauls), small turbot (up to 22 hauls), and small wolffish (up to 25 hauls) had grid cells where this false presence share was out of >10 hauls. For all other species and size groupings, the false presence share was applying to <10 hauls passing through a false positive cell. Smaller sizes were affected more than the larger sizes by the false presence in TOR, the lack of a finer information assuming small fish to distribute on where they were not found in reality (i.e. in SIF), and this was particularly consistent for monkfish, turbot, and wolffish, which showed signs for smaller fish to not be distributed evenly but encountered patchily.

Distribution of landed amount and spatial resolution effect

Higher SPAEF coefficient was found for monkfish of the size grouping "large" (Figure 2) compared to monkfish of the size grouping "small" (Figure 4). In addition, small grid cells (VMS) produce larger SPAEF output (Figure 2) compared to large grid cells (ICES square) (Figure 3). That is, for monkfish in 2017, the difference in spatial distribution of abundance data between SIF and TOR is higher for the small size grouping of monkfish and also becomes higher if data are aggregated to grid cells with substantial spatial extend (ICES squares) compared to grid cells with a relatively small spatial extent (VMS). The difference in the gradient scale extend between Figures 2 and 3 is caused by the aggregation of more samples into each grid cell when the spatial extent of a grid cell is relatively large (ICES squares) compared to relatively small grid cells (VMS).

Cod, haddock, hake, lemon sole, ling, large monkfish, small pollack, saithe, turbot, large witch flounder, and large wolffish have SPAEF values close to 1 when moving from large grid cell sizes (ICES, 0.5° by 1.0°) towards small grid cell sizes (VMS, 0.05° by 0,05°) (Figure 5). Small monkfish, large pollack, small witch flounder, whiting, and small wolffish do not show the same tendency. Small monkfish, large Pollack, and small witch flounder have the main increase in SPAEF value when moving from the largest grid cell size (ICES, 0.5° by 1.0°) to the medium grid cell sizes (0.1° by 0.2°) and with no apparent increase in SPAEF value going from medium grid cell sizes to the smallest grid cell sizes (VMS, 0.05° by 0,05°). Whiting and small wolffish have no apparent increase in SPAEF value regardless of grid cell sizes, if any change, rather a potential decrease in SPAEF value when moving from large grid cell sizes (ICES, 0.5° by 1.0°) towards small grid cell sizes (VMS, 0.05° by 0,05°). For the species and size groupings with a tendency for an increase in SPAEF value when grid cell sizes are reduced, the main SPAEF metric behind the increased SPAE value is the histogram overlap.

Discussion

We set out to estimate the potential mismatch that occurs between the fish size composition in the marine-wild fisheries landings data only collected at the individual trip-at-sea level compared to the more accurate but less available haul-by-haul level. If redistributing trip-based data to hauls are routinely done, e.g. in Denmark, it remains crucial to examine and confirm if such an approach does provide actual benefits with better estimates. We used opportunistically the data collected by a traceability system (SIF), to make this estimation. However, the data were only available for a subset of the Danish fleet and mainly for large-scale demersal trawlers.

Our findings show that spatial mismatch in species landings distribution, for instance due to "false presence" records, do arise from the lack of fish body size information at the haul level. While the mismatch occurs for both large and small size groups, it is more profound for small individuals compared to the large individuals. A possible explanation for this is that in general, the large animal size groupings contain more commercial size classes than the small animal size group. Thereby, the information

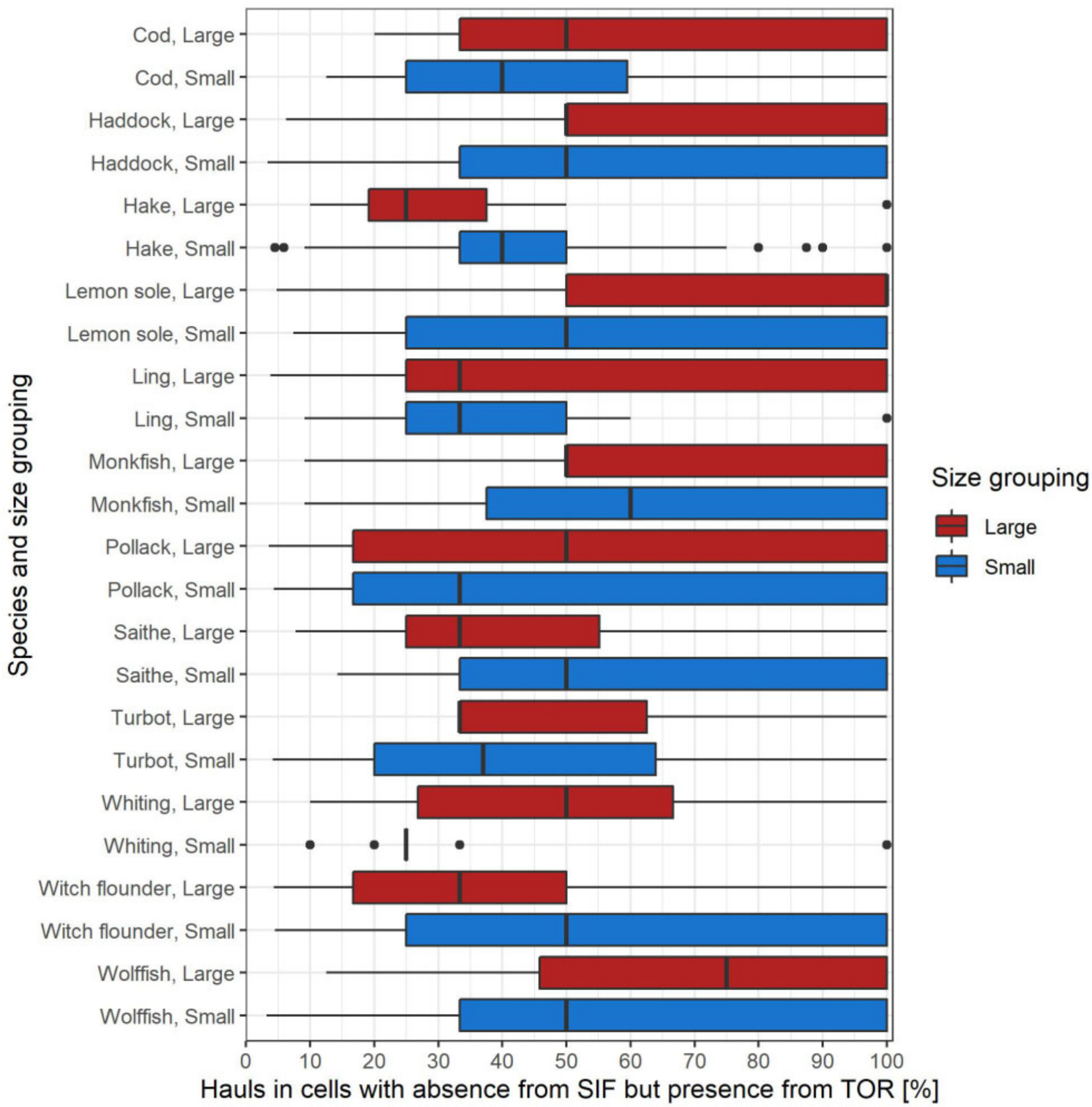

Figure 1. The box-and-whiskey plot of the share of "false presence" samples (hauls) in grid cells of 0.1° latitude by 0.2° longitude where species are absent in SIF but present in TOR. The *x*-axis shows species and size grouping, and the *y*-axis shows the percentile share of hauls with a "false positive" record in TOR out of the total amount of hauls passing through a cell.

aggregation for larger size classes resembles that of size data collected at a trip level more than that of the small size classes. The focus of this study was to present the added value of size level at the haul level and the influence of the geographical resolution chosen for the gridding. Hence, we divided the landings per size group related to a price index to illustrate this added value. If this grouping could appear coarse, our findings already measure a substantial spatial mismatch between the two levels of data resolution, which underpins the influence of the data record level.

Besides, when aggregating data spatially, the specific area size and shape will affect which samples fall within the area and thereby affect the modelled outcome (Guisan *et al.*, 2007; Amoroso *et al.*, 2018a). In theory, this problem could be avoided if each observation is analysed individually (Jelinski and Wu, 1996). In reality, it is often necessary to aggregate data spatially, e.g. due to the spatial resolution at which data are available and thereby the scale at which it is reasonable to present the data (Salmivaara *et al.*, 2015; Amoroso *et al.*, 2018b; Kroodsma *et al.*, 2018). When choosing the grid cell size for modelling spatial gradient data, a balance between the data record level and the wanted analysis has to be made.

The outcome of the mismatch analysis for most species and size groups in our study was that the mismatch reduced when the used grid was fine. At first, this might give the impression that

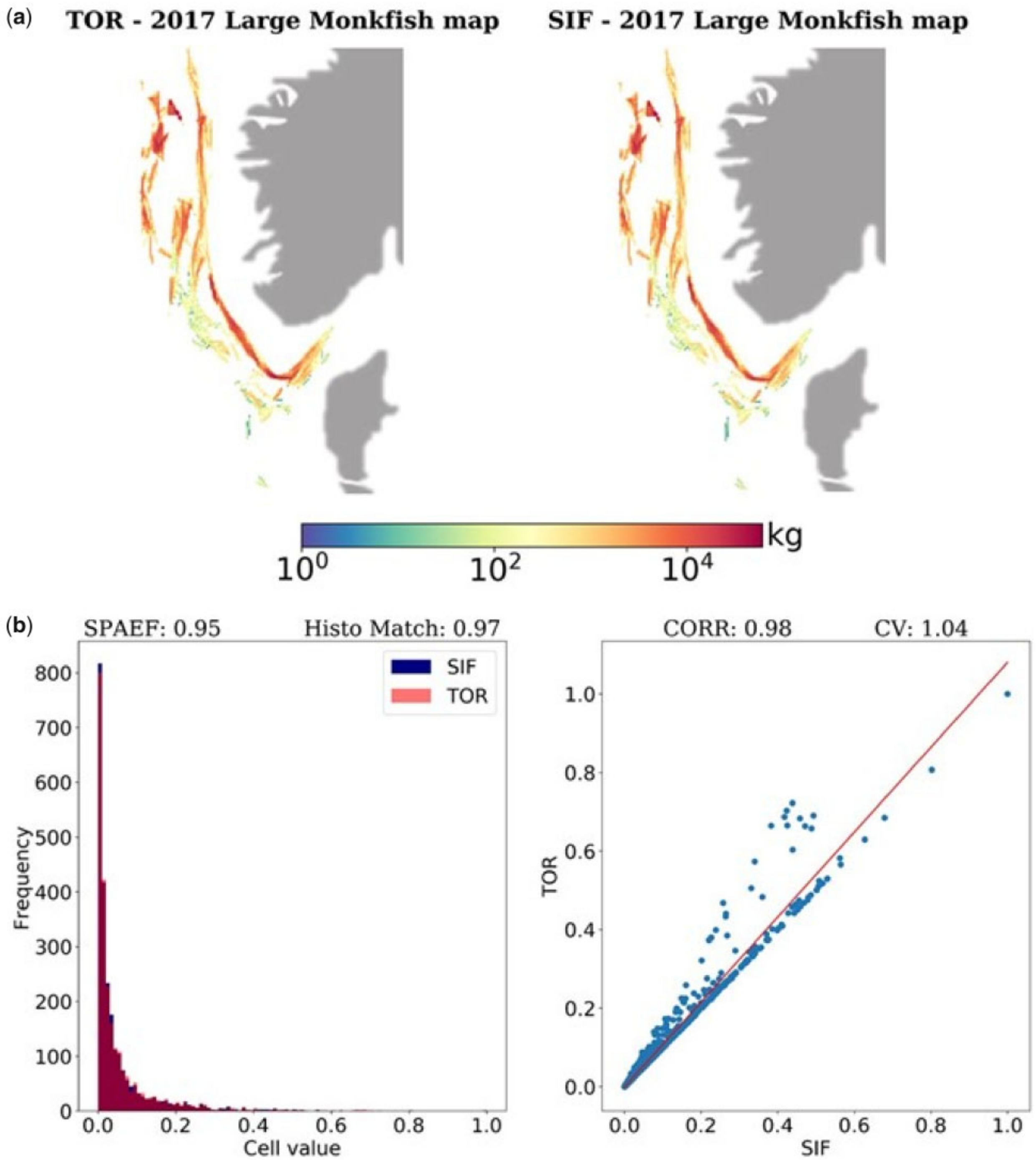

Figure 2. SPAEF output when using VMS grid cell sizes (0.05° by 0.05°) for large monkfish in 2017. Subplot (a) compares the spatial overlap for TOR and SIF. Gradient colour is the amount of monkfish in kg associated with each grid cell on a logarithmic scale. Grey area is a sketch of western Norway and Denmark. Subplot (b) compares the histogram overlap and the correlation between TOR and SIF. SPAEF coefficient is 0.95, histogram overlap is 0.97, Pearson correlation is 0.98, and *C.V./C.V.* is 1.04.

grid cell sizes should simply be as small as possible. However, one has to take into account whether the data record level truly allows for pinpointing data to small grid cell sizes. Otherwise, one risk representing data in grid cells that in fact did not contain these records in reality. While most species show a trend towards a higher SPAEF value when grid cell size decreases, the trend is asymptotic with the main increase in the degree of overlap achieved when moving from ICES grid cells to lat. 0.1° by long. 0.2° grid cell sizes. In addition, the SPAEF metric, which mainly drives this increase, is the histogram overlap, meaning that whether a data record truly originate from a grid cell or not is key. That is, whether false presences or absences are inserted

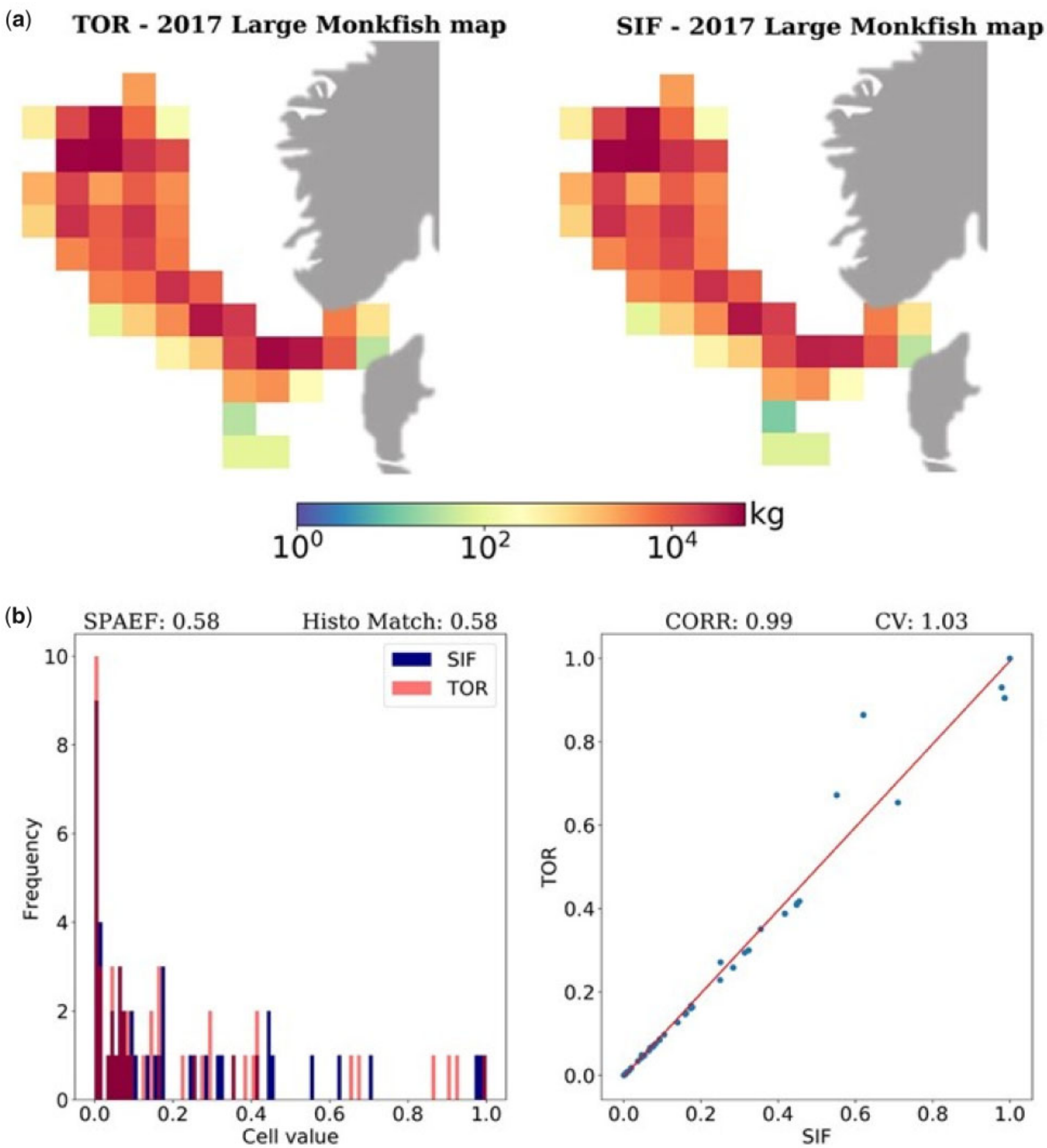

Figure 3. SPAEF output when using ICES grid cell sizes (0.5° by 1.0°) for large monkfish in 2017. Subplot (a) compares the spatial overlap for TOR and SIF. Gradient colour is the amount of monkfish in kg associated with each grid cell on a logarithmic scale. Grey area is a sketch of western Norway and Denmark. Subplot (b) compares the histogram overlap and the correlation between TOR and SIF. SPAEF coefficient is 0.58, histogram overlap is 0.58, Pearson correlation is 0.99, and *C.V./C.V.* is 1.03.

into the data when aggregating into grid cells. False absence or methodological absence occurs when the method for data collection is unable to ensure a valid record of absences, whereby data records will have absences where presences should have been observed (Lobo *et al.*, 2010; Barbet-Massin *et al.*, 2012). What our analysis shows (Figure 1) is that the reverse situation, false presence, may also occur when relying on fishery-dependent data as a source of data. Unlike the false absence, the false presence does not present itself at the species level as the species was actually caught. When integrating commercial fisheries data with scientific surveys to boost the data availability (Rufener *et al.*, 2018), there is a risk of inducing false presences for fish body size into the distribution of the commercial fisheries data if potential false presences are not accounted for. However, for most species in our analysis, such mismatch can be decreased using smaller grid cell sizes.

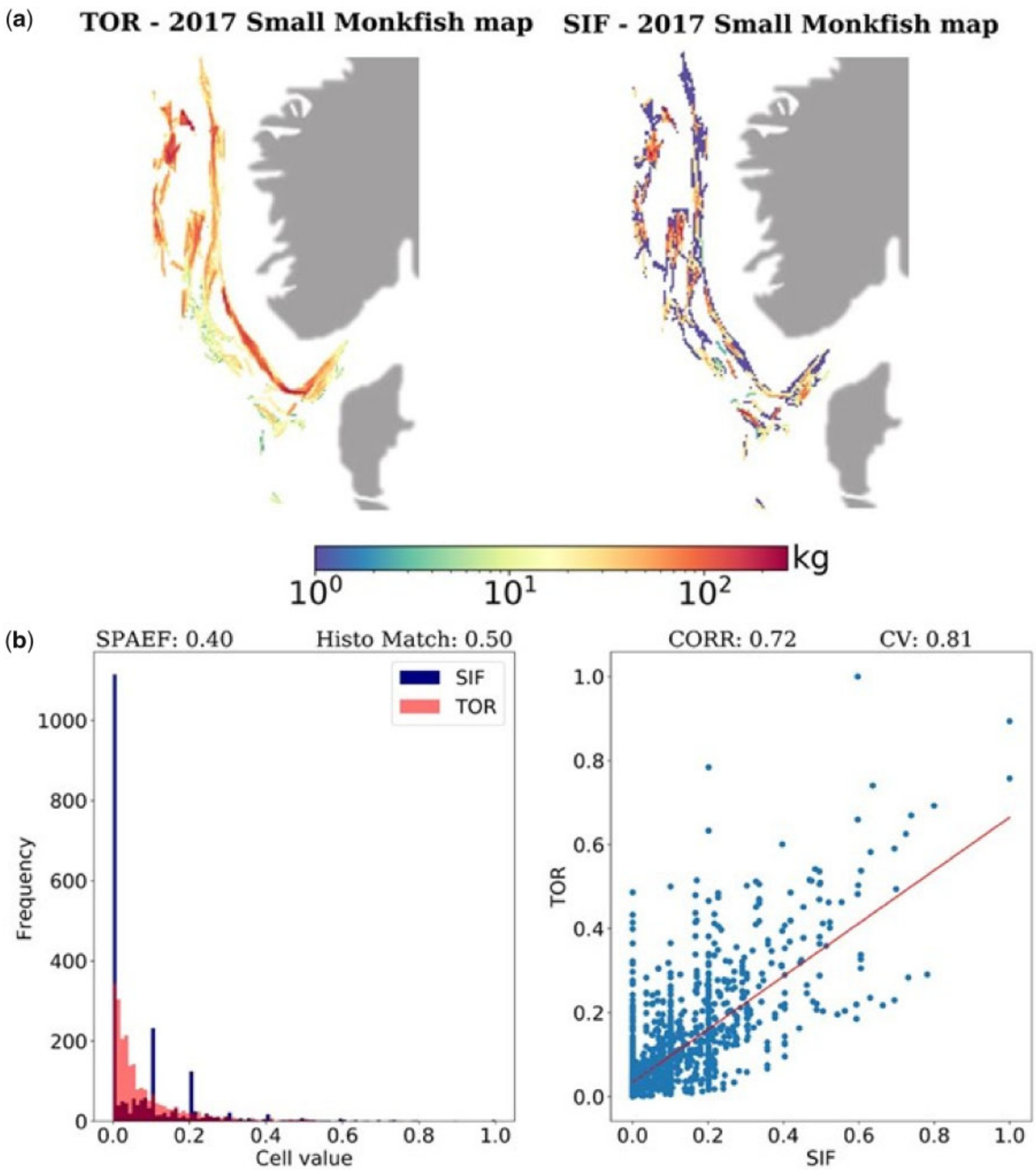

Figure 4. SPAEF output when using VMS grid cell sizes (0.05° by 0.05°) for small monkfish in 2017. Subplot (a) compares the spatial overlap for TOR and SIF. Gradient colour is the amount of monkfish in kg associated with each grid cell on a logarithmic scale. The grey area is a sketch of western Norway and Denmark. Subplot (b) compares the histogram overlap and the correlation between TOR and SIF. SPAEF coefficient is 0.40, histogram overlap is 0.50, Pearson correlation is 0.72, and *C.V./C.V.* is 0.81.

Our findings suggest that, besides fish body size records at the haul level, positional data records of fishing activities (effort data) recorded at a fine-scale also will lower the mismatch between size class collected at the haul level or the trip level. Fine-scale effort data will allow for finer grid cells because the positional data will represent the correct track line of the fishing vessel better than when coarser positional data are used (Needle *et al.*, 2015). Several possibilities to achieve this exist. Since EU fishing vessels are already required to carry VMS, in theory higher precision of effort data could be recorded by simply increasing the ping rate. That is, instead of recording position, speed, and course at every 1 to 2 hr, the record could be done at, e.g. a 5-min interval, just like that of AIS data (Gerritsen *et al.*, 2013; Girard and Du Payrat, 2017). Another option would be to use AIS data from the fishing fleet. One should keep in mind, however, that AIS was developed for security and navigational purposes (IMO, 2019) and therefore skippers can turn AIS equipment on and off as they wish, contrary to the VMS. A third option would be to use electronic monitoring systems that record positional data at 10 s intervals besides recording the on-going fishing activities with sensors on the

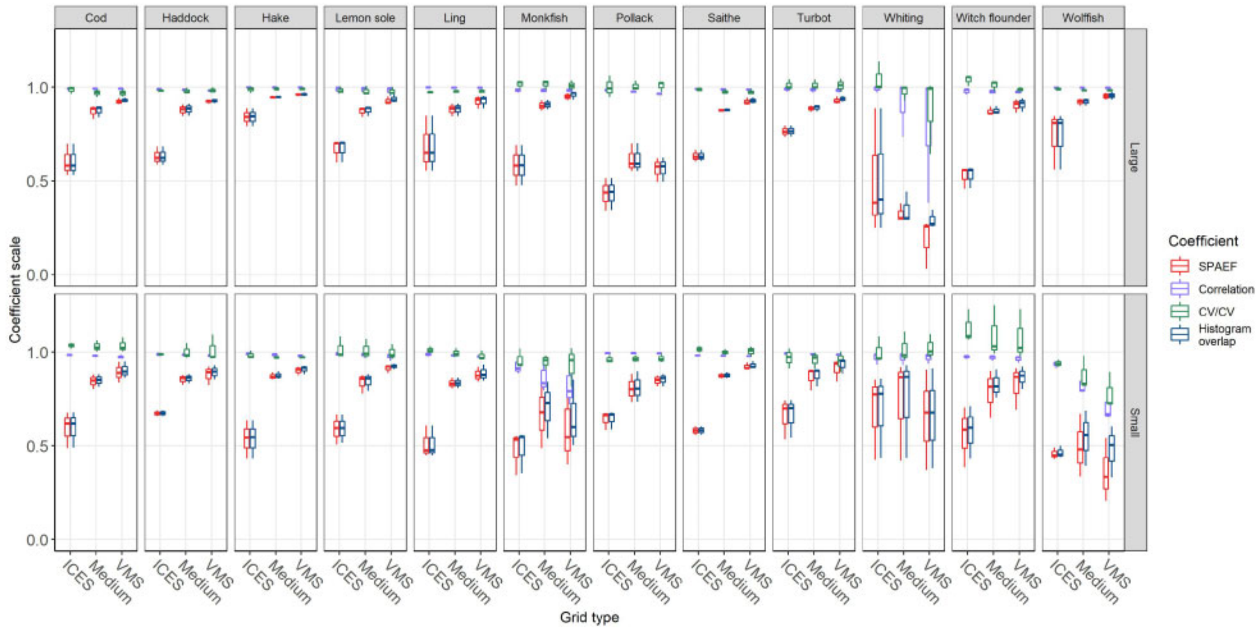

Figure 5. Box-and-whiskers plot of outcome for SPAEF and its three composite coefficients for the large and small size groups of the 12 species by the three grid cell sizes for the years 2015–2017. A SPAEF at 1 means full match between the two trip-based TOR and haul-based SIF spatial patterns.

fishing gear (Plet-Hansen *et al.*, 2019; van Helmond *et al.*, 2020). Indeed, such electronic monitoring systems, where no video feed is installed but merely sensor and GPS equipment, are already mandatory for certain mussel fisheries in Denmark and Scotland (Nielsen *et al.*, 2014).

In our study, there are a few cases where a higher resolution of spatial effort data does not seem to translate into a higher degree of overlap. Whiting, small monkfish, large pollack, small wolffish, and arguably small witch flounder show no obvious improvement in spatial allocation when using smaller grid cell sizes. Indeed for whiting and small wolffish, it seems that the use of smaller grid cell sizes even makes the spatial allocation mismatch larger. One reason could be that these species and size classes are landed in lower amounts than for instance species and size classes like large monkfish or wolffish or species like cod, haddock, or saithe. The lower amount of entries for SPAEF to be run on may simply make the statistics less robust. Whether this is the case or if other factors like different spatial distribution of these species and size classes are at play could be subject for further study.

From an ecological modelling perspective, more data availability of size records is of interest to feed into species distribution models (Elith and Leathwick, 2009) given that fish tend to distribute differently along their life stages while fishing activities select only a fraction of the overall abundance. On-going advances using image recognition could increase the relevance of grading machine data, including data from sea-packing grading machinery, by automating the recording of fish lengths of fish packed in boxes according to the EU commercial size class specifications (Álvarez-Ellacuría *et al.*, 2019). However, because fishers target specific species of commercial interest and use specific fishing techniques, which are differently selective over fish body sizes, commercial fishing is by nature a non-random process, which means that the fishery-dependent data cannot be assimilated to stratified random sampling (Smith, 2000; Sims *et al.*, 2008; Madsen and Valentinsson, 2010; Fauconnet and Rochet, 2016). Using such kind of data source for the species distribution modelling would risk biasing the modelling with "false absence" (Barbet-Massin *et al.*, 2012) that may originate from the spatial, temporal, and technical selectivity of the commercial fisheries data (Lobo *et al.*, 2010).

In this study, size grouping was based on categories that would relate to fishers' behaviour and thereby fisheries management. This is because the actual size composition of catches and landings is the result of, among other driving factors, the fish quota availability and the fish price per kg that influence the targeting behaviour of fishers (Graham *et al.*, 2007; Bourdaud *et al.*, 2019; Robert *et al.*, 2019). If species-related non-sized data may be sufficient in informing the possible avoidance of unwanted catches, including fish body size-related information will also help to support other economic drivers for the fishers to optimize their fishing effort spatially. Anticipating the possible size composition of the following hauls holds both ecological and economic values that are likely to influence fishers' decision-making (Little *et al.*, 2009; Bourdaud *et al.*, 2019). Such refined information as used in this study may help in adapting management measures to fit management goals better by accounting for the adaptive behaviour of fishers (Abbott and Haynie, 2012) and by supporting the fisheries sector with documentation and tools, easing the compliance with the rules, and eventually minimizing the fishing impacts (Bradley *et al.*, 2019; Hintzen *et al.*, 2019; Reid *et al.*, 2019). It is important to keep in mind, however, that the commercial fisheries data used in this study only contain information on landings and thereby lack information for potential discards.

Conclusion

Our study measured to what extent using commercial fisheries data to deduce the spatial distribution of species and sizes comes with the risk of assuming that fish sizes are distributed to where they are not. We compared data recorded at the haul level to the same data arranged as if it was recorded at the trip level. The mismatch was found to be greater for small sizes of a species compared to larger sizes. Using commercial fisheries data records recorded at the trip level may be useful or even necessary. Yet it is important to acknowledge the limitations and potential bias of one's data sources. A clear limitation with the commercial fisheries data used in this study is that it relies solely on records of landings, whereby the influence of potential discards cannot be covered. Our findings do however suggest that the potential bias induced by redistributing sizes recorded at the trip level onto the haul level could be decreased if the positional data for the actual fishing activities are collected at an interval allowing for refined fishing effort data. For certain species, however, fine-scale effort data did not help, while size information recorded at the haul level still did. While this might be influence by low landing volumes, other factors such as different spatial distribution of these species could be a potential reason too. Further studies are needed to investigate this.

Supplementary data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

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Date availability

The data underlying this article cannot be shared publicly due to the privacy of fishers and data protection of personal information. The data will be shared on reasonable request to the corresponding author.

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