Estimating annual CPUE indices for perch (*Perca fluviatilis*) from monthly logbook data of a gill-net fishery in the Bothnian Bay, Baltic Sea

Antti Lappalainen^{1)*}, Juha Hyvönen²⁾, Pirkko Söderkultalahti¹⁾ and Juha Heikkinen¹⁾

¹⁾ Natural Resources Institute Finland, Latokartanonkaari 9, 00790 Helsinki, Finland (*corresponding author's e-mail: antti.lappalainen@luke.fi)

²⁾ Natural Resources Institute Finland, Ounasjoentie 6, 96200 Rovaniemi, Finland

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Catch per unit effort (CPUE) indices, derived from daily logbooks of open sea fisheries or from standard gill-net surveys have traditionally been used as a source of information on trends in fish stock biomass or abundance. Nowadays, the systematic collection of catch and effort data from coastal small-scale fisheries has gradually been launched as well, e.g., in the Baltic Sea. The data from coastal fisheries is typically collected in monthly logbooks. We demonstrate that raw CPUEs, CPUEs based on subsetted data and CPUE indices based on linear mixed models (LMMs) from coastal gill-net fishery data covering a 20-year period yield different results on trends in abundance. The use of advanced counting methods is recommended to reduce the amount of the annual variation not attributable to changes in abundance. Thereafter, CPUE indices based on the monthly logbook data can produce valuable and cost-effective information on fish abundance.

Introduction

The catch per unit effort (CPUE), i.e., the amount of animals caught by a certain effort (e.g., fish weight/gill-net/day), is an indirect measure of the abundance of a target species (e.g., Gulland 1983). CPUE indices of fish have commonly been used in fishery science, as well as for environmental monitoring and assessments. In the Baltic Sea, trends in abundance of key coastal fish species and coastal fish key functional groups have been monitored based on CPUE indices counted from standard gill net surveys (e.g., Ådjers *et al.* 2006, Bergström *et al.* 2016). These results have been further used in thematic assessments of biodiversity in the Baltic Sea (HELCOM 2018). CPUE indices based on gillnet surveys are also widely used in the ecological classifications of lakes according to the EU Water Framework Directive in several European countries (e.g., Olin *et al.* 2011, Argillier *et al.* 2012, Kelly *et al.* 2012).

Although the CPUE indices should, ideally, be based on fishery-independent data collection methods, such as the above-mentioned gill-net surveys, large data sets of fishery independent data are often extremely costly to collect (Maunder and Punt 2004). On the other hand, there is a vast amount of catch and effort data available from logbooks of commercial sea fishery, but this data is certainly much less standardized. The scientific literature on the methodology of CPUE indices of commercial fishery is often based on data from open sea fisheries using trawl, purse seine or longline (e.g., Battaile and Quinn II 2004, Campbell 2004, Maunder *et al.* 2006, Mikkonen *et al.* 2008, Quirijns *et al.* 2008, Tsai *et al.* 2015, Helle *et al.* 2015), derived typically from daily logbooks.

Shortages and risks of misinterpretation of CPUE indices are often acknowledged (e.g., Hilborn and Walters 1992, Harley et al. 2001). The risks associated to raw CPUE indices, i.e., total catch of a fishery divided simply by the sum of effort associated with the catch, have been known for a long time (see Biseau 1998, Maunder and Punt 2004 and references therein). Maunder et al. (2006) and ICES (2017) state that raw CPUE indices should not be used unless there is a very good justification to accept them. Thus, various approaches have been developed for daily logbook data to avoid biased results related to raw indices. An initial step when analyzing large logbook data sets often involves identification and discarding of observations that are considered to be uninformative or even misleading. Stephens and MacCall (2004) refer this process as subsetting the data. A simple example could be discarding observations where the species of interest is caught only occasionally as a bycatch or including only data from selected vessels (e.g., Helle et al. 2015). Still, several factors, e.g., spatial or temporal changes in catchability, vessel and gear properties and targeting behavior of fishermen can cause extra variation and bias to CPUE indices as an indicator of abundance. Hence, various standardization approaches have been developed to remove the effect of these factors on CPUE indices for trawl and longline fisheries (e.g., Battaile and Quinn II 2004, Campbell 2004, Maunder and Punt 2004, Maunder et al. 2006, Bishop et al. 2008, Quirijns et al. 2008). General linear models and other advanced statistical methods have often been used in the standardization (see Battaile and Quinn II 2004, Campbell 2004, Stephens and MacCall 2004, Bishop et al. 2008, Mikkonen et al. 2008, Tsai et al. 2015), a major advantage being that a wide

variety of factors can be accounted for in a relatively simple analysis.

The systematic collection of catch and effort data from small-scale coastal fisheries, e.g., commercial gill-net fishery, has gradually been initiated e.g., in the Baltic Sea, where the obligation to deliver monthly logbook data is applied even to the smallest (< 10 m) vessels in most countries. In Finland, this sort of data collection from monthly logbooks started already in 1980. However, only a few scientific papers using monthly logbook data have so far been published. CPUE indices based on monthly logbook data, instead of gill-net monitoring data, have been used along the Finnish coast of the Baltic Sea to assess abundance of coastal perch (Perca fluviatilis) and Cyprinids (freshwater fish of family Cyprinidae) (HELCOM 2018). Recently, these CPUE indices have been used in studies of the effects of great cormorant (Phalacrocorax carbo) predation on coastal perch and pike-perch (Sander lucioperca) stocks (Lehikoinen et al. 2011, Heikinheimo and Lehtonen 2016, Lehikoinen et al. 2017). The CPUE indices in these reports and scientific papers have been typical raw CPUEs, produced by summing all the annual catches of a certain gill-net type (e.g., mesh-size 36-50 mm) for all fishermen and months and then dividing by the summed fishing efforts of those observations where catches (> 0 kg) of the species were reported. The risk for biased results is thus evident. The use of data collected from monthly logbooks, such as data from the Finnish coast, to calculate CPUE indices poses certain extra challenges compared to the use of daily data from open sea fisheries. The small-scale coastal fishery, typically with gill-nets or trap-nets, is very often a mixed fishery. The problems in allocating the effort to various species are also well known e.g., concerning mixed trawl fishery data collected from daily logbooks (e.g., Biseau 1998), but the problems are likely to be emphasized with monthly logbook data. The fishing sites and target species of a coastal fisherman might vary during a calendar month, and in a one-month period, the probability of individuals of bycatch species entering among those reported is obviously higher than in daily reporting. Another aspect of the monthly logbook data is that the variation in the amount of effort between observations (i.e., monthly efforts of fishermen) can also be extremely high, varying in the gill-net fishery from a few gill-net days to several thousand gill-net days per a month.

The aim of this study is to develop more advanced and less biased approaches to use monthly logbook data from coastal commercial fishery to calculate CPUE indices. Additionally, the aim is to promote the use of logbook data of coastal fishery in other areas as well. The monthly logbook data from commercial gill-net fisheries on the Finnish coast of the Bothnian Bay over a twenty-year period (1996-2015) was used to estimate CPUE indices for perch. During this period, the annual commercial gill-net catch of perch in the area has doubled. This is among the most important species for small-scale commercial fisheries in the northern Baltic Sea, e.g., along the Finnish coast, where perch comprises 15-20% of the annual commercial catches if pelagic species and cod are excluded. It is an important target species also for recreational fisheries and the total catches of these fisheries generally exceed those of commercial fisheries (see Official Statistics of Finland 2017a, 2017b). Perch is also regarded as a key species in the coastal food webs and the abundance of perch is used as an indicator of a good environmental status (EU Marine Strategy Framework Directive) in the area (HELCOM 2018). Strong annual variation in abundance is typical for perch in the Baltic Sea region, as temperatures during the first year have clear effects on the year-class strength (e.g., Böhling et al. 1991) and fish from a strong year-class can dominate the catch for several years in large areas. There are obviously several overlapping perch populations on our study area, but the reasoning for a regional assessment covering the entire Finnish coast of the Bothnian Bay was that identical regional assessment units are used in the thematic assessments of biodiversity in the Baltic Sea (HELCOM 2018). The logbook data and similar methodology can also be used at a more local scale.

We begin with the raw CPUE, which has been used so far in monitoring perch abundance in the area. Thereafter, we improve the CPUE indices by sub-setting the data. In the third phase, we calculate abundance indices using linear mixed models (LMMs). We also demonstrate that various versions of CPUE indices do not lead to similar conclusions on the abundance trends of the studied stock. Finally, we shortly discuss the future potential of CPUE indices based on monthly logbook data of coastal fisheries.

Material and methods

Data

Catch statistics for the Finnish commercial fisheries have been compiled almost in their present form since 1980. The central register of commercial fishermen (or family enterprises) also includes part-time fishermen. The register was renewed in 1995, when Finland joined the EU, and as a consequence, the number of registered fishermen slightly increased. At the same time, the classification of gill-nets in the logbooks was renewed. Thus, in this study we focus on data collected for the 1996-2015 period. Coastal fishing with passive gears is carried out with vessels under ten meters long and these vessels have been included in the data collection system during the entire period. The reporting is mandatory. The data from these fisheries is entered into a monthly logbook (coastal fishing journal) stating the total monthly catch (kg) by species, the fishing area expressed in ICES statistical rectangles (ca. 30×30 nautical miles), the monthly mean amount of gear used and the number of active fishing days per month. All the abovementioned information is entered separately for each "gear class" (altogether 14 classes, see Appendix Table A1).

In this study, we use the monthly logbook data from the Finnish coast of the Bothnian Bay (Fig. 1), which is the northernmost basin of the Baltic Sea. Due to its low salinity (around 3 ppm at the surface), freshwater species and migratory species dominate the coastal areas, with perch and European whitefish (*Coregonus maraena*) among the most abundant catch species at the small-scale coastal fisheries. Other common freshwater species include pike (*Esox lucius*) and Cyprinids. During the 20-year study period, the commercial perch catch along the Finnish coast of the Bothnian Bay has



Fig 1. Grey rectangles denote ICES statistical rectangles included in this study.

increased, from 35-70 t/year in the late 1990s to 60-95 t/year in the first half of the 2010s (Official Statistics of Finland, 2017a). Fyke-nets and trap-nets are commonly used in the coastal fisheries, but the bulk of the commercial perch catch is taken with gill-nets. Gill-nets with mesh sizes of 36-45 mm form one "gear class" in the logbook and these mesh sizes are the most suitable for targeted perch fishing. Thus, we restricted our CPUE calculation to this "gear class". In addition to perch fishing, these gillnets have been widely used for whitefish fishing. Perch catches with these gill-nets show a similar increasing pattern during the 20-year period, as seen in the total perch catch, while catches of whitefish have decreased (Fig. 2). Perch and other freshwater species typically caught by gillnets are generally found in shallow coastal areas around the year, but as a cold-water species, whitefish is less restricted to sheltered coastal areas compared to perch.

Annual raw CPUEs

The monthly raw data, containing reported catches of perch with gill-nets had altogether 9378 observations from 602 fishermen. An observation was defined by fisherman, year, month and fishing area (ICES rectangle). The annual number of fishermen with reported perch catches varied from 111 to 196.

Annual raw CPUEs were estimated by summing (over all fishermen) the monthly perch catches (in weight) and monthly fishing efforts and then dividing the summed catch by the summed effort. Monthly efforts of a single fisherman were calculated for those months where perch catches were reported as gill-net days by multiplying the reported number of fishing days by the reported mean number of gill-nets used during the calendar month.

This simple method estimates the annual CPUE as the weighted mean of the monthly CPUEs (weighted by the monthly efforts). As the annual distribution of the monthly CPUEs were highly skewed to the right (a mass of the distribution on the low values, but a long tail towards high values) we estimated also annual weighted medians with 25% and 75% weighted percentile ranges.

Annual CPUEs for subsetted data

In the Bothnian Bay, perch is also caught as a by-catch in gill-net fishing targeting other



Fig 2. Commercial catch (tonnes) of perch and whitefish with gill-nets with mesh sizes 36–45 mm in the study area along the Finnish coast of the Bothnian Bay in years 1996–2015.

species, mainly whitefish. The coastal gillnet fishing for whitefish has undergone some changes during our study period (see details in the Discussion section). To avoid major biases caused by changes in the gill-net fishing, we attempted to exclude observations where whitefish was the evident main target species. Thus, we discarded all observations (monthly reports) where proportion of whitefish among the gill-net catch was greater or equal to 50%. In addition, there is also a temporal pattern in the perch fishing, the high season being between April/May and September when around 70-90% of the annual gillnet catch is taken. There is ice cover during the winter in the area and the annual timing of the ice melting might affect the fishing conditions, particularly in April. Hence, we included only catches and efforts from May to September.

The subsetted data (fulfilling the above two conditions) consisted of 3032 observations from 407 fishermen. The annual number of fishermen varied from 39 to 113. Annual CPUE indices were estimated similarly as for the raw data.

Annual CPUEs for subsetted data using linear mixed models

The subsetted data was further analyzed using a linear mixed model in order to take into account: 1) the effects of several explanatory variables (see Eq. 1); 2) correlations of CPUE observations of a single fisherman; 3) the skewness of the CPUE distribution; and 4) non-constant variation of CPUE observations (weighting of observations).

When two observations had the same fisherman-year-month combination but different fishing areas (ICES rectangles, Fig. 1), only the observation with the most used fishing area for the fisherman was chosen to simplify modelling. The modelling data had 3027 observations.

The catch per unit effort (kg/gill-net days) (data range 0.0025–11.0, median 0.25, mean 0.43) was explained by the fixed effects of year (20 categories), month (5 categories), fishing area (9 categories), proportion of whitefish in the catch (6 categories with midpoints, as a percentage: none, 5, 15, 25, 35 and 45) and effort (continuous) and hierarchical random effects accounting for variation between fishermen as:



Fig 3. The median CPUE of perch (line) with a 25 and 75 percentile range (bars) in categorized efforts for the modelling data. in years 1996–2015.

$$\ln(\text{CPUE}_{iym}) = \beta_0 + \beta_{1,y} + \beta_{2,m} + \beta_{3,a(i,y,m)} + \beta_{4,p(i,y,m)} + \beta_5 \times \ln(E_{iym}), (1) + \varepsilon_i + \varepsilon_{iy} + \varepsilon_{iym}$$

where a(i,y,m) is the fishing area of fisherman, *i*, during the month, *m*, of year, *y*; E_{iym} is the effort; CPUE_{*iym*} is the resulting catch per unit effort; and p(i,y,m) is the categorized proportion of whitefish in the catch. The fixed effects parameters to be estimated are: the intercept β_0 , representing the reference levels of the categorical variables; $\beta_{1,y}$ for the 19 other years than the reference year, representing the difference between year, *y*, and the reference, similarly $\beta_{2,m}$ for 4 months; $\beta_{3,a}$ for 8 areas; $\beta_{4,p}$ for 5 whitefish proportion categories; and β_5 represents the parameter of logarithmic effort.

Although observations with the greatest proportions (\geq 50%) of whitefish were excluded, the proportion was still used in the modelling to provide rough information on the targeting behavior of the fisherman. It was included as a categorical variable, because in 34% of the catches (observations) there were no whitefish. The logarithmic effort was included in the model because the effort seemed to have a nonlinear effect on the CPUE (Fig. 3).

The random effects of fisherman, ε_i , and the year for fisherman, ε_{iy} , were included in the model to take account of the evident correlations between CPUE observations of a



Fig 4. Distribution of the marginal residual (bars) with a fitted normal distribution for the linear mixed model (see Eq. 1).

single fisherman. All random terms ε_i , ε_{iy} , and ε_{iym} were assumed to be normally distributed, independent between fishermen and mutually independent, except that autoregressive covariance structures were assumed for the repeated measures of year and month, i.e., for the time series of ε_{iy} with a fixed *i* and ε_{iym} with fixed *i* and *y*.

After fitting the model, the annual means of ln(CPUE) with their 95% confidence limits were estimated using the fixed part of the model and adjusting other variables than the year to their means effects. The means were then back-transformed to the original scale, where they can be considered estimates of the median of the right skewed distributions. This interpretation is based on the symmetric distribution the residuals of the fixed part (marginal residuals; Fig. 4) and monotonicity of the logarithmic transformation (Mukherjee *et al.* 1998).

There were large differences between the monthly efforts (data range 2–3200, median 120, mean 251). CPUE observations associated with large efforts have smaller variations than those associated with small efforts (Fig. 3), which might suggest that they should receive more weight in parameter estimation. However, in addition to normalizing the model residuals (Fig. 4), logarithmic transformation of the CPUE also homogenized them (Fig. 5) and re-weighting was therefore unnecessary.



Fig 6. Raw CPUE (weighted mean CPUE; dashed line) and weighted median CPUE (solid line) for perch with weighted 25 and 75 percentile ranges in years 1996–2015 for the raw data (left) and for the subsetted data (right).

Linear trends over years for CPUEs based on the three estimation methods were examined for two time periods (1996–2015 and 2003–2015). For the CPUEs from raw data and subsetted data, linear trend was tested using simple regression model (20 observations in 1996–2015 and 13 observations in 2003–2015). For the mixed model CPUE, linear trend was tested within the model (at the logarithmic scale). Year was used as continuous variable in all trend analyses.

The SAS statistical software (ver. 9.4; SAS Institute Inc.) was used in the analyses. The statistics for the raw and subsetted data were estimated using the MEANS procedure, while the linear mixed model was analyzed using the MIXED procedure.

Results

The raw CPUE suggests that there is a continuous increasing trend in perch abundance both in the 20-year study period and in 2003–2015 (p < 0.001; Fig. 6), and the annual raw CPUEs during the first years (0.06–0.12 kg/gill-net day) have approximately doubled in the last years (0.17–0.23 kg/gill-net day). After subsetting, including only those observations from May to September where the proportion of whitefish was less than half, the general level of the CPUEs increased (range 0.19–0.47) and the annual variation increased considerably too. The CPUE suggests a slight increasing trend (p = 0.04) for the 20-year study period, but the trend was not evident (p = 0.24) any more in 2003–2015 (Fig. 6).



Fig 7. Median CPUE for perch (solid line) with a 95% confidence interval in years 1996–2015 for the linear mixed model.

The annual medians showed a similar pattern over the years but the medians were considerably lower than the means.

The annual medians estimated by the linear mixed model with year, month, fishing area, proportion of whitefish and effort as the explanatory variables (p < 0.001 for each; see Appendix Table A2) showed an increasing trend (p < 0.001) for the 20-year study period (Fig. 7). The CPUEs stayed at the same level for the 2003-2015 period and no trend (p = 0.65) was detected. The annual medians varied from 0.11 to 0.22 kg/gill-net day. Correspondingly, the estimated medians of the month varied from 0.14 (September) to 0.21 (July), while the medians of the fishing area varied from 0.08 to 0.32, with the three lowest areas being the southernmost statistical rectangles. The medians of the proportion of whitefish in the catch varied from 0.12 (category 45%) to 0.28 (category 5%) kg/gill-net day. Repeated measures correlations between CPUE observations of single fishermen were strong. Correlation between CPUE observations of two successive months of single fishermen was 0.67, and similarly, correlation between CPUE observations of two months in successive years was 0.53.

Discussion

There is no fishery independent data available on perch abundance for the Finnish coast of the Bothnian Bay and the commercial catch and effort data is the only available source of information. The continuous increasing trend in the raw CPUE, as well as in the total gill-net catch, suggests increased abundance of perch in the area. The trend, however, was not evident based on the annual estimates of the linear mixed model using subsetted data after the first years were excluded. Similar differences in various CPUEs were demonstrated also by Helle et al. (2015). They studied the CPUEs of ling (Molva molva L.) in a Norwegian long-line mixed-species fishery and showed that different perceptions of the state of a stock can be formed from different CPUE series, depending on whether the series is based on all the catches, or only on those in which the species were targeted.

A likely reason for the differences in our example, especially since 2003, is the wellknown fact that raw CPUE data is sensitive to biases in cases there are changes in the fishing (see Maunder et al. 2006, ICES 2017). In the Bothnian Bay, perch and whitefish have been the most common target species for gill-net fishing. The main fishing sites for these species partly overlap and catches of both species were commonly reported simultaneously in our data collected from the monthly logbooks. During our 20-year study period, local gill-net fishing has undergone changes. The abundance of ringed seals in the Bothnian Bay has roughly doubled from 4000 to 8000 individuals (HELCOM 2018). Grey seals are also common nowadays in large areas of the Baltic Sea including the Bothnian Bay. The growth of the population was strong during our study period. In 2000, the minimum grey seal population in the Baltic Sea was about 10 000. More than 20 000 grey seals were seen during the monitoring counts in 2009 and around 23 000 in 2010 (Kauhala et al. 2012). The increasing number of seals has hampered gill-net fishing in the Bothnian Bay, especially for whitefish, as the main fishing sites of this species are located often in outer archipelago areas connected to the open sea, where seals are also more common than in the inhabited inner areas of the coast (Alpo Huhmarniemi, pers. comm.). Hence, it is evident that the focus of gill-net fishing, even when targeting whitefish, has gradually been shifted towards the inner coastal areas close

to large islands, bays and estuaries, i.e., into habitats preferred also by perch and other freshwater species such as pike and Cyprinids.

In addition to this, the appreciation of perch has increased among consumers and commercial fishermen. This is also reflected in the producer prices of these species as the producer price of ungutted perch has doubled from the early 2000s to 2013-2015. At the same time, the producer price for gutted whitefish has increased by only 30%, though the price of whitefish is still almost double of that of perch (Official Statistics of Finland 2017c). This has likely increased the profitability of fishing for perch in the inner areas. Unfortunately, the spatial resolution of the logbook data, i.e., the ICES statistical rectangles, is too low to perceive any changes of this scale in the fishing areas. The logbooks do not record the target species either. It is clear that our raw CPUE indices were not able to take into account these sorts of changes in the fishing and the raw CPUE indices rather reflected the annual total catches. The lower annual variation in the raw CPUE indices compared to the two other indices suggests that the raw CPUE indices probably also underestimated the annual variation in abundance, which is typical for perch in the Baltic Sea region (Böhling et al. 1991).

Our model-based estimates of the annual CPUEs are adjusted for the variable allocation of the effort between areas, fishers, and months, and are standardized to a fixed level of effort. Such adjusted and standardized estimates, using relevant available explanatory variables, are much more robust for changes in fishing and reflect the true trends in stocks more reliably than raw CPUE indices. Fisherman-specific random effects allowed us to take into account the autocorrelation of the CPUEs of one fisherman between subsequent months and years. With linear mixed models, we were also able to control the non-constant variation of observations by transforming the response variables, and assessing the need for re-weighting the observations.

In the choice of the statistic for the central tendency, the median is usually preferred over the mean in skewed distributions because it is robust to outliers and its interpretation is clear: half of the values are smaller and half are larger than the median. The raw CPUEs, used e.g., in a few studies of coastal fish in the Baltic Sea (Lehikoinen et al. 2011, Heikinheimo and Lehtonen 2016, Lehikoinen et al. 2017), however, are means and often from highly skewed data. In the raw CPUEs of our study, the annual means exceeded the 75% percentiles in many years indicating that a few observations with high values have a substantial impact of the means. Thus, the means for both the raw data and subsetted data were much higher (doubled) than the respective medians, which would be more suitable for this type of data. With the linear mixed models used here, when the monotonic nonlinear transformation (e.g., logarithm) of the response variable is required, estimates of the median are also more easily available than those of the mean. If the residuals in the transformed scale are symmetrically distributed, estimates of the median are obtained on the original scale from the fixed part of the model. If it is necessary to estimate the means with mixed models, some bias correction is needed for the fixed part predictions to be back-transformed to the original scale. However, the methods for bias correction are usually very complicated.

In this study, we calculated CPUEs for the entire 350-km long Finnish coastline of the Bothnian Bay. Lehikoinen et al. 2017 calculated raw CPUEs for single ICES statistical rectangles (there were ten rectangles in our study area). Similarly, it is possible to estimate CPUEs for more local level by the linear mixed model, but it is likely that the confidence limits will grew wider as the number of observations decrease. Misreporting is a potential source of bias in logbook data. Hentati-Sundberg et al. 2014 studied misreporting in the Swedish pelagic fishery in the Baltic Sea and concluded that total catches have been underestimated during part of their study period (1996-2009) and that systematic misreporting of species composition has taken place over the whole study period. The pelagic fishery in the Baltic Sea is regulated by annual quotas and due to the overcapacity in the fishery there is an obvious economic incentive explaining the misreporting. There are, however, no quotas or other evident reasons for misreporting in the coastal fishery for perch and other freshwater species in our study area. Neither is there any relevant information available of the issue and thus misreporting remains an uncertainty factor in our monthly logbook data.

Concluding remarks

We demonstrated that various methods to estimate CPUE indices from coastal gill-net fishery data can yield different results and conclusions. The risk of biased results with raw CPUEs is emphasized in monthly based data form mixed fisheries, such as in our case, as the allocation of the reported fishing effort for various catch species is often difficult or impossible. Then even small changes in the targeting behavior of fishermen might add bias into the results. Thus, standardization by subsetting and modelling is recommended to remove most of the annual variation in the data not attributable to changes in abundance. An advantage of using modelling techniques is also their ability to produce information for precision estimates. We finally conclude that monthly logbook data should not be underrated and CPUEs based on that data can produce usable information on fish abundance for various needs, especially in cases where fishery independent data is not available.

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Appendix

Table A1. Classification of gears in the Finnish monthly logbook.

Herring trap Salmon trap Whitefish trap Other trap Gill-nets for herring and sprat Gill-net trap Other gill-nets, mesh size under 35 mm Other gill-nets, mesh size 36-45 mm Other gill-nets, mesh size 46-50 mm Other gill-nets, mesh size 51-60 mm Other gill-nets, mesh size over 60 mm Other longline of hook gear Pot Push-up trap Other gear

Table A2. Estimates of the fixed effects parameters of the linear mixed model for the logarithmic CPUE of perch (kg/gill-net days). Reference classes of categorical predictor variables are indicated by zero estimate value. Estimate on row "Intercept" is the expected log-CPUE, when all categorical predictors are set to their reference values and continuous predictors to 0. The estimates in the other rows indicate differences from the intercept.

Effect (and value)	Estimate	Standard error	Degrees of freedom	t-value	Probability > I t-value I
Intercept	-1.2732	0.1865	1194	-6.83	< 0.001
Year, 1996	-0.4011	0.1578	1154	-2.54	0.0112
Year, 1997	-0.1723	0.1352	1002	-1.27	0.2028
Year, 1998	-0.1032	0.1396	1147	-0.74	0.4597
Year, 1999	-0.2940	0.1306	1138	-2.25	0.0246
Year, 2000	-0.3866	0.1254	1094	-3.08	0.0021
Year, 2001	-0.6261	0.1307	1199	-4.79	< 0.001
Year, 2002	-0.3374	0.1214	1027	-2.78	0.0056
Year, 2003	0.0515	0.1174	1070	0.44	0.6609
Year, 2004	-0.0344	0.1197	1139	-0.29	0.7737
Year, 2005	-0.1058	0.1188	1171	-0.89	0.3735
Year, 2006	0.0576	0.1111	1029	0.52	0.6042
Year, 2007	-0.0544	0.1125	1045	-0.48	0.6292
Year, 2008	-0.0829	0.1103	1053	-0.75	0.4526
Year, 2009	-0.2570	0.1068	1119	-2.41	0.0163
Year, 2010	-0.1869	0.1015	1092	-1.84	0.0660
Year, 2011	0.0017	0.0967	1071	0.02	0.9863
Year, 2012	0.0323	0.1007	1139	0.32	0.7487
Year, 2013	0.0323	0.0924	1164	0.35	0.7268
Year, 2014	0.0658	0.0890	1154	0.74	0.4597
Year, 2015	0				
Month, 5	0.2219	0.0460	2470	4.82	< 0.001
Month, 6	0.1950	0.0479	2456	4.07	< 0.001
Month, 7	0.3682	0.0456	2483	8.10	< 0.001
Month, 8	0.3101	0.0409	1873	7.58	< 0.001
Month, 9	0				

Effect (and value)	Estimate	Standard error	Degrees of freedom	t-value	Probability > I t-value I
Fishing area, 2	0.9228	0.1896	541	4.87	< 0.001
Fishing area, 3	1.1875	0.2120	840	5.60	< 0.001
Fishing area, 6	1.0801	0.1796	724	6.01	< 0.001
Fishing area, 7	0.9084	0.1689	613	5.38	< 0.001
Fishing area, 11	0.6752	0.1666	574	4.05	< 0.001
Fishing area, 12	1.2699	0.1876	895	6.77	< 0.001
Fishing area, 15	-0.1648	0.1831	756	-0.90	0.3685
Fishing area, 19	0.3735	0.1747	592	2.14	0.0329
Fishing area, 20	0				
Proportion of whitefish, 0%	0.6559	0.0598	2846	10.96	< 0.001
Proportion of whitefish, 5 %	0.8350	0.0637	2738	13.11	< 0.001
Proportion of whitefish, 15 %	0.4539	0.0601	2728	7.56	< 0.001
Proportion of whitefish, 25 %	0.1978	0.0597	2664	3.31	< 0.001
Proportion of whitefish, 35 %	0.1083	0.0576	2735	1.88	0.0604
Proportion of whitefish, 45%	0				
Logarithmic effort	-0.3349	0.0168	2964	-19.93	< 0.001

Table A2. (continued)