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NAFO Division 4TVn Fall Spawning Atlantic Herring (*Clupea harengus*) Assessment Framework Review: Catch per Unit Effort Abundance Index

Laurie D. Maynard, Lysandre Landry, and Jacob Burbank

Fisheries and Oceans Canada
Gulf Fisheries Centre
343 Université Avenue, P.O. Box 5030
Moncton, NB, E1C 9B6

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Foreword

This series documents the scientific basis for the evaluation of aquatic resources and ecosystems in Canada. As such, it addresses the issues of the day in the time frames required and the documents it contains are not intended as definitive statements on the subjects addressed but rather as progress reports on ongoing investigations.

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ABSTRACT

Catch per unit effort (CPUE) is a widely used index of relative fish abundance. CPUE can only be a reliable abundance index if factors are properly accounted for such as spatial and temporal targeting variation, harvester experience, fishery regulations, environmental factors, and gear technology. A revision of the CPUE index currently used in the North Atlantic Fisheries Organization (NAFO) 4TVn Atlantic Herring (*Clupea harengus*) stock assessment model was conducted in 2022 and identified fundamental issues. The objective of this revision was to address these identified issues, update the aggregation process, and the model for standardizing the CPUE index and determine the reliability of this index in the updated framework for assessing NAFO 4TVn fall spawning Atlantic Herring. Data quality was addressed by correcting several issues with data entry and by imputing missing values with medians. The nominal CPUE was standardized using a Generalized Additive Model (GAM) that included temporal, spatial, and gear-related variables. The CPUE-GAM had generally higher values than the previous CPUE index performed with a Generalized Linear Model (GLM). Despite these improvements, many gaps, issues, and uncertainties remained. It is, thus, imperative to question the reliability and usefulness of this index within the stock assessment model. We, thus, recommend that the future of this index use either the science logbook and/or the electronic logbooks and mandatory detailed logbooks, which both include precise metrics of effort. This shift of approach would, however, greatly decrease the data available and the continuity of the time series would be negatively impacted.

INTRODUCTION

Catch per unit effort (CPUE) is a widely used index of relative fish abundance. However, CPUE can only serve as a reliable abundance index if catchability is constant through time and space or if that changes can be quantified and incorporated into its calculation. Many factors may affect catchability and the CPUE's proportionality to true population abundance such as spatial and temporal targeting variation (Walters 2003; Carruthers et al. 2011; Hoyle et al. 2024), harvester experience (Punt et al. 2001; Ward et al. 2013; Feenstra et al. 2019), fishery regulations (Maunder and Punt 2004; Cheng et al. 2023), environmental factors (Hoyle et al. 2024), and gear technology (Wilberg et al. 2010). Standardization is therefore required to isolate the signal of population abundance from noise due to these confounding factors (Campbell 2004; Hoyle et al. 2024). To achieve this, models such as generalized linear models (GLMs; Gavaris 1980; Yuan et al. 2024), generalized additive models (GAMs; Jones et al. 2025), generalized linear mixed models (GLMMs; Maunder and Punt 2004; Hsu et al. 2022), or more advanced spatio-temporal models (VAST; Thorson 2019; Yuan et al. 2024) are used.

For Atlantic Herring (*Clupea harengus*) in NAFO (North Atlantic Fisheries Organization) Division 4TVn, the fixed gear gillnet fishery has been the primary source of commercial Herring landings since 1981.The fall fixed gear fishery occurs at night and targets spawning grounds at depths of 5 to 20 m in 4T coastal waters typically from August through October (Maynard et al. 2024). Multiple gillnets are set once a school of sufficient size is located (LeBlanc et al. 2012), these nets are set for short durations, and may be hauled once to multiple times a night before coming to port and weighing the catch. An ideal effort metric for such a fishery would be soaking time (Hubert and Fabrizio 2007), but effort could also be inferred with the number of hauls in one outing.

A fishery that targets spatial and temporal concentration of spawning fish results in highly concentrated fishing effort. This can pose a challenge when using a CPUE index to track stock abundance, because catchability may remain high even as overall stock abundance declines, a phenomenon known as hyperstability (Hilborn and Walters 1992). The opposite pattern, hyperdepletion, can also occur. In this case, the abundance index declines even if the population as a whole is stable. This occurs when previously fished regions are no longer targeted for reasons independent of the abundance, such as new regulation, protected areas, or changes in how variables are recorded. To limit the effect of hyperdepletion, one solution is to standardize the nominal CPUE using only areas that have been consistently fished over time and impute the remaining spatial and temporal gaps in data (Carruthers et al. 2011; Hoyle et al. 2024). Another solution is weighting by the surface area of core fishing grounds to address spatial unevenness in fishing effort (Hoyle et al. 2024). Ideally, including detailed spatial and temporal effects such as geographic coordinates and exact date and time of each fishing event in the standardization model would further reduce the effects from uneven spatial and temporal distribution of fish and effort (Maunder et al. 2020).

The number, mesh size, and length of gillnets have changed through time depending on management measures, fishing area, and harvester preference. The most commonly used mesh size throughout the time series is 2.63 inches, however historically a small percentage used 2.75 or 2.88 inches mesh. Nets used are generally around 14 to 15 fathoms. In some Herring Fishing Areas (HFA), some nets are fished with one end tied to the boat and the other end anchored, whereas in most other areas, nets are anchored at both ends (LeBlanc et al. 2012). All of this variability, among many others, presents significant challenges to the development of a reliable CPUE abundance index and the ability to standardize to a constant catchability. These changes can increase or decrease the catch for a stable effort. Similarly, a more experienced harvester generally has higher success, sometimes independently from abundance and with reduced effort compared to a less experienced harvester. Removing less experienced harvesters or the first year of activity could be a way to account for this variation among harvesters (Punt et al. 2001; Ward et al. 2013), but it would not account for variations among more experienced harvesters. Furthermore, a harvester looking to commercially sell their catch may exhibit different behavior than when fishing for bait or personal consumption. Changes in regulations and data recording methods can also bring in biases among fishers or recording mean (electronic logbooks vs paper logbooks; Cheng et al. 2023). There are several ways to address these differences, but mainly, including gear characteristics, harvester identifications, years of experience and data source into the standardization process could improve our ability to detect and adjust for these underlying biases (Punt et al. 2001; Ward et al. 2013; Cheng et al. 2023).

For Atlantic Herring NAFO 4TVn assessment, the CPUE standardized with a GLM (CPUE-GLM) has been used as an abundance index in the stock assessment model (Maynard et al. 2024). This index was revised in 2022 to understand and document what had been done in the past while also translating the code from SAS to R (Landry et al. 2024). This review identified fundamental issues that required rethinking and further revision. For example, the standardization model only included temporal effects (year and week) and net length embedded in the effort. It also aggregated and removed data from criteria that needed to be revisited after changes in data recording methods through time.

The objective of this revision is therefore, to address most of these identified problems, update the aggregation process given the constraints related to data availability and quality, update the correction and standardization of the data, incorporating recent improvements in effort information, and finally improve CPUE model with knowledge and advancements in best practices (Hoyle et al. 2024). Following the implementation of these improvement, the reliability of this index was assessed.

METHODS

DATA

Catch data is recorded in purchase slips, DMP (Dockside Monitoring Program) reports, and ZIFF (Zonal Interchange File Format) files collected by the Statistics Branch of Fisheries and Oceans Canada (DFO). The ZIFF files are based on information collected by the DMP that provides accurate, timely, and independent third-party verification of fish landings. Contracted companies are hired by the fishing industry to observe the offloading of fish and to record and report the landings information to DFO (Figure 1; Claytor et al. 1992; Claytor 1998; Leblanc et al. 2001).

ZIFF files are prioritized as the source for the catch data during the time series and supplemented by purchase slips for missing data from 1986 to 2002. Catch data by vessel and trip are only available beginning in 1985. Thus, the time series used is from 1986 to 2023 and is available by fishing trip, defined by vessel identifier, fishing area, landing port, and landing date. Most fishing trips are associated with a catch location reported as a NAFO subdivision and/or HFA. Records with missing vessel identifier, date, or port were removed. Since the changes of mandatory logbook in 2022 (hereafter updated logbooks) and voluntary electronic logbooks (e-logs) in 2024 (Figure 1; DFO 2025), variables such as catch date and location (latitude and longitude) have been included, along with others informative variables about fishing effort (Table 1). Zero values (effort with no catch) were not recorded consistently through the time series, but have been increasingly reported recently (Table A1).

We obtained the proportion of fall herring spawners in a catch using the gonadosomatic index of mature fish and by otolith for immature fish sampled at port by DFO staff (Cleary et al. 1982; McQuinn 1989). We match a sample data to a fishing trip catch using nearest sample; landing date and fishing area as NAFO subdivision (Figure 2), and then use this nearest proportion of fall herring to scale the fishing trip catch. This is a change from the CPUE-GLM methodology that used 100% of the catch from weeks 27 to 43 in the CPUE calculation.

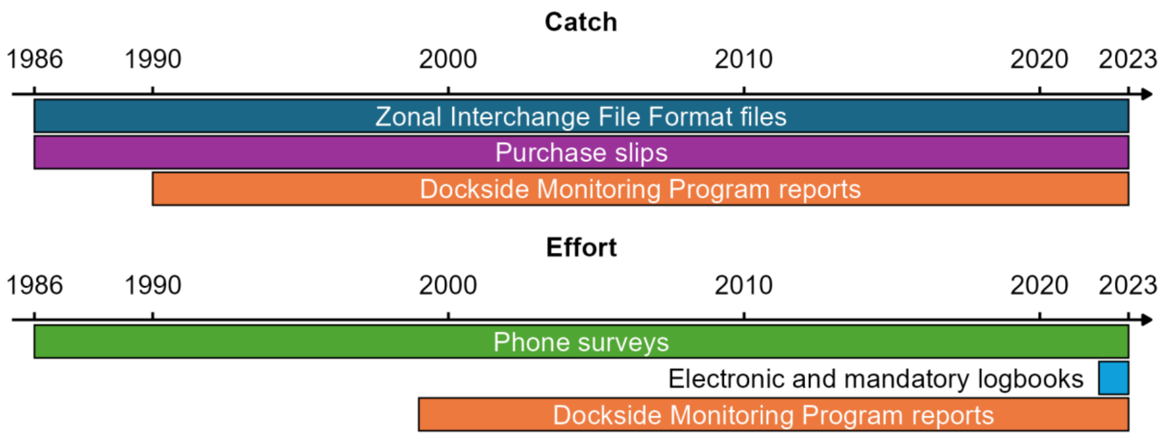

Figure 1. Timeline of data source available for catch and effort data.

Effort data have been recorded by the DMP since 1999 (Figure 1), however the completeness of these data vary markedly (Table 1). Specifically, DMP records the number of nets set and the number of nets fished, the net length and the mesh size used for a fishing trip. We aimed to accurately interpret the historic definitions of "nets set" and "nets fished" used in previous scripts and assessments. These definitions have been reviewed to: "net sets" as the number of nets that were set, and "nets fished" as the number of nets that were hauled. Thus, to address years without e-logs and updated logbook data, we created a "number of hauls" variable calculated as the number of nets fished divided by the number of net sets. The DMP effort information is not consistently recorded on all trips.

Effort information is also collected through an annual telephone survey, conducted since 1986, which aims to interview approximately 30% of active commercial licence holders, stratified by area (Table 1, Figure 3). The telephone survey systematically gathers data, on a variety of effort information including the number of nets and hauls, net length, and mesh size used by season and vessel identifier after 1992 (or vessel manager identifier before 1992; LeBlanc and LeBlanc 1996; Table 1). Since 2006, the telephone survey also included a question on the number of fishing days where no fish were caught, however this information is only available for the most recent period, it is not included in the calculation of fishing effort.

Table 1. Availability of variables for CPUE standardization across data sources.

COMPONENTS	EFFECTS	VARIABLES	DATA SOURCES: ZIFF files	Purchase Slips	DMP reports	Phone surveys	Science / Mandatory logbooks
Catch	-	Real quantity	X	X	X	-	-
		Estimated quantity	-	-	-	X	X
Effort	-	Soaking time	-	-	-	X	X
		Number of hauls	-	-	Partial	By year	X
Standardization	Time	Date	X	X	X	-	X
	Spatial	Coordinates	Partial	-	-	Spawning ground	X
		Fishing area	X	X	X	X	X
	Fisher	Vessel or Fisher ID	X	X	X	X	X
	Gear	Number of nets	-	-	Partial	By year	X
		Net length	-	-	X	By year	X
		Mesh size	-	-	X	By year	X
		Net height	-	-	-	By year	X

For the effort data sources, we imputed the most probable fishing areas (i.e., NAFO subdivision and HFA; Figure 2) for a vessel identifier by date and port, or by season and year if missing. We also imputed the median net length and mesh size for missing data by fishing area, season, year or by season, year, if missing. In the CPUE-GLM, when information on net length was missing for the CPUE calculation, a default value of 15 fathoms was used until 2013 and 14 fathoms in 2014 and beyond as these net lengths were the means for the respective time period (McDermid et al. 2016; Landry et al. 2024). Records still missing date, or fishing area as well as missing information on number of nets, were removed, because they could not be used to inform the effort calculation. The level of spatial aggregation has been changed from the CPUE-GLM methodology which previously aggregated the data by telephone survey area (Figure 3) and region (North, Middle, and South; Figure 2).

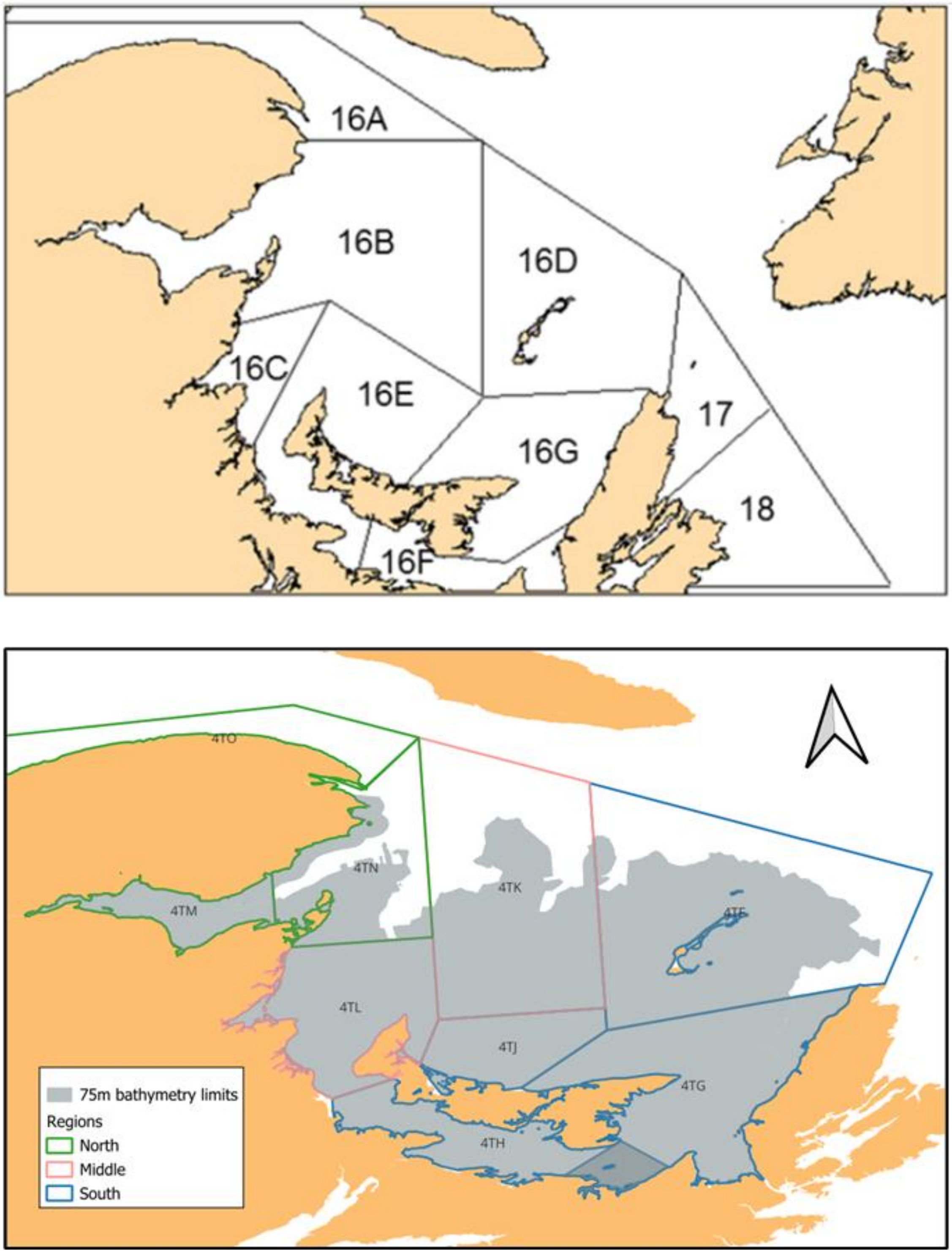

Figure 2. Upper panel southern Gulf of St. Lawrence Herring Fishing Areas (HFA) for fisheries management. Lower panel is the Northwest Atlantic Fisheries Organization (NAFO) Division 4T subdivisions. Areas surrounded by green boxes represent the North Region, red boxes represent the Middle Region, and blue boxes the South Region. The grey area represents the surface area of each NAFO subdivisions used and corresponds to the limit of 75 m bathymetry lines for each subdivision. Regions are spawning ground areas used by each corresponding fall herring subpopulation.

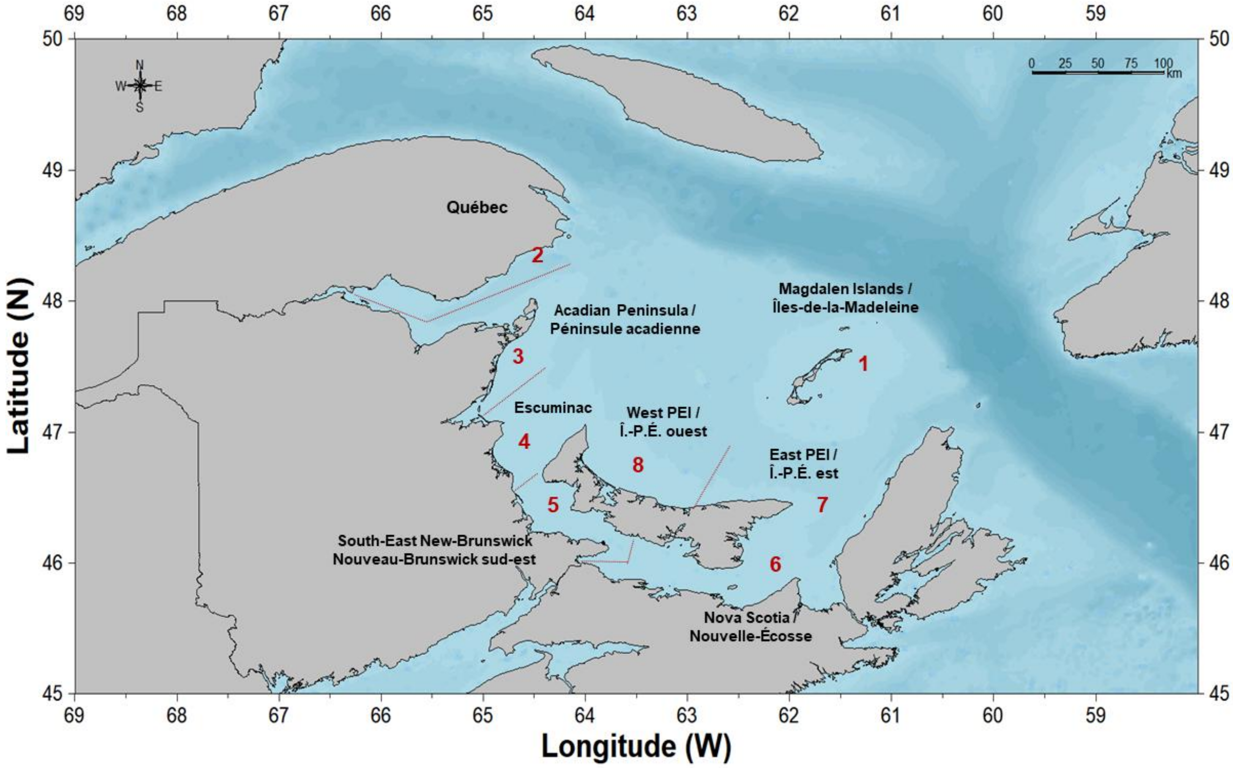

Figure 3. Telephone survey areas.

DATA STANDARDIZATION AND CORRECTIONS

The fall season definition have been adjusted to correspond to the catch at age definition of seasons for subregional fixed fisheries (Turcotte et al. In press). In the previous review fall season correspond to month greater or equal to 7, more precisely to week 27 to 43, it's now correspond to month between 7 and 10; corresponding to week 26 to 44.

Errors in the raw data on net length and mesh size were corrected as in previous assessments taking into account inconsistencies in measurement units (Landry et al. 2024).

EFFORT AND NOMINAL CPUE CALCULATION

Due to a misinterpretation of the SAS effort calculation scripts during the translation to R in Landry et al. (2024), the calculation of fishing effort for the fall fishery (specifically the number of net hauls) relied exclusively on telephone survey data, unlike in the historical stock assessment research documents which prioritized the data source (DMP or telephone survey) that had the largest sample size. The updated methodology incorporates additional data from DMP and logbooks including mesh size and spatial level. We also calculated a 'number of hauls' variable from the 'net set' and 'net fish' columns in DMP reports (see section above). In the e-logs and updated logbooks, the number of hauls is entered directly for each fishing event and was thus used for years 2022 and onwards (Figure 4).

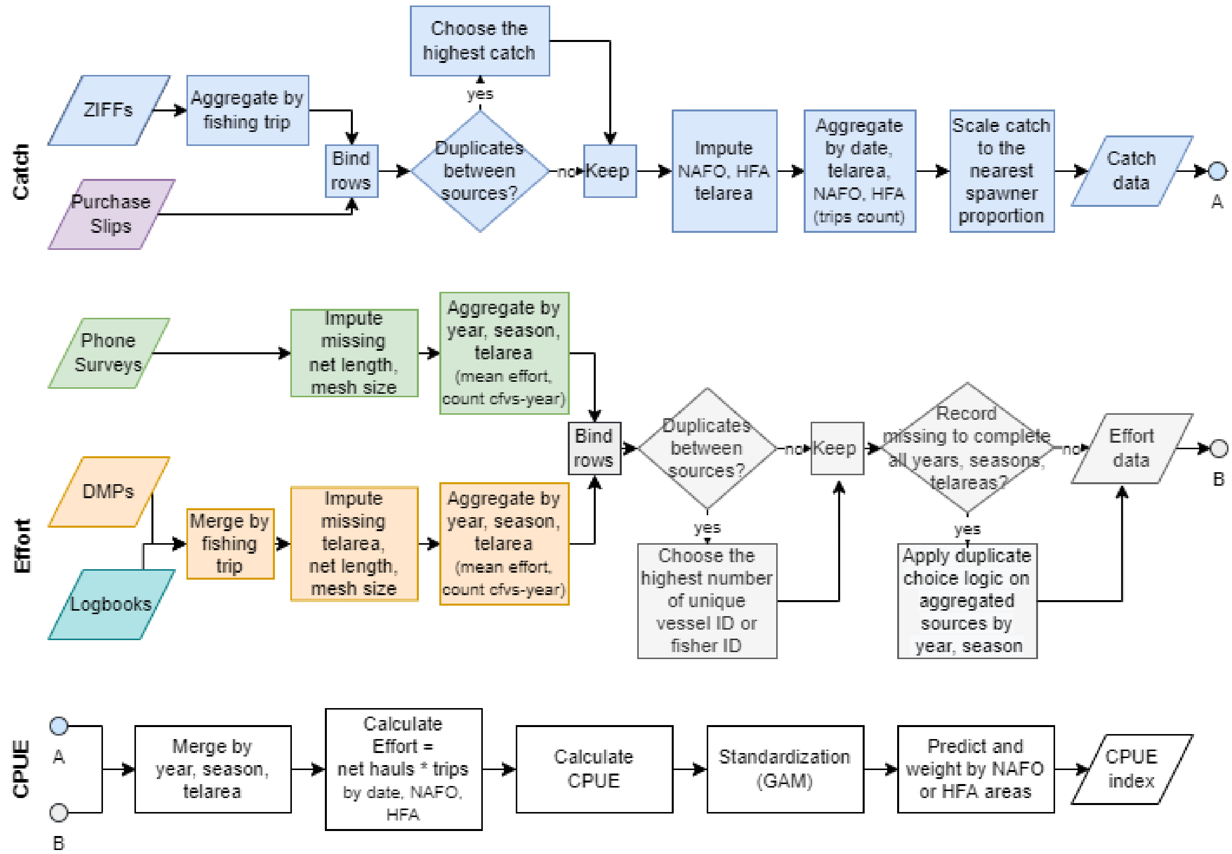

Figure 4. Flow chart of the catch and effort data computation and CPUE standardization process.

The average number of net hauls per vessel (or record) is calculated for each data source, stratified by year, season, and telephone survey area (telarea; Figure 3). To determine the final estimate for number of net hauls (i.e., number of hauls * number of nets) to be used for the effort calculation, the source with the highest number of observations (defined by the count of unique vessels or harvesters) is selected for each stratum. Missing stratum values are imputed using averages calculated by year and season where the source with the larger sample size is again prioritized. The method is also consistent with LeBlanc et al. (2008) which preserved effort information from telephone surveys prior to the recording of the vessel identifier in 1992, or when vessel identifier or harvester was missing. These methods also improved coverage through all years and fishing areas (Landry et al. 2024).

The effort values are then applied by landing year and telephone survey area to the corresponding scaled catch data. Finally, nominal CPUE is calculated as the daily landing (kg) per vessel, divided by the number of trips per mean number of nets per number of hauls.

$$nominal\ CPUE\ = \frac{Landing\ (kg)}{Trips * Mean\ (Nets *\ Hauls)}$$

CPUE STANDARDIZATION

To standardize the nominal CPUE and estimate an abundance index the following was used:

$$\text{nominal CPUE} \sim year +\ s(week) +\ s(meshSize) + s(netLength)$$
$$+\ spatialLevel\ +\ sourceEffort$$

The formula was modelled using a Generalized Additive Model (CPUE-GAM) with the R *mgcv* package (Wood 2017). We used *GCV.Cp* criterion for smoothing parameter estimation (Wood 2008). For temporal effect, non-linear smoothing functions (i.e., $s()$) were applied to the week of the year, but year was kept as a fixed factor for predicting purposes. Spatial level, corresponding to either the NAFO subdivision (North and South models) or the HFA (Middle model; Figure 2), was added as a fixed effect to account for spatial heterogeneity and effects. We used the HFA for the Middle model because this subpopulation only comprises two different NAFO subdivisions (4Tl and 4Tk) and there was no catch data in 4Tk. A non-linear smoothing function was also applied to mesh size and net length to account for gear effect. We also added a fixed effect for the provenance of the effort calculation (net hauls) as the source of that value changed with new regulations over the years. All knots were set as default value of *k = 10*, except for mesh size which was set at *k = 3* given the limited variation in value that could not allow smoothing with higher number of windows. Other values of knots were not explored in this version of the revision but are recommended for any further use of the CPUE index.

Different error distribution were tested (sensitivity analysis) to land on the distribution that achieved the best fit while meeting the model assumptions. Given our dataset is composed of positive continuous value (Figure 5), a Tweedie distribution with a logarithmic link function was utilized (Wood et al. 2016). The Tweedie distribution allows for the choice of the power parameter (*p*) enabling the variance to scale proportionally to the mean. As *p* increases from 1 to 2, the underlying distribution transitions from a Poisson distribution (*p = 1*), through a compound Poisson-Gamma distribution (*1 < p < 2*), to a Gamma distribution (*p = 2*) (Kendal 2004; Wood et al. 2016). The *mgcv::tw* function was used to automatically choose the appropriate *p* distribution.

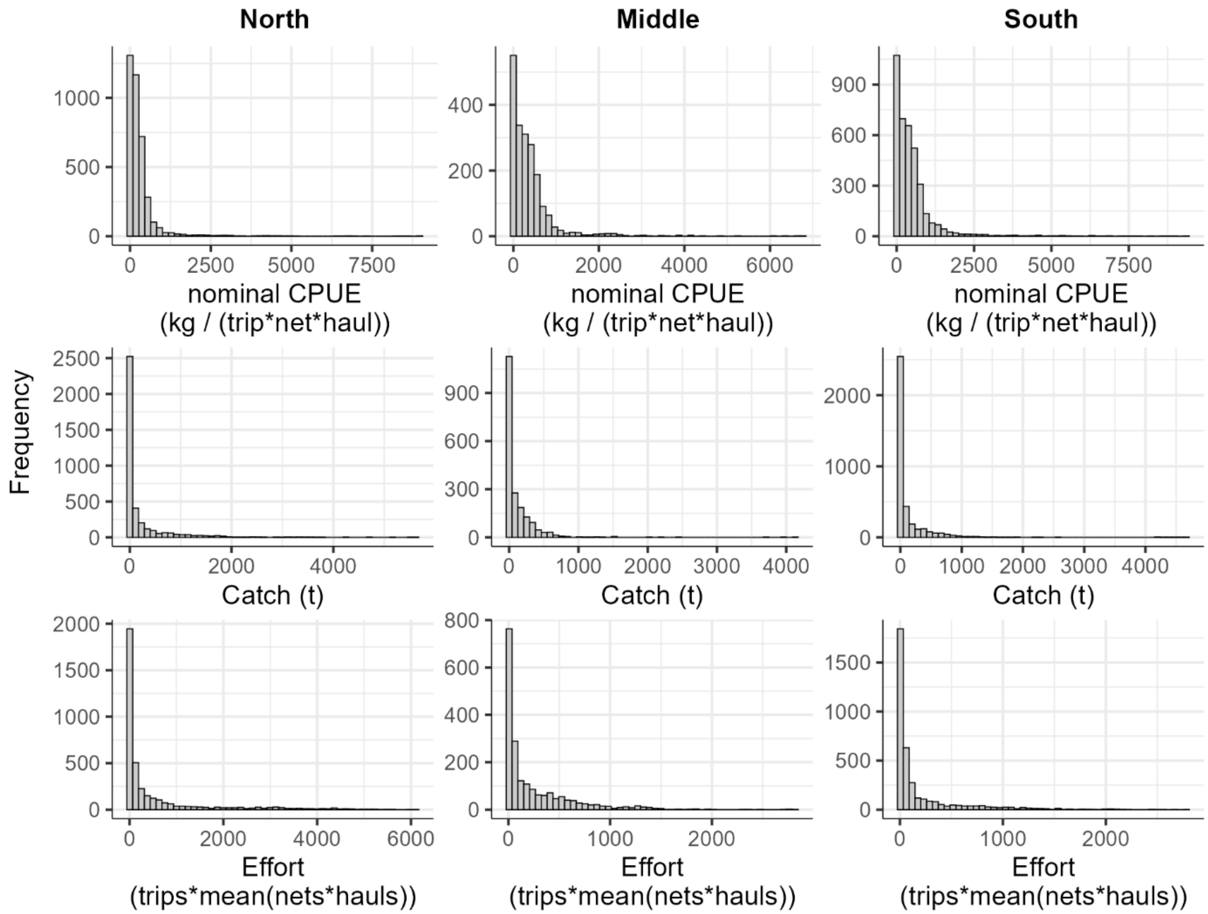

*Figure 5. Histogram of nominal CPUE (kg / trip*net*haul; top), catch(tonne; center) and effort (trips*mean(nets*hauls); bottom) data frequency for each fall herring subpopulations (North: left, Middle: center, South: right).*

We also tested a different alternative approach using catch as the response variable and including the log-transformed effort as an offset instead of modelling the nominal catch per unit of effort ratio. To decide on the best error distribution, we evaluated the estimated dispersion parameter $\hat{\phi}$. Values from 1.5 to 3 were considered moderately overdispersed, but acceptable for highly aggregating species like pelagic schooling fish. Values of 3 and above were considered severely overdispersed, potentially indicating the wrong choice of distribution, the presence of outliers, or the absence of one or more important explanatory variables (Maunder and Punt 2004; Zuur et al. 2009). We also visually inspected the homoscedasticity and normality of the residuals using Q-Q plots, residual versus fitted values plots, and boxplots of residuals against factor levels.

Once the best error distribution was selected, different variable combinations were tested to selected the best model to use for predicting the abundance index (Table 2). To select the best model we used a hierarchical selection model framework and chose the model with the lowest Akaike Information Criteria (AIC; Table 2). The spatial level (NAFO subdivisions or HFAs) and the source of effort data (telephone surveys or DMP reports) were kept in all models. Models were separated by subpopulations (North, Middle, and South) to generate a regional index and fit to the stock assessment models (Maynard et al. 2024; Turcotte et al. In press).

Table 2. Hierarchical model selection process when standardizing the nominal CPUE.

Models	Variables						Number of variables
M1	year	+ week	+ meshSize	+ NetLength	+ sourceEffort	+ spatialLevel	6
M2	year	+ week		+ NetLength	+ sourceEffort	+ spatialLevel	5
M3	year	+ week	+ meshSize		+ sourceEffort	+ SpatialLevel	5
M4	year	+ week			+ sourceEffort	+ spatialLevel	2
M5	Year				+ sourceEffort	+ SpatialLevel	3
M6	Year					+ spatialLevel	2
M7	Year						1

To extract an index from the model, we generated a data frame by expanding with each level of week, year and spatial level. We averaged mesh size and net length over all the years and chose the telephone survey as the source of effort to standardize the index of abundance. We then used *mgcv::predict.gam* function to estimate the CPUE value for each iterations. We then averaged the weekly predicted CPUE value by year and spatial level (NAFO subdivisions or HFAs).

We then calculated the area-weighted sum of the CPUE by year (Maunder et al. 2020). We first extracted the surface area of the spatial level in the model, from the coast to depths < 75 m as the gillnet fishery is unlikely to occur in deeper waters (Figure 2). In spatial levels where waters were generally deeper near the coast, we added a buffer of 10 km around the coastline to still reflect spatial availability. We then estimated a weight by spatial level by dividing the surface area of the spatial level by the sum of all surface areas of spatial level within a subpopulation (i.e., North, Middle, South). The CPUE by year and spatial level was multiplied by the weight. This is meant to scale local density to the available habitat area, mitigating biases caused by uneven distribution of fishing effort across spatial levels (fishery effect). Finally, to produce one value per year, we summed the spatially-weighted abundance index for each year.

COMPARISON OF GAM AND GLM

Both the GAM and GLM were run separately for North, Middle, and South. There are several key differences in the dataset, methodology, and variables included in each analysis. This differences include:

- The nominal CPUE for the CPUE-GLM was calculated after standardizing number of nets to a net length of 14 fathoms, therefore, net length was not incorporated as an explanatory variable. For the CPUE-GAM, CPUE was calculated with unstandardized number of nets, so net length was included as a variable in the model.
- Mesh size was also not included in the CPUE-GLM but included in the CPUE-GAM.
- CPUE-GLM spatially aggregated by region. CPUE-GAM includes spatial level as a factor in the model and the spatial level is NAFO subdivisions or HFAs.
- CPUE-GLM data is aggregated by week and missing data are filled in by mean values at this summarized level for analysis, however the CPUE-GAM keeps each individual catch record (i.e. fishing trip) and fills in missing values with mean values at the individual record level. As a result, the two analyses are being conducted on different starting data.

The CPUE-GLM and CPUE-GAM models were each run on their respective datasets and results were compared between the historical and revised methodology. To further compare between the differences in starting datasets, the GLM was also re-run on the revised dataset.

RESULTS

ERROR DISTRIBUTION AND MODELLING APPROACH

For error distribution, the two options that performed the best were the Gamma distribution (Tweedie, $p = 2$) with or without using the log-transformed effort as an offset. These models had dispersion parameters varying from 1.39 to 1.84 , however homoscedasticity and normality assumptions were slightly better for the model without the offset (Table A2 - A4; Figure A1 - A3). Analysis of model residuals revealed independent errors for the Middle subpopulation, but minor residual autocorrelation at short lags (1, 2) for the North and South subpopulations, and lags of 7 to 10 for the North subpopulation; this was acknowledged but not corrected in the final models (Figure A4). Therefore, the following sections present the outputs of the GAMs using a Gamma error distribution without using the log-transformed effort as an offset. From this point, we will refer to these models as the CPUE-GAM models.

Overall, the CPUE-GAM models provided a better fit to their respective data sets, furthermore the CPUE-GAM was better able to address the large number of small CPUE values when compared to the CPUE-GLM (Figure A5). Additionally, the standardization CPUE-GAM model did not show patterns in residuals against factor levels (Figure 7).

A notable issue for the CPUE-GLM is that the early weeks are consistently under fit while the later weeks are over fit (Figure 6; Figure A5). This systematic issue does not appear to be as strong in the CPUE-GAM perhaps because missing data is more appropriately replaces by the most relevant spatial, temporal, and individual level and not at an aggregated level.

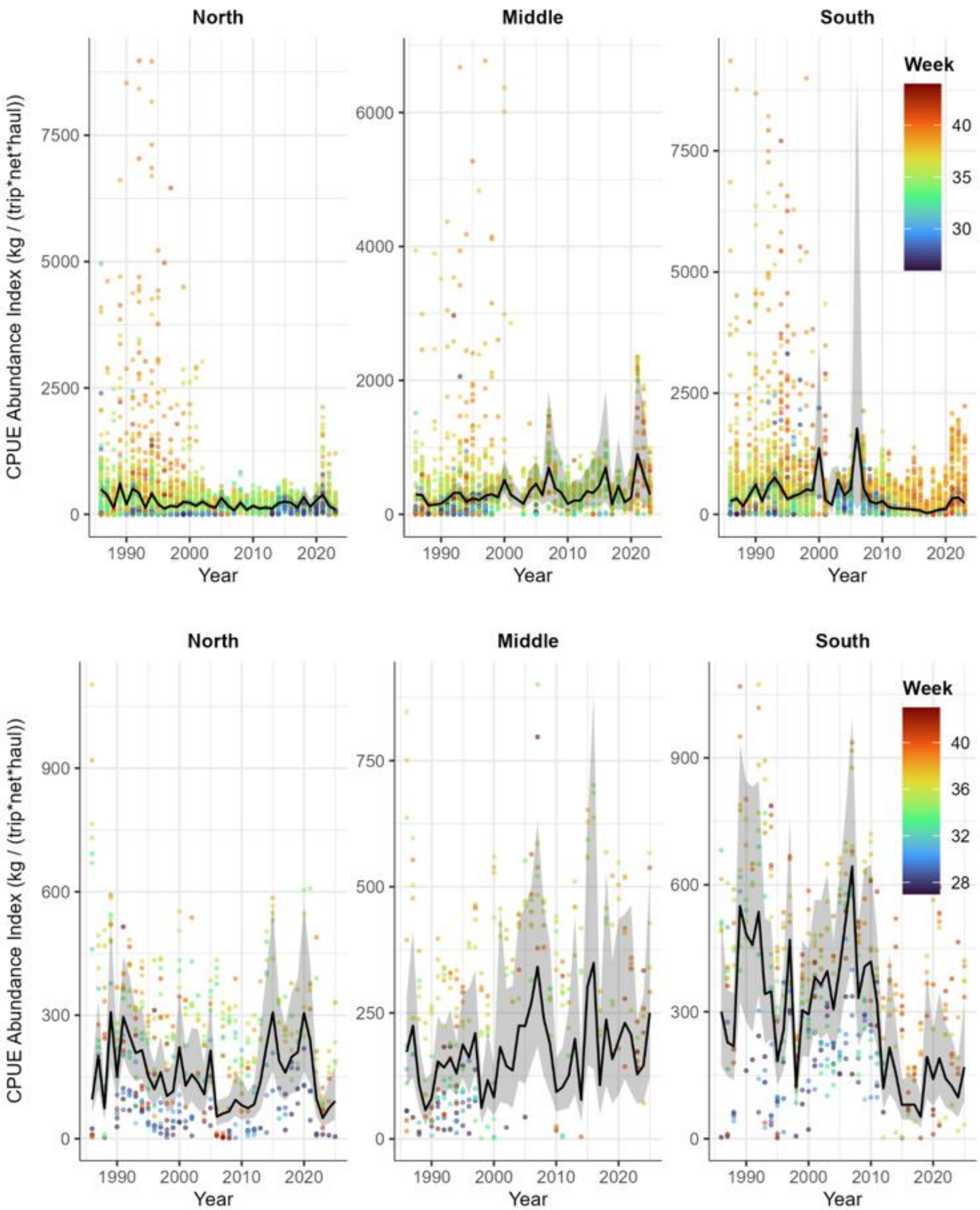

Figure 6. Nominal CPUE values over years (1986 to 2023) and weeks (26 to 44: top; 27 to 43: bottom) for each fall herring subpopulations (North: left, Middle: center, South: right) with their respective CPUE abundance index. The top row presents the CPUE-GAM method (black line; this research document; whereas the bottom row presents the CPUE-GLM method (Rolland et al. 2022): bottom).

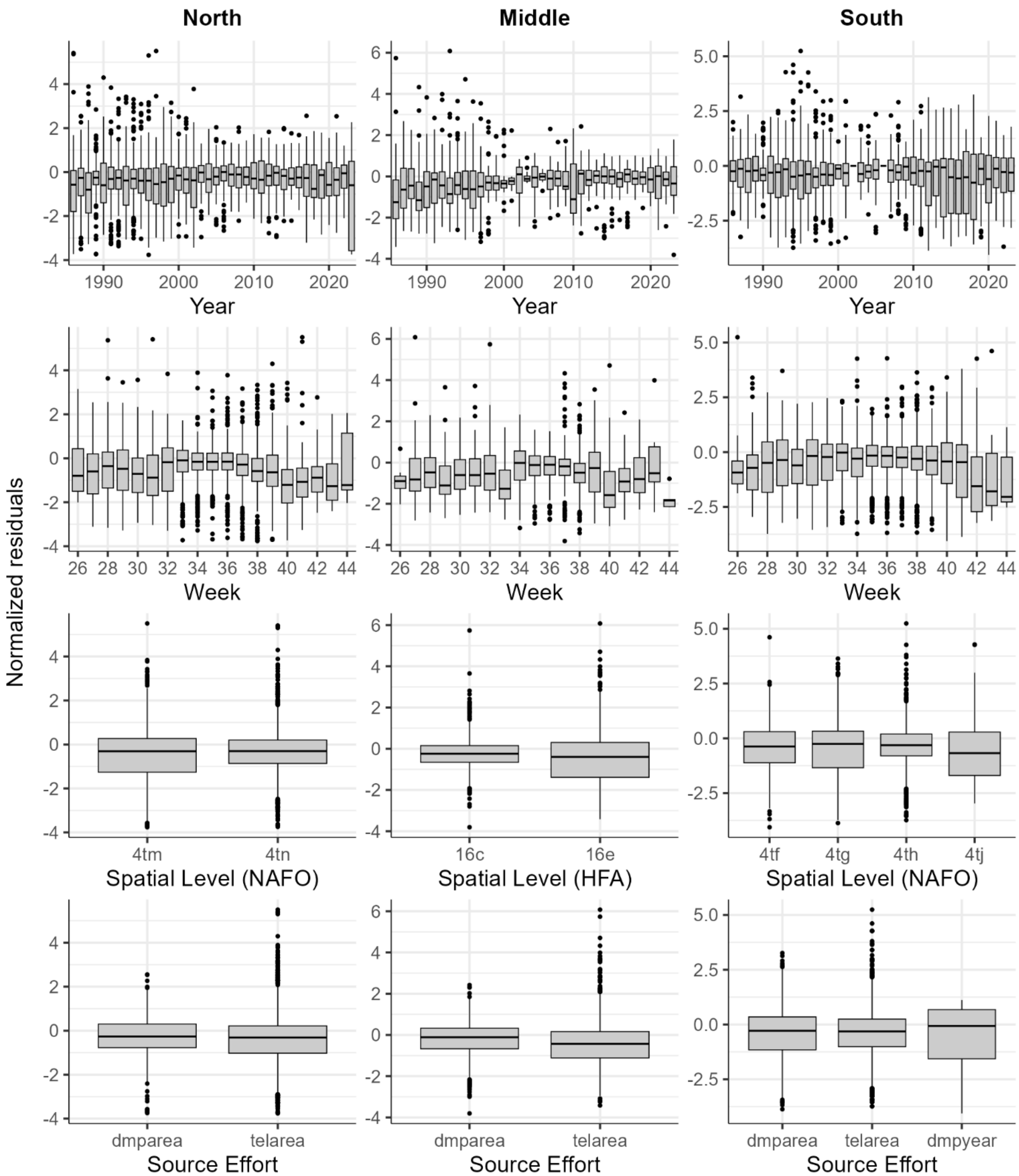

Figure 7. Boxplots of residuals against factor level for year, spatial level and source of effort by subpopulation (North; left, Middle; center and South; right) from the CPUE-GAM model. Week was also added to show lack of temporal patterns in the residuals.

ABUNDANCE INDEX

The selected models with the lowest AIC, for North, Middle and South subpopulations were models that used all variables (Table 3).

Table 3. Models with the lowest AIC for each subpopulation.

Models	Variables	AIC	dAIC
North			
M1	**year + week + meshSize + netLength + sourceEffort + spatialLevel**	**48982**	**0**
M2	year + week + netLength + sourceEffort + spatialLevel	48992	9
M3	year + week + meshSize + sourceEffort + spatialLevel	49041	59
M4	year + week + sourceEffort + spatialLevel	49039	56
M5	year + sourceEffort + spatialLevel	50773	1791
M6	year + spatialLevel	50770	1787
M7	year	50815	1833
Middle			
M1	**year + week + meshSize + netLength + sourceEffort + spatialLevel**	**26460**	**0**
0M2	year + week + netLength + sourceEffort + spatialLevel	26476	15
M3	year + week + meshSize + sourceEffort + spatialLevel	26486	26
M4	year + week + sourceEffort + spatialLevel	26498	38
M5	year + sourceEffort + spatialLevel	27120	660
M6	year + spatialLevel	27117	656
M7	year	27060	599
South			
M1	**year + week + meshSize + netLength + sourceEffort + spatialLevel**	**50928**	**0**
M2	year + week + netLength + sourceEffort + spatialLevel	50974	46
M3	year + week + meshSize + sourceEffort + spatialLevel	51070	143
M4	year + week + sourceEffort + spatialLevel	51132	205
M5	year + sourceEffort + spatialLevel	51793	865
M6	year + spatialLevel	51812	884
M7	year	52143	1216

The index varies from 23.06 to 1,177.35 kg / (trips * net * haul). The South subpopulation shows the greatest variations with a general decline over the time series. The other two subpopulations vary moderately, with the Middle subpopulation peaks in the early 2020s before declining and the North subpopulation a general decline throughout the time series (Figure 8).

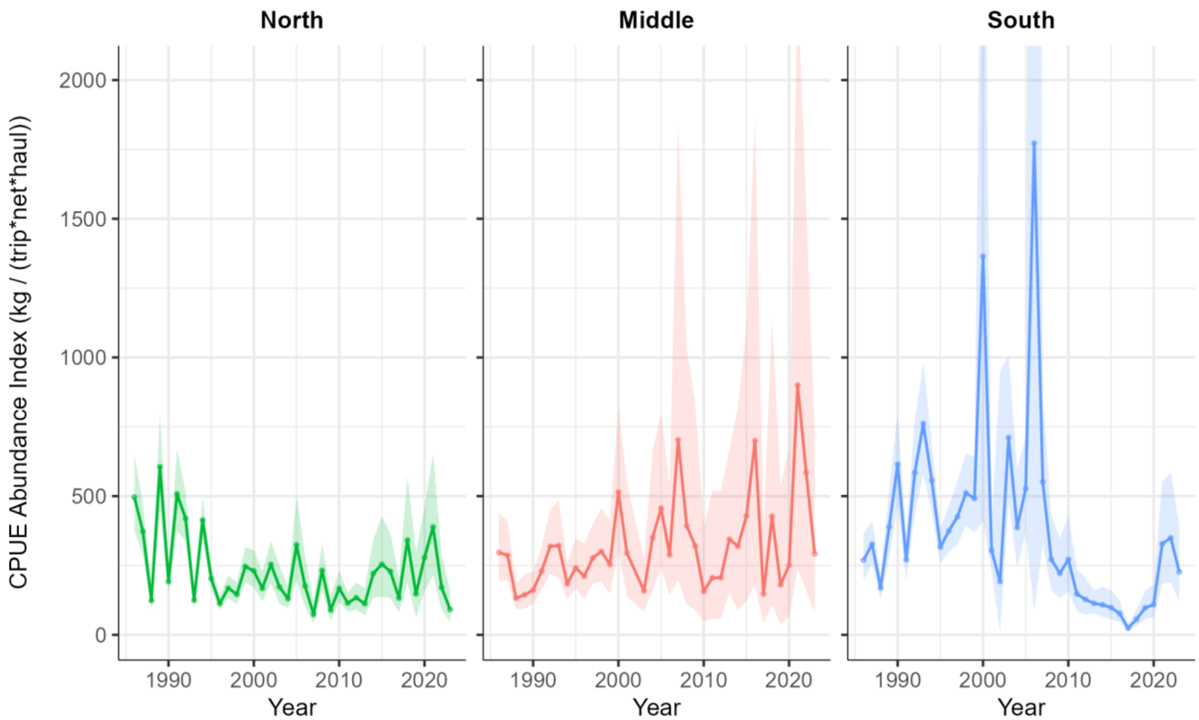

Figure 8. Abundance index of CPUE over years (1986 to 2023) for each fall herring subpopulation (North: top, Middle: center and South: bottom). Shaded ribbons represent the 95% confidence intervals for each model.

The CPUE for all subpopulations generally increases, peaking between weeks 38 and 40, before declining as the season advances and the quota is caught. However, in the Middle subpopulations, CPUE decreases through the 42nd week and then increases again thereafter which may coincide with the switch from the competitive 16CE quota to the dedicated quota. In the Middle, there are small increases in CPUE in the early weeks which likely reflect the summer fishery in that region. CPUE showed a more minimal and contrasting region-specific effect response to mesh size, with larger mesh sizes increasing CPUE in the North and Middle subpopulations, while reducing CPUE in the South subpopulation. The fishery has been conducted with nearly 100% of 2.63 inches mesh size since 2008. CPUE also shows variation across net lengths for all subpopulations. In the North subpopulation, CPUE decreases with increasing net length, with some small-scale variability indicating decreased returns for longer nets, while in the South population the opposite pattern is observed with higher CPUE at intermediate to longer net lengths and greater variability overall. The Middle region showed minimal variation but does suggest a slight peak in CPUE at a net length of approximately 14 fathoms (the average net length; Figure 9).

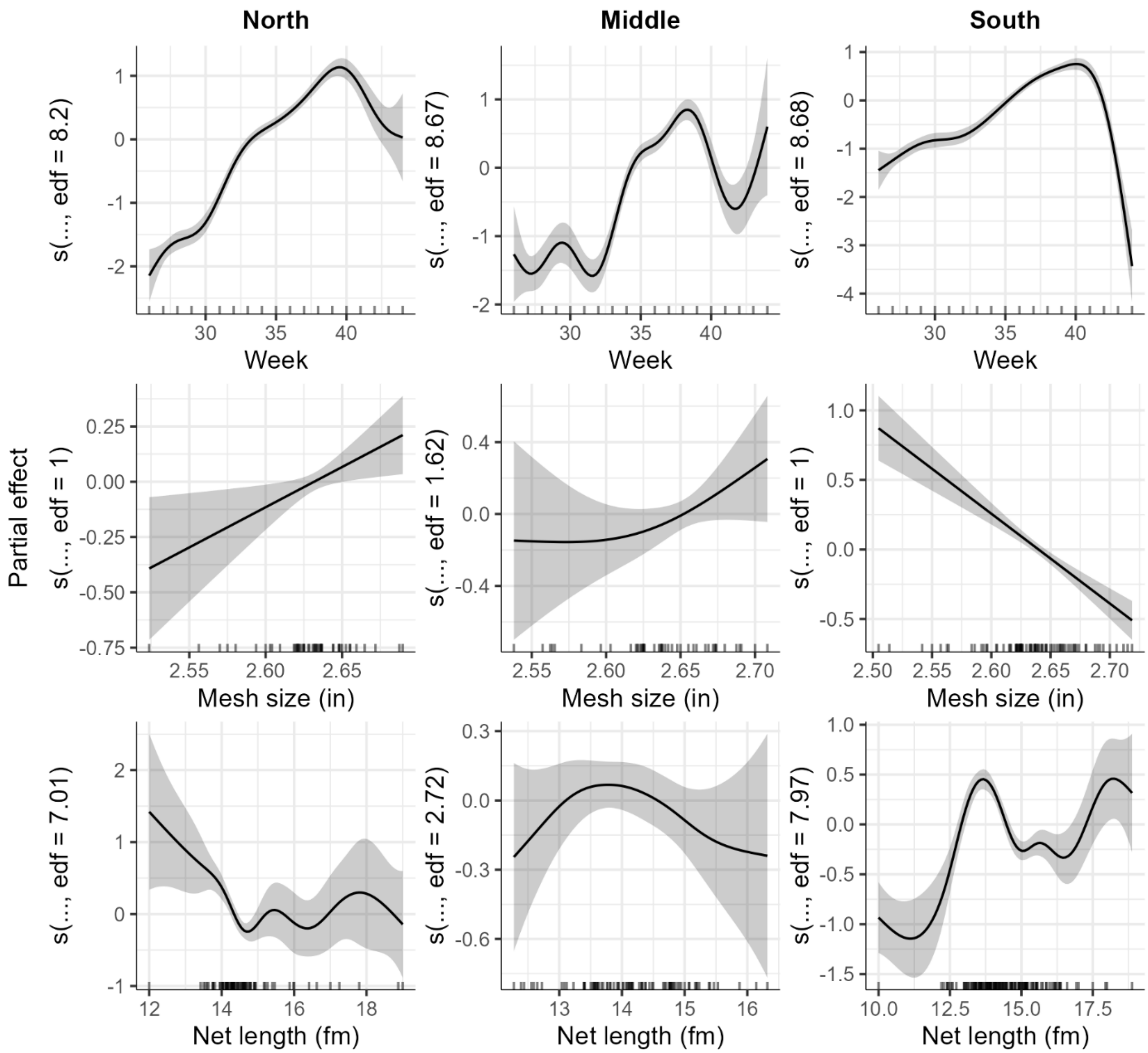

Figure 9. Smoothed parameter estimates for week, mesh size (inches; in) and net length (fathoms; fm) for each fall herring subpopulation (North: left, Middle: center and South: right).Y axis is smoothed values of the response variable (nominal CPUE) and edf (estimated degree of freedom) is the number of knots used by the model.

The CPUE-GAM is often higher than the previous CPUE-GLM in a given year (Figure 10). Overall the CPUE-GAM and CPUE-GLM show similar temporal patterns when predicting at the mean net length. There are year specific divergences in CPUE between the two methods. Overall, the CPUE-GAM appears noisier than the CPUE-GLM with greater variations from year to year.

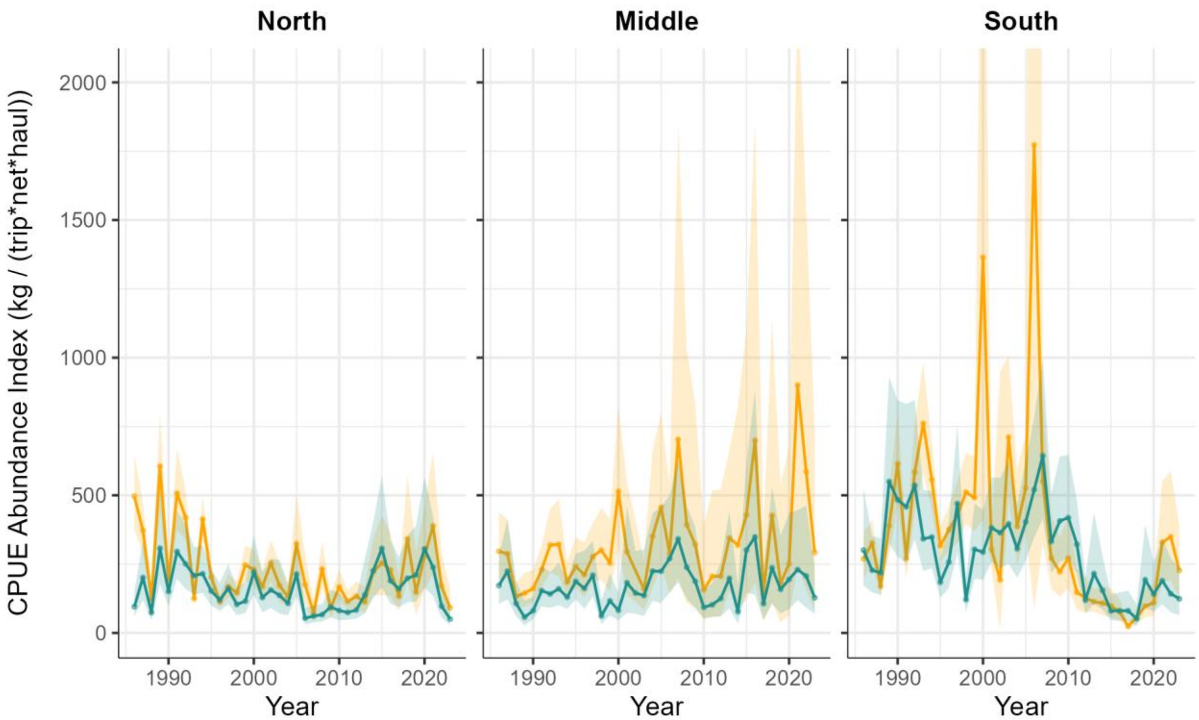

Figure 10. Comparison of CPUE abundance index over years (1986 to 2023) with the new standardization method using a GAM with Tweedie distribution (orange); and old method with a GLM with Gaussian distribution (Rolland et al. 2022; teal) for each fall herring subpopulation (North: left, Middle: center and South: right). Shaded ribbons represent the 95% confidence intervals for each model.

When the GLM model was run on both the historic CPUE-GLM dataset and on the newly revised dataset, the CPUE abundance index shows broadly similar temporal patterns across all three fall spawning subpopulations (North, Middle, and South; Figure 11). This indicates consistency in the direction and timing of major interannual variability despite the changes and enhancements done in implemented the new dataset. The revised dataset generally produces slightly higher peak values, slightly wider confidence intervals particularly during periods of elevated CPUE, and greater interannual variability especially in the recent years. Overall there is overlapping confidence intervals in most years in the three regions suggesting no major divergence in the direction or timing of major changes in abundance.

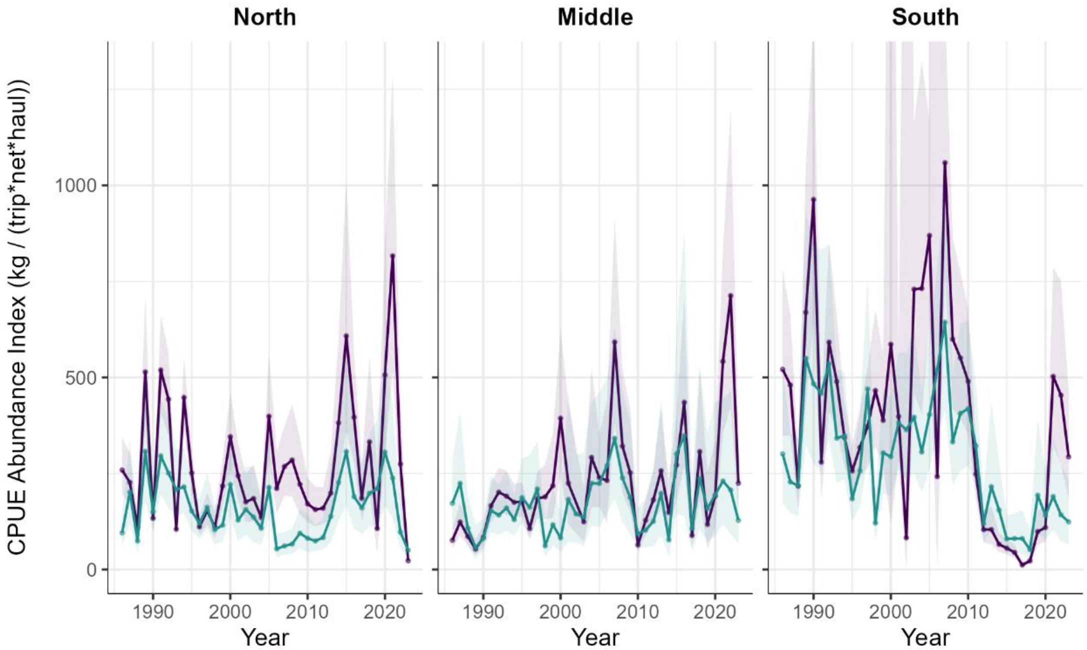

Figure 11. Comparison of CPUE abundance index over years (1986 to 2023) using the CPUE-GLM standardization method on both the new revised dataset (this research document; purple); and the previous dataset (Landry et al. 2024; teal) for each fall herring subpopulation (North: left, Middle: center and South: right). Shaded ribbons represent the 95% confidence intervals for each model.

DISCUSSION

We made substantial efforts to standardize the CPUE despite major gaps and missing information in the herring fishery data. We were able to fix many issues at the data sources and include variables previously omitted from the CPUE-GLM. While the CPUE-GAM was generally higher in values than the CPUE-GLM, it could be the result of data corrections (e.g.; keeping all fishing trips instead of mean per week per spatial level) which integrated more data into the model than previously. However, despite the improvements in the model diagnostic and performance, the abundance index remains noisy, generally noisier than the previous CPUE-GLM. The CPUE-GAM model appears to better account for the many low (near zero) catch values in the data which may contribute to the greater noise.

Seasonal timing is consistently important to CPUE across all regions, but the direction and magnitude of gear effects vary strongly by region. These results highlights the importance of accounting for region-specific relationships when standardizing catch rates or interpreting spatial differences in CPUE. More critically, essential variables needed to properly quantify fishing effort are still absent, creating weaknesses at the core of the calculation (Figure A6 - A8). Because of these limitations, the abundance index derived from CPUE may not provide an accurate reflection of true stock abundance.

One substantial drawback of the current approach is that the effort estimation itself is not particularly robust mainly because there is much uncertainty on the number of hauls from the DMP and telephone survey data. Choosing the telephone survey to estimate the number of hauls as an alternative means significantly lowering the resolution of the data. Since the telephone survey only records one or two values (i.e., peak and non-peak effort) for the entire fishing season, as a result there is a significant loss of the potential variations in harvester behaviour among fishing events and as the season progresses. Potentially, using a regression to standardize to number of hauls between sources before the effort calculations could help reduce this bias and allow us to remove the source variable from the standardization model later on (Cheng et al. 2023). Yet, the number of hauls is still not an ideal metric of effort. Rather, soaking time would be more representative of effort, where we could possibly expect a more proportional relationship between catch and effort and this information is only available from the telephone survey and therefore only available for the whole year.

This is true of other variables as well since we often only have partial information (DMP reports) or yearly information (telephone surveys) on effort variables. For the gear effects, while we have relevant information about the mesh size and the net length, several assumptions are made around these values. The mesh size and net length is often lacking in DMP reports and purchase slips, and we either use a median relative to vessel, season, and year (or vessel and year) to fill the gaps. This is less problematic when compared to net hauls as harvesters are unlikely to change the length and mesh size of gear used throughout the fishing season. When the information is lacking at the vessel level the median value for the spatial level and year is used. Having accurate and complete information would reduce this uncertainty, and the updated logbooks and e-logs will greatly improve the effort information if filled in correctly and completely.

While we were able to include the subpopulation of fishing in the model (i.e., NAFOs, HFAs) and test some area-weighting options, Maunder et al. (2020) describe this tactic as flawed relative to the use of true spatial components (geographic coordinates) and spatiotemporal models. Furthermore, while NAFO subdivision is recorded in the ZIFF data, the HFA is associated with the homeport and licence and may not accurately represent the area in which the fishing activity took place. For example, there isn't a real separation between 16C and 16E as it is a shared fishing area that begins the season with a competitive quota for the combined regions that becomes a province-specific quota (which can also be fished in both 16C and 16E) when the competitive quota is caught. The temporal effect however, is likely the only effect with suitable precision as the date is consistently recorded throughout our data. Yet, errors and bias may still be present, especially in early years where reports were not necessarily entered promptly. Therefore, early in the timeseries there is still sometimes uncertainty around the recorded date and whether it represents the date of fishing or the date the report was finally submitted, but this is likely more of an issue in the spring fishery (Landry et al. 2024).

An additionally challenge with the data is that harvester and fishery effect can not be adequately accounted for in the models. Because we aggregate by landing date due to paucity of data, we remove the information that may identify a harvester and thus remove the possibility of accounting for it in a mixed model. While we explored the possibility of not aggregating landing date, the resulting data frame had even more gaps to fill which ended up diluting the response significantly. We were, however, able to use the surface area of the NAFO subdivisions or HFAs to account for spatial availability for the fishery (Maunder et al. 2020) which provides a modest step toward precisely estimating a harvester or fishery effect on CPUE. In the future, approaches to account for these effects could include using the science logbooks, which are filled yearly by a few fishermen by subpopulation but include complete information on daily effort and catch.

We also note that the standardization model did not include environmental variables such as sea temperature or bottom depth, despite their recognized importance (Hoyle et al. 2024; Jones et al. 2025). Although averaged environmental values could have been incorporated, the ideal approach would require geographic coordinates and detailed catch-and-effort data at the fishing-event level to avoid diluting environmental effects.

CONCLUSIONS

In addition to these issues, it is also important to consider herring are naturally aggregative (i.e., school) and can be caught in large quantities with minimal effort despite variations in abundance (hyperstability; Hilborn and Walters 1992). It is, thus, imperative to question the reliability and usefulness of this index within the stock assessment model. The uncertainty around the effort calculation is unlikely to be resolved across the entire time series and as a result many of these challenges will remain. However only using the science logbook (1995+ depending on the region) and/or the e-logs and updated logbooks (2022+), would allow us to include both precise metrics such as soaking time, complete net characteristics and geographic coordinates but it would substantially truncate the timeseries which may result in making it less informative.

In the near future, there are some steps that can be taken to improve the CPUE index. First, restructuring the data integration process by using the telephone survey as the foundational dataset and merging the catch data into it. The telephone survey encompasses other important effort variables that are not yet digitized or taking into account, such as harvester identifiers, specific spawning grounds fishing locations, harvester experience, soak time, and net height. Once the database is consolidated, the model can incorporate these new covariates. For instance, utilizing net height would allow us to calculate the true net surface area rather than relying solely on net length, which will provide a more accurate representation of effort. We could also examine whether including effort information from the multiple data sources (DMP reports, telephone surveys, and Science logbooks) would improve the uncertainty in the CPUE model. Finally, several statistical adjustments should be explored to optimize the model. To account for varying data quality, a lower statistical weight should be applied to imputed data. The model could also incorporate a year-by-spatial-level interaction term (*year * spatialLevel*) to capture spatio-temporal dynamics in the fishery. As sensitivity analyses, we recommend running alternative models using exclusively the high-quality datasets mentioned above (i.e., only the science logbooks or only the mandatory logbooks) to evaluate the overall robustness of the index.

REFERENCES CITED

Campbell, R.A. 2004. CPUE standardisation and the construction of indices of stock abundance in a spatially varying fishery using general linear models. Fish. Res. 70(2-3 SPEC. ISS.): 209–227.

Carruthers, T.R., Ahrens, R.N.M., McAllister, M.K., and Walters, C.J. 2011. Integrating imputation and standardization of catch rate data in the calculation of relative abundance indices. Fish. Res. 109(1): 157–167.

Cheng, M.L.H., Rodgveller, C.J., Langan, J.A., and Cunningham, C.J. 2023. Standardizing fishery-dependent catch-rate information across gears and data collection programs for Alaska sablefish (*Anoplopoma fimbria*). ICES J. Mar. Sci. 80(4): 1028–1042.

Claytor, R.R. 1998. Assessment of the NAFO Division 4T Atlantic herring stock, 1997. DFO Can. Stock Assess. Sec. Res. Doc. 98/047. 10 p.

Claytor, R.R., Nielsen, G., Dupuis, H.M.C., and Mowbray, F. 1992. Assessment of Atlantic herring in NAFO division 4T, 1991. Can. Atl. Fish. Sci. Advis. Comm. Res. Doc. 92/076. 1–88.

Cleary, L., Hunt, J., Moores, J., and Tremblay, D. 1982. Herring aging workshop, St. John's, Newfoundland, March 1982. DFO Can. Atl. Fish. Sci. Advis. Comm. Res. Doc. 82/041. 10 p.

DFO. 2025. Rebuilding plan: Atlantic Herring, Clupea harengus, spring spawner component - NAFO Division 4T.

Feenstra, J., McGarvey, R., Linnane, A., Haddon, M., Matthews, J., and Punt, A.E. 2019. Impacts on CPUE from vessel fleet composition changes in an Australian lobster (*Jasus edwardsii*) fishery. New Zeal. J. Mar. Freshw. Res. 53(2): 292–302.

Gavaris, S. 1980. Use of a multiplicative model to estimate catch rate and effort from commercial data. Can. J. Fish. Aquat. Sci. 37: 2272–2275.

Hilborn, R., and Walters, C.J. 1992. Quantitative Fisheries Stock Assessment. Springer US.

Hoyle, S.D., Campbell, R.A., Ducharme-Barth, N.D., Grüss, A., Moore, B.R., Thorson, J.T., Tremblay-Boyer, L., Winker, H., Zhou, S., and Maunder, M.N. 2024. Catch per unit effort modelling for stock assessment: A summary of good practices. Fish. Res. 269: 106860.

Hsu, J., Chang, Y.J., and Ducharme-Barth, N.D. 2022. Evaluation of the influence of spatial treatments on catch-per-unit-effort standardization: A fishery application and simulation study of Pacific saury in the Northwestern Pacific Ocean. Fish. Res. 255: 106440.

Hubert, W.A., and Fabrizio, M.C. 2007. Analysis and Interpretation of Freshwater Fisheries Data. *In* Analysis and Interpretation of Freshwater Fisheries Data. American Fisheries Society. pp. 279–326.

Jones, A.W., Mercer, A.J., Duarte, D.G., and Curti, K.L. 2025. Combining sources of high-resolution fishery-dependent data from the northeast United States to develop a catch rate time series. ICES J. Mar. Sci. 82(3): 32.

Kendal, W.S. 2004. Taylor's ecological power law as a consequence of scale invariant exponential dispersion models. Ecol. Complex. 1(3): 193–209. Elsevier.

Landry, L., Turcotte, F., Rolland, N., McDermid, J.L., Cosandey-Godin, A., and Harbicht, A.B. 2024. Mise à jour de programmes de calcul de capture par unité d 'effort pour les sous-populations de hareng du sud du Golfe du Saint-Laurent par la traduction du langage SAS vers le langage R. Rapp. manus. can. sci. halieut. aquat. 3286: x + 66 p.

LeBlanc, C., and LeBlanc, L. 1996. The 1995 NAFO Division 4T Herring Gillnet Telephone Survey. DFO Atl. Fish. Res. Doc. 96/077. 1–37.

LeBlanc, C.H., Chouinard, G.A., and Poirier, G.A. 2001. Assessment of the NAFO 4T southern Gulf of St. Lawrence herring stocks in 2000. DFO Can. Sci. Advis. Sec. Res. Doc. 2001/045. 108 p.

LeBlanc, C.H., MacDougall, C., and Bourque, C. 2008. Assessment of the NAFO Division 4T southern Gulf of St. Lawrence herring stocks in 2007. DFO Can. Sci. Advis. Sec. Res. Doc. 2008/061. iv + 133 p.

LeBlanc, C.H., Mallet, A., MacDougall, C., Bourque, C., and Swain, D. 2012. Assessment of the NAFO Division 4T southern Gulf of St. Lawrence herring stocks in 2011. DFO Can. Sci. Advis. Sec. Res. Doc. 2012/111. vi + 167 p.

Maunder, M.N., and Punt, A.E. 2004. Standardizing catch and effort data: A review of recent approaches. Fish. Res. 70(2-3 SPEC. ISS.): 141–159.

Maunder, M.N., Thorson, J.T., Xu, H., Oliveros-Ramos, R., Hoyle, S.D., Tremblay-Boyer, L., Lee, H.H., Kai, M., Chang, S.K., Kitakado, T., Albertsen, C.M., Minte-Vera, C. V., Lennert-Cody, C.E., Aires-da-Silva, A.M., and Piner, K.R. 2020. The need for spatio-temporal modeling to determine catch-per-unit effort based indices of abundance and associated composition data for inclusion in stock assessment models. Fish. Res. 229(2): 105594.

Maynard, L.D., Burbank, J., DeJong, R., Turcotte, F., McDermid, J.L., Sylvain, F.-É., and Rolland, N. 2024. Supporting material for stock assessment of NAFO Division 4TVn southern Gulf of St. Lawrence Atlantic herring (*Clupea harengus*) in 2022-2023. DFO Can. Sci. Advis. Secr. Res. Doc. 2024/058: xiii + 149 p.

McDermid, J.L., Mallet, A., and Surette, T. 2016. Fishery performance and status indicators for the assessment of the NAFO division 4T southern Gulf of St. Lawrence Atlantic herring (*Clupea harengus*) to 2014 and 2015. DFO Can. Sci. Advis. Secr. Res. Doc. 2016/060: ix + 62 p.

McQuinn, I.H. 1989. Identification of Spring- and Autumn-Spawning Herring (*Clupea harengus harengus*) using Maturity Stages Assigned from a Gonadosomatic Index Model. Can. J. Fish. Aquat. Sci. 46(6): 969–980.

Punt, A.E., Pribac, F., Walker, T.I., and Taylor, B.L. 2001. Population modelling and harvest strategy evaluation for school and gummy shark. CSIRO Mar. Res. 99/102: 136 p.

Rolland, N., Turcotte, F., McDermid J L, DeJong, R.A., and Landry, L. 2022. Assessment of the NAFO division 4TVn southern Gulf of St. Lawrence Atlantic herring (*Clupea harengus*) in 2020-2021. DFO Can. Sci. Advis. Secr. Res. Doc. 2022/068: xii + 142 p.

Thorson, J.T. 2019. Guidance for decisions using the Vector Autoregressive Spatio-Temporal (VAST) package in stock, ecosystem, habitat and climate assessments. Fish. Res. 210: 143–161.

Turcotte, F., Landry, L., McDermid, J.L., Maynard, L., and Burbank, J. In press. NAFO Division 4TVn Fall Spawning Atlantic Herring (*Clupea harengus*) Assessment Framework Review: Fisheries and Surveys Data. DFO Can. Sci. Advis. Sec. Res. Doc.

Walters, C. 2003. Folly and fantasy in the analysis of spatial catch rate data. Can. J. Fish. Aquat. Sci. 60(12): 1433–1436.

Ward, H.G.M., Askey, P.J., and Post, J.R. 2013. A mechanistic understanding of hyperstability in catch per unit effort and density-dependent catchability in a multistock recreational fishery. Can. J. Fish. Aquat. Sci. 70(10): 1542–1550.

Wilberg, M.J., Thorson, J.T., Linton, B.C., and Berkson, J. 2010. Incorporating time-varying catchability into population dynamic stock assessment models. Rev. Fish. Sci. 18(1): 7–24.

Wood, S.N. 2008. Fast stable direct fitting and smoothness selection for generalized additive models. J. R. Stat. Soc. B 70: 495–518. [accessed 17 March 2026].

Wood, S.N. 2017. Generalized additive models: An introduction with R, second edition. *In* Generalized Additive Models: An Introduction with R, Second Edition, CRC Press.

Wood, S.N., Pya, N., and Säfken, B. 2016. Smoothing Parameter and Model Selection for General Smooth Models. J. Am. Stat. Assoc. 111(516): 1548–1563. American Statistical Association.

Yuan, T.L., Xu, H., Lu, B.J., and Chang, S.K. 2024. Comparison of linear and nonlinear modeling approaches to develop an abundance index based on voyage and market data for a data-limited fishery. Front. Mar. Sci. 11: 1344181.

Zuur, A.F., Ieno, E.N., Walker, N., Saveliev, A.A., and Smith, G.M. 2009. Mixed effects models and extensions in ecology with R. Springer New York, New York, NY.

APPENDIX A

Table A1. Number of zero landings in the ZIFF files and purchase slips dataset for each year and NAFO subdivision sorted by region.

Year	North					Middle		South		
	4Tm	4Tn	4To	4Tp	4Tq	4Tl	4Tf	4Tg	4Th	4Tj
1992	0	0	0	0	0	0	0	3	0	0
1993	0	0	0	0	0	0	0	1	0	0
1994	0	0	0	0	0	0	0	1	1	0
1995	0	0	0	0	0	0	0	1	0	0
1998	0	0	0	0	0	0	0	1	0	0
1999	0	0	1	0	0	0	0	1	0	0
2000	0	0	0	0	1	0	0	0	0	0
2002	0	0	0	0	0	0	0	1	0	1
2003	0	0	0	0	0	0	0	2	0	0
2004	0	0	0	0	0	0	0	4	0	0
2005	0	0	0	0	0	0	1	20	2	0
2006	0	0	0	0	0	0	5	19	0	0
2007	0	0	0	0	0	0	17	0	0	0
2008	2	1	0	1	0	0	14	0	0	0
2009	0	0	0	0	0	0	0	5	0	0
2010	0	0	0	0	0	0	0	6	0	0
2011	0	0	1	0	0	16	0	24	3	11
2012	0	0	0	0	0	15	0	16	1	12
2013	0	0	0	0	0	2	0	1	2	2
2014	0	1	0	0	0	2	0	1	3	6
2015	1	5	0	0	0	6	0	2	1	1
2016	6	5	0	0	0	0	15	2	0	1
2017	14	4	0	0	0	1	0	12	1	0
2018	4	2	0	0	0	2	16	2	0	1
2019	75	19	32	0	0	1	14	1	0	0
2020	43	5	34	0	0	0	13	0	0	0
2021	35	20	44	0	0	1	3	1	1	1
2022	1	0	2	0	0	0	0	0	0	0
2023	0	1	0	0	0	1	0	0	0	0

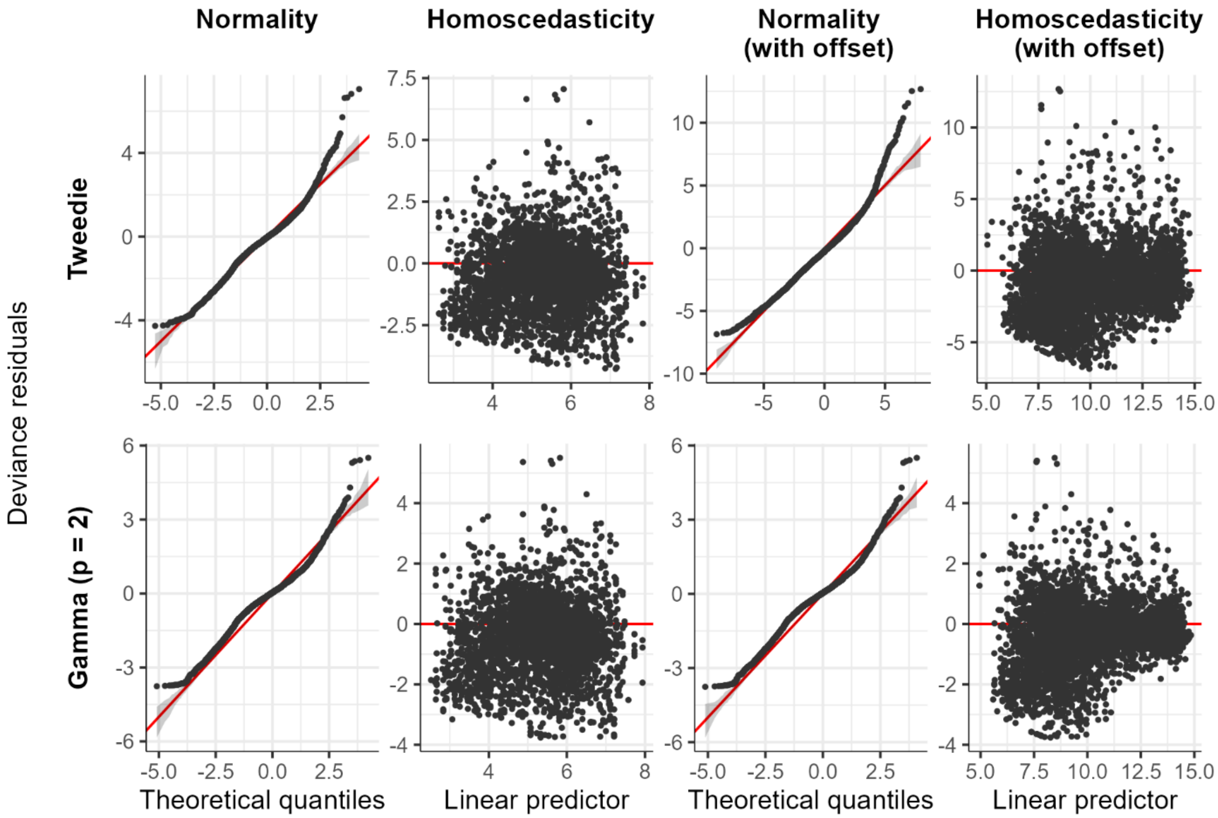

Figure A1. CPUE-GAM North subpopulation (fall spawners) QQ plots and residuals vs fitted values plot to select parameter p (distribution of data). Two right panels are diagnostics for model with an effort as an offset and the two left panels are without offset.

Table A2. North subpopulation diagnostics for CPUE-GAM model distributions selection. The tested distributions are defined by the index parameter (p) and offset (effort) and best error distribution model is diagnosed using the dispersion parameter (ϕ) and checks for normality and homoscedasticity (Figure A1).

Subpopulation	p	offset	ϕ	Normality	Homoscedasticity
North	1.926	no	1.641	OK	OK
North	2	no	1,592	OK	OK
North	1.818	yes	5.344	skewed	OK
North	2	yes	1,592	OK	trend

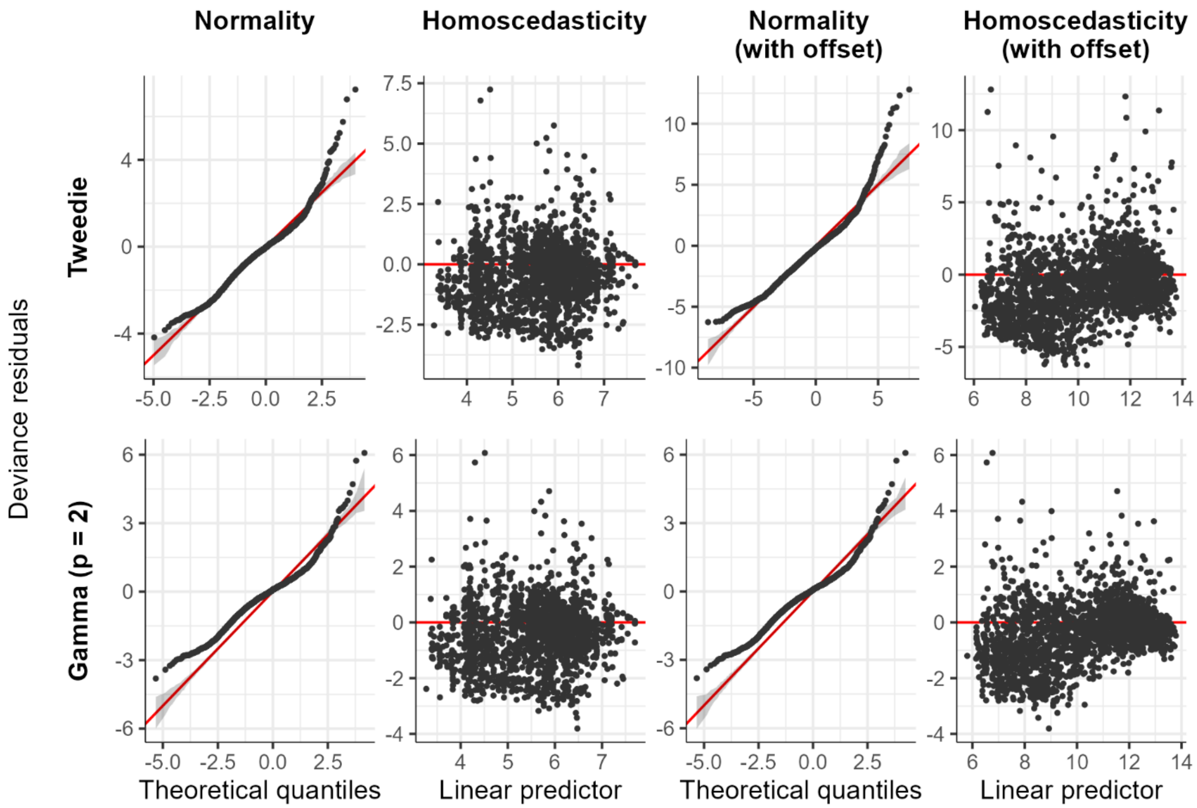

Figure A2. CPUE-GAM Middle subpopulation (fall spawners) QQ plots and residuals vs fitted values plot to select parameter p (distribution of data). Two right panels are diagnostics for model with an effort as an offset and the two left panels are without.

Table A3. Middle subpopulation diagnostics for CPUE-GAM model distributions selection. The tested distributions are defined by the index parameter (p) and offset (effort) and best error distribution model is diagnosed using the dispersion parameter (ϕ) and checks for normality and homoscedasticity (Figure A2).

Subpopulation	p	offset	ϕ	Normality	Homoscedasticity
Middle	1.934	no	1.552	skewed	OK
Middle	2	no	1,849	OK	OK
Middle	1.818	yes	5.285	skewed	OK
Middle	2	yes	1,849	skewed	trend

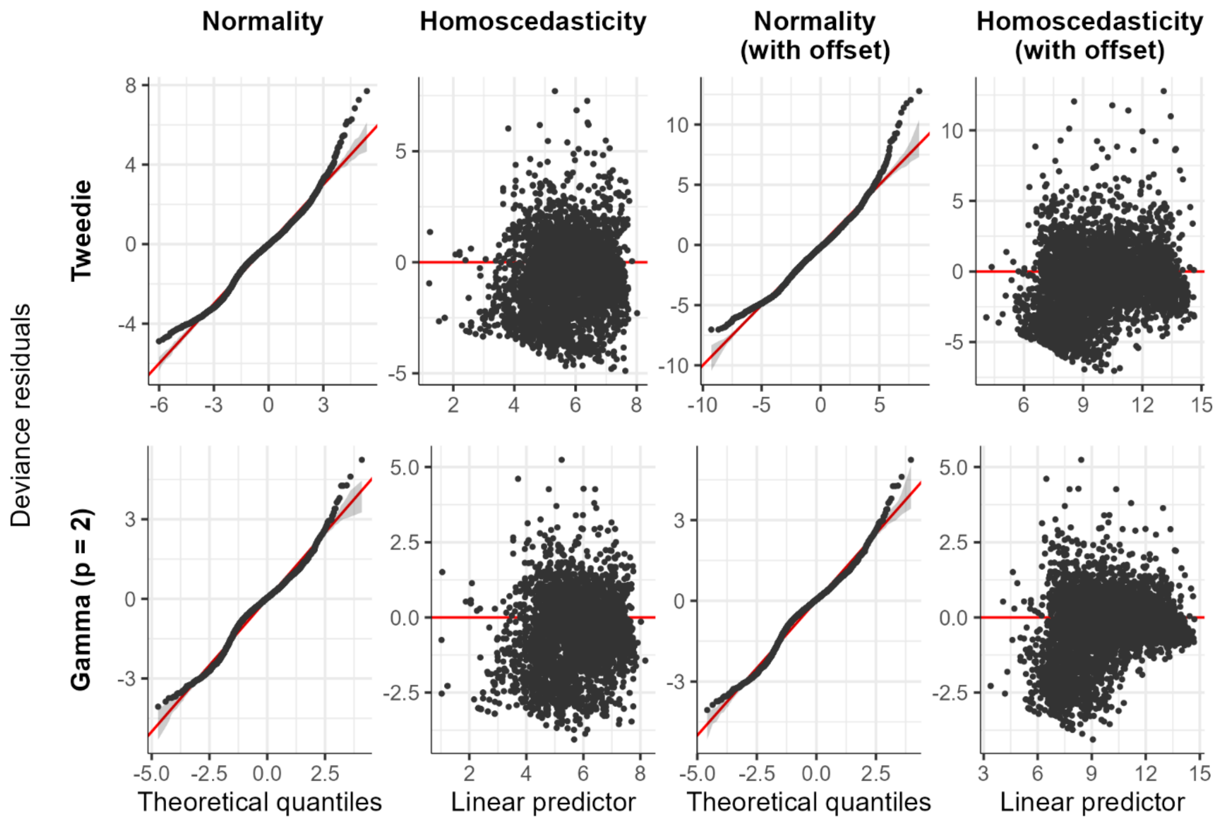

Figure A3. CPUE-GAM South subpopulation (fall spawners) QQ plots and residuals vs fitted values plot to select parameter p (distribution of data). Two right panels are diagnostics for model with an effort as an offset and the two left panels are without offset.

Table A4. South subpopulation diagnostics for CPUE-GAM model distributions selection. The tested distributions are defined by the index parameter (p) and offset (effort) and best error distribution model is diagnosed using the dispersion parameter (ϕ) and checks for normality and homoscedasticity (Figure A3).

Subpopulation	p	offset	ϕ	Normality	Homoscedasticity
South	1.855	no	2.498	skewed	OK
South	2	no	1,393	OK	OK
South	1.804	yes	5.983	skewed	trend
South	2	yes	1,393	OK	trend

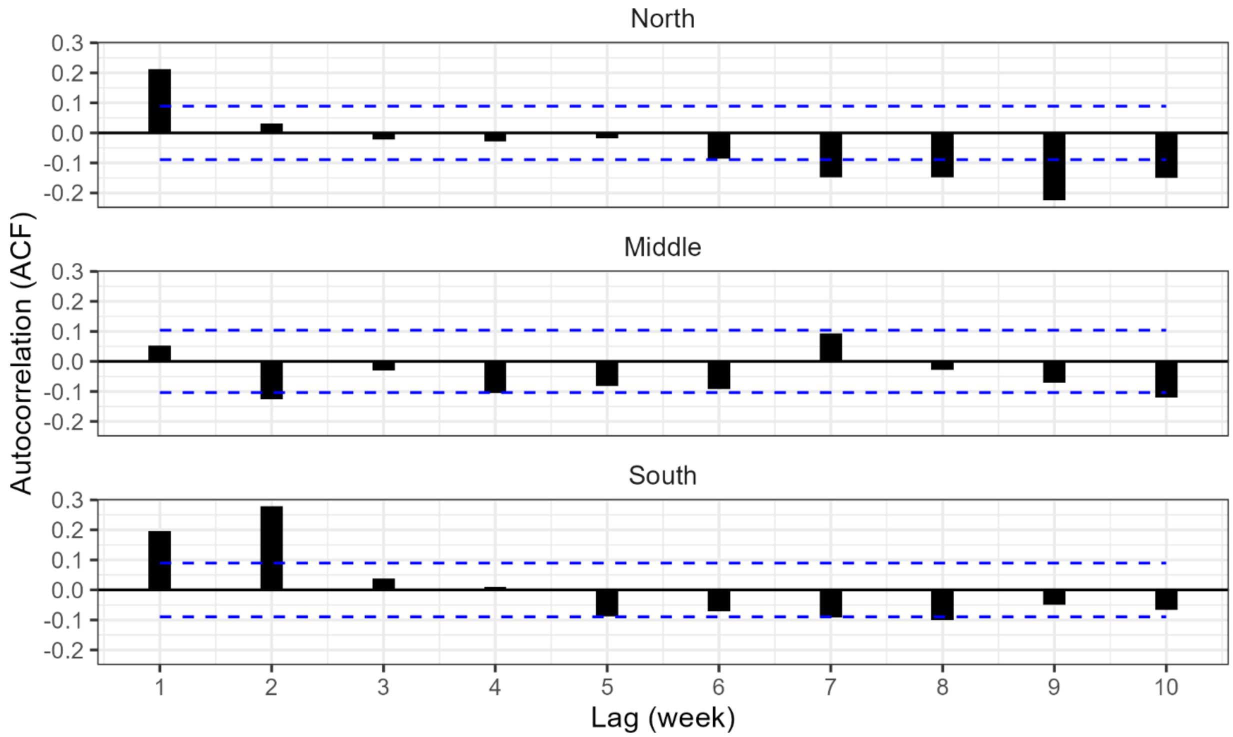

Figure A4. Temporal autocorrelation of model residuals over weekly lags for each fall herring subpopulation (North: top, Middle: center, South: bottom). Blue dashed lines represent the 95% confidence intervals indicating significant autocorrelation.

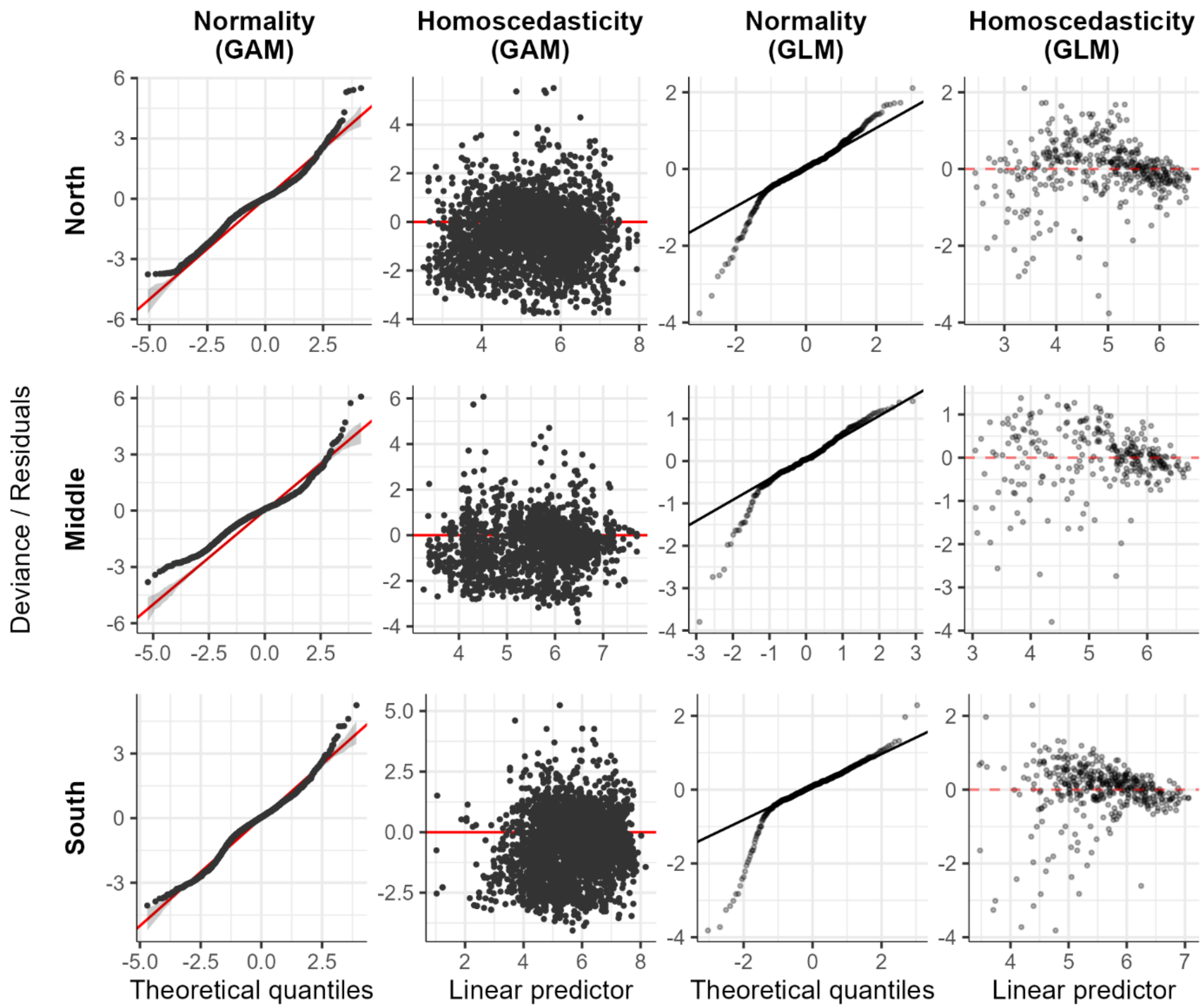

Figure A5. Diagnostics QQ plots and residuals vs fitted values plot between CPUE-GAM (two left panel) and CPUE-GLM (two right panel) for each fall herring subpopulation on their respective datasets (North: top, Middle: center, South: bottom).

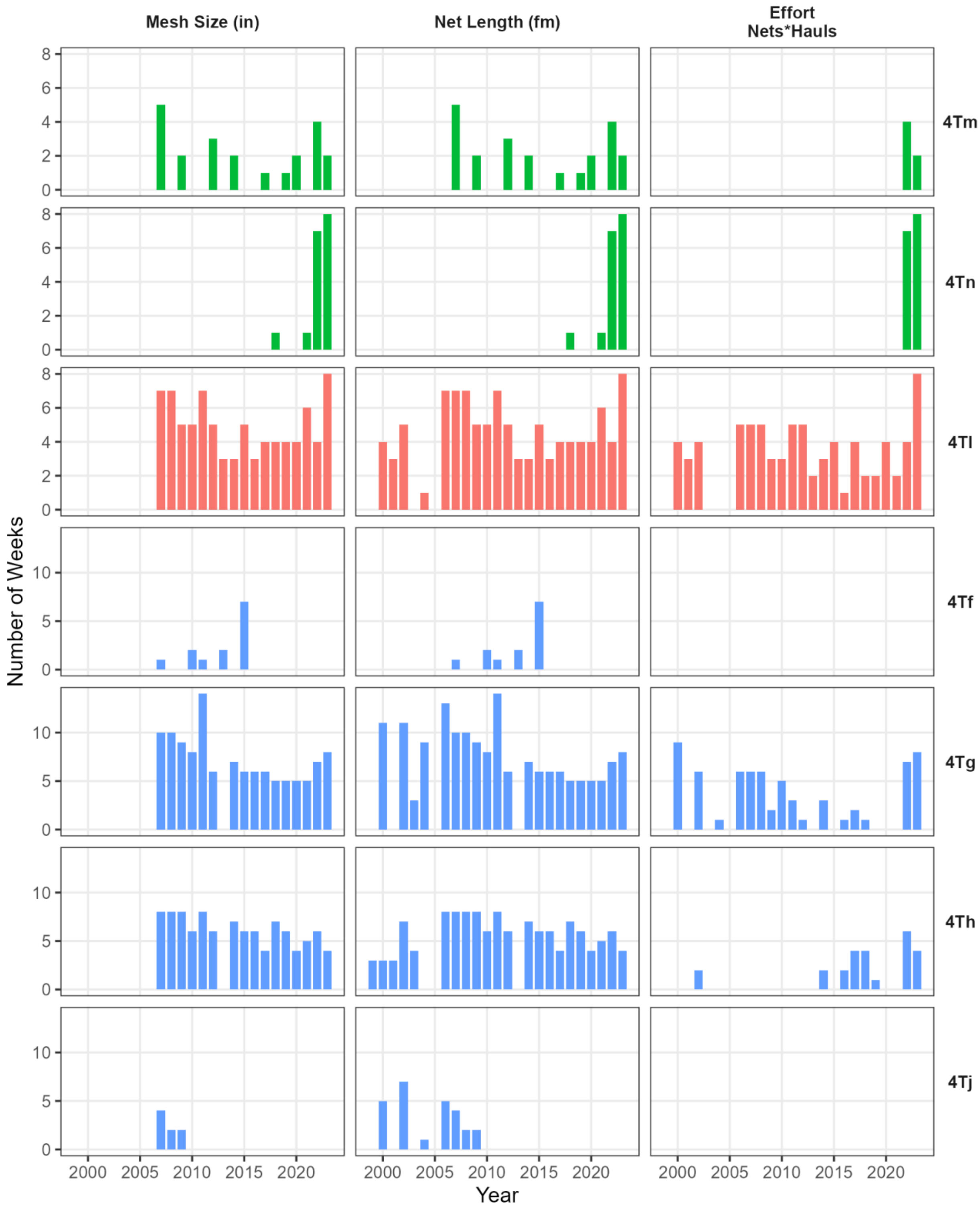

Figure A6. Number of fishing weeks in data for each year (1999:2023) and NAFO subdivision for fall herring subpopulations (North: green, Middle: red, South: blue) in DMP reports for each effort variables (mesh size (in): right, net length (fm): center, number of net hauls: left).

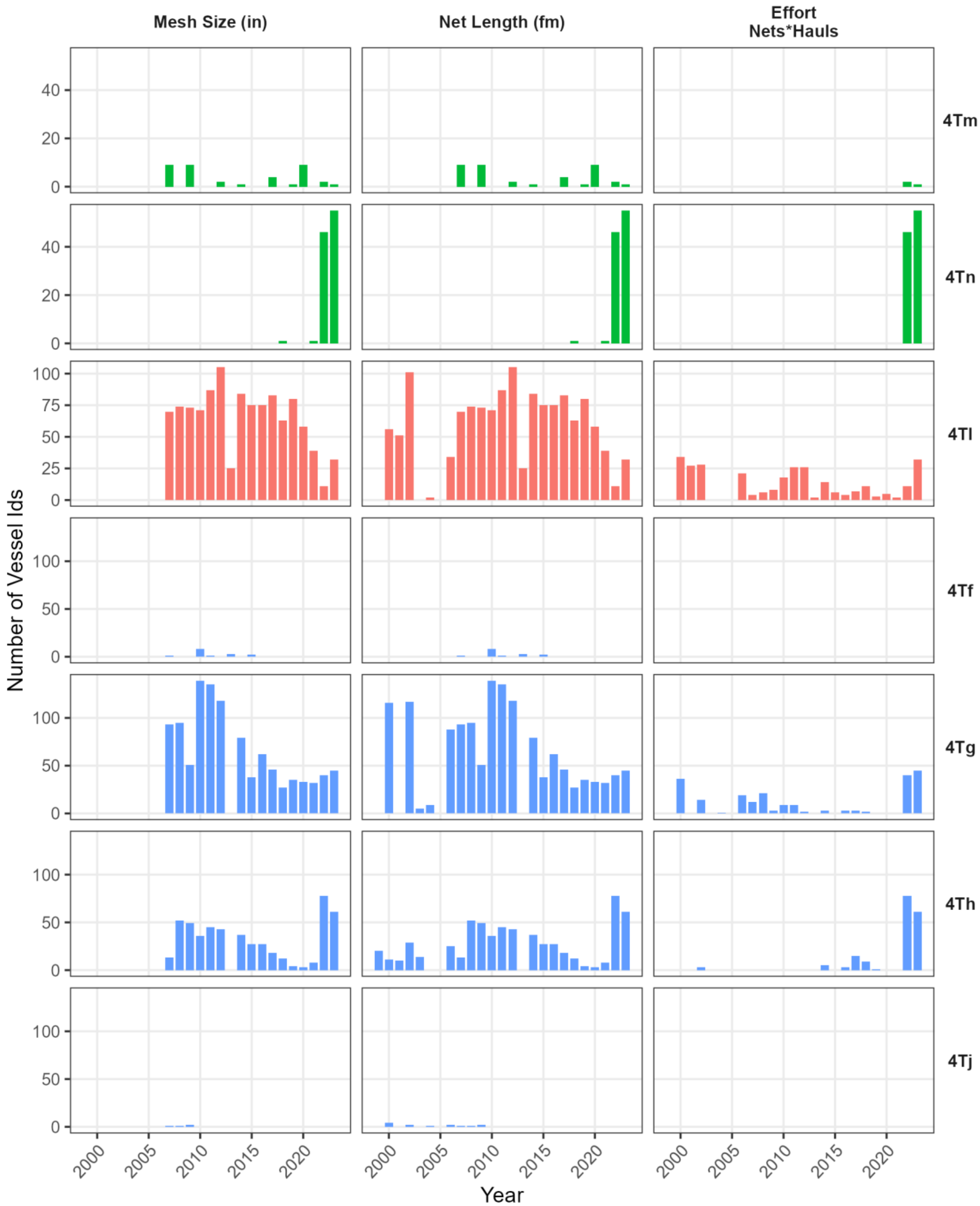

Figure A7. Number of unique vessel identifiers contributing to data for each year (1999:2023) and NAFO subdivision for fall herring subpopulations (North: green, Middle: red, South: blue) in DMP reports for each effort variables (mesh size (in): right, net length (fm): center, number of net hauls: left).

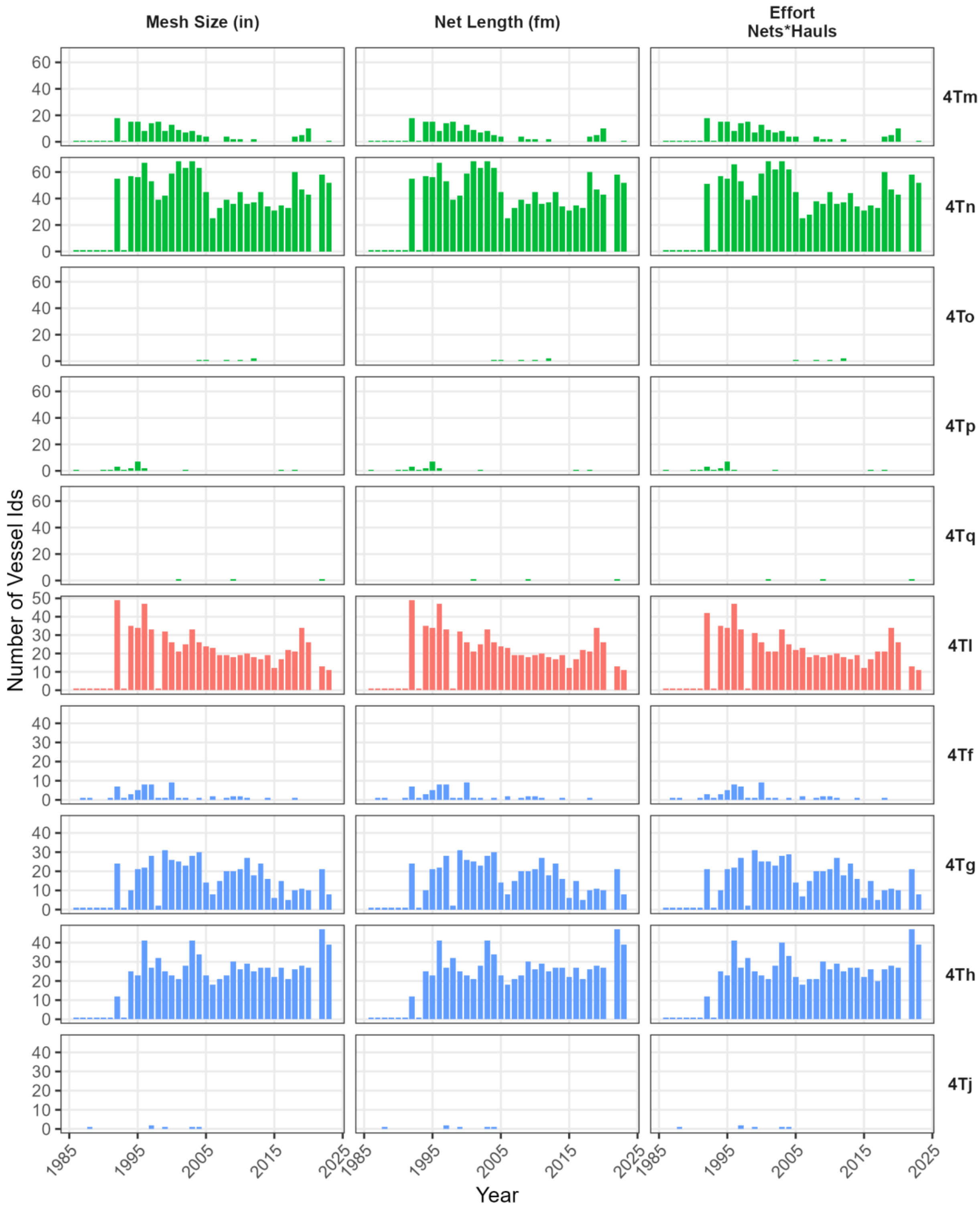

Figure A8. Number of unique vessel identifiers contributing to data for each year (1986:2023) and NAFO subdivision for fall herring subpopulations (North: green, Middle: red, South: blue) in yearly telephone survey reports for each effort variables (mesh size (in): right, net length (fm): center, number of net hauls: left).