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Examining High-Resolution Monkfish CPUE Indices Across Gillnet, Trawl, and Scallop Dredge Fisheries

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ABSTRACT

This study analyzed high-resolution monkfish CPUE from gillnet, trawl, and scallop dredge fisheries (2000-2024) in the northeast U.S. to enhance existing abundance indices for population trend assessment. We compiled data from the NEFSC Study Fleet and Northeast Fisheries Observer Programs, examining trawl, gillnet, and scallop dredge catches and incorporating co-occurring species. Nominal and standardized CPUEs were calculated using Generalized Additive Models (GAMs) and compared to long-running bottom trawl surveys. The potential impact of technology creep was examined for all time series. Trawl and scallop dredge CPUE trends correlated strongly with independent trawl surveys, while gillnet CPUEs showed weaker correlations and appeared to lag. Size differences across gear types were observed, with gillnets catching larger fish. Ismooth multipliers varied by gear and region, with trawl and dredge generally yielding higher values than gillnet. Sensitivities indicated that spatially balanced samples mitigated increasing Gini index patterns, and incorporating skate catches or targeting information minimally impacted trends. This research suggests that high-resolution fishery data contain valuable signals of monkfish population abundance, and that spatially balanced sampling can help account for shifts in fishing effort over time.

1. INTRODUCTION

Monkfish is a commercially important species in the northeast U.S., harvested with both trawl and gillnet gear (Richards et al. 2008, Haring and Maguire 2008, Siemann et al. 2018). There's a growing belief among fishermen and managers that a catch-per-unit-effort (CPUE) index could significantly improve the existing abundance index derived from the long-running bottom trawl survey, thereby enhancing population trend assessment. This interest has spurred the development of abundance indices from fishery catches, with several monkfish catch-rate projects currently underway.

A promising approach to constructing regional CPUE abundance indices has involved utilizing higher-resolution fishery data (e.g., Jones et al. 2025). This method has been successfully applied to various stocks, including black sea bass (NEFSC 2023), American plaice (NEFSC 2022), and spiny dogfish (Jiao et al. 2022). The strength of this approach lies in its ability to leverage multifaceted data sources, specifically from the region's robust Observer programs (providing scientifically stratified monitoring) and voluntary research reporting initiatives like the "Study Fleet" program. These programs collectively offer a more granular understanding of fishing effort and catch composition than the required trip-based reporting for all commercial fishing in the region.

While outputs from these high-resolution CPUE analyses have historically provided valuable contextual information in broader stock assessment processes, their quantitative utility warrants further in-depth exploration (Cadrin et al. 2020). This continued investigation is crucial for potentially elevating their role from supplementary information to integral components of quantitative assessment models. For monkfish, the immediate objective is to systematically analyze all available high-resolution fishery data to identify and characterize distinct patterns in catch rates. A key aspect of this investigation will be to critically assess the potential synchrony and concordance of these novel CPUE series with the traditional fishery-independent time series used in established stock assessments. Understanding this relationship is paramount for determining the reliability and robustness of these new indices and for potentially integrating them into future stock assessment models with greater confidence.

CPUE methods are well-established and typically aim to account for the preferential nature of sampling conducted by fishers (Maunder and Punt 2004, Hoyle et al. 2024). While these methods can help mitigate the impacts of changes in management regulations, technology creep, and the adaptive sampling of fishermen, they are not immune to biases. Such biases may cause the estimated time series to not reflect changes in the fish population, but rather changes experienced by the fishing industry. Therefore, their careful application, with thorough consideration of the potential influences of each biasing factor, is essential. This careful application will allow for greater confidence in incorporating CPUE into future stock assessment models and/or management decisions.

2. METHODS

2.1 Data Set Generation

Monkfish catch data were compiled from NEFSC Study Fleet (Palmer 2007, Jones et al. 2022) and Northeast Fisheries Observer Programs (Brooke 2012) records. This compilation largely followed the methodology in Jones et al. (2025), with two key modifications. First, data for trawl, gillnet, and scallop dredge catches from 2000 to 2024 were collected and analyzed (rather than data from only trawl gear). Mesh sizes included in the analysis for trawl and gillnet were not restricted, and for gillnet fell into two modes (~7" and ~12"), while trawl was dominated by a mode ~6.5". Second, instead of a single co-occurring species, a broader suite of five species within the monkfish guild was utilized for each gear type and data source (Figure S1). Separate guilds were established for each data source due to potential variations in species reporting in the Study Fleet, particularly for non-commercial catches.

Data collection encompassed all available regions where monkfish were caught, then trimmed to areas encompassing the monkfish stocks. However, fishery statistical areas with significant sampling gaps (over 5 years without sampling) or limited records (fewer than 30 records annually in most years) were excluded from the analysis. Specifically, for gillnet data, areas 464, 512, 522, 525, 538, 611, 622, and 636 were removed (Figure 1). For trawl data no areas were excluded. Scallop dredge areas dropped due to limited coverage included 513, 515, 538, 611, and 614. The low number of catch records in specific gear types across sampling programs in these specific areas makes inferences about their abundance difficult and potentially misleading. Thus, rather than present potentially misleading trends, those areas were excluded.

Analyses were performed on data configured for three regions: northern and southern management areas (divided by statistical areas roughly above Georges Bank, as shown in Figure 1), and a combined dataset including all areas. The decision to analyze all areas together stems from genetic population analysis (Hasbrouck et al. unpublished data) indicating a single monkfish population, a factor managers have considered for a unified stock instead of the current two (Richardson et al. 2008).

Changing spatial characteristics of a fishery may present challenges for constructing reliable indices (Campbell 2004, Hoyle et al. 2024). To improve the spatial and temporal evenness of sampling and address the common concern about fishery-dependent data focusing on high density areas, we explored methods to subset the data. This involved a simple random selection of sampling events (trawl tows and gillnet sets) within each statistical area and year. The number of sampling events chosen was proportional to the size (km^2) of the statistical area. Specifically, an average-sized statistical area was represented by 60 samples per year, with larger areas receiving more than 60 samples and smaller areas fewer. These random samples of fishing efforts were conducted for each gear type within each regional configuration. Iteratively repeating this sampling allowed us to examine sample-to-sample variability and weigh it against the benefit of using a more spatially balanced set of catch records.

This dataset contains information on monkfish catch (kept and discarded, in pounds), precise fishing location (end of tow latitude and longitude), date and time of fishing events, depth, and target species. For gillnet gear, soak time and the weight of skate complex species caught in the same effort were included. For trawl and scallop dredge gears, tow time in hours was used as an effort metric to calculate catch-per-unit-effort (CPUE). These variables and spatial configurations were then used to explore spatio-temporal patterns in catch-rate, which serves as a proxy for abundance. For gillnet data the target species at the haul level was determined using that reported by the captain (Study Fleet records) or by the observer (Observer Program records).

2.2 Analyses performed

We performed several iterative analyses to explore changing patterns in the data. Initially, we calculated a nominal CPUE for each regional configuration (north and south). This nominal CPUE represented a raw mean of catches per year, regardless of location. Since this was derived from a spatially balanced subset of the total catch data, we repeated the process 100 times to better understand the impact of sampling on trends. Subsequently, we segmented catches by statistical area and recalculated nominal CPUEs for each area. These were then spatially plotted along with the summed weight (total catch from that area) for each statistical area in the dataset for each gear type.

Following this, we employed Generalized Additive Models (GAMs) to standardize the CPUEs for each regional configuration and gear type. The GAMs used for standardization included catch rate as the response variable, year and statistical area as fixed effects, and day of year and fishing event depth as smooth effects. We explored but ultimately excluded the year * area interaction term from models. Though it would increase explained deviance and decrease AIC, the primary trade-off is a significant increase in the uncertainty of estimates (likely due to incomplete sampling/sparse data) and longer run times. As the main trend of interest is consistent across models, we opt for the simpler, faster model without the interaction. The number of knots in the smooths was set to a low number (k=5) to prevent overfitting, which is common with large data sets. A Tweedie distribution with a log link was used as the error distribution for these models. Models were fit using the mgcv package (Woods 2001), and annual index values were generated for each regional configuration using the ggeffects package (Lüdecke 2018), as demonstrated in Jones et al. (2025).

Standardized index values were then compared to those from the region's bottom trawl survey (both spring and fall). These long-running seasonal surveys have been conducted consistently throughout the time series we examined. Although a vessel change occurred mid-series, calibration factors were applied to create a single time series (Miller et al. 2010). These surveys provide key information for up to 50 stocks in the region and, despite occasional criticism, are generally considered the best available source of abundance information for many of these stocks. As a preliminary step, all indices were transformed by dividing each value by the standard deviation of the full series, giving the series a positive mean that typically is between 0.5 and one, essentially putting indices on similar scales. This basic transformation allows for the easiest visual comparison of trends among series, while maintaining positive values, and does not affect the correlation among series. Pearson's correlations were then used to assess their correlation/synchrony. Typically, a Pearson correlation exceeding 0.5 indicates strong evidence of correlation between series (Cohen 1988).

Advances in technology are known to increase the catchability of fishing vessels over time (Sherrer and Galbraith 2020, Kleiven et al. 2022). This creates a change in how the time series estimated from fishery-dependent data reflects actual changes in the population (Hutton et al. 2025). It is commonly referred to as technology creep. The amount and timing of these changes is hard to estimate due to the learning associated with new technology and how quickly it spreads throughout the fleet. Typical values reported in the literature range from 0.5 to 4% per year. We demonstrate the impact of two possible values for technology creep on the estimated time series. Application of technology creep to the time series results in reductions of the original time series because some of the CPUE is due to an increased ability to catch fish, not a reflection of a change in the population. Accounting for technology creep could allow for a better estimate of the actual population changes.

We also examined patterns of spatial aggregation over time in each region using the Gini index (Gini 1912). This analysis utilized each spatial configuration (all, north, south) for each gear type. We evaluated Gini index patterns for each subset to determine if spatial aggregation in catches increased, decreased, or remained constant. For this, monkfish catches in each configuration were gridded by year and summed. Specifically, each haul was assigned to a spatial five arc-minute grid cell (~65 km^2) using the latitude and longitude of the end of the haul. For each spatial configuration considered (combined, north, and south) we then summed the catches of monkfish in each year for each grid cell. The distribution of the summed catches was then approximated with the Gini index (Edvardsson et al. 2018), where lower Gini index values indicated more evenly distributed catches.

To gain a clearer understanding of catch sizes and potential selectivity differences across data sources, particularly gear types, we gathered available monkfish length data from the observer program. While primarily focused on discarded catch, this data also offers insights into kept catch for each gear type. Using this information we calculated the average length per disposition, year, gear, and region group. These results are then weighted by the proportion of the catch from each disposition to derive a single overall mean length for that region, gear, and year.

To evaluate how the generated indices might influence the current approach used for management advice, we repeatedly generated a standardized CPUE using the aforementioned methods. This process included taking a spatially balanced sample of records, fitting the standardization model, and subsequently inputting the resulting index from the model into the Ismooth function (Legault et al. 2022). The Ismooth function estimates a catch multiplier used to set future quotas based on recent changes in the survey or other index of abundance. Finally, we plotted the distribution of multipliers for each gear type and region.

3 RESULTS

3.1 Data sets

After initial data cleansing to remove highly improbable records (e.g., extreme effort metrics), the complete gillnet dataset comprised approximately 75,000 records, with approximately twice as many records from the northern region as from the southern region (Table 1). The full trawl data set is much larger (due to data sampling intensity in the sampling programs) with close to 350,00 records again with a larger share coming from the northern region. For scallop dredge, the comprehensive dataset included approximately 420,000 records, with the vast majority (~ 350,000) coming from the southern region. Catch rates constructed for each gear type utilize subtly different effort metrics, and as a result the absolute values of the catch rates are difficult to compare. For each data set, the standard deviation of catch rates was high and the median was lower than the mean, as a result of skew in the catch rate distributions. The following analyses are all based on 100 samples of spatially-balanced data for each gear and region.

3.2 Nominal CPUE

Nominal CPUE for gillnet gear showed distinct regional patterns (Figure 2). The southern region exhibited two clear abundance peaks (approximately 2005 and 2019), while the northern region showed a declining trend through 2014 followed by a strong increase to much higher values with peaks in 2016 and 2022. When combined across all statistical areas, two larger abundance peaks can be seen: one around 2005 and another later in the 2019-2022 period, with the second having a notable dip in 2020. Nominal CPUE for trawl gear presented a different pattern. In the south, a broad peak in abundance was visible in the early 2000s (roughly 2003 - 2006), followed by a general decline with subtle peaks in 2011 and 2018. The north showed a distinct early peak in 2004, a low period from 2007-2015, and a later plateau from 2016 - 2024. Scallop dredge patterns in the south showed a general decline over time, although with large interannual fluctuations while in the north showed a dramatic drop from 2000 to a relatively constant level afterwards.

To understand how the spatially-balanced subsampling impacted the nominal CPUE trends we repeated the sampling 100 times and generated nominal CPUEs for each subset. This can be seen in Figure 2 with a single sample making up a single line through time. As most lines from repeated samples overlap one another, it indicates that consistent time series of catch rates were seen across nominal CPUE replicates. A limited number of iterations showed distinct patterns in the trawl data likely due to the inclusion or exclusion of catch outliers. Outliers have a larger effect on nominal CPUEs constructed here because they use an arithmetic mean, and the underlying catch rate distribution have a strong positive skew.

3.3 Nominal CPUE in space

Catch rates varied spatially across all three gear types (Figure 3). Gillnet data showed increasing patterns in three areas and decreasing trends in seven. Trawl data indicated several areas with increasing patterns that peaked in abundance then declined. Scallop data showed many areas with the lowest values in recent years. Using a subset of records significantly impacted regional patterns, particularly for gillnet catches, due to the highly uneven weighting in the full dataset (Figure S2). This spatial subsetting was a critical step for balancing the dataset and mitigating the influence of localized "hot spots" of fishing effort, which can otherwise bias regional estimates. While temporal hot spots (e.g., concentrated fishing during certain months) may also influence CPUE, they are likely confounded with these spatial hot spots and are addressed primarily through this effort to achieve spatial balance.

3.4 Standardized CPUE

Annual index values from CPUE standardization generally align with nominal CPUEs (Table 2, Figure 2, Figure 3). Gillnet gear standardization revealed distinct regional patterns: increasing catches in later years in the north, and two distinct abundance peaks in the south. Some shifting in the timing of peaks is apparent and the later peak in the combined data set is consolidated. For trawl gear, regional patterns were more similar, with peaks occurring in comparable years. In the south, these peaks were slightly smaller, and the trend following the second peak diverged between regions (increasing in the north, decreasing in the south). Analysis of scallop dredge gear catches showed trends similar to those observed with trawl gear. Across the entire area, standardizations for all three gears consistently exhibited a larger peak early in the series and late in the series with both trawl and scallop showing a smaller peak in the 2011 time frame.

Analyzing the complete gillnet dataset yielded annual index trends consistent with those observed in the data subset (Figures S2A, S2B). While limiting the dataset to only targeted trips, again those trips where monkfish were listed as a target species by captains or observers, significantly increased average catch rates, it did not substantially alter the temporal trend in catches for either the northern or southern regions (Figures S3A, S3B). Together Figures S2B and S3B demonstrate that the when the data are analyzed in this way, the combined region aligns much more closely with the north than the spatially-balanced dataset; this skew is driven by higher gillnet effort in the north and underscores the necessity of spatial balancing.

3.5 Technology creep

Changes in the population trend underlying the CPUE time series for all gears in both regions are noticeable when the effect of technology creep is applied (Figure 5). Trends generally continued the larger pattern of the CPUE (e.g., annual trends up or down are congruent), however the scale of the series was shifted downwards in recent years. Differences were most notable for trawl and gillnet gears with the largest differences occurring in the northern series. This indicates that if technology creep were occurring at these rates in these fisheries the trend in the standardized index could diverge from the true population trend by potentially this much.

3.6 Comparison to the bottom trawl indices, and among CPUEs

Standardized CPUEs from the trawl fishery indices showed strong correlations with regional fishery-independent trawl surveys (Figure 6). For the northern region, Pearson correlation coefficients (r) ranged from 0.40 to 0.58 (Table 3), approximately the same correlation between spring and fall bottom trawl indices ($r = 0.54$) over the same period. In the southern region, the standardized trawl data index was highly correlated with both the fall survey ($r = 0.76$) and the spring survey ($r = 0.61$). The scallop dredge CPUE was mostly highly correlated with both surveys

(r range 0.60-0.79), except for the south correlation with the spring BTS (r = 0.27). All the gillnet CPUE correlations with the BTS were low, ranging from 0.20 to 0.41. Among CPUE series correlations were higher in the southern region, 0.53 - 0.77, than the north, 0.09 - 0.46 (Table 4), with the highest correlations among the southern trawl and dredge gears. Conversely correlations were weakest between the northern gillnet gear and other series.

3.7 Average length by gear type

Figure 7 illustrates the variability in average lengths across different gear types. This variation can be attributed to differences in the sizes of discarded catches and the proportion of kept versus discarded components per tow, despite the consistent size of kept catches across gears. These approximate estimations indicate that mean lengths for trawl gear in a given year aligned with observations from bottom trawl surveys, and scallop dredge gear produced fish lengths falling between those from gillnet and trawl gears.

3.8 Ismooth multiplier

Ismooth multipliers displayed distinct patterns between region, gear type, and terminal year (Figure 8). When generated for the full area, the multipliers were most similar across gear types, becoming more variable when calculated for each regional subset. Mean multipliers for trawl and scallop dredge gears in each regional configuration were generally similar with gillnet typically being more different (Figure 8). Differences in multipliers driven by the terminal year are expected, but the variability among gear types within a given year and region is of greater concern because these multipliers would directly drive different quota outcomes.

3.9 Gini index of catches

After subsetting the records to achieve a more spatially even distribution, the Gini indices for all three gears exhibited a relatively flat pattern (Figure 9). However, analyses of Gini indices derived from the complete gillnet dataset revealed an increasing trend over time (Figure S2C). Furthermore, when the gillnet data was subsetted to include only trips specifically targeting monkfish, the Gini index values also showed an upward trend over time (Figure S3C).

4 DISCUSSION

This study examined monkfish catch rates within the northeast U.S. large marine ecosystem, utilizing a unique dataset with precise catch and effort estimates. The data was refined to include only monkfish and co-occurring species, and then subsampled to ensure spatial evenness of fishery samples annually. This subsample was subsequently used for various analyses to understand abundance trends over time.

Both nominal and standardized CPUEs revealed some similar trends within regions and gear types, though some distinctions emerged as well. Notably, trawl and scallop dredge catch rate trends roughly followed those observed in independent trawl surveys. This similarity for trawl gear is likely attributable to the comparable gear types used in both surveys and commercial fishing. This correspondence in trend is somewhat unexpected as the typical survey gear in the region is not thought to capture the species well (Richards et al. 2008). In contrast, gillnet catch rates diverged from the trawl fishery and surveys, with gillnet trends appearing to lag behind those of the other series, especially in the southern region. Size differences were also apparent, with gillnet fisheries typically catching larger fish. These size variations could be linked to gear selectivity. Informal explorations, not presented here, suggested that adjusting the gillnet index time series to account for size differences improved the Pearson correlation between trawl survey and gillnet catches. A plausible but untested explanation is that gillnets catch larger, older fish, but further investigation is needed to fully understand the drivers of these observed patterns.

Beyond CPUE analyses, the multipliers generated by Ismooth also varied among gears and regions. Additionally, the terminal year used also had an effect on the multiplier produced. Using a terminal year of 2023 in the north, trawl and dredge gear types yielded multipliers near 1.05, while in the south, both gears produced multipliers of 0.78 and 0.95. Conversely, gillnet gear consistently showed lower values than trawl and dredge in both northern and southern regions. Analyses using 2024 as the terminal year showed some potentially important differences in the value produced such as decreases in the multipliers produced from all gillnet indices and increased multipliers for all dredge multipliers. This behavior is a feature of the Ismooth method, as the method is meant to be responsive to the most recent abundance values from the input indices. The variability in the multipliers from different random samples of spatially balanced data should be considered if this approach is used for management purposes. These multipliers all assume zero technology creep because there are no studies available to estimate this factor for any of the fleets and no consensus on an appropriate default value. Future research should examine technology creep if CPUE is used in stock assessment modeling as an index of population abundance.

Gini index analysis indicated that spatially balancing the catch subsamples helped mitigate the increasing Gini index pattern seen in sensitivities. Furthermore, sensitivities incorporating skate catches and targeting into CPUE standardizations had impacts on the overall trends, but suggested that spatial balancing of the catch records was more important, especially when an index for combined region was generated. Collectively, these analyses provide a detailed exploration of the available catch data, and suggest that high-resolution fishery catch data for the two monkfish stocks contain some signals of population abundance. Perhaps the biggest takeaway is that spatially balanced catch samples can help mitigate the effects of spatial shifts in effort over time. Notably, the results indicated that the trends derived from the trawl survey were congruent with multiple fishery catch indices, despite the differences in sampling methodology.

While the spatially balanced sampling approach used in this study addresses the critical issue of non-random fishing effort, it is important to acknowledge other factors that can influence commercial CPUE independently of population changes. Over the long time series examined here (2000-2024), a variety of unmodeled influences could affect the generated indices. These include dynamic management regulations (e.g., trip limits, quotas, minimum size regulations, and area closures), shifts in targeting practices for monkfish or other species due to market conditions or socio-economic factors, and the incremental but cumulative effect of 'technology creep' on fishing efficiency. As summarized by Hoyle et al. (2024), these potential confounding factors represent common challenges in the use of fishery-dependent data. Although the similarity between our trawl and scallop dredge CPUE indices and the fishery-independent surveys suggests we have captured a robust signal of abundance, future work could seek to further refine these indices by explicitly accounting for these additional operational and regulatory variables.

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DATA AND CODE AVAILABILITY

Data for this study come from sources that are confidential in nature and must be requested by an authorized user (e.g. haul-level catch and effort information). Inquiries can be sent to the Northeast Fisheries Observer Programs and the Cooperative Research Branch of the United States National Marine Fisheries Service Northeast Fisheries Science Center (https://www.fisheries.noaa.gov/about/northeast-fisheries-science-center). Code used to conduct this study are freely available from this GitHub repository: https://github.com/AJONES8/MONKFISH_CPUE.

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TABLES

Table 1. Data set details for each gear type used in the analysis. The number of records in the full data set as well as by region are shown. Additionally details of an example subset used for analysis.

Feature	Gillnet	Trawl	Scallop Dredge
Total Records	77,462	363,034	418,975
Percent positive records	61%	65%	65%
Northern Records	55,299	218,809	64,076
Southern Records	22,163	144,225	354,899
Effort Metric	Net Soak Duration (hours)	Tow Duration (hours)	Tow Duration (hours)
Effort Range	1 - 72 hours	0.5 - 5 hours	0.2-2 hours
Analysis Subset	13,116	17,586	20,008
Catch Rate Range	0 - 15,014	0 - 12,996	0 - 2,962
Mean Catch Rate	9.9	51.0	63.0
Median Catch Rate	2.85	9.75	21.60
Catch Rate SD	29.4	122.0	120.0

Table 2. Index values from the GAM standardization after being divided by the series standard deviation. Annual values are shown for each regional configuration and correspond to plotted values in Figure 5.

Year	Northern Region			Southern Region			Combined Regions		
	Gillnet	Trawl	Dredge	Gillnet	Trawl	Dredge	Gillnet	Trawl	Dredge
2000	0.98	1.13	1.36	1.28	1.19	1.19	1.21	1.21	1.63
2001	1.57	1.05	3.48	1.25	1.12	1.32	1.53	1.15	1.38
2002	0.79	1.58	0.80	0.51	1.57	1.12	0.77	1.58	1.23
2003	0.81	1.92	0.72	1.04	1.09	1.57	0.97	1.59	1.39
2004	0.65	1.65	1.93	1.22	1.49	1.07	1.01	1.58	1.13
2005	0.97	1.27	0.60	1.67	1.95	1.35	1.53	1.61	1.37
2006	0.61	0.95	0.67	1.79	1.58	1.35	1.32	1.30	1.27
2007	0.53	0.67	0.45	1.08	1.66	1.02	0.84	1.10	0.99
2008	0.36	0.44	0.29	1.16	1.05	1.09	0.83	0.78	0.95
2009	0.33	0.51	0.25	0.83	0.51	0.75	0.66	0.53	0.75
2010	0.28	0.52	0.26	0.64	0.65	0.67	0.55	0.61	0.65
2011	0.25	0.65	0.18	0.62	1.13	0.85	0.50	0.88	0.78
2012	0.22	0.56	0.35	0.72	0.63	1.03	0.56	0.61	1.00
2013	0.31	0.58	0.25	0.58	0.48	0.94	0.50	0.56	0.78
2014	0.46	0.47	0.22	0.70	0.47	0.65	0.64	0.50	0.60
2015	0.55	0.53	0.27	0.62	0.62	0.47	0.61	0.60	0.45
2016	0.76	0.75	0.93	0.86	0.54	0.72	0.86	0.69	0.71
2017	1.12	0.93	0.43	0.53	0.57	1.23	0.67	0.79	1.09
2018	0.87	1.01	0.85	0.89	0.62	1.04	0.92	0.83	1.18
2019	1.11	1.09	0.46	0.98	0.67	1.09	1.04	0.93	1.02
2020	0.72	0.79	0.40	0.85	0.38	0.29	0.82	0.60	0.28
2021	1.65	0.83	0.61	1.05	0.31	0.87	1.39	0.61	0.83
2022	1.96	0.80	0.47	1.08	0.31	0.56	1.39	0.59	0.59
2023	1.46	0.96	0.73	0.66	0.40	0.33	1.06	0.76	0.44
2024	1.79	0.98	0.56	0.26	0.36	0.45	1.02	0.77	0.43

Table 3. Pearson's correlations (*r*) between time series for each region and gear type. The third and fourth columns show the correlation between the CPUE for each gear type and the fall or spring bottom trawl survey series. The last column shows the correlation between the two bottom trawl surveys (spring and fall).

Region	Gear	*r* (CPUE vs. NMFS fall BTS)	*r* (CPUE vs. NMFS spring BTS)	*r* (NMFS fall BTS vs. NMFS spring BTS)
North	*Gillnet*	0.41	0.34	0.54
South	*Gillnet*	0.27	0.20	0.37
North	*Scallop dredge*	0.60	0.79	0.54
South	*Scallop dredge*	0.78	0.27	0.37
North	*Trawl*	0.40	0.58	0.54
South	*Trawl*	0.76	0.61	0.37

Table 4. Pearson's correlations (*r*) between CPUE time series for each region and gear type.

Region	Gear 1	Gear 2	*r*(CPUE vs CPUE)
South	*Trawl*	*Scallop dredge*	0.77
South	*Gillnet*	*Trawl*	0.57
South	*Gillnet*	*Scallop dredge*	0.53
North	*Trawl*	*Scallop dredge*	0.46
North	*Gillnet*	*Trawl*	0.39
North	*Gillnet*	*Scallop dredge*	0.09

FIGURES

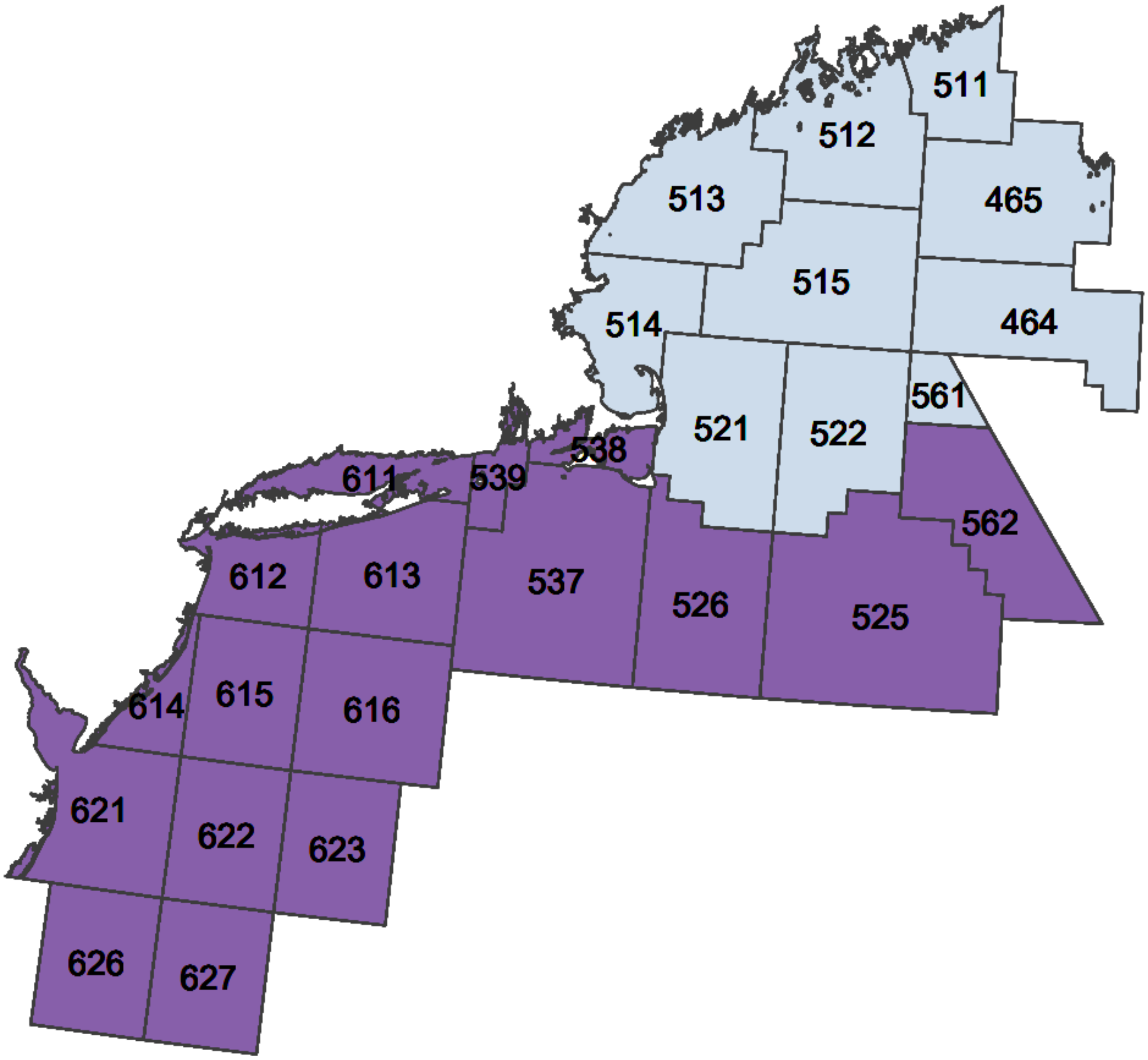


Figure 1. Map of the general breakdown of statistical areas into regional configurations. Northern areas are shown in light blue and southern areas are shown in purple.

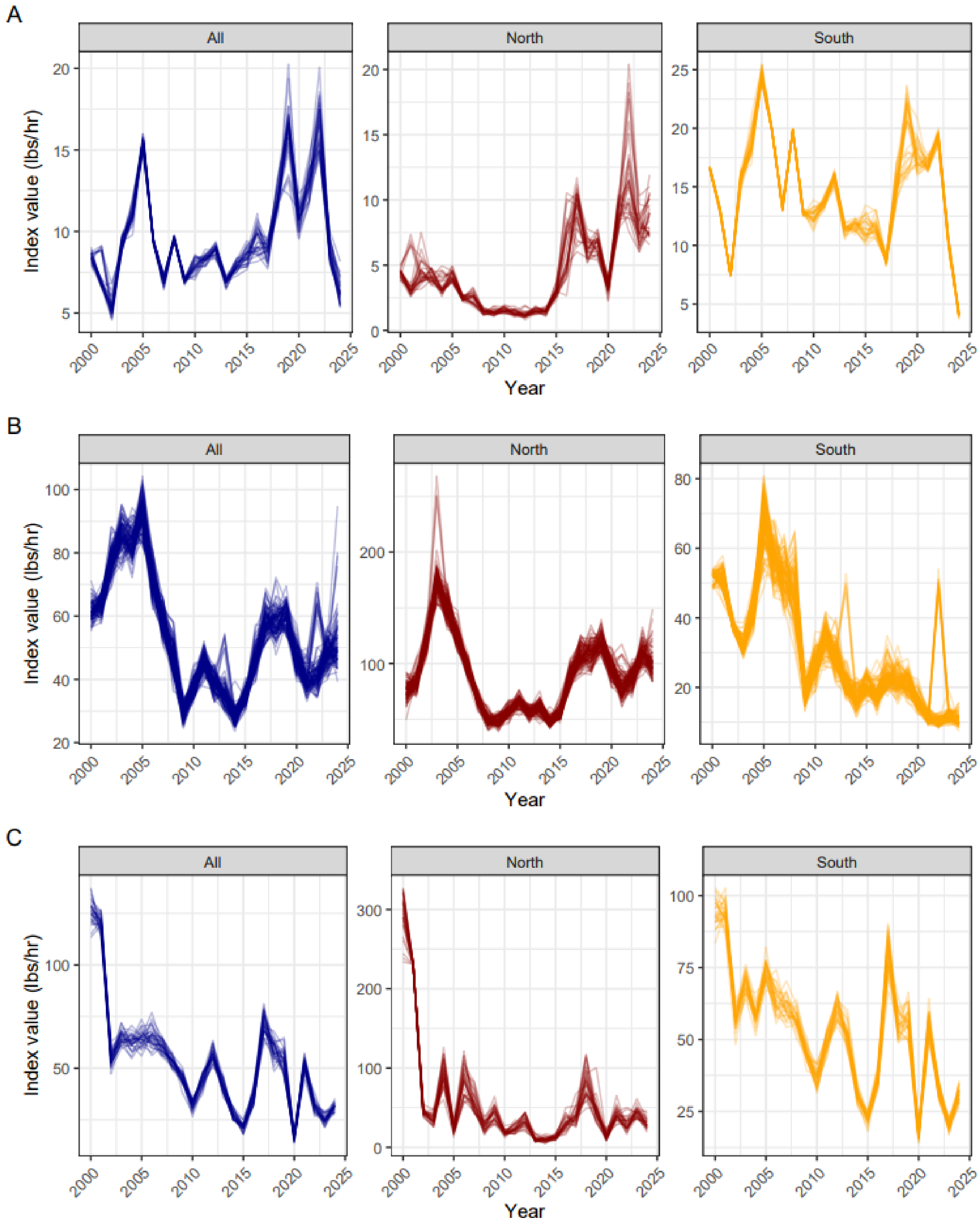


Figure 2. Nominal CPUEs for each regional configuration. A) for gillnet, B) for trawl, and C) for scallop dredge. Multiple iterations for independent subsets are shown. These are the spatially balanced samples of catches, repeated 100 times.

Figure 3. Nominal CPUEs for each statistical area. The total catch contributing to the trendline is shown with a fill color (white for lower summed catches and blue to purple for higher catches). A) for gillnet, B) for trawl, and C) for scallop dredge gears.

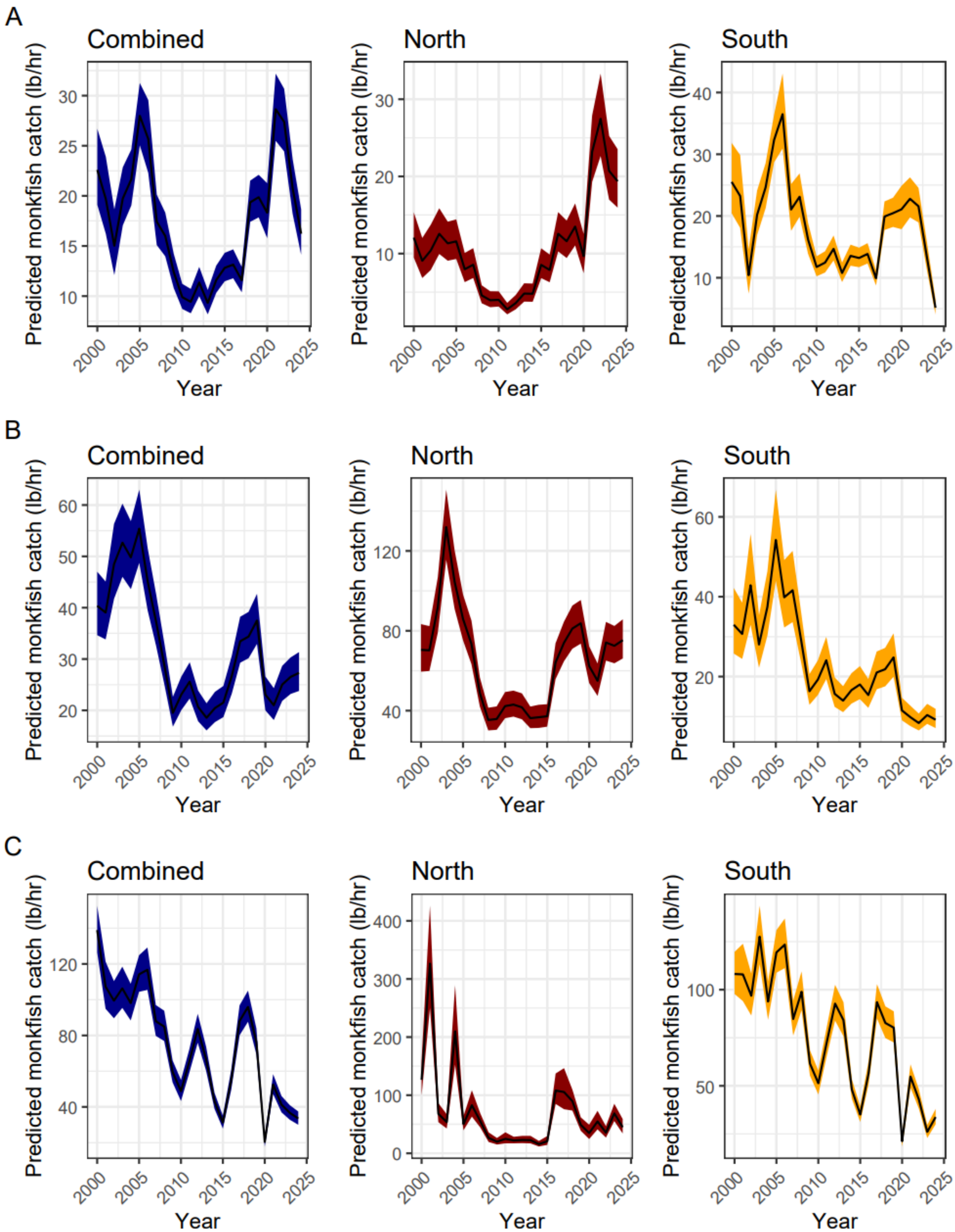


Figure 4. Standardized CPUEs for each regional configuration. An average value with a ribbon indicating 95% confidence intervals. A) for gillnet and B) for trawl gear, and C) for scallop dredge.

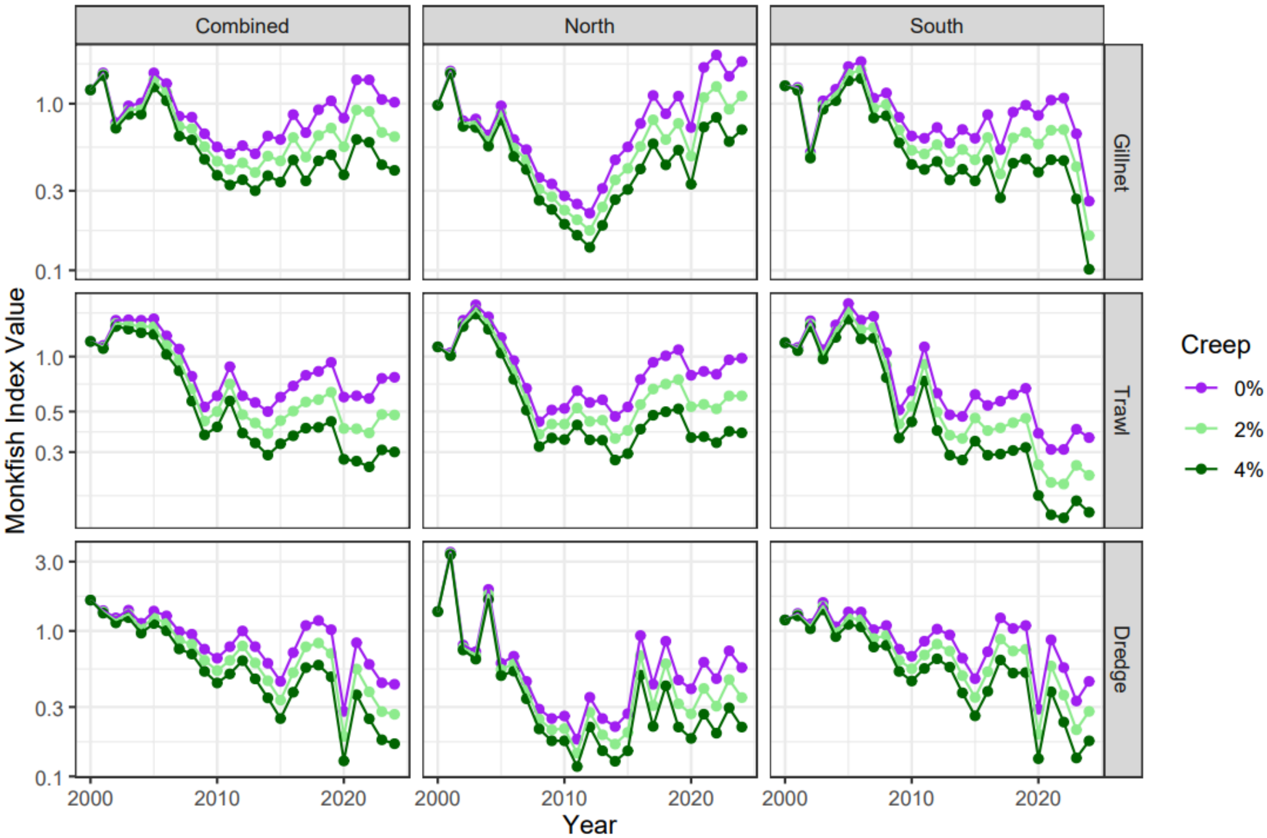


Figure 5. Technology creep of 0%, 2%, and 4% applied to the standardized monkfish CPUE time series for all three gears and both regions. Given a high correlation between a CPUE series and the population, a creep rate of 0% (purple) would suggest that the population trend is the same as the standardized CPUE. Alternatively, including a creep of 2% or 4% demonstrates how much the population trend might diverge from the observed value over the course of the time series. Note the use of logarithmic scale for the y-axes to make the changes more easily seen.

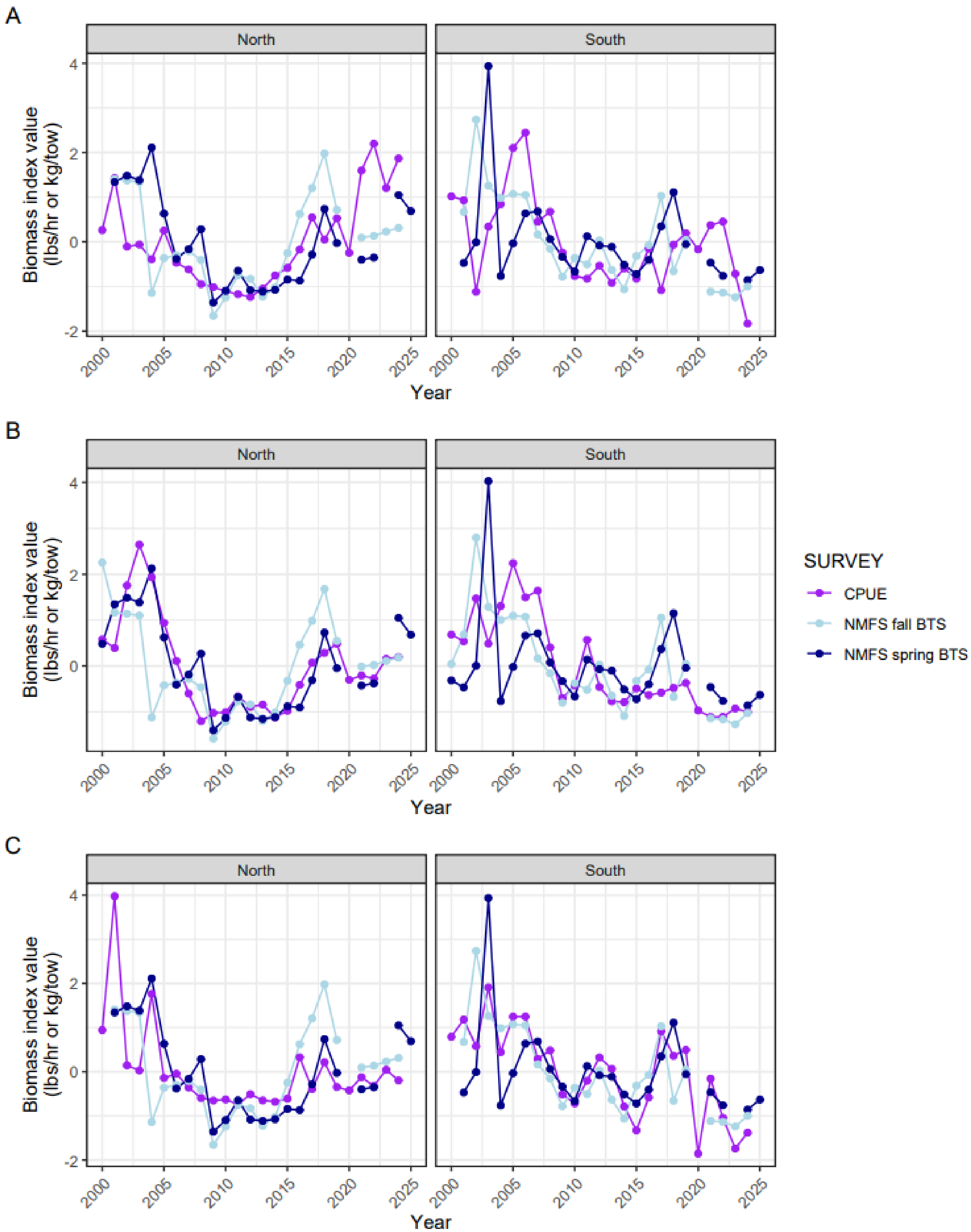


Figure 6. Comparison between the transformed CPUE indices (originally in lbs of catch per hour fished - but now unitless) for each region and gear and the fishery-independent trawl survey indices (BTS Spring and BTS Fall - originally in kgs of catch per tow but now unitless) : A) for gillnet, B) for trawl, and C) scallop dredge. Values correspond to those in Table 2.

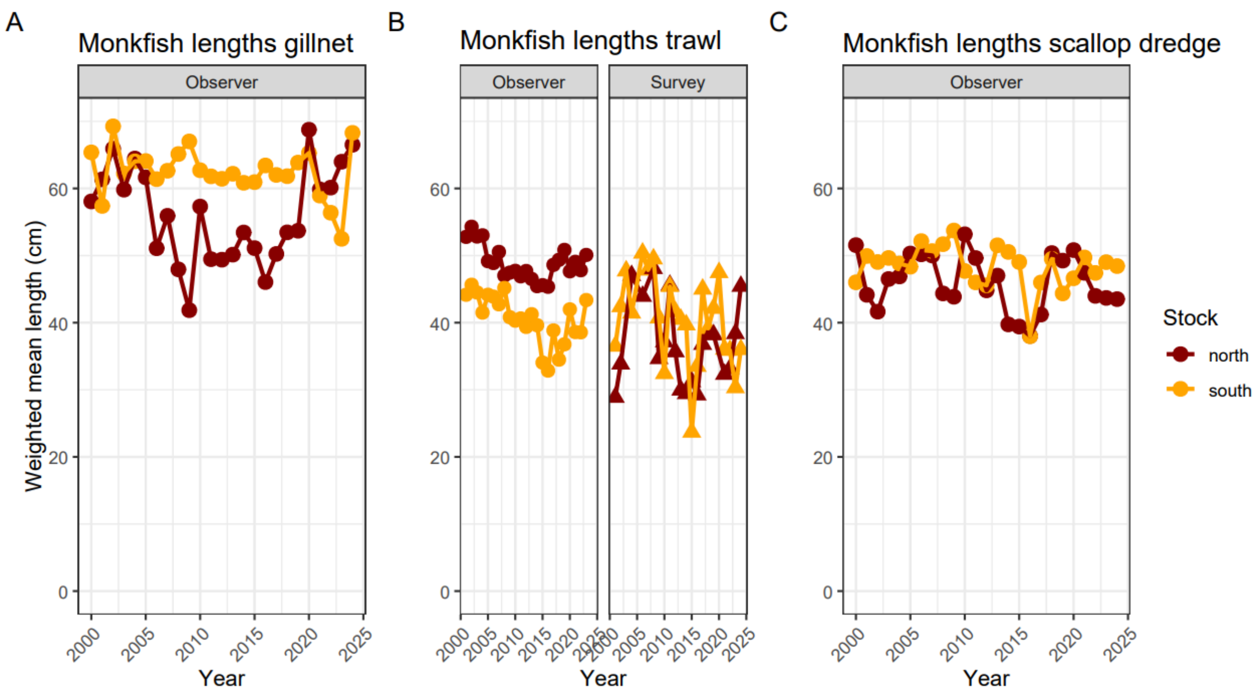


Figure 7. Length A) for gillnet, B) for commercial trawl and survey trawl, and C) for scallop dredge. These means are weighted to account for differences in length between kept and discarded catch.

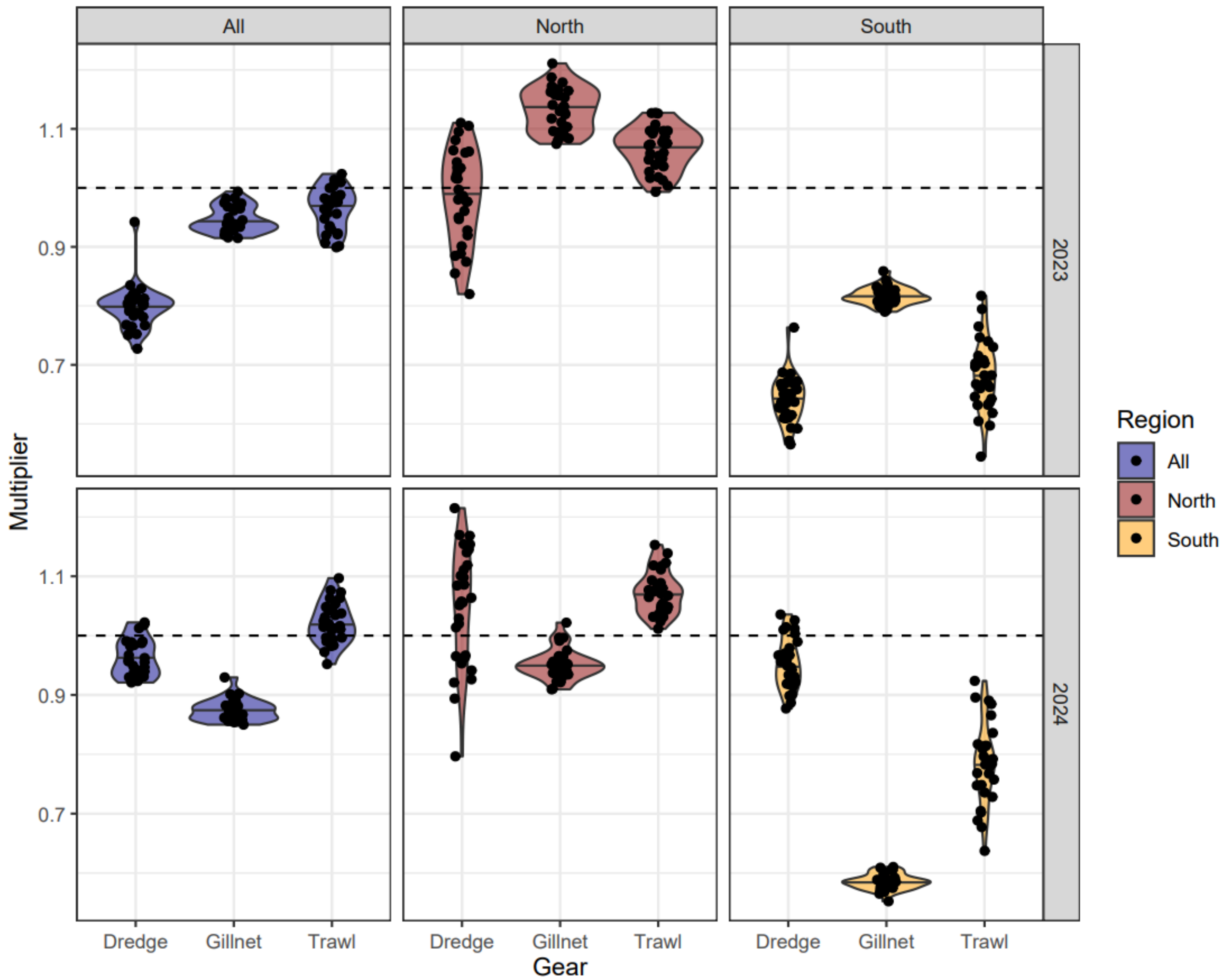


Figure 8. Ismooth multipliers for each region and gear type, with the two most recent years (2023, and 2024) used as the terminal year. Each combination of gear and regional configuration represents 30 iterations of a CPUE standardization and then Ismooth multiplier calculation. Each replicated sample and standardized CPUE iteration is shown as a point, median values are shown as a black line within a filled violin plot. A multiplier of one is shown as a dashed line.

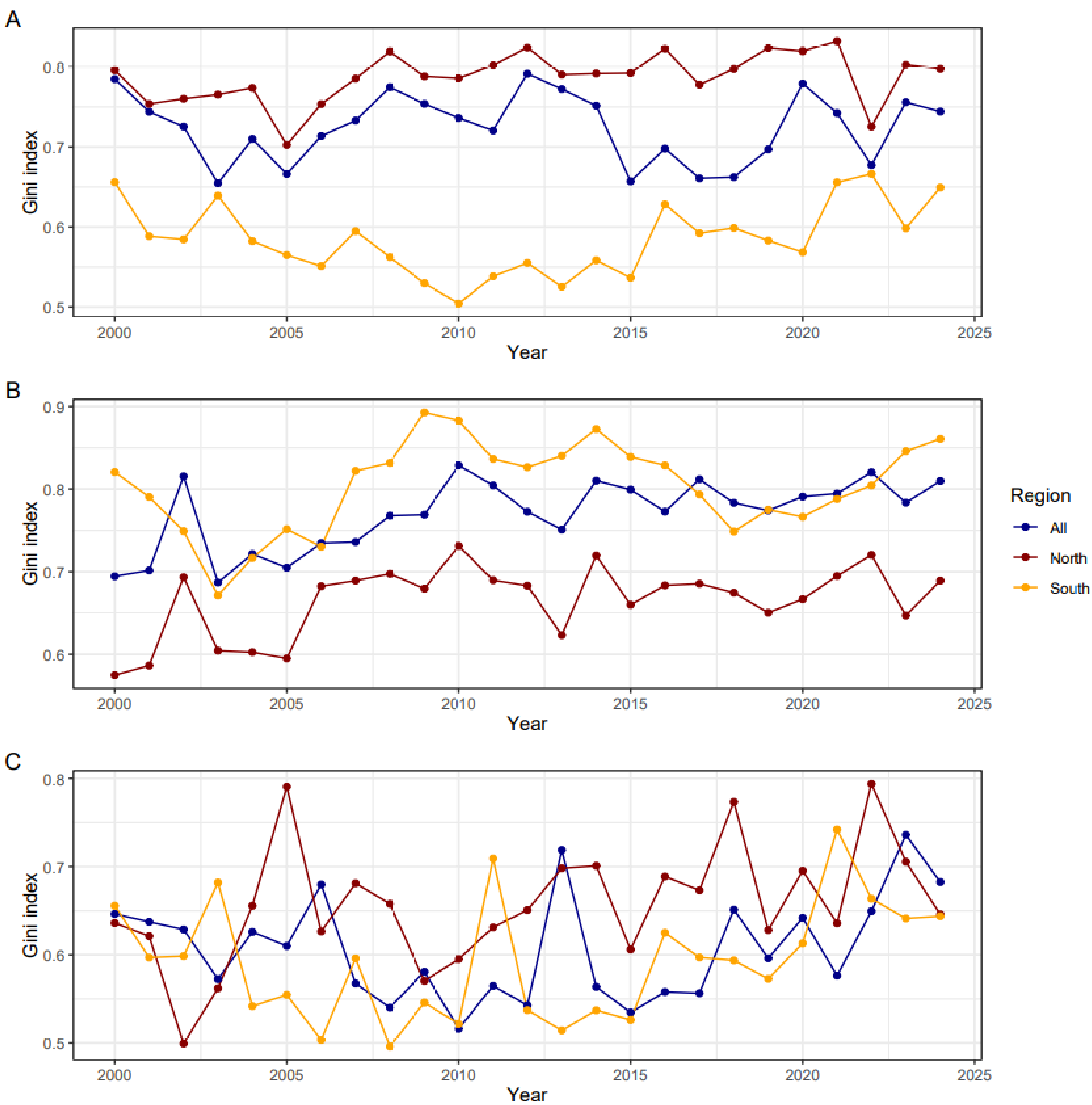
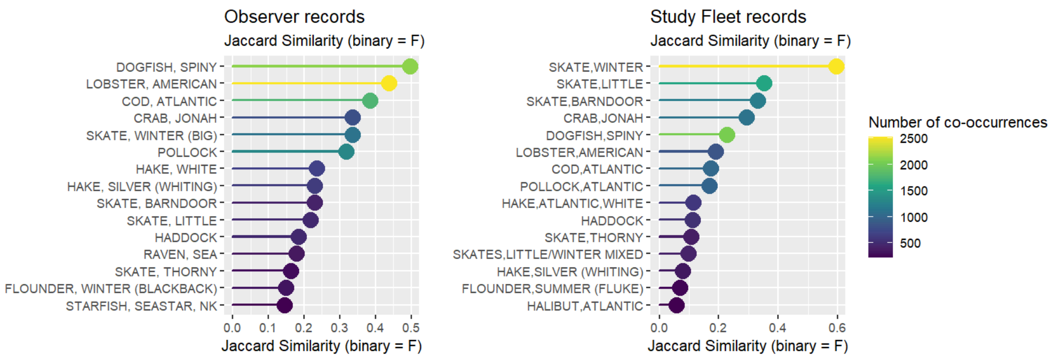


Figure 9. Gini index values for each regional configuration in the subset data used for other analyses. A) for gillnet, B) for trawl, and C) for scallop dredge.

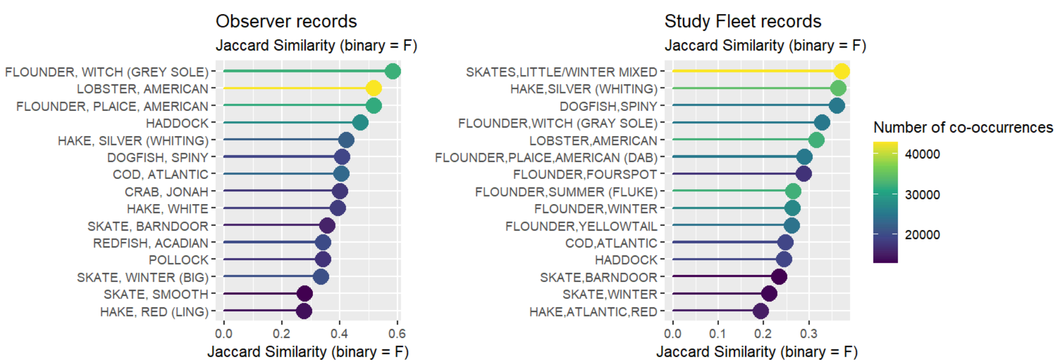
APPENDIX

Figure S1: Jaccard indices for each gear type and data source. The top five species were leveraged in each data source to build a data set of fishing events for the analyses. A) for gillnet, B) for trawl, and C) for scallop dredge gear.

A)



B)



C)

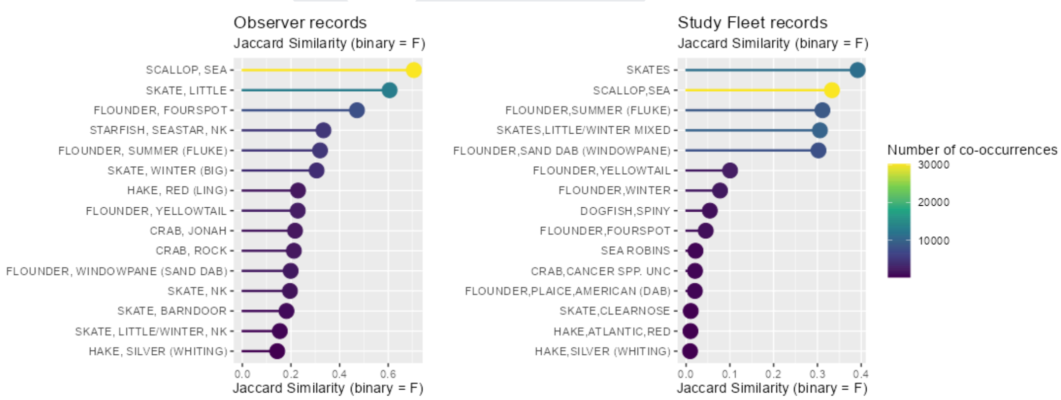
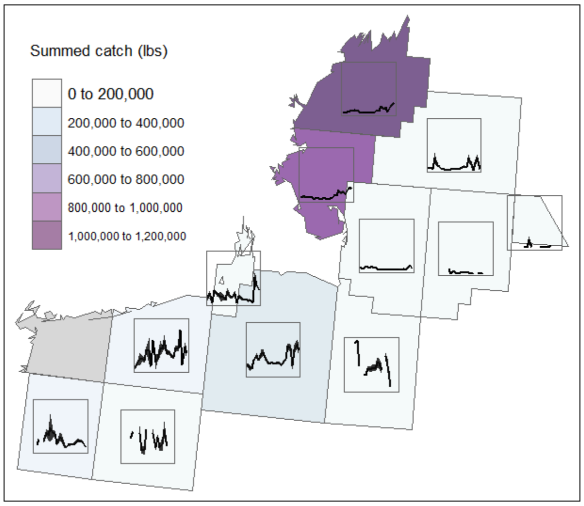
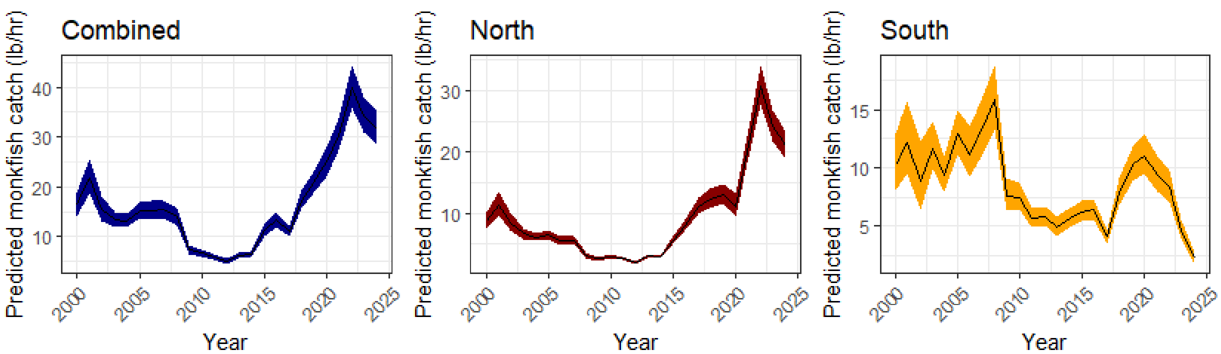


Figure S2: Sensitivity analyses of the full gillnet data set. First in A) we see the distribution of catches in space for the full gillnet data set. B) the standardized CPUE for each regional configuration for the full gillnet data set. C) the Gini index values for each region

A)



B)



C)

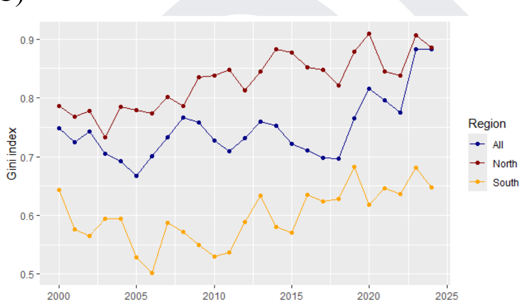
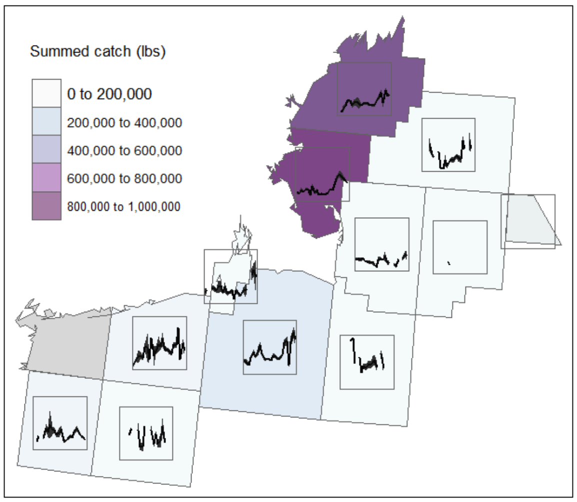
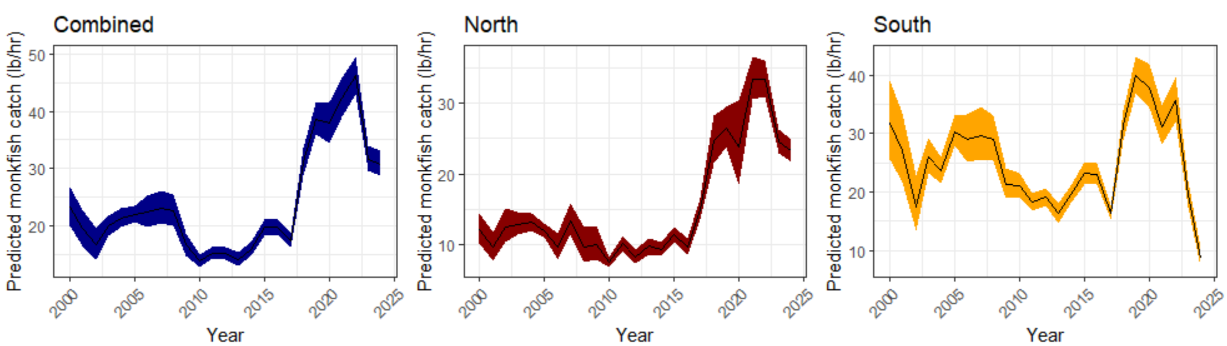


Figure S3: Sensitivity analyses of the targeted gillnet data (i.e., where monkfish were listed as a target species). First in A) the standardized CPUE for each regional configuration where only monkfish targeted gill data are included, B) the standardized CPUE for each regional configuration for the full gillnet data set. C) the Gini index for monkfish targeted gillnet data.

A)



B)



C)