Title

An investigation of fine-scale CPUE for northern shortfin squid (*Illex illecebrosus)* using NEFSC Study Fleet data

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Abstract

Here we explore the fine-scale catch and effort data from the Northeast Fisheries Science Center's Study Fleet Program to improve our understanding of the northern shortfin squid (*Illex illecebrosus*) fishery. We describe fishing behavior over space and time and compare these results to previously reported fishing patterns. Additionally, we fit generalized additive models to the Study Fleet catch data to standardize catch per unit effort estimates. Finally, we explore seasonal and annual patterns in the catch data and discuss the potential of monitoring these patterns using haul-level data as a means to help inform management of this dynamic and valuable fishery.

Introduction

The northern shortfin squid (*Illex illecebrosus*) is harvested in the Northeast US and Canadian waters. Shortfin squid is a transboundary stock managed by the Northwest Atlantic Fisheries Organization (NAFO). Through the 1980s, shortfin squid were fished by a large international fishery. The US fleet transitioned to a domestic bottom trawl fleet in the late 1980s with the establishment of the US exclusive economic zone (EEZ), with some early activity being joint ventures with foreign processors. This portion of the stock has been managed by the Mid-Atlantic Fishery Management Council (MAFMC) via annual specifications to a Fishery Management Plan (FMP). Over this period the total allowable catch (TAC) has been set by a variety of methods and has declined from ~ 30,000 t to ~ 20,000 t. Catches over this time have fluctuated from between ~2,000 t to ~ 25,000 t, with catch exceeding the TAC in a number of recent years (1998, 2004, 2017, 2018 and 2019).

Shortfin squid are similar to other cephalopods (Arkhipkin *et al.* 2015) having a brief lifespan (less than one year), and recruitment that is strongly influenced by environmental conditions (Hendrickson 2004, Hendrickson and Holmes 2004, Dawe *et al.* 2007). The magnitude of the fishery removals has not consistently been reflected in indices of abundance (Macho and Humberstone 2019), hampering the development of a stock-recruitment relationship. Currently, reference points exist for this species, however they are not being used for management, because assessment models cannot estimate fishing mortality or biomass (Macho and Humberstone 2019). Because of this ambiguity, there is an interest from scientists, managers, and industry in exploring additional available data to characterize potential trends in abundance as well as approaches for in season management.

Previous explorations of fishing behavior have provided valuable insight into *Illex* fleet dynamics (Hendrickson *et al.* 2003, Powell *et al.* 2003, Powell *et al.* 2005), but this information has not been updated recently and may not reflect the current fleet. More recent investigates have utilized coarse-scale catch and effort data and, thus, may not capture the fine-scale dynamics of this fishery. To help guide management approaches and potentially provide input for questions about the state of the fishery, we explore patterns in the fishing behavior of the vessels participating in the northern shortfin squid (hereafter *Illex*) fishery from the Northeast Fisheries Science Center's (NEFSC) Study Fleet program. In addition to exploring patterns of behavior for vessels targeting *Illex*, we develop a standardized catch rate for the vessels participating in this fishery from Study Fleet. Vessels participating in this program are contracted by the NEFSC's Cooperative Research Branch to report their catches on a haul-level (a finer resolution than mandated vessel trip reports). Many of these vessels also carry instrumentation to record fine scale effort (depth and speed) as well as water temperature data (described in Bell *et al.* 2017).

Estimates of fishery catch per unit effort (CPUE) are widely used as indices for assessing the abundance of exploited populations in fishery management where dedicated surveys are not available or sufficient (Maunder *et al.* 2006). However, to obtain appropriate CPUE index values, it is essential to standardise catch-effort data. A common method for standardization of catch rates is to develop a statistical model that controls for variation among vessels, targeting, and other important variables (*sensu* Maunder and Punt 2004). Generalized linear models (GLMs) are a common tool for this process and typically are applied by fitting models to catch (or catch rate) data with specific covariates that describe variation in catch rate among vessels or time periods. Generalized additive models (GAMs) are a similar tool that have some advantages over GLMs and their use in CPUE standardization has been increasing. For example, GAMs allow relationships between the dependent variable and covariates to be non-linear in a data defined manner, and existing software for fitting GAMs can automatically estimate an appropriate degree of nonlinearity for smoothers. By developing a GAM-based standardized catch rate metric for the *Illex* squid fleet we hope to answer several questions: 1) Are patterns in the Study Fleet dataset qualitatively similar to those in other data sets (*i.e.*, survey indices or VTR CPUE), and thus is this data set a valuable source of fine-scale information about the fleets fishing; 2) Could high-resolution reporting, such as that conducted by the Study Fleet, help inform in season management by providing timely information about seasonal trends; and 3) Are the fine-scale patterns in fishing behavior similar to those estimated previously, and thus able to help inform efforts to model fishing behavior?

Methods

Data sets used

For this project we used the NEFSC Study Fleet data set, which contains a wealth of information on commercial *Illex* squid catch and effort collected at a high resolution. The modern Study Fleet program was initiated in 2006 to enable fishermen to electronically collect fine-scale catch and effort data to improve understanding of fishery and ecological dynamics. A number of vessels fishing for *Illex* have participated in the Study Fleet, with increasing participation in recent years. The majority of the Study Fleet catch and effort data are paired with effort-specific environmental conditions. This includes the precise fishing location (*i.e.*, GPS coordinates of the effort paths) as well as information on the water temperature and depth at which the gear fished (both mean temperature and temperature variation). While this highly detailed information is unique and valuable, it is derived from only a subset of vessels that have participated in the *Illex* fishery over the last twelve years. For the last three years, a larger proportion of the total *Illex* landings have come from Study Fleet vessels, however the total percentage of landings captured by Study Fleet vessels has varied between 2% and 25% through time (Figure 1). Study Fleet vessels collecting *Illex* squid data have participated in the fishery for an average of approximately four years (Figure 2), with small mesh bottom trawl being the predominant gear in the fishery.

Within the Study Fleet data set, *Illex* catches range from hundreds to tens of thousands of pounds (Figure 3). Currently there is no unambiguous way to identify all trips that are specifically targeting *Illex*. For previous analyses (*e.g.*, environmental assessments used for management) a threshold of > 50% *Illex* catch on a trip level (by weight) has been used (Figure 3). Here we are utilizing a similar threshold for identifying a set of 'targeted' trips. We also relax this threshold and utilize a set of hauls on which the catch comprises > 10% *Illex* and landed more than 100 lbs of *Illex* (hereafter the 'comprehensive' data set). Thresholds for selecting efforts were applied at the trip level for the targeted data set so as to be consistent with the previously used criteria, and at the haul level for the comprehensive data set, however explorations which applied the thresholds in different ways (e.g., selecting the targeted data set with a haul level threshold) did not significantly change results.

There is a clear trade-off between the two subsets. The targeted data set provides information about trips where vessels are participating in the targeted *Illex* fishery, while the other provides a broader set of trips where vessels may not specifically target *Illex*, but likely target a variety of co-occurring species (*i.e.*, longfin squid, whiting, *etc*.). Generally, the catches in the more comprehensive dataset occur in the same geographic regions (along the shelf edge) as those from the targeted data set and the larger VTR data set (Wright *et al.* 2020). Utilizing a larger data set allowed us to include information captured on trips that occur at the beginning and end of the season, as well as a larger number of trips where environmental data were available (specifically information on temperature which may have an important effect on the distribution of *Illex*). The workflow for this analysis was to fit initial models to the comprehensive data set where more records and variables were available. Once an initial model was established, we performed a second round of variable selection on the targeted data set. We discuss the results of this model fitting, and we characterize the potential consistencies between the comprehensive and targeted data sets.

Fine-scale fishing behavior

To explore patterns in this data set that could help to better understand information in aggregate effort metrics (*e.g.*, a fleet wide VTR data set), we present descriptions of key metrics of fishing behavior in the haul-by-haul Study Fleet data. These metrics are only calculated for the targeted data set as that made the results more straightforward to apply to other VTR based analyses (where a similar threshold is applied when subsetting trips). Specifically, we describe patterns in a few key metrics of fishing behavior including the time search before a first haul, the time between hauls, the portion of the day that is typically fished, as well as the total number of hauls on a trip. These metrics are qualitatively compared to previous findings (*e.g.*, Powell *et al.* 2003) to explore variation in fishing behavior through time.

CPUE model fitting

To standardize CPUE, we fit generalized additive models (GAMs) to each data set. GAMs are much like their generalized linear counterparts (*e.g*., allow for data to come from a variety of distributions), but do not presume that the effect of all of the predictors is captured by a simple linear relationship (Wood 2017). Models are fit by additively combining multiple basis functions (generally polynomials) to generate smooth functions that relate predictors to a response. These models are incredibly flexible while also being highly interpretable. They also avoid overfitting by penalizing the complexity of smoothers (wiggliness) when calculating metrics of model fit.

In CPUE standardization, a model is fit to catch and effort data so as to control for variation in confounding variables (Gulland 1956, Cambell 2004). GAM models are being increasingly used in CPUE standardization (*e.g.*, Maunder and Punt 2004, Basson and Farley 2014, Chiu *et al.* 2017, Forrestal *et al.* 2019), because of their flexibility, and because the software packages available to fit them have become well vetted and extensive. Specifically, commonly used software packages automate the selection of the degree of smoothness for each explanatory variable. For the CPUE standardization we perform here, the response variable for all models was haul-level *Illex* catch in pounds (lbs). Using haul-level *Illex* catch in pounds divided by distance towed was also thoroughly explored, but it did not improve model fit (both haul length and haul time were loosely correlated with catch at the haul level - R^2 = 0.28). All the GAM models were fit using the mgcv package (Wood 2011) for R using R version 3.6.1 (R Core Team 2019).

Fisheries dependent data sets tend to be information rich, and allow for a large number of variables to potentially be included (Table 1). Here we explore a set of what we believed to be the most relevant variables that are currently available. These included those that have been shown to be significant in predicting CPUE in previous studies of *Illex* (*e.g.*, Powell *et al.* 2003). To assess the impact of a given variable on the model (and thus the standardized CPUE) we inspected how the AIC of the model changed when the variable was included in the model. Additionally, we inspected the change in the explained deviance with and without each variable. Further, models were fit in the R package mgcv using the argument ‘select’ equals ‘TRUE’. This approach adds a penalty to each term, such that when the smoothing term parameter estimation is conducted, variables with limited effects are effectively removed from the model (penalized to zero effect). For simplicity and interpretability all considered variables were included as smooths of additive terms. Vessel identity was considered as random effects in the model. Year was included as a smooth rather than a factor so as to capture interannual trends such as oceanographic processes, however fitting with year as a factor produced highly comparable results.

Model fit varied slightly depending on the size and scale of the data set used to fit the model. More data points are available to assess model fit with the comprehensive (lower threshold) data set. Because of this, models receive more information about variables that could be important (such as temperature) or variation in catch associated with the beginning and end of the season. As a first step in our model fitting, we assessed the fit of simple models using a variety of families (error distributions), including a negative-binomial model and Poisson model. Additionally, a Gaussian model fit to log-transformed data was fit to the data. Model diagnostics (*i.e.*, QQ plots, residuals plots, predicted vs. observed plots -- see Appendix A & B) were evaluated for each, and the best fitting model (based on AIC, explained deviance, and our interpretation of model diagnostic plots) was used for the subsequent variable selection process. The GAM models were fit using a set of smooths: thin-plate spline, cyclic cubic, a two-dimensional tensor-product surface smoother to account for spatial effects attributable to the location (latitude, longitude) of each haul. Smoothness parameters and *k* (the dimension of the basis or number of knots) for each variable were determined by examining model diagnostics (e.g., the gam.check function in the mgcv package) and refitting a model with just one variable at a time.

Because our ultimate goal was to construct an annual relative index of CPUE, once we fit a final model to a data set we needed to estimate what the CPUE of *Illex* would have been under standardized conditions. The first step in constructing such an index was to set up a prediction data set with each of the covariates included in the final model. To make this data set we chose median values for the covariates (*e.g.*, week, year, hour, *etc.*). Predicted values are obtained on a natural log scale and are back-transformed prior to plotting. The resulting indices (one for each data set) are used as indicators of trends in abundance, as standardized catch should be proportional to the species abundance. A second prediction data set was generated in a similar manner to visualize predicted catches in space and time following the methods of Miller *et al.* (2013). These spatio-temporal predictions are meant to help visualize and check modeled outcomes rather than provide estimates of CPUE.

Results

Descriptions of each data set

As described in the methods, two data sets of haul-level *Illex* catches were used for analyses: 1) a ‘comprehensive’ data set of *Illex* catches where more than 100 lbs where caught in a given haul and > 10% of the catch (by weight) was *Illex*; and 2) a ‘targeted’ data set where more specific trip-level criteria were met to ensure that the targeted data set was comparable to those being considered from other data sources and previous analyses (*e.g.,* the larger sub-trip VTR data set). Applying these strict criteria (see Methods) reduced the total number of haul records used in the analysis from the ~4,800 to ~2,000 records. The raw distribution of haul-level catch weights for each of these data sets were both positively (right) skewed (Appendix C). After natural logarithm transformation, the data sets were both approximately normally distributed, with a mean slightly lower for the comprehensive data set than for the targeted data set. Another important distinction between the two data sets was the number of records that contained temperature data. For the comprehensive data set the number of hauls with temperature data was larger (~1,800), while the number of haul records from the more targeted trips was much lower (~760). Similarly, haul records from the comprehensive data set came from the full span of weeks in the year while hauls from the targeted data set were only available for weeks 20 - 40 (beginning of May through the end of September).

Exploring fishing behavior

To explore patterns of fishing behavior, we focused on the targeted data set, which is most similar to the VTR data set, to provide mechanistic details for modeling behavior in the larger VTR data set. Exploratory analyses suggested a number of interesting facts about fishing practices. First, because of the location where vessels fished, the time to reach the fishing grounds and searching prior to a first haul was approximately 15-20 h (although this varied slightly by port -- with southern ports exhibiting search times that are slightly shorter). These values did not change through time, even though the locations along the shelf break do shift north in later years. Almost all hauls occurred during daylight hours, and for hauls during the day, the time between hauls was approximately 2-3 hrs. This time is measured between setting one haul and beginning another and depended on the hour of the day, as fishing activity was quite rare at night and thus the time between the last haul of one day and first haul of the next could be much longer (almost 12 hr). Haul times averaged 2.5 hr with standard deviation of 1.1 hr. There was some variation between vessels in the average tow time, with a minimum of 1.78 and a maximum of 3.76. Generally, haul times and haul lengths were tightly correlated (R^2 = 0.81). Average haul length was 12.3 km, with again some variation among vessels (maximum was 22 km and the minimum was 8 km). Together these results shed some light on the fishing behaviors of *Illex* fishing vessels (Figure 4).

GAM Models Fitting

The final GAM model fit to the larger comprehensive data set explained 76% of the deviance and had an adjusted R^2 of 0.75 (Table 2A). Including additional variables increased the explained deviance slightly (and decreased model AIC); however, improvements were minor (1-4% explained deviance). Smooths and factors that were significant and impactful predictors of catch in the model included (Figure 5A): 1) a unimodal (hump shaped) relationship between week of the year and catch, 2) a non-linear smoother on year that decreased and then increased, 3) a tensor between latitude and longitude with increasing catches in the southeast, 4) a smooth of the hour of the day that increased around sunrise and decreased throughout the day, and 5) a random effect for the vessel ID.

This same model was then fit to the more targeted data set, where it again explained a large percent of the deviance (44%) and had a relatively high R^2 (0.43, Table 2B). Again, exploration which included additional variables increased the explained deviance slightly, but not enough to warrant inclusion (*i.e.*, < 5% in explained deviance). Patterns for the smooths in this model were similar to those fit to the comprehensive data set (Figure 5B). There were some exceptions including higher values for predicted catch in northern regions (near the New England Canyons region), and some subtle variation in the shapes associated with the smooth of year and the hour of the day. Given the difference in size between the data sets (~2,000 vs ~4,800 records) it is surprising to see the high degree of similarity in both the smooth shapes and the relative impact of the selected variables.

After standardizing CPUE via GAM models, values of the catch per haul in each year were plotted to show the trend through time as well as the variation in standardized CPUE estimates (Figure 6). Trends present in both data sets are again highly similar (as we might expect), but vary in scale (the mean catch per haul is lower in the comprehensive data set). In both data sets the general trend is high early in the time series (2007 - 2010), followed by a decrease in the early teens (roughly 2011 - 2013), and then finally an increase back to early catch rate levels in the later teens (2016-2019) (Figure 6). Finally, we predicted spatio-temporal patterns in catches to visualize model results (Figure 7). Predicting these associations allows us to compare predictions to other analyses as well as the raw data and provide some confidence in modeled results. As we observed in the raw data and in other modeling efforts, model predictions suggested high catches along the shelf edge in most years with higher catches at the beginning and end of the time series matching our expectations.

Seasonal patterns across years

In addition to the aforementioned trends through time in CPUE in each data set, we also observed an annual cycle in CPUE within each year (Figure 8). The intensity of the season peak in CPUE varies across years, such that in years with higher sustained catch rates the rate of increase in CPUE appears to be higher. This pattern was more apparent in the larger comprehensive data set, because those observations span a larger number of weeks of the year (only the pattern from the comprehensive data set is shown). The closure of the fishery in 2017, 2018, and 2019 seems to align with a seasonal reduction in effort in years where the fishery was not closed.

Discussion

The fine-scale catch and effort data from the Study Fleet enables us to quantitatively explore fishing behavior of *Illex* vessels and our analyses reveal several pertinent fishing behaviors, including a long transiting and searching period at the initiation of trips. This transiting and search period is shorter for the vessels from Mid-Atlantic ports, but does not appear to vary with years. These patterns are quite similar to those reported in earlier studies (*e.g.*, Powell *et al.* 2003), although haul durations in this data set are slightly shorter (2.5 hr rather than 3.3 hr) and haul lengths were also shorter (~12 km vs. 18 km). These shifts are subtle and suggest that despite significant fluctuations in availability of and markets for *Illex*, fishing behavior has remained relatively stable.

As expected, there was a strong seasonal component to *Illex* fishing effort that was evident in the GAM modeling as well as the explorations of mean catches by week. These patterns are similar to those that have been observed previously, correspond with the seasonal migration of *Illex* onto the shelf (Hendrickson and Holmes 2004), and provide some evidence that vessels participating in Study Fleet fish in a manner that is consistent with the larger fleet. This seasonal pattern likely has important implications for the management of this fishery. Specifically, it reinforces the notion that environmental drivers have large effects on the distribution of *Illex*, and that availability of this species to the fishery is limited in space and time.

Other covariates that were important in predicting *Illex* catch included the hour at which a haul occurred as well as the geographic location. These patterns are again logical given what we know of the fishery and the species; *Illex* are a deep-water species that migrates onto the shelf to feed, and the fishery primarily occurs at the shelf edge (Hendrickson 2004). Bottom temperature has been suggested as a driver of the distribution of *Illex*, and potentially important in influencing catches, however previous work found little evidence to support this idea (Powell *et al.* 2003). Here again, temperature was not an important predictor of catch. In both data sets, including mean temperature (or temperature variance) only improved model fit slightly (explained deviance increased by < 5%). Another factor that has been shown to be important to *Illex* CPUE is the type of storage a vessel uses for its catch, with recirculated sea water (RSW) vessels having higher catches (Powell *et al.* 2003). This pattern was apparent in our data set, but similar to a number of other variables (*e.g.*, vessel length, vessel horsepower, etc.) including catch storage type in the model did not improve model performance significantly.

The temporal pattern of standardized *Illex* CPUE derived from fine-scale Study Fleet data is consistent with the patterns in larger VTR CPUE data sets. Specifically, *Illex* CPUE was high between 2007-2010, decreased to a low 2012-2013, and then increased to a peak between 2017-2019 (Hendrickson and Showell 2016, Macho and Humberstone 2019). This temporal pattern in CPUE was much clearer in the comprehensive data set, possibly due to limited *Illex* vessel participation in the Study Fleet early in the time series (the number of records is smallest early in the targeted data set - Figure 2). For the time period examined here, the CPUE pattern in the comprehensive data set is congruent with the indices of relative abundance (stratified mean number per tow) and biomass (stratified mean kg per tow) derived from NEFSC fall bottom trawl survey data (Hendrickson 2018). Trawl survey indices were not calculated for 2017 because of mechanical issues with the vessel. The time series fluctuates tightly around the long term median for the years in this time series (neither high or low is particularly extreme). Taken together, this suggests that despite some limitations (*e.g.*, limited coverage and continuity of individual vessels) that a standardized Study Fleet *Illex* CPUE is representative of the fleet and indicative of *Illex* availability on the shelf.

The seasonal trends evident in Study Fleet *Illex* CPUE are similar to those seen in the larger VTR data set (Figure 8, Hendrickson and Rago 2020). Specifically, Study Fleet data suggest that haul-level *Illex* catch increases more rapidly in years of higher abundance (Appendix D). Thus, using higher resolution haul-level data provides specific advantages and insights, such as identifying sharp increases early in the *Illex* fishing season. Using haul-level data such as that collected by the Study Fleet might also have an advantage over length data (e.g., Rago 2020) in that the data are already routinely submitted and processed by the science center. Thus the logistical and technical hurdles associated with mechanisms to process data quickly (i.e., in near real-time for in season management) have already been largely overcome.

This work provides an examination of the Study Fleet data and its potential application to understanding and managing the northern *Illex* squid fishery. Results highlight unique strengths of the Study Fleet data set (quantification of transit/search time and daily fishing behavior) and identify ways in which haul-level Study Fleet data can supplement information from other coarse-scale data sets (e.g. VTR). The Study Fleet data are the most informative in years where *Illex* vessel participation is highest, and given the limited size of the fishery, sustaining or expanding participation in haul-level reporting could be valuable. While environmental data here did not improve overall model fit to catch data, the pairing of environmental data with other biological variables could help improve our understanding of the environmental drivers of population fluctuations.

Tables

Table 1

Variables explored as part of the GAM-based CPUE standardization. The variable name is given along with the source used to access the data. A brief description of the data as well as the range present in the information are shown. A column indicated whether the variable was included in the final model, and whether the data was available in the targeted or comprehensive data sets. The types of splines explored in model fitting as well as the type used in the final model for each variable are shown. Vessel storage type was provided by Cooperative Research Branch technicians familiar with each vessel. Smooth are either splines (s) or tensor products (te) with basis types: ‘cc’ - cyclic cubic spline, ‘tp’ - thin plate spline, ‘gp’ - gaussian process, and ‘re’ -random effects.

Variable	Source	Description	Range	Included	Present	Smooth forms considered	Final smooth
Week	VTR	The week of the year that the catch was recorded on	1 - 52	Yes	Targeted, Comp.	s(,bs=(‘cc’, ‘tp’))	cc
Year	VTR	The year in which a catch was recorded	2008 - 2019	Yes	Targeted, Comp.	s(,bs=(‘tp’))	tp
Latitude	VTR	The latitude at which a haul was completed	35 - 40	Yes	Targeted, Comp.	te(,bs=’tp’,’gp’’)	gp
Longitude	VTR	The longitude at which a haul was completed	63 - 73	Yes	Targeted, Comp.	te(,bs=’tp’,’gp’’)	gp
Depth (m)	VTR/GTE	The depth at which a haul was completed	0 - 187	No	Targeted, Comp.	s(,bs=’tp’)	
Hour	VTR	The hour of the day when a haul was completed	0 - 23	Yes	Targeted, Comp.	s(,bs=(‘cc’, ‘tp’))	cc
Vessel ID	VTR	A number assigned to an individual vessel	1 - 34	Yes	Targeted, Comp.	s(Vessel ID,bs=’re’)	re
Mean Temperature (°C)	GTE	The mean temperature at which a haul was completed	8.3 - 14.2	No	Targeted, Comp.	s(,bs=’tp’)	
Variance in Temperature (°C)	GTE	The variance in temperature across a haul	0 - 2.1	No	Targeted, Comp.	s(,bs=’tp’)	
Vessel Horsepower	CFDBS	The estimated horsepower of a vessel	250 - 2100	No	Targeted, Comp.	s(,bs=’tp’)	
Vessel Length (ft)	CFDBS	The estimated length of a vessel	43 - 146	No	Targeted, Comp.	s(,bs=’tp’)	
Vessel storage	OTHER	The type of product storage used by a vessel	Fresh, re-circulated seawater, or frozen	No	Targeted, Comp.	factor(Vessel Storage)	

Table 2

Significance of each variable in the final models fit to the A) comprehensive and B) targeted data sets. For the targeted data set explained variance was 44%, whereas for the comprehensive data set explained variance was 76%. Adding additional variables to the trimmed model led to subtle decreases in AIC and increases in deviance explained. Typically these changes in explained deviance were < 5% and thus not contributing significantly to model performance.

A)

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
(Intercept)	7.9823	0.1695	47.0973	< 0.0001
B. smooth terms	edf	Ref.df	F-value	p-value
s(YEAR)	7.1132	11.0000	194.3426	0.0003
s(WEEK)	6.9487	8.0000	509.9613	< 0.0001
s(VESSEL_NAME)	17.5406	20.0000	44.7361	< 0.0001
s(HOUR)	5.2983	11.0000	11.7642	< 0.0001
te(START_HAUL_LON,START_HAUL_LAT)	9.2999	24.0000	43.7030	< 0.0001

B)

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
(Intercept)	8.6311	0.2546	33.8973	< 0.0001
B. smooth terms	edf	Ref.df	F-value	p-value
s(YEAR)	7.5953	10.0000	160.5302	0.0857
s(WEEK)	5.7565	8.0000	33.7919	< 0.0001
s(VESSEL_NAME)	13.5521	15.0000	44.2184	< 0.0001
s(HOUR)	2.5260	11.0000	10.3012	< 0.0001
te(START_HAUL_LON,START_HAUL_LAT)	4.2562	23.0000	4.0218	0.2388

Figures

Figure 1

The percentage of total *Illex* landings captured in the Study Fleet data set. Data presented are derived from the NEFSC's commercial dealer database as well as Cooperative Research's Study Fleet tables.

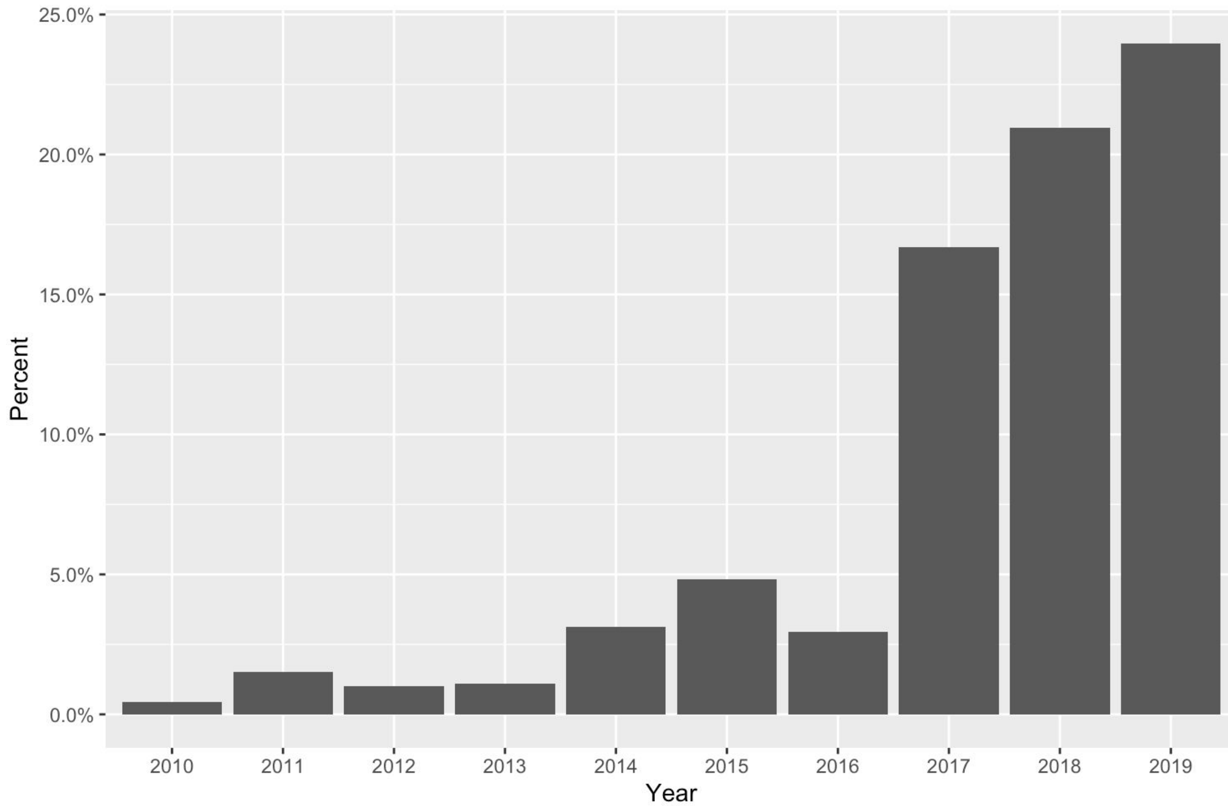


Figure 2

Years when vessels participating in the Study Fleet program caught *Illex*. The number of hauls where a vessel landed *Illex* is shown by the size of the point. The color of the point corresponds to the number of hauls in each of the data sets. Red shows the number of hauls in the targeted data set (> 50% by weight and > 10,000 lbs at the trip level), whereas blue shows the number of hauls in the more comprehensive data set (hauls with > 100 lbs of catch).

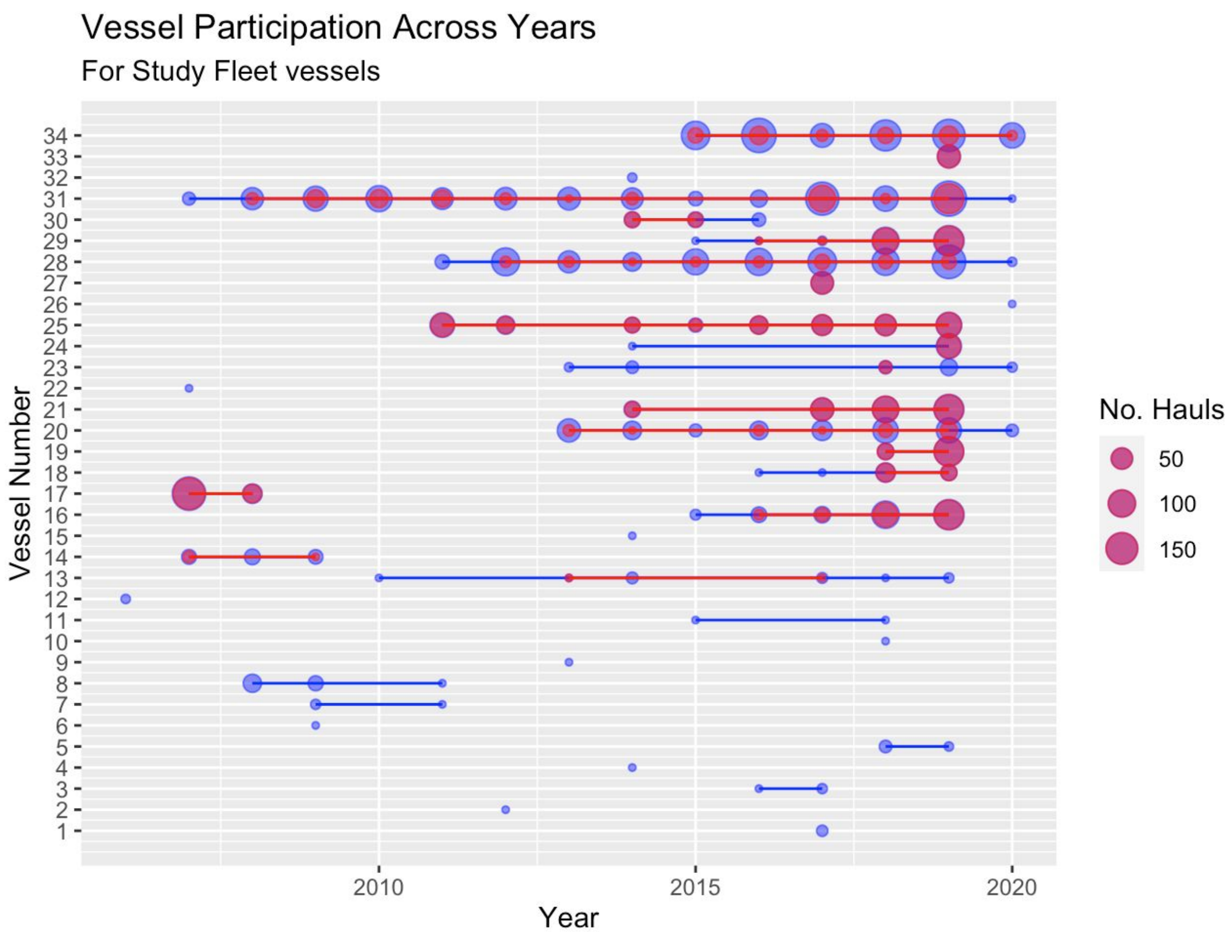


Figure 3

The distribution of haul weights and percent (by weight) *Illex* in the catch. The historic criteria used to classify whole trips as being part of the Illex fishery has been a threshold of 50% (by weight) and a total weight of > 10,000 lbs of *Illex* landings (shown in the right red panel).

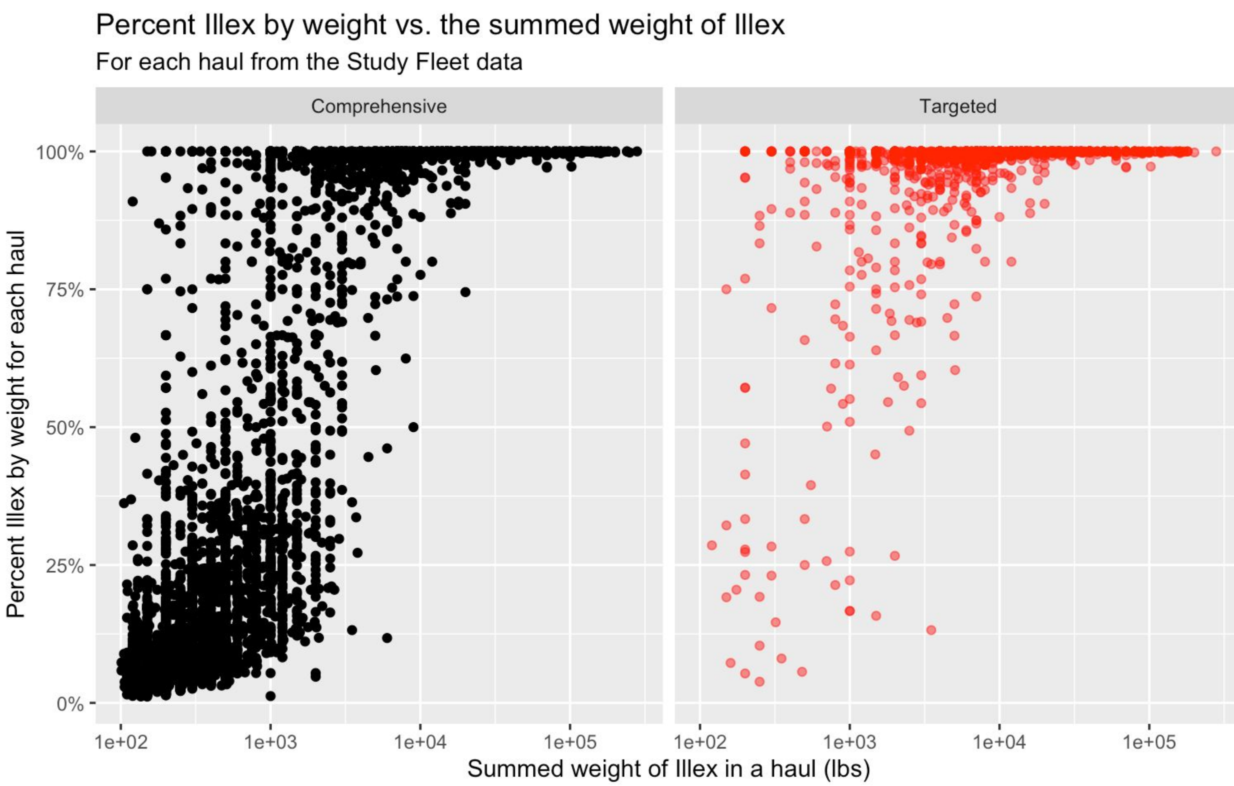
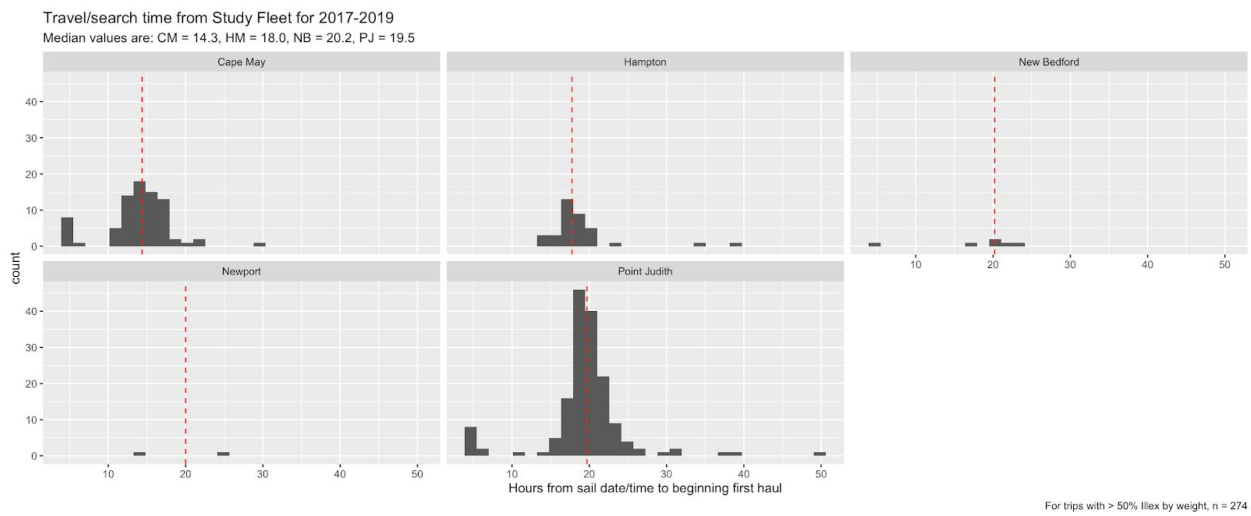


Figure 4

Metrics of fine-scale *Illex* fishing behavior from the targeted Study Fleet data set. A) show the time from sailing to the first haul beginning (in hours). B) shows the time between hauls for the same vessels and trips. Data are broken down geographically in A). In B) each panel represents the number of hours between hauls. Panels are broken to show this relative to the hour of the day when hauls begin. Very few hauls begin at night or in the early morning (0-6), and thus for hauls in the morning (7-12) there can be a greater time since the previous haul.

A)



B)

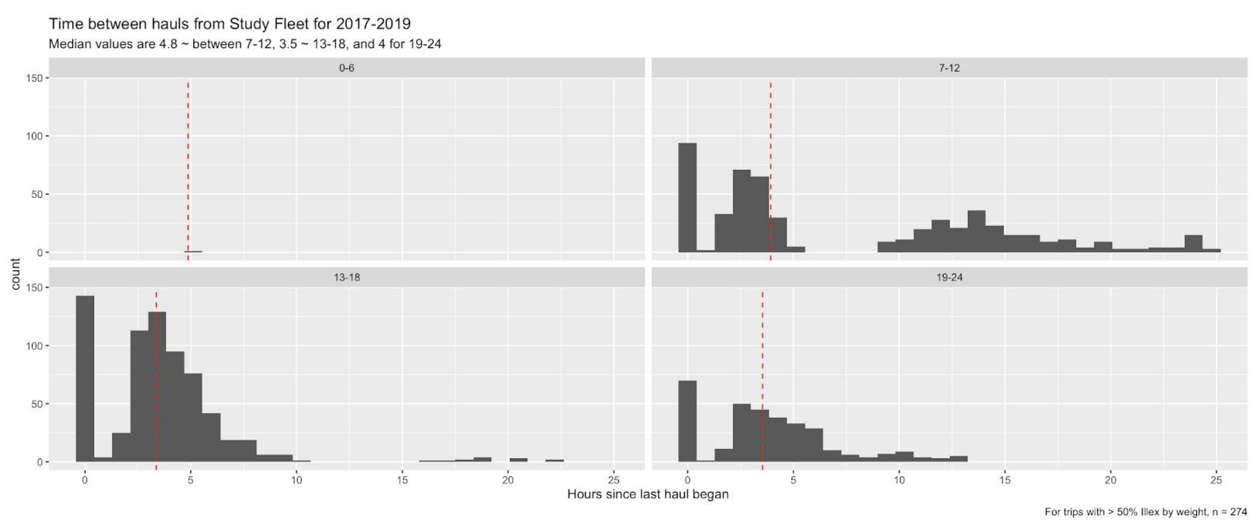
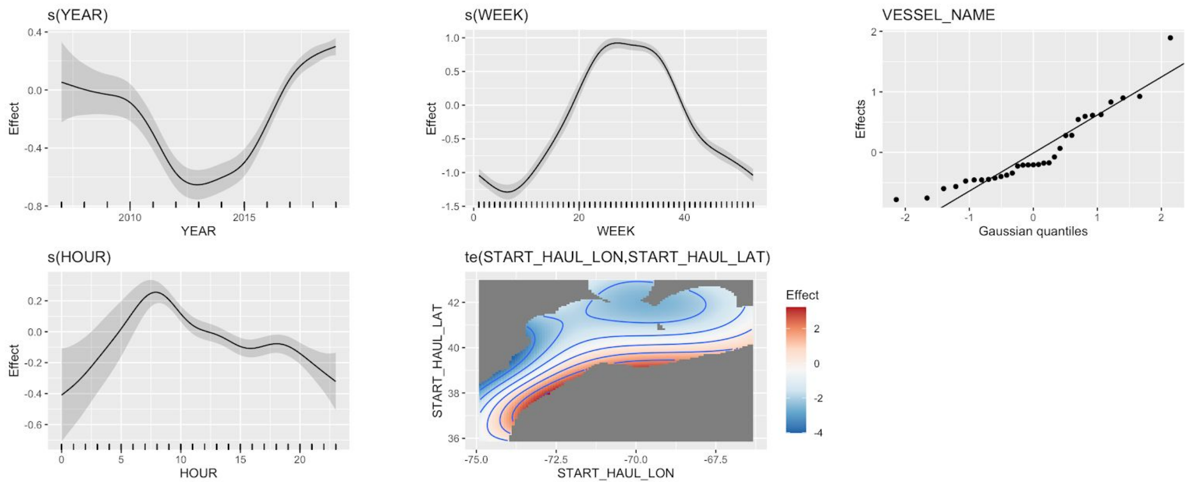


Figure 5

Smooths associated with the final *Illex* CPUE model for each data set. Smooths for the comprehensive data set are shown in A). The same variables fit to the smaller targeted data set are shown in B). The tensor shown in both A and B represent the latitude and longitude of a haul with contours and shading to show the effect (positive in red negative in blue). Areas without data are shown in gray. Geographic bounds for these plots approximate those in Figure 7.

A)



B)

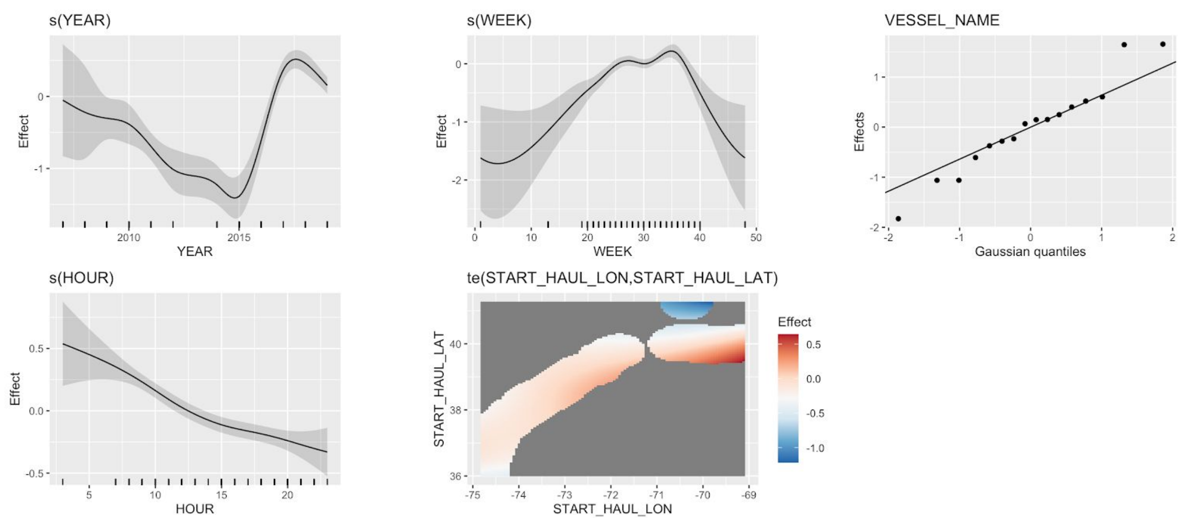
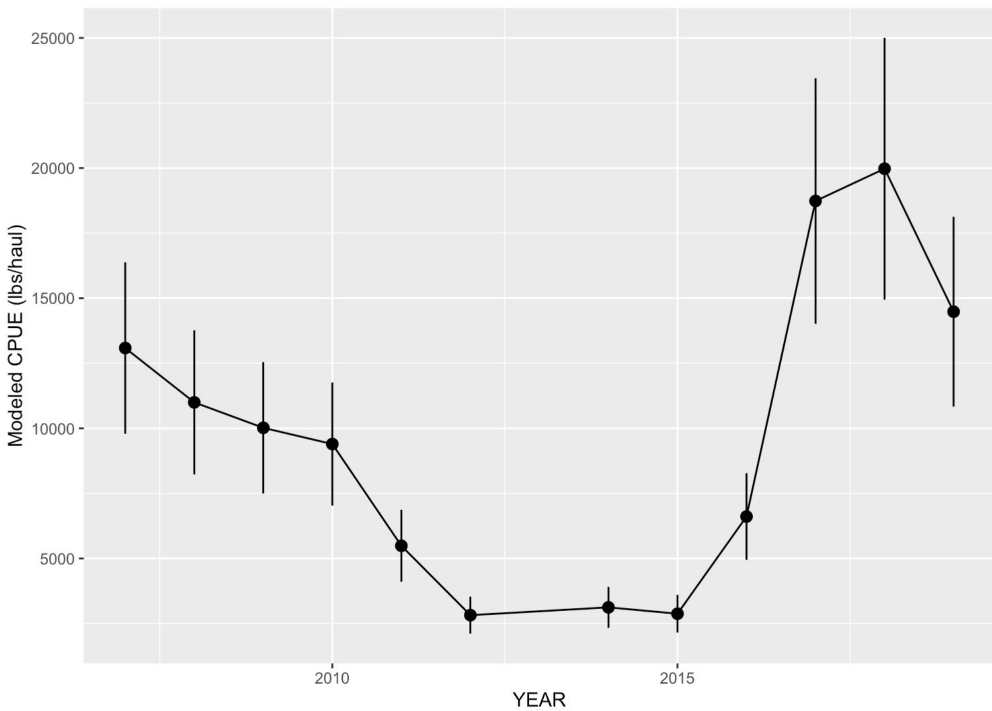


Figure 6

Illex CPUE estimate through time for each data set. The trend for the smaller targeted data set is shown in A). The trend for the larger comprehensive data set is shown in B).

A)



B)

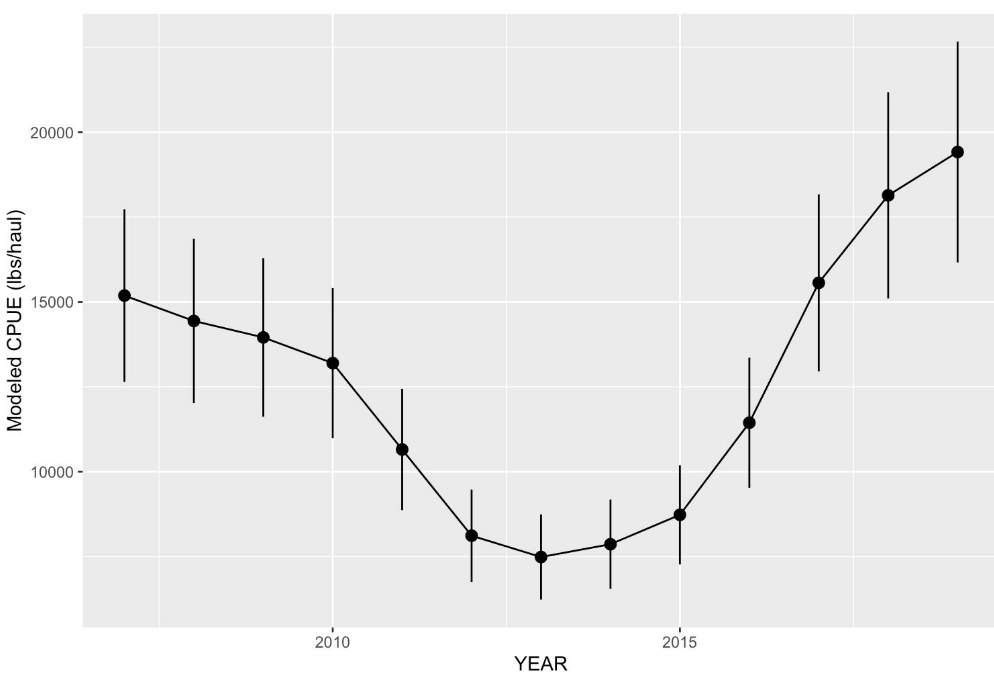


Figure 7

Predicted standardized *Illex* CPUE based on the GAM model fit to the Study Fleet data. Higher predicted CPUE values are shown in greens and yellows, while lower predicted CPUEs are shown in blues and purples. The locations of the raw data (binned by ten minute squares) are shown in red and tend to overlap with the larger VTR effort data set (Wright *et al.* 2020 - Figure 2). Median values of all variables outside of latitude and longitude (*i.e.*, hour, week, *etc.*) were used to generate a data set for predictions.

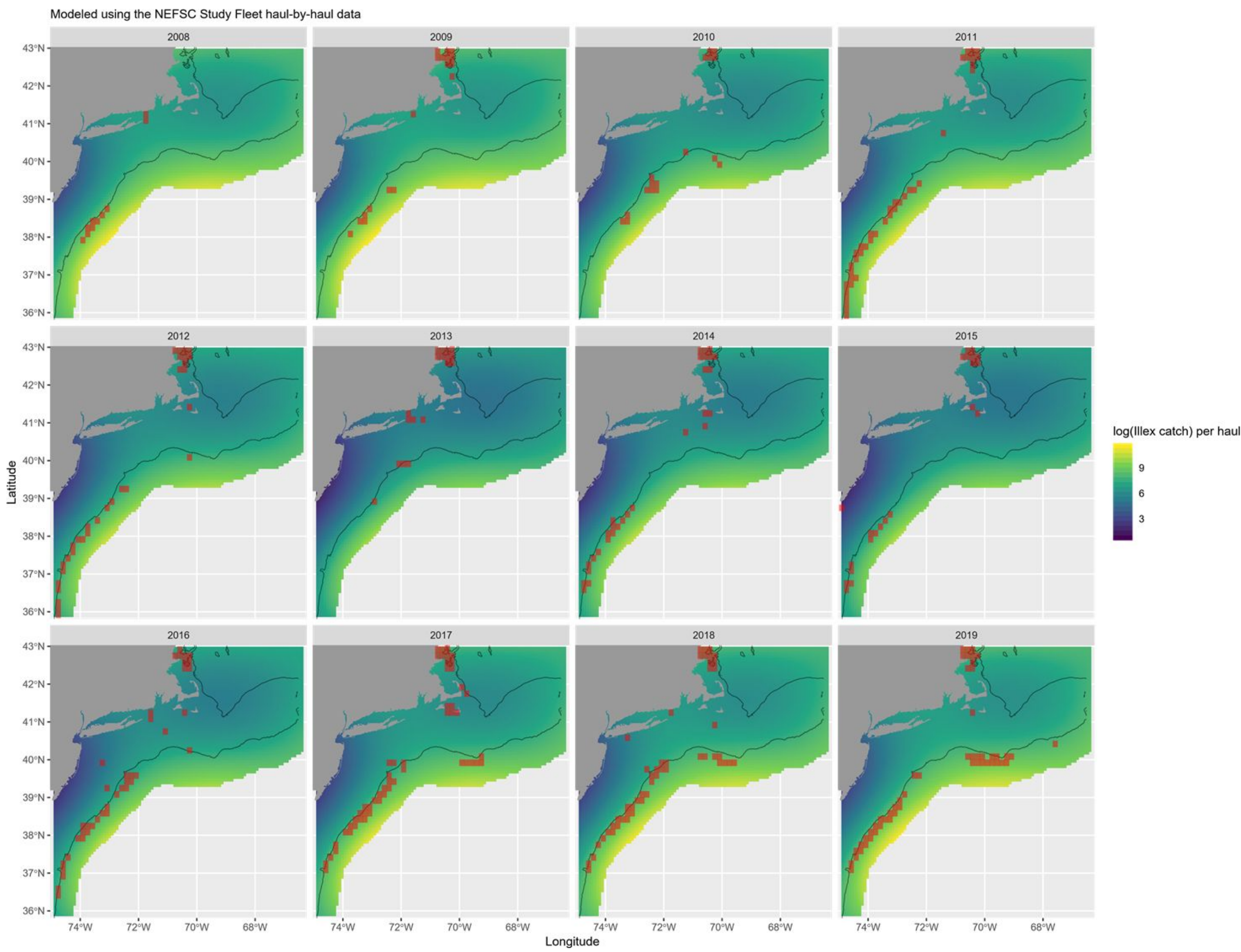
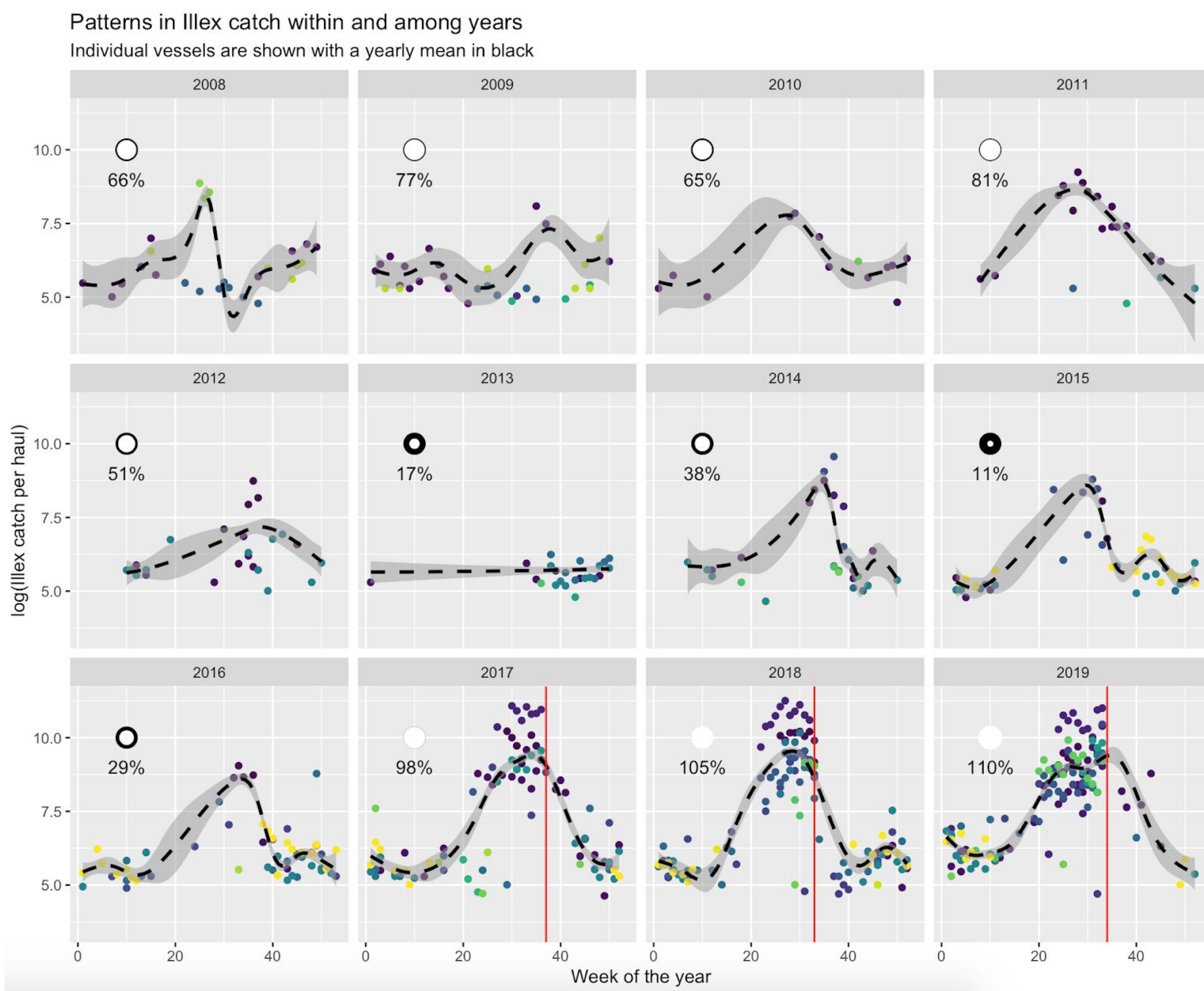


Figure 8

Seasonal pattern of *Illex* catches from the comprehensive data set. Points represent average *Illex* CPUE (ln(catch) of *Illex* per haul) for a given vessel in a given week. Black splines represent a loess (moving average) fit to the data, and are meant to help visualize the seasonal trend. Red vertical lines show the week of a fishery closure. Large black and white points in the top left of each panel show the percent of quota caught in a given year. Similar seasonal patterns are apparent in the targeted data set as well as the records of CPUE from the Northeast Fisheries Observer Program (not shown).



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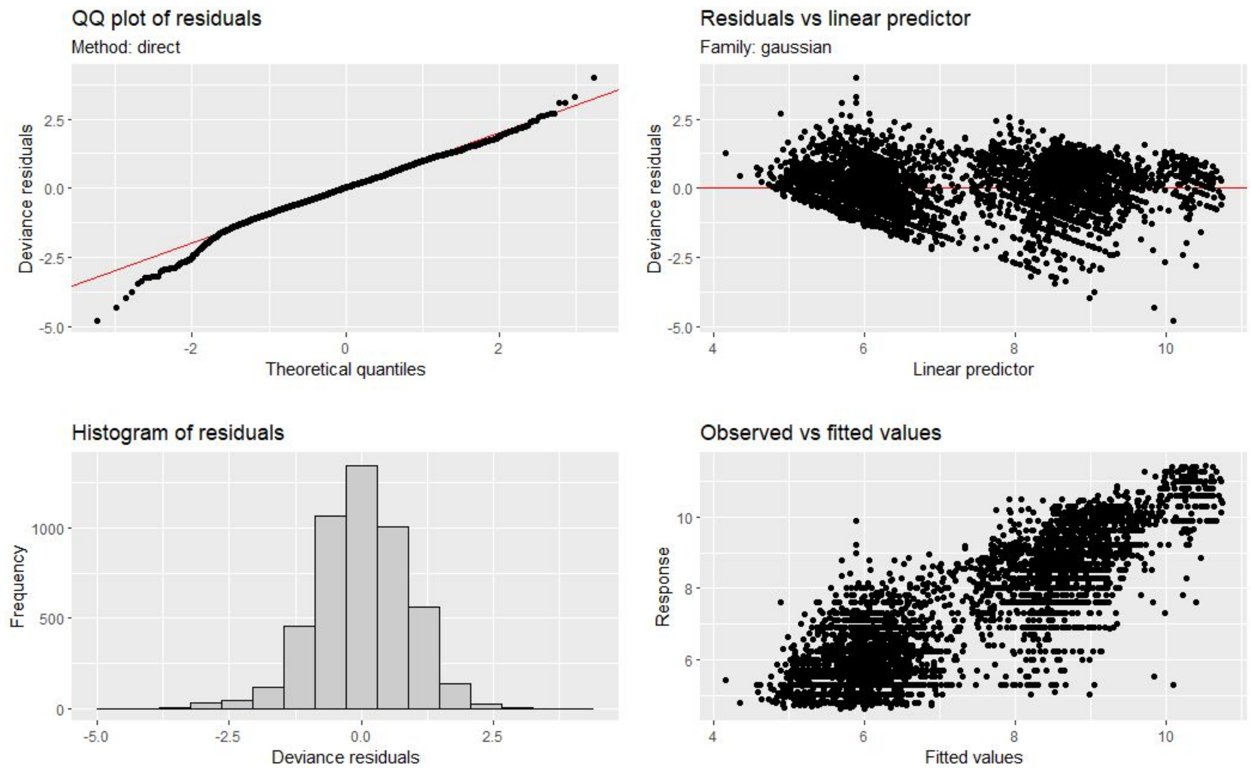
Appendices

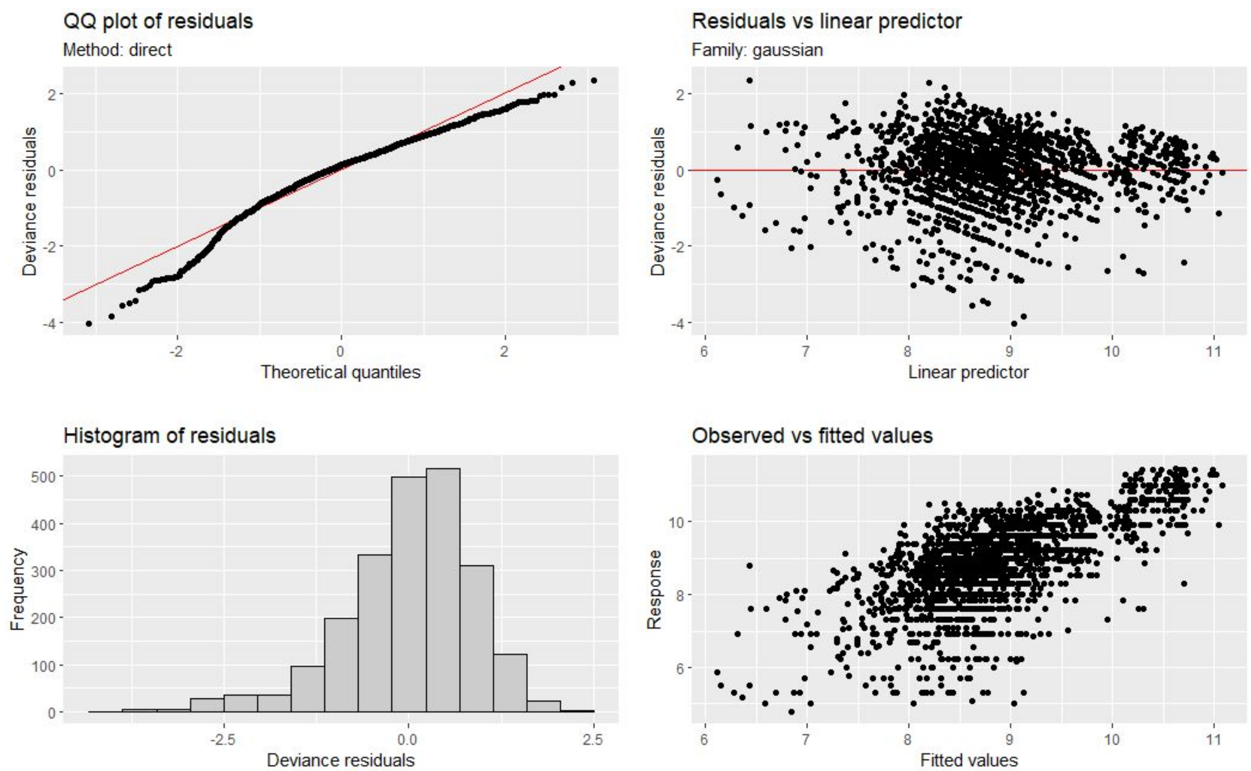
Appendix A

Model diagnostic plots for the GAM model fit to the comprehensive Study Fleet data set.



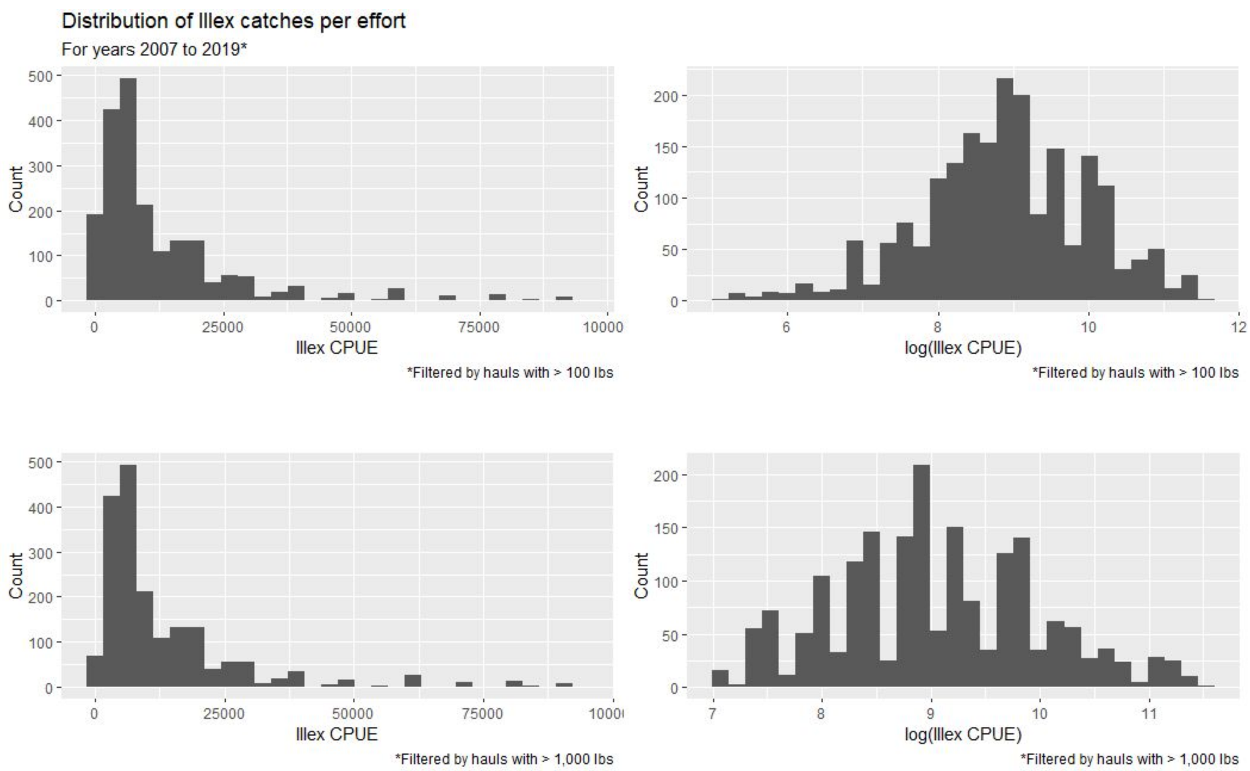
Appendix B

Model diagnostic plots for the GAM model fit to the targeted Study Fleet data set.



Appendix C

Distributions of *Illex* catches in each data set used for this analysis. Note the raw data as well as the natural log transformed data are shown. The comprehensive data set is shown in the top row (haul with >100 lbs of *Illex*). The targeted data set is shown on the bottom (hausl with >1,000 lbs of *Illex*).



Appendix D

An example of a smooth-factor interaction between year and season that shows the rate of increase in *Illex* CPUE values is more rapid in years where the standardized annual CPUE was higher (2016, 2017, 2018, and 2019). It is possible that this type of pattern could be used to help guide in season management.