Report of the *Illex* 2021 Research Track Assessment Working Group

CONTENTS

ABSTRACT

The northern shortfin squid, *Illex illecebrosus*, inhabits the continental shelf and slope waters of the Northwest Atlantic Ocean between Iceland and the east coast of Florida and constitutes a unit stock throughout its range. The species is highly migratory, growth is rapid and the lifespan is short, up to 217 days for individuals inhabiting the U.S. shelf. *Illex illecebrosus* is semelparous and females spawn and die within several days of mating. Age data indicate that spawning occurs throughout the year and that the first several months of the U.S. fishery are supported by the winter cohort. The onset and duration of the fisheries occur in relation to annual migration patterns on and off the continental shelf which appear to be highly influenced by environmental conditions.

The 2005 Stock Assessment Workshop (SAW) 42 Review Panel noted that because there were no reliable research survey indices for *Illex* inhabiting the U.S. Shelf, the assessment relied primarily on fisheries data, mainly Catch Per Unit Effort (CPUE) indices and biological data collected during prior cooperative research projects Due to the lack of adequate data regarding fishing mortality rates and absolute biomass, the SAW 42 Review Panel concluded that stock status for 2003-2004 could not be determined. Since the 2005 SAW 42 assessment, the Northeast Fisheries Science Center (NEFSC) has provided annual fishery and survey data updates to the Mid-Atlantic Fishery Management Council (MAFMC) and National Marine Fisheries Service (NMFS) to inform the specification of the annual Overfishing Limit (OFL) and Acceptable Biological Catch (ABC).

In the current assessment, a suite of Indirect Estimation Methods provides logical bounds on stock biomass and fishing mortality rates based on assumed ranges of survey and fishery catchability and availability and natural mortality. However, the Indirect Estimation Methods point estimates of stock biomass and fishing mortality were not accepted as a basis for stock status determination. A Generalized Depletion Model suggests in a qualitative way that F was lower than M and that stock biomass was lightly fished in 2019. However, the Generalized Depletion Model estimates were not accepted as a basis for stock status determination. The 2021 *Illex* Research Track Assessment Working Group (WG) recommends that the stock status is unknown with respect to reference points-based definitions of overfishing and overfished.

EXECUTIVE SUMMARY

The following Terms of Reference were addressed and are summarized below:

1. Estimate catches from all sources, including landings and discards, and characterize their uncertainty.

Landings from the U.S. commercial fishery on the northeastern U.S. shelf were updated through 2021. A new estimation method (SBRM approach) was used to estimate commercial fishery discards of *Illex* for 1989-2019. Landings from the commercial fisheries involving the northern stock component (Scotian Shelf and Newfoundland) were also updated. Data on recreational fishing for *invertebrates* are generally not collected, but it is believed that recreational catches are negligible.

2. Evaluate indices used in the assessment, including annual abundance and biomass indices based on research survey data and standardized industry CPUE data. Characterize the uncertainty of the abundance and biomass index estimates. Explore the relationship between fishing effort and economic factors (e.g., global market price) in order to determine whether the addition of an economic factor will improve the fit of the CPUE standardization model.

Fishery-independent research survey indices of abundance from all four seasons have been compiled through the most recent years available for consideration in this assessment. These include the winter, spring and fall Northeast Fisheries Science Center (NEFSC) bottom trawl surveys, the Canada Department of Fisheries and Oceans (CA DFO) Division 3LNO spring and fall surveys, the CA DFO Division 4VXW summer survey, the Maine-New Hampshire Division of Marine Resources (ME-NH DMR) spring and fall trawl surveys, the Atlantic States Marine Fisheries Commission (ASMFC) Gulf of Maine northern shrimp summer survey, the Massachusetts Division of Marine Fisheries (MA DMF) spring and fall trawl surveys, the New Jersey Department of Environmental Protection (NJ DEP) summer trawl survey, and the Virginia Institute of Marine Science (VIMS) Northeast Area Monitoring and Assessment Program (NEAMAP) bottom trawl surveys.

Multiple fishery-dependent indices of stock biomass were developed from the U.S. regional commercial fisheries databases. Hendrickson (2020, updated) used landings and effort data from the Dealer/Logbook (Vessel Trip Report; VTR) merged database to develop a directed fishery Landings Per Unit Effort (LPUE) index. The LPUE data for 1997-2019 were modeled using a General Linear Model that considered multiple error structure assumptions and classification variables. A negative binomial model that included year, week, vessel permit (a unique vessel identifier) and statistical area provided diagnostics indicating the best fit. The standardized fishery LPUE indices and the NEFSC fall survey biomass indices (stratified mean kg per tow) showed similar trends and were significantly correlated.

Lowman *et al.* (2022) used the Dealer/Logbook data, the Northeast Fishery Observer Program data (Observer), the Cooperative Research Branch Study Fleet data, and insights from *Illex* processors and harvesters to develop directed fishery LPUE indices by component fleets

(‘Freezer’ and ‘Wet’ vessels) (Mercer *et al.* 2022). Specific effort was made to integrate economic covariates, including *Illex* price, global production of ommastrephids, and fuel price, which were identified by industry members as impactful on fishery dynamics (Mercer *et al.* 2022). Other covariates explored include year, week (when feasible), spatial smoother, distance from fishing grounds to landing port, trip duration, and landing port. The LPUE data were modeled using Generalized Additive Models that considered multiple error structure assumptions, classification variables, and covariates. Results indicated that several factors are important in driving *Illex* LPUE, including year, fishing location, *Illex* market price, trip length, and landing port. Year and fishing location are intuitive, as the *Illex* population has historically exhibited high inter-annual variability and a patchy distribution. Results reveal general synchrony in *Illex* LPUE trends over time, but differences in the scale of LPUE depending on the fleet and standardization approach. The Dealer/Logbook wet boat LPUE GAM standardization results are the most similar in trend and scale to the Hendrickson LPUE GLM standardization results. Insights on the technical and economic factors impacting the *Illex* fishery helped to steer the Lowman *et al.* (2022) LPUE standardization and highlighted the importance of considering socio-economic factors when analyzing and interpreting data from this fishery (Mercer *et al.* 2022).

Although the relationship between observed fishing effort and international market prices was not explicitly considered, both domestic *Illex* price and annual global ommastrephid production, which are tightly coupled with international market price, were directly integrated into the LPUE GAM standardization (Lowman *et al.* 2022).

Salois *et al.* (2022) investigated a suite of oceanographic features, including mesoscale eddies and fronts, to assess and characterize their relationships to *Illex* catch rates. As such, the work addresses aspects of both TOR 2 (indices of abundance) and TOR 4 (environmental factors that may influence body size and recruitment [and by extension stock size and availability]). GAM results identified ten covariates that were significant predictors of *Illex* CPUE, including temporal (year, week), spatial (latitude, longitude, and NAFO subareas) and environmental (bottom temperature, ring footprint index, ring orientation, salinity at the 222 meter isobath, chlorophyll frontal activity, and standard deviation in sea surface temperature) variables. The results suggest a suite of environmental variables which may serve as indicators of *Illex* habitat condition or areas of increased primary productivity. These indicators are of interest due to their implications for identifying potential areas of *Illex* aggregation and better understanding their distribution and availability to the fishery. In particular, bottom temperature and ring footprint index may be useful indicators for habitat conditions relevant to *Illex* juvenile/adult and pre-recruit/larval life stages, respectively, whereas the remaining covariates, ring orientation, salinity, and chlorophyll frontal dynamics are potential indicators of areas of high productivity.

3. Utilize the age, size and maturity dataset, collected from the 2019 landings, to identify the dominant intra-annual cohorts in the fishery and to estimate growth rates and maturity ogives for each cohort. Also use these data to identify fishery recruitment pulses.

The life history of *Illex illecebrosus* is very similar to that of other *Illex* species, such as the well-studied *Illex argentinus*. Both species have a sub-annual lifespan, semelparous reproduction and highly variable inter-annual abundance and rapid growth rates with high plasticity due to the strong influence of environmental factors on *Illex* species' life history traits. Age rather than length data must be used to identify intra-annual cohorts and determine growth rates of squid stocks because two individuals of the same size can be from different cohorts due to differential cohort growth rates. Temporally and spatially representative *I. illecebrosus* samples were randomly sampled from unculled catches of the directed fisheries during 2019 and 2020. Dorsal mantle length (DML), body weight (g), sex and sexual maturity were recorded for 951 and 1,269 individuals, respectively. Statoliths from 400 (2019) and 325 (2020) individuals were extracted and the time-consuming ageing work, two independent counts of the daily growth increments for each statolith, was conducted by two squid aging experts One of the agers experienced with conducting Trace Element Analysis (TEA) on squid statoliths used laser ablation inductively coupled plasma mass spectrometry (LA-ICP-MS) to sample strontium and 12 additional trace element concentrations, with Ca used as an internal standard to account for variation in ablation yield. Trace elements were sampled continuously along a transect of each of 252 statoliths. Due to COVID-19 project delays during 2020 and 2021, a considerable amount of the age-based analyses could not be completed in time for this report. Thus, we focused on cohort identification using Sr:Ca concentrations for this stock assessment and note that he remaining analyses will be completed and published following the *Illex* Management Track Assessment process. The Sr:Ca concentrations from the statolith samples were binned by the same hatch month ranges that the age frequency data identified as the winter and summer cohorts and the data for each cohort were modeled separately, a Gaussian GAMM (identity link, to ensure positive fitted values) to determine whether Sr:Ca ratios were distinct for each assigned cohort and how they changed throughout ontogeny.

The study results showed unimodal and bimodal age and length compositions for the 2019 and 2020 fishery catches, respectively. This difference was explained by the catch age frequencies binned by hatch month and which were used to identify the intra-annual cohorts. The first mode represented the winter cohort, hatch months November-April, and the second mode represented the summer cohort, hatch months May-July. The binned age frequency data also indicated that the summer cohort recruited to the fishery in low numbers during September, but dominated the catches in October. However, a September sample but no October sample was collected during 2019 and an October sample but no September sample was collected during 2020. Thus, the summer cohort mode could only be seen in the 2020 data. The catch age frequencies binned by hatch month confirmed the results of a May 2000 study that two cohorts support the U.S. fishery; a winter cohort that supports the early fishery period (during May-September, although September is a cohort transition month) and a summer cohort (previously inferred as the spring cohort) supports the fishery mainly from October onward. The study results also confirmed continuous spawning noted in the initial ageing study and determined that monthly fishery catches were comprised of two to four different hatch months.

The results of the 2020 TEA analysis confirmed the aged-based assignment of the winter and summer cohorts because the two cohorts have significantly different Sr:Ca ontogenetic signatures. Correct cohort assignment is crucial for the sustainable management of squid stocks because differences in growth and maturation rates between cohorts require each cohort to be assessed separately as if it were a separate stock. Thus, management of the U.S. fishery, should take into account the abundance of each of the two intra-annual cohorts identified for this resource. A good reminder of the need for cohort-specific management of squid stocks is the collapse of the northern stock component (NAFO Subareas 3+4) of *I. illecebrosus* in 1982, following record high catches during 1976-1981. The collapse subsequently led to a 36-year period of low productivity during 1982-2017 that could not support a fishery on this stock component.

The TEA of the 2020 data indicated that the winter and summer cohorts, which confirms the assignment. Future analysis of the 2020 trace element data may help elucidate migration patterns to and from the fishing grounds, but for now presents further evidence that the winter and summer cohort assignments presented at this Research Track Assessment are accurate.

4. Characterize annual and weekly, in-season spatio-temporal trends in body size based on length and weight samples collected from the landings by port samplers and provided by *Illex* processors. Consider the environmental factors that may influence trends in body size and recruitment. If possible, integrate these results into the stock assessment.

Both annual and weekly *Illex* body weight data were collected from the commercial fishery landings during 1997-2019. The body weight data for 1997-2003 was collected as part of a cooperative research study that involved real-time, fishery dependent data collection to evaluate changes in stock productivity. Body weight data for 2004-2006 and 2009-2018 were collected from landings of the directed fishery by staff from the two primary *Illex* processors. *Illex* body length samples were also collected by NEFSC port samplers, with body weight computed by dividing the sample weight by the number of lengths in the sample. Samples collected by port samplers included 100 squid per market category per month. Research survey trends in annual mean body weight are associated with annual trends in *Illex* relative abundance, such that stratified mean body weight is generally lower during years of low relative abundance, and vice versa, on the U.S. Shelf. When trends between the fishery mean body weight time series and the NEFSC fall survey stratified mean body weight time series are compared, the fishery time series does not show the gradual decrease exhibited by the survey time series. In addition to quantitatively exploring trends in *Illex* body size, Mercer *et al.* (2022) also synthesized industry observations on trends in body size within the fishing season and between years. Salois *et al.* (2022) addressed environmental factors that may affect the stock in TOR 2.

5. Develop a model that can be used for estimation of fishing mortality and stock biomass, for each dominant cohort that supports the fishery, and estimate the uncertainty of these estimates. Compare the results from model runs for years with low, medium and high biomass estimates.

Rago (2020, 2021) developed a suite of Indirect Estimation Methods, including Leslie-Davis Depletion, Mass Balance, Envelope of bounds, Escapement given fishing mortality, and the analysis of Vessel Monitoring System catch and effort data to develop logical bounds on population biomass and fishing mortality rates and provide useful catch advice. A Leslie-Davis depletion model did not work very well for *Illex* because key assumptions for model application are violated. A Mass Balance Model shows the magnitude of migration, growth and recruitment effects necessary to offset the differences in relative abundance between the NEFSC spring and fall bottom trawl indices. An Envelope Model approach was used to establish logical bounds on biomass based on assumed ranges of catchability, availability, and fishing and natural mortality rates. The basic constructs of the Envelope Model were used to establish potential ranges for an Escapement Model for existing and hypothesized ABC values. Vessel Monitoring System data were analyzed to estimate effective fishing mortality rates over the entire population. The WG concluded that when considered together, the Indirect Estimation Methods suggest that the overall *Illex* population is likely to be large and relatively low chances of high fishing mortality rates over a broad range of assumed parameter extremes. However, the point estimates of stock biomass and fishing mortality were not accepted as a basis for stock status determination.

Manderson & Mercer (2022) evaluated Generalized Depletion Modeling (GDM; Roa-Ureta 2012, 2015, 2020), a technique that can explicitly account for in-season pulses of animals onto and off of fishing grounds in the estimation of parameters useful for assessment. Specifically, GDM can be used to un-confound the effects of in-season migration on estimates of N_0, M, F and fishery escapement H. Manderson & Mercer (2022) reviewed the technique and applied intra-annual GDM to weekly landings and individual weights of squid measured by processors during 5 recent US *Illex* fishing seasons (2013, 2016-2019). GDM involves multi-model inference about the timing of in-season ingress and egress of animals onto the fishing ground based usually on fishery dependent indicators. Steps in development and evaluation of a 2 fleet GDM (freezer trawler and RSW + ICE Boats) for the 2016 fishing season were demonstrated in detail. The sample size was largest in 2016 (N=38) and "best" GDM produced plausible values and reasonable CVs (<57%) for most perimeter estimates. Caution is warranted in interpreting and applying the GDM results since high CVs were produced for some parameter estimates associated with the fishing process and catch perturbations due in part to relatively small sample sizes. Fleet specific parameters associated with the fishing process, and the timing and magnitudes of pulses detected in landings were particularly problematic. Moving to a time step of a day could produce sample sizes necessary for GDM to produce parameter estimates and derived quantities accurate and precise enough for operational assessment of the risk of overfishing in the US *Illex* fishery.

The WG believes GDM is promising but requires further research. The WG found that the GDM results suggest in a qualitative way that F was lower than M (from internal GDM F to M ratios results) and that stock biomass was lightly fished in 2019 (from comparison of the estimated range of annual biomass to the Rago (2021) Mass Balance bounds). The WG concluded that the GDM (as currently configured with weekly fishery landings data) does not provide an adequate quantitative basis for stock status determination using any of the candidate BRPs, including Mass Balance bounds, F to M ratios, or previously published estimates of biological reference points for the stock (i.e., Hendrickson and Hart 2006).

6. Describe the data that would be needed to conduct in-season stock assessments for adaptive management and identify whether the data already exist or if new data would need to be collected and at what frequency.

As *Illex* is a sub-annual species, assessments should be based on data from the current year. However, stock assessments are prepared for the previous year because data for the current year are unavailable at the time of the assessment. Consideration of the timing of the *Illex* assessment and the collection of in-season assessment data are needed to remedy these issues.

The data, analytical, and management needs for in-season assessment and management of *Illex* include: Precise fishing locations, precise catch and effort data (daily), individual *Illex* size, weight, and sex data throughout the fishing season by fleet (freezer and wet boat), operational oceanographic indicators of *Illex* biomass and availability, a functional depletion model, and an in-season management process.

Some of these data needs would require Council approval and a rule-making action which could take 18 months or more before implementation. It is recommended that sufficient data needs are met and in place and the assessments completed for at least 1 full fishing year before considering implementing measures that could make an in-season adjustment to the quota. Overall, additional research and resources are needed prior to pursuing in-season assessment or management for northern shortfin squid.

7. Update or redefine Biological Reference Points (BRP point estimates for B_{MSY}, $B_{THRESHOLD}$ and F_{MSY}) or BRP proxies, for each dominant cohort that supports the fishery, and provide estimates of their uncertainty. If analytical model-based estimates are unavailable, consider recommending alternative measurable proxies for BRPs. Comment on the scientific adequacy of existing and recommended BRPs or their proxies.

Although new age and maturity data were collected during 2019 and 2020 for the current assessment, the number of mature females in the aged samples were too few to run the Hendrickson and Hart (2006) models to estimate updated values of natural mortality. Statolith-based ageing of squid samples is very expensive and there are few squid ageing experts available globally. These facts, combined with the need for an adequate number of mature females, suggest aged-based estimation methods for BRP proxies might not be practical for this southern stock component of the northern shortfin Illex stock managed by the U.S.

An extension (Rago 2022) of the Hendrickson and Hart (2006) was considered by the WG. The extended model recast the continuous time model as a discrete monthly time step model with a seasonal fishery. The model provided useful insights into the magnitude of population compensation necessary to offset the force of fishing mortality and the protective effects of seasonal (vs continuous) fisheries. However, it was not sufficient to redefine an alternative basis for a biological reference points or MSY proxies. The revised matrix model may have utility as a dynamic estimation model for future assessments.

8. Recommend a stock status determination (i.e., overfishing and overfished), for each dominant cohort supporting the fishery, based on new modeling approaches developed for this peer review.

The WG recommends that the stock status is unknown with respect to reference points-based definitions of overfishing and overfished.

9. Define the methodology for performing short-term projections of catch and biomass under alternative harvest scenarios, including the assumptions of fishery selectivity, weights at age, and maturity.

The WG does not consider the use of traditional multi-age projection methods commonly used in Northeast U.S. finfish assessments to be appropriate for the *Illex* stock on the U.S. shelf. The reason is the stock's life span of less than one year and subsequent lack of multiple age class 'inter-annual memory' in the population that makes such projections useful for multi-age finfish stocks. If some 'projection' approach is needed to satisfy management requirements, the Illex WG proposes the 'PlanBsmooth' approach (NEFSC IBMWG 2021) as a guide for forecast OFL/ABC advice.

10. Review, evaluate and report on the status of the Stock Assessment Review Committee (SARC) and Working Group research recommendations listed in the most recent SARC-reviewed assessment and review panel reports. Identify new research recommendations.

The WG provided updated responses to Research Recommendations from the previous benchmark assessments and MAFMC SSC 2020-2021 meetings. The WG developed 11 new prioritized Research Recommendations.

11. Develop a "Plan B" alternate assessment approach to providing scientific advice to managers if the analytical assessment does not pass review.

The WG recommends that the MAFMC and NMFS continue to use the current Indirect Estimation Methods approach (Rago 2021) to establish future ABC.

WORKING GROUP PROCESS

The WG met virtually many times during 2021-2022 to discuss data, concepts, modeling results, and the content of the report: January 5, February 23, March 31, April 16, June 15, August 18, September 29, November 15, and December 16-17 2021, January 24 2022, February 2 & 4 2022, and February 7 2002.

The WG also convened an Industry Listening Session to inform the assessment process with industry and public perspectives on July 13, 2021. A professional facilitator was hired to help manage the WG process beginning with the September 29, 2021 meeting.

The *Illex* 2021 Research Track Assessment Working Group (WG) comprised the following scientists and managers:

Name	Organization
Jason Didden	MAFMC
Patrick Field	Consensus Building Institute (CBI; Senior Mediator)
Lisa Hendrickson	NMFS NEFSC PDB (Assessment Lead)
Brooke Lowman	NMFS NEFSC CRB; Virginia Marine Resources Commission
John Manderson	OpenOcean Research
Anna Mercer	NMFS NEFSC CRB Chief
Alyson Pitts	NMFS GARFO
Carly Bari	NMFS GARFO
Paul Rago	MAFMC SSC Chair
Mark Terceiro	NMFS NEFSC PDB (WG Chair)
Robert Vincent	Massachusetts Institute of Technology (MIT)

In addition to the WG, the following people also participated in all or some of the WG meetings:

Name	Organization
Charles Adams	NMFS NEFSC PDB
Anthony Allen	public
Katie Almeida	The Town Dock
Alan Bianchi	North Carolina DMF
Russ Brown	NMFS NEFSC PDB Chief
Douglas Christel	NMFS GARFO
Chad Demarest	NMFS NEFSC SSB
Alexander Dunn	NMFS NEFSC
Jay Elsner	public
James Fletcher	United National Fishermen’s Association
James Gartland	Virginia Institute of Marine Science (VIMS)
Daniel Hocking	NMFS GARFO
Kimberly Hyde	NMFS NEFSC EDAB

Andrew Jones	NMFS NEFSC CRB
Jeff Kaelin	MAFMC Mackerel, Squid, Butterfish Advisory Panel
Meghan Lapp	Seafreeze Fisheries
Eric Reid	MAFMC Mackerel, Squid, Butterfish Committee
Greg DiDomenico	Lund's Fisheries
Sarah Salois	NMFS NEFSC EDAB
Thomas Swaider	NMFS NEFSC CRB
Michael Simpkins	NMFS NEFSC READ
Michele Traver	NMFS NEFSC READ
Alissa Wilson	New Jersey DFW

INTRODUCTION

The northern shortfin squid, *Illex illecebrosus*, inhabits the continental shelf and slope waters of the Northwest Atlantic Ocean between Iceland and the east coast of Florida and is assumed to constitute a unit stock throughout its range (Dawe and Hendrickson 1998). The northern stock component extends from Newfoundland to the Scotian Shelf and is assessed annually and managed by the Northwest Atlantic Fisheries Organization (NAFO) based on a total allowable catch (TAC). The southern stock component extends from the Gulf of Maine to the east coast of Florida and is managed by the Mid-Atlantic Fisheries Management Council (MAFMC) based on an annual Overfishing Level (OFL) and Acceptable Biological Catch (ABC). This Research Track Assessment (RTA) pertains to the southern stock component on the Northeast regional U.S. continental shelf (U.S. Exclusive Economic Zone [EEZ] from the Gulf of Maine to Cape Hatteras, NC), but also summarizes landings and research survey data from the northern stock component to provide context (Newfoundland and the Scotian Shelf). Fisheries and research survey data and analyses were compiled through 2019.

The life history and habitat requirements of *I. illecebrosus* are summarized in Hendrickson and Holmes (2004). The northern shortfin squid is a highly-migratory ommastrephid that lives for up to one year (Dawe *et al.* 1985; Dawe and Beck 1997; O'Dor and Dawe 1998; Hendrickson 2004). Temporal and spatial distribution patterns are highly variable at the northern limit of this species' range (Newfoundland) and are associated with environmental factors (Dawe *et al.* 1998). Recruitment dynamics are complex and have not been fully elucidated for the U.S. EEZ component of the stock, so reliable predictions of annual recruitment levels are not currently possible. Stock structure is complex and, in Newfoundland waters, is complicated by overlapping seasonal cohorts that migrate through the fishing grounds (Dawe and Beck 1997). Mean size at maturity varies between northern and southern geographic regions in some years (Coelho and O'Dor 1993). However, it is not known if these differences are due to inherent population structure. O'Dor and Coelho (1993) speculated that changes in the seasonal spawning patterns could have played a role in the collapse of the Canadian fishery during the early 1980's.

The *Illex* stock is fished on the continental shelf from Newfoundland, Canada to Cape Hatteras, North Carolina. However, there are no stock-wide indices of relative abundance or biomass. The Northeast Fisheries Science Center (NEFSC), Canada Department of Fisheries and Oceans (CA DFO), and other state agency bottom trawl surveys considered in the assessment do not cover the entire habitat range of the species and it is unknown whether the research survey indices measure relative abundance or availability to the survey gear. In addition, the Catch Per Unit Effort (CPUE) data for the U.S. fishery is generally coarse in temporal and spatial resolution (Hendrickson 2004). As a result, research recommendations in previous assessments have emphasized the need for improved stock assessment data, particularly given the short lifespan and short fishing season (4-5 months on average for the U.S. fishery).

Amendment 5 of the Squid-Mackerel-Butterfish (SMB) Fishery Management Plan (FMP) was enacted (MAFMC 1995b; 1996b) in recognition that the domestic resource was approaching full utilization and that expansion of the U.S. fleet might lead to overcapitalization. Amendment 5 established a permit moratorium to limit entry into the directed fishery, required mandatory logbook and dealer reporting as of January 1, 1997, and established a 5,000-pound trip limit for incidental catches of *Illex* by non-moratorium vessels. Amendment 6 (MAFMC 1996c) provided a mechanism for in-season closures of the *Illex* fishery, and established an overfishing definition of $F_{20\%}$ and procedures for the specification of annual quotas based on $F_{50\%}$. Amendment 7 (MAFMC 1998b) was enacted to achieve consistency between FMP's with regards to Limited Access Federal permits. Based on the requirements of the Sustainable Fisheries Act (SFA), Amendment 8 (MAFMC 1998c) established MSY-based biological reference points. Threshold and target fishing mortality rates were specified as F_{MSY} and 75% of F_{MSY}, respectively. In addition, a biomass target and minimum biomass threshold were specified as B_{MSY} and 50% of B_{MSY}, respectively. Amendment 8 also defined the essential habitat of *Illex* in the U.S. EEZ and established a framework adjustment process for specific management measures. Amendment 9 extended the moratorium on new entry indefinitely. Amendments 12 and 15 set and then revised a Standardized Bycatch Reporting Methodology. Several actions from 2010-2020 set and revised a Council risk policy that limits catch increases for a stock like Illex with no accepted assessment, and now requires the Council's Scientific and Statistical Committee to not increase catch recommendations unless: Biomass-based reference points indicate that the stock is greater than BMSY and stock biomass is stable or increasing, or if biomass based reference points are not available, best available science indicates that stock biomass is stable or increasing; and the SSC provides a determination that, based on best available science, the recommended increase to the ABC is not expected to result in overfishing. Any such deviation must include a description of why the increase is warranted, description of the methods used to derive the alternative ABC, and a certification that the ABC is not likely to result in overfishing on the stock. A pending Amendment proposes to reduce the number of permits in the *Illex* fishery, require daily catch reporting via VMS, and require hold measurements, but has not yet been approved by NMFS. Commercial fisheries for *Illex* occur from Newfoundland to Cape Hatteras, North Carolina. The bottom trawl fishery operating within the U.S. EEZ (Northwest Atlantic Fisheries Organization [NAFO] Subareas 5 and 6) is managed by the Mid-Atlantic Fishery Management Council (MAFMC) and fisheries operating within NAFO Subareas 2, 3 and 4 are managed by NAFO (Figure 1.1). During most years since 1983, a majority of the total stock landings have come from the U.S. fishery (Hendrickson and Showell 2016). Since the beginning of the U.S. fishery in 1987, landings have ranged from 26,097 metric tons (mt) in 2004 to 1,958 mt in 1988. In recent years, U.S. landings decreased from 18,797 mt in 2011 to 2,422 mt in 2015. Since 2015 landings have increased substantially. *Illex* landings for 2019 totaled 27,164 metric tons and a 2019 total catch of 28,449 mt, and increased again in 2020 to landings of 28,135 mt and a total catch of 31,234 mt, the highest of the U.S. fishery time series (Table 1.1, Figure 1.2).

Fishery-independent research survey indices of abundance from all four seasons have been compiled through the most recent years available for consideration in this assessment. These include the winter, spring and fall NEFSC bottom trawl surveys, the CA DFO Division 3LNO spring and fall surveys, the CA DFO Division 4VXW summer survey, the Maine-New Hampshire Division of Marine Resources (ME-NH DMR) spring and fall trawl surveys, the Atlantic States Marine Fisheries Commission (ASMFC) Gulf of Maine northern shrimp summer survey, the Massachusetts Division of Marine Fisheries (MA DMF) spring and fall trawl surveys, the New Jersey Department of Environmental Protection (NJ DEP) summer trawl survey, and the Virginia Institute of Marine Science (VIMS) Northeast Area Monitoring and Assessment Program (NEAMAP) bottom trawl surveys.

The *Illex* stock assessment is considered to be "data-poor" because the existing Northeast regional fishery-dependent datasets are not collected at the high temporal and spatial resolution (i.e., daily, tow-based catch, effort, fishing location and biological data) that have been used for in-season depletion-type models used for other ommastrephid squid stocks (NEFSC 1999; Arkhipkin *et al.* 2015; Arkhipkin *et al.* 2021b). The existing fishery data requires merging of the Dealer and Vessel Trip Report (VTR) databases to obtain trips that are a 1:1 match. Trips that are not matched do not contain the data needed for CPUE analyses. In addition, the spatial (large Statistical Areas for reporting fishing locations primarily resulting in a single location per *Illex* trip) and temporal (average tow duration and number of tows by subtrip) resolution of these data is inadequate for accurate in-season stock assessment.

The application of most conventional stock assessment methods are inappropriate for *I. illecebrosus* and other cephalopod species given their unique life histories and population dynamics (Hendrickson 2004; Arkhipkin *et al.* 2015; Arkhipkin *et al.* 2021b). Like other ommastrephids, *I. illecebrosus* is semelparous and spawns throughout the year with several peaks that result in the presence of multiple, overlapping sub-annual cohorts. The species has a lifespan of less than one year (Dawe and Beck 1997; Hendrickson 2004). Since 1997, the NEFSC has conducted multiple cooperative research projects with the *Illex* fishing industry that have increased our knowledge about the age, growth and life history of *Illex* in U.S. waters (Hendrickson 2004) and that have improved the spatial and temporal resolution of fisheries catch, effort and biological data in real-time via electronic logbook reporting (Hendrickson *et al.* 2003). The products of these research projects have been used extensively in the analyses and models attempted in this assessment that take into account the semelparous life history of *Illex illecebrosus*.

The *Illex* stock was last fully assessed Stock Assessment Workshop 42 in 2005 (2005 SAW 42; NEFSC 2006). That assessment included fisheries and research survey data through 2004. An in-season (weekly) assessment model that incorporated recruitment, landings and effort data, mean body weights from the fishery, and natural mortality rates computed from a maturation-natural mortality model were used to estimate initial stock size and fishing mortality rates in the U.S. fishing area during 1999 but the model was considered preliminary because additional testing was required (NEFSC 2003). The SAW 42 assessment also included a weekly yield-per-recruit (YPR) and egg-per-recruit (EPR) analysis which was also considered premature. With respect to stock status, the 2005 SAW 42 Review Panel concluded that it was not possible to evaluate the current stock status because there were no reliable estimates of absolute stock biomass or fishing mortality rate.

Since the 2005 SAW 42 assessment, the NEFSC has provided annual fishery and survey data updates to the MAFMC to inform the specification of the annual Acceptable Biological Catch (ABC). Given unusually high catches in 2017-2018 and the lack of an accepted stock assessment model, in 2019 the MAFMC formed a workgroup to consider "data poor approaches" for setting ABCs. The Council's SSC used the results of that workgroup in 2020 and 2021 to increase ABCs, from 26,000 MT to 30,000 MT (2020) and then 33,000 MT (2021). Those data poor approaches updated with the most recently available data, along with attempts at new modeling approaches, are the main analytical components of this stock assessment.

TOR 1: Estimate catches from all sources, including landings and discards, and characterize their uncertainty.

LANDINGS

A bottom trawl fishery for *Illex illecebrosus* occurs on the U.S. shelf (NAFO Subareas 5+6) and an artisanal jig fishery occurs in inshore Newfoundland waters (NAFO Subarea 3; Figure 1.1). Historically, a bottom trawl fishery also occurred on the Scotian Shelf in NAFO Subarea 4 (Hendrickson *et al.* 2005). The timing and duration of the fisheries are determined primarily by the migration of the species through the fishing grounds on the continental shelf. The inshore migration into Subarea 3 generally occurs during July, approximately three months later than it occurs on the continental shelf in Subareas 4, 5 and 6. This delay in the arrival of squid on the fishing grounds is presumably a result of the position of the Gulf Stream, the hypothesized transport mechanism for paralarvae hatched during the winter (Trites 1983), being located further from shore in this northern region. An unusually early inshore arrival of squid occurred in Subarea 3 during June 1987, when 78% of the landings for that year were taken. *Illex* remains on the shelf longer in Subarea 3 so the fishing season often extends into November after landings reach a peak in September (NEFSC 1999). Since 1992, the U.S. fishery and the Subarea 4 fishery have generally occurred during June through October with a peak in July (NEFSC 1999). Historically, foreign trawlers involved in the silver hake and argentine fishery in Subarea 4 also targeted *Illex* if it became available before the July closure of the silver hake fishing season (Mark Showell, pers. comm. 1999). However, the mixed fishery for silver hake, argentine and *Illex* has not operated in Subarea 4 since 2000 (Hendrickson *et al.* 2004). Domestic fishing effort is greatly influenced by the global market demand for squid and is limited by onshore and at-sea freezer storage capacity as well as the availability of *Illex* to the bottom trawl fishery. The Vessel Trip Report (VTR) database and NEFSC Sea Sampling database indicate that the U.S. EEZ *Illex* fishery occurs primarily at depths between 128 and 366 meters. Gear limitations prevent fishing in waters deeper than 457 meters (Glenn Goodwin, pers. comm. 1999).

Illex landings (mt) during 1963-2020 are presented for the southern stock component inhabiting the U.S. EEZ (NAFO Subareas 5+6) as well as the northern stock component (NAFO Subareas 3+4, Table 1.1, Figure 1.2). U.S. EEZ landings are partitioned into foreign and domestic components and the total allowable catches (TACs) for Subareas 3+4 and Subareas 5+6 are also presented. During 1963-1976, U.S. EEZ landings of squid by distant water fleets (foreign landings) were not consistently reported by species. In addition, domestic landings of squid were not recorded by species in the commercial fisheries dealer database until 1979. As a result, U.S. EEZ landings during 1963-1978 were derived from prorations based on the temporal and spatial landings patterns of *Illex illecebrosus* and *Loligo pealeii*, by country, from fisheries observer data (Lange and Sissenwine 1980). U.S. EEZ landings for 1979-2020 were obtained from the Weighout and Dealer databases, which consist of fish purchases by dealers, and also include landings from joint ventures that occurred during 1982-1990 between U.S. and foreign fishing vessels. Dealer reporting of *Illex* purchases has been mandatory since January 1, 1997.

Total *Illex* landings have varied considerably since 1963 (Figure 1.2). A period of high landings, which occurred during 1976-1981 when distant water fleets were active in all NAFO fishing areas, was bracketed by periods of substantially lower landings. During 1963-1967, total landings were low, averaging 7,354 mt, and were primarily from the Subarea 3 inshore jig fishery. During 1968-1974, total landings averaged 13,470 mt and were predominately from distant water fleets that had begun fishing in Subareas 5+6. However, this trend was reversed during 1976-1981, when landings were predominately from Subareas 3+4. During this time, total landings averaged 100,300 mt, and in 1979, reached the highest level on record (179,333 mt). Thereafter, landings from Subareas 3+4 declined rapidly from 162,092 mt in 1979 to 426 mt in 1983. However, landings from Subareas 5+6 remained stable and did not exceed 25,000 mt, in part, due to effort limitations placed on the distant water fleets. Since its inception in 1987, landings from the domestic bottom trawl fishery have comprised a majority of the total landings. The exception occurred in 1997, when landings from Subareas 3+4 (15,485 mt) exceeded U.S. EEZ landings (13,629 mt) and were at their highest level since 1982. Landings from Subareas 3+4 declined to 57 mt in 2001, and then gradually increased to 2,034 mt in 2004. Since 2000, landings from Subareas 3+4 have primarily been from the Newfoundland jig fishery (Hendrickson *et al.* 2004).

As noted earlier, U.S. EEZ landings have been characterized by distinct periods of high and low landings. During 1968-1982, U.S. EEZ landings were predominately taken by distant water fleets, peaking at 24,936 mt in 1976. U.S. EEZ landings subsequently declined to 1,958 mt in 1988 when foreign participation in the U.S. *Illex* fishery became prohibited in order to foster development of a domestic fishery. A majority (> 97%) of the annual landings from the U.S. EEZ since 1987 are taken with bottom trawls. During 1988-1998, landings from the domestic fishery increased from 1,958 mt to 23,568 mt and then decreased again to 2,750 mt in 2002. Landings increased to 18,797 mt by 2009 before falling again to 2,422 mt in 2015. Since 2015 landings have again increased substantially. *Illex* landings for 2019 totaled 27,164 metric tons and a 2019 total catch of 28,449 mt, and increased again in 2020 to landings of 28,135 mt and a total catch of 31,234 mt, the highest of the U.S. fishery time series. Preliminary U.S landings in 2021 are 30,714 mt (Table 1.1, Figure 1.2).

While some recreational fishing is known to occur, the NMFS Marine Recreational Information Program (MRIP) does not collect information on invertebrates, and the scale is believed to be negligible compared to commercial fishing.

DISCARDS

Two sources of data are available for estimating *Illex* commercial fishery discards, the NEFSC Observer Program Database and the VTR Database. Although the reporting of discards is required on VTRs this direct reporting of *Illex* discards is inconsistent. Therefore, *Illex* discards were quantified based on data from fishing trips monitored at sea by the Northeast Fisheries Observer Program (NEFOP) observers for 1989-2019 (2020 data required for estimation not available at the time of this assessment).

The Standardized Bycatch Reporting Method (SBRM) Omnibus Amendment to the fishery management plans of the U.S. Northeast region was implemented in February 2008 to address the requirements of the Magnuson-Stevens Fishery Conservation and Management Act to include standardized bycatch reporting methodology in all FMPs of the New England Fishery

Management Council (NEFMC) and Mid-Atlantic Fishery Management Council (MAFMC). The SBRM for the estimation of discards (e.g., Wigley *et al.* 2021) has now been adopted for most NEFSC stock assessments that have been subject to a benchmark review since 2009. The SBRM was used in this assessment to update the estimated discard of *Illex* squid in the commercial U.S. bottom trawl fisheries. The SBRM can be viewed as the combination of sampling design, data collection procedures, and analyses used to estimate bycatch and allocate observer coverage in multiple fisheries. The SBRM discard estimation approach generally uses a broad stratification (region, gear type, mesh group, access area, and trip category) that can be tailored to the needs of a specific stock or fishery if required. In the SBRM, the sampling unit is an individual fishing trip. *Illex* discards were estimated using a stratified discard-to-kept (d/k) ratio estimator (Cochran 1963) where d = observed discard pounds of *Illex*, and k = observed kept pounds of all species, raised by the trip landings of all species as reported by VTR or Dealer records, to provide estimates of *Illex* discards by stratum. The *Illex* discard estimates for bottom trawl trips (gear code = 050) in the New England and Mid-Atlantic regional fisheries were stratified by codend mesh size (large => 5.50 inches; medium = 2.50 to 5.49 inches; small = 0.50 to 2.49 inches) and calendar quarter. Further computational details are provided in Wigley *et al.* (2011, 2021).

The estimated total discards (a 100% discard mortality rate is assumed) of *Illex* ranged from 58 mt (Coefficient of Variation [CV] =37%) in 1995 to 1,850 mt (CV = 34%) in 2005, averaging 707 mt (average CV = 0.36%) during 1989-2019 (Table 1.2). Over the time series, small mesh trips have accounted for 71% (499 mt with CV = 54%) of the estimated discards, followed by medium mesh trips (15%; 107 mt with CV = 61%) and large mesh trips (14%; 102 mt with CV = 45%; Tables 1.3-1.5; Figure 1.3). The time series trend in estimated total discards generally follows the trend in reported total landings, except for a few years in the mid-1990s when the discards were estimated to be very low (including 1994, when due to small numbers of sampled trips had to be interpolated from adjacent years; Figure 1.4).

TOR 2: Evaluate indices used in the assessment, including annual abundance and biomass indices based on research survey data and standardized industry CPUE data. Characterize the uncertainty of the abundance and biomass index estimates. Explore the relationship between fishing effort and economic factors (e.g., global market price) in order to determine whether the addition of an economic factor will improve the fit of the CPUE standardization model.

RESEARCH SURVEYS

Although there are no stock-wide indices of abundance or biomass for the *Illex* stock, several seasonal research surveys provide information about abundance trends on the U.S. Shelf and the Scotian Shelf. Fishery-independent research survey indices of abundance from all four seasons have been compiled for consideration in this assessment. These include the winter, spring and fall NEFSC bottom trawl surveys, the Canada Department of Fisheries and Oceans (CA DFO) Division 3LNO spring and fall surveys, the CA DFO Division 4VXW summer survey, the Maine-New Hampshire Division of Marine Resources (ME-NH DMR) spring and fall trawl surveys, the Atlantic States Marine Fisheries Commission (ASMFC) Gulf of Maine (GOM) northern shrimp summer survey, the Massachusetts Division of Marine Fisheries (MA DMF) spring and fall trawl surveys, the New Jersey Department of Environmental Protection (NJ DEP) summer trawl survey, and the Virginia Institute of Marine Science (VIMS) Northeast Area Monitoring and Assessment Program (NEAMAP) spring and fall bottom trawl surveys.

NEFSC bottom trawl surveys

The NEFSC winter (1992-2007) and spring (1968-2019) bottom trawl surveys occur in February and March through May, mainly prior to the U.S. fishery, but capture relatively low densities of squid at fewer stations in comparison to the NEFSC fall survey because the winter and spring surveys occur at a time when *Illex* are migrating onto the continental shelf (Hendrickson 2004). The NEFSC fall survey occurs in September through October when *Illex* are migrating off the shelf. The fall survey indices can be considered as an index of spawner escapement because the survey occurs near the end of the fishing season. A portion of the *Illex* stock resides outside the range of the NEFSC surveys. The outer shelf and continental slope are important *Illex* habitats (Lange 1981) that are not intensively sampled during NEFSC bottom trawl surveys. In addition, the survey bottom trawl gear is not likely to sample pelagic species efficiently. Therefore, the NEFSC survey indices may represent the on-shelf availability of *Illex* rather than a measure of relative abundance or biomass.

NEFSC survey procedures and details of the stratified random sampling design are provided in Azarovitz (1981). Standard survey tows in offshore strata 1-40 and 61-76 (Figure 2.1) were used to compute relative abundance and biomass indices which were adjusted for differences in research vessel effects. A vessel conversion coefficient of 0.81 was applied to the FSV *Delaware II* stratified mean weight per tow values, prior to computing the fall survey indices, to standardize *Delaware II* catches to the FSV *Albatross IV* catches through 2007 (Hendrickson *et al.* 1996). The *Albatross IV* was replaced in spring 2009 by the FSV *Henry B. Bigelow* as the main platform for NEFSC research surveys, including the spring and fall bottom trawl surveys. The size, towing power, and fishing gear characteristics of the *Bigelow* are significantly different from the *Albatross IV*, resulting in different fishing power and therefore different survey catchability. Calibration experiments to estimate these differences were conducted during 2008 (Brown 2009), and the results of those experiments were peer reviewed by a Panel of three non-NMFS scientists during the summer of 2009 (Anonymous 2009). The calibration coefficients to convert *Bigelow* indices to their *Albatross IV* equivalents are 1.3797 for numbers and 1.4093 for weight in kilograms (Miller *et al.* 2010).

The NEFSC winter trawl survey was conducted from 1992-2007 to provide improved abundance indices for flatfish, including summer flounder. The surveys targeted flatfish concentrated offshore during the winter. A modified trawl was used that differed from the standard trawl employed during the NEFSC spring and fall surveys in that long trawl sweeps (wires) were added before the trawl doors to better herd fish to the mouth of the net, and the large rollers used on the standard gear were replaced on the footrope with a chain "tickler" and small spacing "cookies." The design and conduct of the NEFSC winter survey (timing, strata sampled, and the use of the modified trawl gear) resulted in equal to greater equal catchability of most species (including flatfish, elasmobranchs, most roundfish, and some pelagics) compared to the NEFSC spring and fall surveys.

The NEFSC winter survey abundance indices averaged 1.00 per tow (average CV of 31%) and biomass indices averaged 0.06 kg per tow (average CV of 29%). The mean weight of individual squid caught in the winter survey averaged 71 grams. The winter survey indicated low abundance during 1999-2002 and peak abundance in 2006 (Table 2.1, Figure 2.2).

The NEFSC spring survey indices are more variable than those from the winter and fall surveys due to variability in the timing of Illex migrations onto the shelf in the spring. NEFSC spring survey abundance indices averaged 1.25 per tow (average CV of 39%) and biomass indices averaged 0.05 kg per tow (average CV of 34%). The mean weight of individual squid caught in the spring survey averaged 53 grams. The spring survey index of pre-recruits ranged from 0 per tow for several years in the 1970s and in 1989 to 5.48 in 2012. The spring survey indicated low abundance during the early 1970s and early 2000s and peak abundance since 2010. The spring survey proportion of tows with positive tows for *Illex* increases with increasing abundance and has been highest since 2010 (Table 2.2, Figures 2.3-2.4).

The NEFSC fall survey abundance indices averaged 9.71 per tow (average CV of 23%) and biomass indices averaged 1.42 kg per tow (average CV of 23%). The mean weight of individual squid caught in the fall survey averaged 133 grams. The fall survey index of pre-recruits ranged from 0.04 per tow in 1967 and 1973 to 4.82 in 2018. The fall survey indicated lowest abundance during the late 1960s-early 1970s and the mid-1980s, with highest abundance during the early 1980s and the mid-2000s. The fall survey proportion of tows with positive tows for *Illex* was highest during the late 1970s, the late 1980s-early1990s, and since 2010 (Table 2.3, Figures 2.5-2.6).

CA DFO bottom trawl surveys

Canada Fisheries and Oceans (CA DFO) has conducted annual depth stratified random multispecies trawl surveys covering offshore areas in NAFO Division 3 in the spring since 1971 and fall since 1990 and in NAFO Division 4 since 1970. The areas relevant for *Illex* are NAFO Division/Areas 3LNO off the southeast coast of Newfoundland and Division/Areas 4VXW off the southeast coat of Nova Scotian (the Scotian Shelf).

The spring and fall 3LNO surveys have gone through multiple vessel and gear changes since their inception, as well as multiple changes in planned survey coverage (Rideout *et al.*, 2017). The Campelen 1800 shrimp trawl has been used as the standard trawl gear since the fall 1995 and spring 1996 surveys. The research vessels used to conduct the surveys over that time period have been a combination of the CCGS Wilfred Templeman (decommissioned in 2008), CCGS Alfred Needler, and CCGS Teleost. Generally, two vessels were used to complete the fall survey and only a single vessel used to conduct the spring survey. The spring surveys cover depths down to a maximum of 732 meters, whereas the fall surveys extend down to 1500 meters.

The summer 4VWX survey follows a depth stratified random sampling design using a bottom otter trawl. The net and vessel conducting the survey were changed in 1982 and 1983, along with some changes in data collection protocols (Clark and Emberley, 2011). The bottom trawl surveys depths of about 30 meters to 400 meters (Halliday and Kohler, 1971). All survey strata were used in the computations and the indices could not be standardized for gear and vessel changes that occurred in 1982, 1983 and 2004 due a lack of data from comparative fishing experiments (Hendrickson et al 2005). Since the Scotian Shelf 4VXW summer survey occurs near the start of the directed fisheries, it can be considered as a pre-fishery relative abundance index for the area surveyed. A portion of the *Illex* stock resides outside the range of these CA DFO surveys, and so as with the NEFSC surveys, the CA DFO survey indices may represent the on-shelf availability of *Illex* rather than a measure of relative abundance or biomass.

The CA DFO 3LNO spring survey abundance indices averaged 1.20 per tow (note no CVs provided) and biomass indices averaged 0.06 kg per tow. The mean weight of individual squid caught in the spring survey averaged 65 grams. The spring survey indicated lowest abundance during the early 2000s and early 2010s, with highest abundance in 2008 and 2018 (Table 2.4, Figure 2.7).

The CA DFO 3LNO fall survey abundance indices averaged 0.33 per tow (note no CVs provided) and biomass indices averaged 0.06 kg per tow. The mean weight of individual squid caught in the fall survey averaged 165 grams. The fall survey indicated lowest abundance during the early 2010s, with highest abundance in 2018 (Table 2.5, Figure 2.7).

The CA DFO 4VWX summer survey abundance indices averaged 42.34 per tow (note no CVs provided) and biomass indices averaged 4.79 kg per tow. The mean weight of individual squid caught in the summer survey averaged 95 grams. The summer survey indicated lowest abundance during the early 1970s, the late 1990s-early 2000s, and the early 2010s. The summer survey indicated highest abundance during the late 1970s, early 1990s, early 2000s, and during 2017-2019 (Table 2.6, Figure 2.8).

ME-NH inshore groundfish trawl survey

The Maine-New Hampshire (ME-NH) Department of Marine Resources (DMR) inshore groundfish trawl surveys have not been included in previous assessments. The ME-NH survey began in fall 2000 and has been conducted in the spring and fall annually in the nearshore waters of the Gulf of Maine (Sherman *et al.* 2005). Because the ME-NH surveys are conducted in relatively shallow waters and are limited in their spatial extent, they may not provide an index of the total stock resource, and may be susceptible to resource availability due to timing of onshore/offshore seasonal movements.

The ME-NH spring survey abundance indices averaged 0.03 per tow (average CV of 178%) and biomass indices averaged 0.0012 kg per tow (average CV of 188%). The mean weight of individual squid caught in the spring survey averaged 25 grams. It should be noted that 10 of the 17 indices in the ME-NH spring time series are 0 and the average CVs are very high. The spring survey indicated high abundance in the late 2000s and in 2018 (Table 2.7, Figure 2.9).

The ME-NH fall survey abundance indices averaged 8.91 per tow (average CV of 43%) and biomass indices averaged 1.22 kg per tow (average CV of 45%). The mean weight of individual squid caught in the fall survey averaged 132 grams. The fall survey indicated lowest abundance during the mid-2010s, with highest abundance during the late 2000s and since 2016 (Table 2.8, Figure 2.9).

ASMFC summer shrimp survey

The Atlantic States Marine Fisheries Commission (ASMFC) Gulf of Maine (GOM) northern shrimp summer survey has not been included in previous assessments. The ASMFC has conducted the annual northern shrimp survey during August in the Gulf of Maine since 1983. Because the ASMFC summer shrimp surveys are conducted only in the Gulf of Maine, they may not provide an index of the total stock resource, and may be susceptible to resource availability due to timing of onshore/offshore seasonal movements.

The ASMFC GOM summer shrimp survey abundance indices averaged 2.96 per tow (average CV of 26%) and biomass indices averaged 0.33 kg per tow (average CV of 23%). The mean weight of individual squid caught in the summer shrimp survey averaged 113 grams. The summer shrimp survey indicated lowest abundance during the late 1980s, early 200s and early 2010s. The summer shrimp survey indicated highest abundance in 1990, the mid-2000s, and since 2017 (Table 2.9, Figure 2.10).

MA DMF bottom trawl survey

The MA DMF bottom trawl surveys have not been included in previous assessments. The MA DMF has conducted research bottom trawl surveys during the spring and fall since 1978. A complete description of the MA DMF trawl survey is provided in King *et al.* (2010). The survey strata included in the MA DMF survey primarily includes the nearshore habitat within Massachusetts state waters in the southwestern Gulf of Maine and east and south of Cape Cod. Because the MA DMF surveys are conducted in relatively shallow waters and are limited in their spatial extent, they do not provide an index of the total stock resource, and may be susceptible to resource availability due to timing of onshore/offshore seasonal movements.

The MA DMF spring survey abundance indices averaged 0.01 per tow (average CV of 87%) and biomass indices averaged 0.0005 kg per tow (average CV of 89%). The mean weight of individual squid caught in the spring survey averaged 81 grams. It should be noted that 30 of the 41 indices in the MA DMF spring time series are 0. The spring survey indicated high abundance in the early 1980s, and late 2000s (Table 2.10, Figure 2.11).

The MA DMF fall survey abundance indices averaged 0.69 per tow (average CV of 37%) and biomass indices averaged 0.11 kg per tow (average CV of 39%). The mean weight of individual squid caught in the fall survey averaged 112 grams. The fall survey indicated lowest abundance during the mid-1980s, and late-2000s, to early-2010s, with highest abundance during the early 1980s, late-1980s to mid-1990s, mid-2000s, and since 2017 (Table 2.11, Figure 2.11).

NJ DEP bottom trawl survey

The NJ DEP bottom trawl surveys has not been included in previous assessments. The NJ DEP has conducted a standardized bottom trawl survey in New Jersey coastal waters since 1988. Because the NJ DEP survey is conducted in relatively shallow waters and are limited in their spatial extent, they do not provide an index of the total stock resource, and may be susceptible to resource availability due to timing of onshore/offshore seasonal movements.
The NJ DEP survey abundance indices averaged 11.32 per tow (average CV of 48%) and biomass indices averaged 0.13 kg per tow (average CV of 50%). The mean weight of individual squid caught in the fall survey averaged 14 grams. The survey indicated highly variable during the time series, with peaks in abundance in the late-1990s to early 2000s, early 2010s, and in 2018 (Table 2.12, Figure 2.12).

NEAMAP bottom trawl surveys

The Virginia Institute of Marine Science (VIMS) Northeast Area Monitoring and Assessment Program (NEAMAP) bottom trawl surveys have not been included in previous assessments. The NEAMAP has conducted standardized bottom trawl surveys in spring and fall in Rhode Island to North Carolina coastal waters since fall 2007. Because the NEAMAP surveys are conducted in relatively shallow waters and are limited in their spatial extent, they do not provide an index of the total stock resource, and may be susceptible to resource availability due to timing of onshore/offshore seasonal movements. There has been no catch of *Illex* in the NEAMAP fall surveys, so only the spring surveys are considered in this assessment. The 2017 spring survey began late due to a vessel fire.

The NEAMAP survey abundance indices averaged 10.89 per tow (average CV of 58%) and biomass indices averaged 0.29 kg per tow (average CV of 58%). The mean weight of individual squid caught in the fall survey averaged 26 grams. The survey catches before 2017 were very low at less than 1 per tow with a high CV and just a few positive tows, but increased to indicate high abundance in 2017-2018 (Table 2.13, Figure 2.13).

General survey trends

As might be expected for a sub-annual species with environmental effects on availability and recruitment, all of the *Illex* survey indices show a large degree of inter-annual variability. To help understand any general trends in abundance and biomass, the indices from the surveys detailed above were 'standardized' (each index divided by its' time series mean, to place them all on the same relative scale) and grouped by seasons. Winter and spring, summer, and fall surveys were grouped together in Figure 2.14 in this look for common trends. Winter and spring, summer, and fall surveys generally all indicate periods of high abundance during the late 1970s-early 1980s, summer and fall surveys indicate moderate abundance in the mid-1990s, all seasonal groups indicate high abundance from about 2005-2010, and all seasonal groups indicate high abundance again (on par with the high abundance of the late 1970s) from about 2016-2019. Notable general periods of low abundance occurred in the mid-to-late 1980s, the late-1990s to early-2000s, and from 2010-2015.

Simple correlation analysis was performed to identify surveys that indicate similar trends. An ad-hoc criterion of at least r = 0.4 for a series of 20 years was used to identify a 'significant' positive correlation. The longest and largest areal coverage surveys, the NEFSC spring and fall and the CA DFO spring, summer, and fall surveys, did not have significant positive correlations with each other. The NEFSC winter survey abundance indices (number per tow) had a number a strong correlation with other surveys, but ended in 2007. The CA DFO 3LNO (Grand Banks) spring and fall surveys were significantly correlated with the Gulf of Maine state agency surveys (the ME-NH spring and fall and ASMFC summer shrimp surveys) and with the NEAMAP spring survey. The MA DMF spring and MH-NH fall surveys had a significant positive correlation - although the MA DMF sparing and fall surveys did not. The NEAMAP spring, ME-NH spring, CA DFO 4VWX summer, and ASMFC summer shrimp surveys has the strongest correlations (0.41-0.55) with U.S. commercial fishery landings.

Trends in mean body weight (grams) were examined for the 6 surveys with the most synoptic spatial coverage, the NEFSC and the CA DFO seasonal surveys. In the NEFSC surveys mean body weight is generally lowest in the spring and highest in the fall, and here is a long term trend of decreasing mean weight since the early 1980s. In the CA DFO surveys mean body weight is generally lowest in the spring and highest in the fall, and while there have been periods of higher (late 1970s) and lower (mid-to-late-1990s) weights, but there is no obvious long term trend in mean body weight from the most representative summer survey (Tables 2.1-2.6; Figure 2.15).

FISHERY CATCH PER UNIT EFFORT (CPUE)

Fishery Background Information

A series of semi-structured conversations with *Illex illecebrosus* processors and harvesters elucidated several aspects of the harvesting, processing and marketing of *Illex* that may cause fishing effort, selectivity and landings trends to become decoupled from biological indicators of population condition, such as abundance, distribution, body size, and age (Mercer *et al.* 2022). The most commonly described factor impacting *Illex* catch, effort, and landings was vessel hold type (freezer, or wet boat, which includes ice and Refrigerated Sea Water (RSW)). Other factors that *Illex* processors identified as important included: market demand and prices, including size preferences, capture production of other ommestrephids globally, especially Argentine shortfin squid (*Illex argentinus*) and Japanese flying squid (*Todoroides pacificus*), availability and proximity of fishing grounds to ports that process northern shortfin squid, and landing limits imposed by some processors when shore-side processing capacity is reached. Baseline market demand and prices for northern shortfin squid, including size preferences, are set by capture production from fisheries of closely related squid species in the southwest Atlantic and western north Pacific, where capture production is on average 30-35 times larger than in the northwestern Atlantic (Mercer & Manderson 2022). Argentine shortfin squid production is particularly important because the season closes each year in the south Atlantic just before the fishery for northern shortfin squid begins. Northern shortfin squid have always been sold into bait and international food markets that both require a high quality product. Domestic food markets have become increasingly important and have been dominant since 2018. Changes in the global market, changes in the availability of northern shortfin squid and other stocks, and increasing investment in shoreside processing have caused the fishery to change from one dominated by trawlers freezing squid at sea, to a fishery in which shoreside processor/dealers both purchase and process squid caught by vessels that store squid in refrigerated sea water systems (RSW) or on ice and purchase frozen squid from freezer trawlers. In recent years, demand and prices have been high for food grade northern shortfin squid because 1) landings of squid have been relatively low in the south Atlantic and north Pacific and 2) the US fishery has been certified as sustainable by the Marine Stewardship Council. Northern shortfin squid have also been consistently available on fishing grounds both north and south of the Hudson Canyon, near processing plants located from Hampton, Virginia to Gloucester, Massachusetts. This increase in availability has allowed RSW and ice vessels to transport highly perishable squid from fishing grounds to processing plants within 72 hours, before the squid spoil. At sea freezer trawlers have had an advantage in the past when squid have been less concentrated on fishing grounds that could be distant from shoreside infrastructure. Changes in the availability of the squid, other stocks and fishing opportunities have also led to significant investments and increases in shoreside freezing and cold storage capacity for northern shortfin squid. The shift to shoreside processing has resulted in some plants establishing landings windows for fishing vessels and for some vessels to negotiate deliveries to specific plants to maximize product quality, stay within plant capacities, and maximize participation of vessels in the fishery. Global market preferences, prices, changes in the characteristics of the northern shortfin squid fishing fleet, changes in the shoreside infrastructure supporting the northern shortfin squid fishery, and plant-specific (and geographically-specific) landing limits have important and complex effects on fishing effort, selectivity, and landings.

Northern shortfin squid harvesters described several of the same factors that processors identified as impacting catch, landings, and fishing effort, including northern shortfin squid market and price, proximity to fishing grounds, and processor landing limits. Other factors that impact northern shortfin squid catch, landings, and fishing effort that were identified by harvesters included: fuel price, hold/tank/freezer capacity, catch processing technique and associated time requirements, length of time that catch remains fresh, gear restricted areas and gear conflicts, unwritten agreements about when to begin fishing, recent increase in participation in the northern shortfin squid fishery, weather, and time of day. In addition to identifying these factors, harvesters also classified years as poor, average, or good fishing years (Mercer *et al.* 2022). This is helpful for comparison to landings, which are often used as a metric of fishery performance, but do not reflect the socio-economic factors that may influence landings (such as high prices in other fisheries, low prices for northern shortfin squid, etc.).

The factors identified by processors and harvesters are useful in interpreting northern shortfin squid fishery landings data and should be incorporated into standardizations of fishery data. Breaking fishery data out into two fleets (freezer and wet boat), and considering weekly northern shortfin squid price, annual pre-season production of *Illex argentinus* and *Todoroides pacificus*, proximity of the location of fishing grounds to ports, and fuel price are particularly important. Pursuing research related to the oceanographic and environmental drivers of northern shortfin squid distribution, abundance, and availability, is also a priority, as both processors and harvesters asserted the importance of these factors, but were unable to provide concrete mechanisms. In order to ensure that technical and socio-economic factors are accounted for appropriately, frequent and meaningful dialogue with members of the northern shortfin squid fishery is necessary.

Recent research also elucidated the importance of using the appropriate effort metrics when calculating catch per unit effort for northern shortfin squid (Mercer *et al.* 2022). Given the highly variable tow times, catch handling techniques and technical constraints on trip length, it is important to use tow time, rather than days absent or number of tows, as an effort metric in catch per unit effort analyses. Accompanied with precise fishing locations and data on squid sizes and weights, catch per unit effort indices can be a powerful tool for understanding, assessing, and managing the northern shortfin squid fishery. Given the complex and stochastic nature of the northern shortfin squid fishery, it will be critical to maintain open communication and working relationships with processors and harvesters, who hold key information to ensuring that fishery data is used and interpreted appropriately.

Traditional fishery data modeling (Hendrickson 2020 updated)

Fishery Landings Per Unit Effort data

The in-season pattern of CPUE reflects the balance of recruitment, fishing and natural mortality, and emigration from the fishing area (Caddy 1991). In Caddy's formulation, the boundaries between these processes are sharp and are assumed to induce point changes in the slope of log CPUE versus time. Implementation of an in-season depletion model would require an ability to detect such point changes in the CPUE trends. However, previous Illex assessments have revealed that a declining trend in weekly Landings Per Unit Effort (LPUE) data from the U.S. *Illex* fishery is not detectable in some years (NEFSC 1999). In order to better understand LPUE trends, spatial changes in fishing patterns were evaluated and the effects of various factors on the standardization of fishing effort were assessed.

Fishing effort in the *Illex* fishery is affected by catch values determined largely by the global squid market, particularly the Falklands squid fisheries, and the abundance of *Illex* on the U.S. Shelf. The *Illex* fishery is a volume-based fishery and effort patterns vary for the two fleet sectors involved in the directed fishery, refrigerated seawater system trawlers (RSW vessels) and freezer trawlers (FT vessels). The RSW vessels tend to be of smaller size than the freezer trawlers and store their catches in chilled seawater. Both factors result in shorter trips, generally less than four days, than those made by FT vessels (up to 14 days) which are larger and freeze their catches at sea. The home ports for FT vessels are North Kingston and Point Judith, Rhode Island and Cape May, New Jersey. Effort patterns for the RSW fleet are primarily determined by the travel distance between a shore side processing facility and the offshore fishing grounds. The home port for most of the RSW vessels is Cape May, New Jersey, where there is a major *Illex* processing facility, but other home ports include Wanchese, North Carolina, Hampton Roads, Virginia and several Rhode Island ports (MAFMC 1998c).

Both annual and weekly time series of catch-per-unit-of-effort (CPUE) have been derived in previous *Illex* assessments (NEFSC 1999; NEFSC 2003; NEFSC 2006). For this analysis, landings-per-unit-of-effort (LPUE) was assumed to be representative of CPUE because the most recent and the current assessment have indicated that *Illex* discards generally comprised a small portion (0.5-6.0%) of the annual catches (NEFSC 2006). The LPUE acronym has been used here to be clear that the subject analysis does not include discard data. Landings, fishing effort and location data were retrieved from the NEFSC commercial fisheries database that includes merged trips from the Dealer Landings Database and the Vessel Trip Report Database. The methodology used to create the merged database is described in (Wigley *et al*. 2008). Only trips with 1:1 matches between the Dealer and VTR Databases contain the fishing effort and Statistical Area data necessary to compute LPUE. From this subset of trips available for LPUE estimation the dataset was further subset to include only directed trips. Directed trips were defined as trips with *Illex* landings > 10,000 lb, > 50% of the total trip weight, and during calendar year weeks 17-45. This combination of landings thresholds was used to exclude longfin squid trips with *Illex* bycatch from the LPUE dataset. Data from 1997-2019 were included in the LPUE analysis because although Dealer and VTR reporting became mandatory on May 2, 1996, 1997 was the first complete year of reporting (MAFMC 1994). The 2020 merged Dealer-VTR dataset was not available in time for inclusion in this work (Table 2.14).

Based on weekly nominal LPUE values, the *Illex* fishing season occurred during weeks 17-45 and averaged 18 weeks in duration during 1997-2019. The first week of the fishing season ranged between weeks 17 and 25, with an average start week at week 22. Discounting years with fishery closures (i.e., 1998, 2004 and 2017-2019), the duration of the fishing season ranged between 14 and 25 weeks and averaged 20 weeks.

The proportion of total *Illex* landings represented by trips with 1:1 matches between the Dealer and VTR Databases (i.e., landings from trips available for LPUE analysis) gradually improved during 1997-2019, but proportions were much lower during the early part of the time series (dashed line in Figure 2.16). Nearly all of the landings from the trips available for LPUE analysis were used to derive the LPUE indices (blue line versus red line in Figure 2.16 top panel). Therefore, the landings proportions indicated by the dashed line in Figure 2.16 are also representative of the landings proportions included in the LPUE dataset. During 1997-2001, the proportions were lowest and ranged between 0.51 in 1997 and 0.67 in 2001. During most years between 2002 and 2019, the landings proportion were near or above the mean of 0.78. The proportions were highest (average = 0.95) during 2011-2019. In summary, the 2011-2019 LPUE data comprise the highest proportion of total *Illex* landings, followed by the 2002-2010 and then the 1997-2001 estimates.

Fleet size during 1997-2019 ranged from 4 vessels in 2015 to 27 vessels in 1998 (Figure 2.16 bottom panel). With respect to fishing effort, the number of trips conducted and fleet size showed trends that were similar to the number of nominal days fished (DF) during most years. The exceptions were 2017 and 2018, when DF did not increase as rapidly as the numbers of trips and vessels. Days fished reached a peak in 2011 and the numbers of trips and vessels peaked in 2018 and 1998, respectively.

When characterized by vessel type, landings (mt) and effort (days fished; DF) showed similar trends, although more they were more variable for FTs, which was likely due to the lengthier trips of FTs in comparison to RSW and ice boats. Landings and effort trends varied slightly between vessel types whereby peaks in both variables occurred during 2011 for FTs, but landings peaks for ice and RSW boats occurred in 2019 when the ice and RSW boats harvested most of the landings (Figure 2.17). Landings were high for all three vessel types during 1998 and 2004.

A major change in the fleet composition occurred during 1997-2019. Prior to 2008, the fleet was dominated by FTs which harvested most of the landings (75% on average). After 2008, FTs still harvested most (63%) of the landings, but landings by RSW boats increased in conjunction with the increase in numbers of RSW boats. The numbers of RSW and ice boats increased rapidly after 2017 and peaked in 2019 at 14 and 12, respectively (Figure 2.17). The number of FTs peaked at 11 in 2004 and decreased to only 7 vessels by 2019. The 2019 data for number of vessels by vessel type were obtained from the VTR data to illustrate the change in fleet composition in recent years. Based on discussions with *Illex* fishermen and processors, the increase in RSW boats coincided with a reduction in FTs because some have been converted to RSW boats and multiple FTs have either sunk or sold their *Illex* permits. Although FTs converted to RSW boats may have similar per-trip harvest capacities, their annual harvesting capacities can surpass those of FTs because RSW boats make shorter, more frequent trips than FTs and several of the RSW boats are large capacity vessels.

RSW and ice boat trip durations are shorter because they are limited by the rapid degradation of *Illex* catches and averaged four days during 1997-2019. FTs make longer trips (eight on average) than RSW or ice boats because they sort and freeze their landings at sea (Figure 2.18). Crew sizes for FTs and RSW and ice boats averaged 9 and 4, respectively. The number of DF reached a peak in 2011 for both FTs and RSW, but FT DF was much higher than for RSW boats. This trend reversed during 2018 and 2019. The average DF during 1997-2019 was more variable for FTs than ice and RSW boats and comprised 24%, 18% and 20% of the average trip duration, respectively. Steam time comprises a large portion of the trip duration because the fishery occurs offshore near the shelf edge (Figure 2.18). The remainder of the trip duration is comprised of time spent searching for productive fishing locations (Powell *et al.* 2003), sorting and freezing the landings for FTs and longer steams between fishing locations, which tend to occur at night because *Illex* fishing occurs during the daytime.

The landings (metric tons; mt) and effort (Days Fished; DF) data used to estimate the LPUE indices were high for all three vessel types during 1998 and 2004, but the peaks varied between vessel types. FTs exhibited an effort and landings peak in 2011 and RSW and ice boats exhibited landings peaks in 2019. During 2017-2019, landings by RSW boats reached their highest levels of the RSW time series; a period when the total LPUE landings were dominated by landings from RSW boats. These landings and effort trends translated into the highest nominal LPUE (mt per DF) indices of the RSW and FT time series during 2017-2019 (Figure 2.19).

Standardization model indices of biomass

The PROC GENMOD SAS procedure was used to derive a standardized LPUE time series. LPUE data (mt per DF), for 1997-2019, were fit to Type 3 General Linear Models (GLM) with normal, gamma and negative binomial error structures. Goodness-of-fit for the three error type models was determined based on model deviance divided by the degrees of freedom. Main effects included in each initial set of models included all possible combinations of year, week, permit (i.e., individual vessel), and vessel type (i.e., freezer trawler (FT), refrigerated seawater (RSW) or ice (ICE) boat), without interactions. Permit and vessel type were included in the models because LPUE is known to vary by vessel type (NEFSC 1999) and because permit incorporates both vessel type and vessel-specific properties that can affect LPUE (e.g., specific captain and crew size). Vessel types identified in previous stock assessments were used in the analysis along with vessel types which were confirmed by industry members for vessels which entered the fishery after 2004. Some subsequent model configurations also included NEFSC 3-digit statistical area (area). LPUE data included in the GLM models were also subset for the *Illex* fishing season, which was identified based on an examination of weekly nominal LPUE data during 1997-2019.

The diagnostics and results of the GLM model runs for annual LPUE standardization are summarized in Tables 2.15-2.16. All model runs converged and all main effects were significant at the 5% alpha level except for vessel type in the normal error structure model. The model with a negative binomial error structure showed the best fit to the LPUE data according to the deviance/degrees of freedom values. Based on the AIC values for this model run, the three-factor model that included year, week and permit provided the best fit for the initial model runs. AIC values were identical for the negative binomial and gamma models, which can occur due to the high number of degrees of freedom and given the high flexibility of the gamma distribution as implemented here with SAS GENMOD, which can allow it to mimic the negative binomial. LPUE estimates for the best fit model for all three error types showed similar trends with the exception of 2018, which showed a decrease for the negative binomial and gamma models and an increase for the normal error structure model.

Additional model runs that included statistical area showed that this factor was not statistically significant at the 5% alpha level. However, the data associated with the largest statistical area coefficient were investigated further by examining the associated VTR images. Misreporting of a statistical area for a single vessel during most of an entire season was found and corrected in the LPUE dataset prior to development of a four-factor model that included statistical area. The results indicated that statistical area was statistically significant for all three error type models and improved the fit of the three-factor negative binomial model. The negative binomial model that included year, week, permit and statistical area provided diagnostics indicating the best fit (Table 2.15). LPUE estimates were fairly precise for most of the time series, but were lowest during 1997-1998 and 2006-2009 (Table 2.16, Figure 2.20). The standardized LPUE indices and the NEFSC fall survey biomass indices (stratified mean kg per tow) showed some similarities in trends (Figure 2.21) and were significantly correlated ($r = 0.469$, $p < 0.05$).

Trip limits were imposed when plant processing capacity was reached (Wayne Reichle, Lund's Fisheries, personal communication). Nominal LPUE and the standardized LPUE estimates were impacted by these trip limits. The unaccounted for landings resulted in an underestimation of *Illex* LPUE indices. Unfortunately, these impacts could not be quantified because the trip limit quantities and dates of implementation, by vessel, were unknown. Any future implementation of trip limits in the *Illex* fishery should consider these impacts on *Illex* biomass estimates derived using LPUE.

Novel fishery data modeling with explicit consideration of technical and economic factors (Lowman *et al.* 2022)

Fishery Catch or Landings-Per-Unit-of-Effort data

The purpose of this research is to investigate multiple fishery datasets and standardize catch rates with respect to fishing behaviors, vessel differences, economic factors and spatiotemporal factors for consideration as indices of *Illex* abundance. Data records from three fishery dependent datasets maintained by the NEFSC) were explored: Dealer/Logbook, Observer program, and the Study Fleet program. Each dataset has strengths and weaknesses that support the consideration of all three. The Dealer/Logbook dataset (also referred to as the "AA data" during WG meetings and correspondence) comprises merged records of *Illex* landings collected by commercial fisheries dealers and *Illex* catch and fishing effort collected by commercial harvesters during their fishing operations through mandatory Vessel Trip Reports (VTR). These data comprehensively describe *Illex* landings and catch, as they have been collected for every *Illex* fishing trip as part of federal reporting requirements since 1996. The spatial resolution and time step of the dataset, however, are relatively coarse. Catch information is recorded at the sub-trip level (i.e. one record per statistical area per fishing trip). Discards are not recorded. Location is recorded as a single GPS coordinate of the approximate center of fishing activity per sub-trip. Thus, this dataset is insufficient for describing the fine-scale spatial and temporal dynamics of the fishery (Mercer *et al.* 2022). Only data where dealer-reported *Illex* landings match VTR-reported *Illex* catch are included in this dataset.

The Observer program dataset comprises catch and fishing effort data collected by independent observers through the Northeast Fisheries Observer Program during a subset of randomly selected *Illex* fishing trips since 2011 (Wigley and Tholke 2020). Observers collect detailed catch, bycatch, and fishing effort information for every tow during a trip. Thus, this dataset provides a finer spatiotemporal resolution (i.e. one catch and effort record per tow) than the Dealer/Logbook dataset. The Observer program dataset, however, is not comprehensive of the entire *Illex* fishery, with observers deployed and data collected during 4-10% of fishing trips in a given year, with lower coverage in recent years.

The Study Fleet dataset is composed of detailed catch and effort data on individual tows that are self-reported by fishermen participating in the Study Fleet program (Jones *et al.* 2022 *in prep*). As participants in the Study Fleet program, fishermen collect detailed catch, bycatch, fishing effort, and bottom water temperature data for every tow during a fishing grip. The Study Fleet is a non-random sample of fishing vessels based on the voluntary nature of the program. Work presented by Jones *et al.* (2020) indicated that the Study Fleet appears to be representative of the overall *Illex* wet boat fleet, with up to 45% of *Illex* fishing trips covered in recent years. Only one freezer vessel, however, participates in the Study Fleet program, thus limiting the utility of these data for freezer fleet LPUE.

The Dealer/Logbook data were pulled from the commercial fisheries database (CFDBS), and the Observer and Study Fleet data were pulled from the Fisheries Vessel Trip Reports database (FVTR) for years 2008-2019. Prior to 2008, there was limited coverage of *Illex* vessels in the Study Fleet. Filters were applied to all three datasets to produce subsets of the data representing only fishing trips that targeted *Illex*, consistent with previous assessment decisions (NEFSC 2006) and Hendrickson (2020). The filtering criteria were: *Illex* comprised >50% of the landings on a trip, >10,000 pounds of *Illex* were landed on the trip, and the trip occurred between the months of May and October, inclusive. Records were omitted if they were missing permit number, landing port, or fishing location. This resulted in a total of 5,277 records from 3,127 trips by 66 vessels in the dealer/logbook dataset; 2,690 tow records on 293 trips by 38 vessels in the Observer dataset; and 1,793 tow records from 317 trips by 10 vessels in the Study Fleet dataset (Figures 2.22-2.23).

CPUE for the Study Fleet and Observer datasets was calculated on an individual tow level as the weight of *Illex* caught divided by the duration of the tow, so that the unit is pounds per hour. Because discards are not recorded in the Dealer/Logbook data, landings per unit effort (LPUE) is the variable considered. Discarding of *Illex* is minimal, so LPUE is a good approximation of CPUE. Individual tow times are unavailable in the Dealer/Logbook records, so the duration of fishing effort is derived from the Days Fished (based on the captain's reported average tow duration and number of tows) divided by 24 to have a consistent unit with the other datasets. This approximation of effort for the Dealer/Logbook records likely results in uncertainty within the LPUE values for this dataset.

Covariate Data

Harvesters consistently emphasized that hold type is a critical factor influencing LPUE (Mercer *et al.* 2022). Vessel hold types (ice, RSW, freezer) were determined by consultation with vessel owners, processors, key industry representatives, and/or port agents. Domestic prices for *Illex* by week are included because some harvesters noted that their fishing behavior changes with price. For example, when price is high they may stay on a less dense aggregation of squid when they would otherwise move onto search for denser fishing ground (i.e. they will accept a lower LPUE when price is high) (Mercer *et al.* 2022). Price data was pulled from the Commercial Fisheries Database (CFDBS). Price is calculated based on total landed value divided by the total landings (pounds) for each week. Prices are adjusted for inflation by standardizing to 2019 USD using the Gross Domestic Product Implicit Price Deflator from the Federal Reserve Economic Data. When joining the price table to the catch data, the prices were lagged one week relative to the start of the trip (to reflect the fact that fishing decisions are made based on the information available when boats leave the dock, not the price when they land).

Global production of ommastrephids was consistently reported by harvesters and processors as a major factor affecting *Illex* LPUE (Mercer *et al.* 2022). The mechanism is unclear but is likely more related to price and demand than to biological productivity because the various squid species and fisheries that comprise the global market are quite different in terms of oceanography, scale of fishing operations, etc. Annual global landings of Argentine shortfin squid (*Illex argentinus*) and Japanese flying squid (*Todarodes pacificus*) are included as indicators of the global ommastrephid squid market. The data were pulled from the FAO landings database on 2021/09/22. The *Illex argentinus* fishery is primarily in the first half of the year (before the U.S. *Illex illecebrosus* fishery), so the same year as our fishing year is used. The *Todarodes pacificus* fishery is primarily in the second half of the year, so the *Todarodes pacificus* landings were lagged one year.

Fuel price was reported to impact fishing behavior in a similar way to the domestic *Illex* squid price (Mercer *et al.* 2022). When fuel is more expensive, fishers are less willing to search/move off a moderately productive spot. Fuel price for New England was pulled from the Energy Information Administration on 2021/10/20. Prices are adjusted for inflation by standardizing to 2019 USD using the Gross Domestic Product Implicit Price Deflator from Federal Reserve Economic Data.

Landing port and days absent (trip duration) were pulled from the NEFSC databases for each trip. Distance to fishing ground was calculated as the straight line distance between the reported fishing location and the landing port.

Standardization model indices of biomass

All statistical analyses were performed using R version 3.6.2 (R Core Team 2019). Generalized Additive Models (GAMs) were fitted using the mgcv package (Wood 2011). The response variable for the Dealer/Logbook dataset was LPUE (pounds/hour fished) because discard data are not available. For consistency, we also used LPUE (pounds/hour fished) as the response variable for the Observer and Study Fleet data in the final round of modeling. Discards are minimal in the *Illex* fishery, so LPUE is representative of CPUE. Potential explanatory variables in the preliminary analyses were: fixed factors for week of the year, vessel type (factor: freezer, ice, or refrigerated seawater [RSW]), and statistical area; random effect for individual vessels; and smooth terms for day of the year, distance from the shelf break (defined as the 200 meter isobath), and smoothed interactions of northing and easting.

Based on histograms of CPUE and LPUE (Figure 2.22), we investigated several error distributions: lognormal, gamma (with log link), and negative binomial (with log link). To eliminate zeros for compatibility with log link, we added one to all CPUE/LPUE observations and rounded CPUE/LPUE to the nearest integer for fitting negative binomial models. For each dataset, we fitted GAMs with year effects only with each distributional assumption. Based on the most promising set of diagnostics (quantile-quantile plots, Cook's distance, and residuals), we built GAMs with the corresponding distribution by forward stepwise selection with AIC and percent deviance explained as the selection criteria. If a decrease in AIC was not accompanied by at least a 2% increase in deviance explained, then the more complex model was not selected.

After initial modeling with only spatial, temporal, and vessel effects, we collated additional data based on industry conversations and completed a second round of model building (Manderson *et al.* 2021a). We opted to separate the data into two distinct fleets (freezer trawlers and "wet boats" consisting of vessels with refrigerated sea water and ice holds) for each dataset based on the knowledge that the two categories of vessels are subject to different constraints (e.g. time constraints for ensuring product quality) and operations (e.g. freezing product at sea) (Manderson *et al.* 2021a). The second round of model building used the same distribution assumption determined from the first round (negative binomial) and considered the following explanatory variables: weekly domestic *Illex* price, global production index, distance to fishing ground, trip duration, and fuel price.

The overall trends in *Illex* LPUE are similar across datasets at the annual scale, though the magnitude is different (Figures 2.24-2.25). All models included the domestic weekly price of *Illex* and a spatial component (Table 2.17). Additional factors impacting LPUE differ between fleets and across the different datasets likely due to the different operations of the two fleets and the resolution and sampling across datasets.

The resolution of the Dealer/Logbook dataset is insufficient to support modeling of *Illex* LPUE with a weekly time-step. This is due to the fact that these data are only submitted once per fishing trip or sub trip, and thus there are many weeks with one or less record. The Observer and Study Fleet datasets in recent years do have adequate data resolution to model the full *Illex* fishing season on a weekly time-step, but they are limited in scope/coverage. In order to support in-season stock assessments for adaptive management of *Illex* (see TOR 6 of the current assessment), catch and effort data would need to be reported at a finer temporal scale from more of the fleet(s).

The freezer trawler fleet has a higher nominal LPUE and different trend than the wet boat fleet, namely a peak in 2014 that is not observed in the wet boat fleet. The standardization of the freezer trawler LPUE series has very little impact in most years, with both the nominal and standardized series remaining relatively stable around 10,000 pounds per hour fished for much of the time series, peaking at 25,000 pounds per hour fished in 2014, and staying relatively high, around 20,000 pounds per hour fished in the final three years of the series. This indicates that freezer vessel LPUE is impacted by factors not considered in these analyses.

The wet boat fleet series is more variable, particularly the standardized series, with LPUE oscillating between 2,000 pounds per hour fished and 37,000 pounds per hour fished. The standardized wet boat LPUE is consistently higher than the nominal wet boat LPUE, but both standardized and nominal wet boat LPUE time series are elevated in recent years (2017-2019). The dealer/logbook wet boat LPUE series shows a trend consistent with the traditional GLM standardization (see this TOR 2 and Hendrickson 2020).

Freezer Trawler: Dealer/Logbook

The selected model for the Dealer/Logbook Freezer Trawler data includes effects of weekly domestic Illex price, a two-dimensional smooth over spatial location, the landing port, and the number of days absent (Tables 2.18-2.19). The year effect suggests a relatively stable catch rate with a peak in 2014 followed by a decline in 2015 and increasing trend in subsequent years (Figure 2.26). The spatial trend is consistent with expectations, with higher catch rates along the shelf break and highest catch rates in the Mid-Atlantic (Figure 2.27). The effect of the landing port suggests higher catch rates for trips landing in North Kingston, Rhode Island and lower rates for trips landing in Point Judith, Rhode Island (relative to the reference level in Cape May; Figure 2.26). There is a negative linear effect of days absent, and a complex smooth effect of weekly domestic price (Figure 2.27). The days absent effect is unsurprising and illustrates the limitation of hold capacity (i.e., vessels return to port when the hold is full which occurs sooner when catch rates are high). The effect of price is less intuitive, suggesting a slightly positive effect at the low end of prices (less than about \$0.40 per pound), and negative effect above about \$0.40 per pound, becoming less negative at prices greater than about \$0.55 per pound. The price effect is statistically significant in the range of \$0.50 to \$0.60 per pound. Conversations with industry suggest that this price effect is a result of specific years when the price was high but catch rates were lower. Generally, freezer trawler operations and catch rates are less responsive to market price, as the vessels are specifically designed to target *Illex* and are unlikely to change target species.

Freezer Trawler: Observer

The selected model for the Observer Freezer Trawler data includes effects of weekly domestic *Illex* price, the distance from fishing location to landing port, and a two-dimensional smooth over spatial location (Tables 2.20-2.21). The year effect suggests a decrease from 2011 to lower but highly variable catch rates in 2013-2015 followed by much higher catch rates with tighter confidence intervals from 2016 to 2019 (Figure 2.28). The effect of weekly price suggests lower catch rates at higher prices (Figure 2.29). This effect is based on relatively little variation in price information, but it is consistent with expectations based on harvesters' insight (tendency to stay on squid aggregations rather than search when price is high even if CPUE is low). The spatial smooth is consistent with expectations and with the effects in the Dealer/Logbook Freezer Trawler model, namely that catch rates are highest at shelf break in the Mid-Atlantic (Figure 2.29). There is a positive linear relationship between distance from fishing location to port and catch rate (Figure 2.29), which is logical given that traveling a long distance would only be financially justified by large catches.

Wet Boats: Dealer/Logbook

The selected model for the Dealer/Logbook Wet Boat data includes effects of weekly domestic Illex price, a two-dimensional smooth over spatial location, days absent, and landing port (Tables 2.22-2.23). The year effect suggests lower catch rates in the late 1990s increasing until 2009 followed by a decline to 2015 and very high catch rates 2017-2019 (Figure 2.30). The effect of price reflects a similar pattern to that in the Dealer/Logbook Freezer trawler data, indicating a slight positive effect at the lowest prices (less than ~\$0.20 per pound), decreasing to a negative effect at middle prices (~\$0.20 - \$0.35 per pound), and increasing to a positive effect at higher prices (Figure 2.31). The spatial smooth suggests more variability in catch rate throughout the region with several hot spots in the Mid-Atlantic (Figure 2.31). There are more wet boats than freezer trawlers, so the increased precision in the effects is not surprising. The negative linear effect of days absent is also consistent with the Dealer/Logbook Freezer trawler data. The effect of landing port suggests higher catches for trips landing at New England ports than for those landing at more southern ports (Figure 2.31).

Wet Boats: Observer

The selected model for the Observer Wet Boat data includes effects of weekly domestic price, a two-dimensional smooth over spatial location, and the state in which catch was landed (Tables 2.24-2.25). Individual ports of landing were combined to the state level in this model due to low sample numbers at individual ports. The year effect suggests much higher catch rates in the last three years of the time series, consistent with the other models (Figure 2.32). The effect of the spatial smoother is also consistent with the freezer trawler models, with highest catch rates along the shelf break (Figure 2.33). The weekly price is a roughly linear negative relationship, similar to that of the Observer Freezer Trawler model. The effect of landing state is consistent with the dealer/logbook LPUE model, indicating highest catch rates from trips landing in Rhode Island and New Jersey (Figure 2.33).

Wet Boats: Study Fleet

The selected model for the Study Fleet Wet Boat data includes effects of weekly domestic Illex price, a two-dimensional smooth over spatial location, and week of the year (Tables 2.26-2.27). The year effect suggests highest catches in the last three years of the time series (Figure 2.34). The effect of the spatial smooth is relatively consistent with other models but more localized, indicating highest catch rates at a single hotspot along the Mid-Atlantic shelf break (Figure 2.35). Weekly price effect is approximately linear, suggesting decreasing catch rates at increasing prices, which is consistent with expectations (Figure 2.35). The effect of week suggests lower catch rates early in the fishing season, peaking at week 34 (late August) and tapering off to the end of the season (Figure 2.35).

Summary Comments

In order to support in-season stock assessments for adaptive management (see TOR 6 of the current assessment), catch, effort, and landings data would need to be reported at a finer scale from a larger portion of the *Illex* fleet(s). Fine-scale *Illex* catch and effort data are also critically needed to advance understanding of the spatial dynamics and oceanographic drivers of the *Illex* population and fishery (see TOR 4 of the current assessment).

This LPUE modelling work indicates that the freezer trawler fleet operates significantly differently than the wet boat fleet (Mercer *et al.* 2022). The freezer trawler fleet is small (<10 vessels) compared to the wet boat fleet (>30 vessels) and their catch and landings rates are heavily driven by operational dynamics. For example, freezer vessels can only freeze a certain quantity of squid at a time, and thus, they have to stop fishing (haul back) to process squid after a certain amount are caught (as indicated by net sensors). Freezer vessels also have the flexibility to spend more time searching for Illex and to fish in areas that are farther from port, as frozen Illex are not highly perishable. Given the unique dynamics of the freezer and wet boat fleets, we recommend continued consideration of separating the freezer and wet boat fleets in LPUE modeling in future work. Each fleet may provide unique insight into population condition and abundance, so should be included in data review and analysis, but freezer and wet boat fleet operations and participation are significantly different, which warrants examining them separately in future work.

The link between price and LPUE is complex, especially in the Dealer/Logbook dataset. All models with price effects seemed generally consistent with the feedback that fishers tend to search for denser aggregations to maximize profit when the price is low, and remain on an aggregation even if CPUE is not high when price is high. However, there may also be a temporal cue wrapped into the effect, due to the weekly aggregation of price. Furthermore, the relationship between price and LPUE is distinct between the freezer and wet boat fleet. Industry representatives noted that the freezer vessels are less apt to respond to prices because they are unable to switch target species during the *Illex* season (Mercer *et al.* 2022). On the contrary, wet boat harvesters noted that they may choose to switch to more profitable fisheries if the price for *Illex* is low (Mercer *et al.* 2022). Disentangling the effects of vessel participation in the *Illex* fishery (and alternative fisheries), price, and LPUE is worthy of further investigation.

These analyses indicate that several factors are important in driving *Illex* LPUE, including year, fishing location, *Illex* market price, trip length, and landing port. Year and fishing location are intuitive, as the *Illex* population has historically exhibited high inter-annual variability and a patchy distribution. Consistent inclusion of a spatial component in all models suggests that we are missing important factors influencing LPUE across space. The work by Salois *et al.* (2022) explores potential environmental drivers of *Illex* availability, and may provide further factors for inclusion in LPUE modeling in future work.

In addition to other annual factors to consider, there are several sub-annual factors that impact LPUE that were not able to be explored here due to data limitations. For example, in years when the *Illex* fishery was closed early (August), the annual LPUE may be lower than expected because the higher LPUEs that often occur towards the end of the fishing season (as evidenced in the Study Fleet dataset) are excluded. Furthermore, in recent years as fishing has begun earlier in the season, lower LPUEs are more common than in the past (when there were "unwritten agreements" to start fishing for *Illex* later in the season to allow them to grow to a larger and, thus, more profitable size). These factors must be considered when interpreting annual-scale LPUE for the *Illex* fishery.

Finally, the wet boat fleet standardized LPUE series presented within this work is the most consistent with the series for all vessels combined using a traditional GLM standardization (Hendrickson 2020). Variability in the trends across datasets is likely due to differences in reporting level (subtrip vs tow) and coverage (all boats vs subsets). Again, in order to fully capture the dynamics of the *Illex* fishery and population, we recommend including both the wet boat LPUE (consistent with current methodology) and freezer boat LPUE in the stock assessment. It is worth noting that several freezer vessels were retrofitted to RSW vessels after 2019, so vessel hold type classifications will need to be updated when expanding these LPUE analyses to more recent years.

Comparison of Fishery LPUE and NEFSC fall survey indices of biomass

To facilitate interpretation and discussion, the results of the fishery LPUE modeling from the GAM-based standardization (Lowman *et al.* 2022), the GLM-based standardization (Hendrickson 2020), and the NEFSC fall bottom trawl survey index for *Illex* were plotted together (Figure 2.36). This visualization reveals general synchrony in *Illex* LPUE trends over time but differences in the scale of LPUE depending on the fleet and standardization approach. The Dealer/Logbook wet boat LPUE GAM standardization is the most similar in trend and scale to the traditional LPUE GLM standardization. The NEFSC fall bottom trawl survey index exhibits similar long-term temporal trends as the fishery LPUE time series, but with more variability than LPUE indices in early years (1997-2008) and less variability than LPUE indices in later years (2008-2019).

RELATIONSHIP BETWEEN FISHING EFFORT AND ECONOMIC FACTORS

The WG explored the relationship between observed fishing effort and economic factors (domestic *Illex* prices, global landings of 'competing' squid stocks, New England fuel prices) in the LPUE standardizations conducted by Lowman *et al.* (2022), as presented earlier in TOR 2. Further research on the impacts of economic factors, including global market prices, on *Illex* fishing effort is warranted. Lowman *et al.* (2022) provides a foundation for further investigation of the relationships between fishing effort and economic factors.

OCEANOGRAPHIC INDICATORS FOR *Illex* (Salois *et al.* 2022)

Oceanographic satellite imagery provides a powerful tool for assessing dynamic marine systems in a rapidly changing ocean. Remotely sensed data are well suited for environmental analysis and ecological forecasting as they provide long-term synoptic, near real-time coverage of oceanographic conditions at high spatial (1-4 km) and temporal (daily) resolutions. This work utilizes these long term time series, as well as global ocean reanalysis physical data, to generate high resolution metrics to serve as potential indicators for understanding the distribution and availability of *Illex*. As such, the work addresses aspects of both TOR 2 (CPUE indices of abundance) and TOR 4 (environmental factors that may influence body size and recruitment [and by extension stock size and availability]). Recent years have seen above average availability to the U.S. fishery, yet the drivers associated with the high abundance years are unknown. It is thought that variable population dynamics exhibited by *Illex* in the U.S. Mid-Atlantic fishery are largely influenced by oceanographic conditions of the Northwest Atlantic (Dawe *et al.* 2007, Hendrickson 2004, Hendrickson and Holmes 2004), which have documented significant changes over the past decade (Gangopadhyay *et al.* 2019, Gonçalves Neto *et al.* 2021, Seidov *et al.* 2021, Silver *et al.* 2021).

The purpose of this work is to investigate a suite of oceanographic features such as mesoscale eddies and fronts to assess and characterize their relationships to *Illex* catch rates. To achieve this goal, we collaborated with a multi-disciplinary group of experts across government, academia, and industry to generate a series of hypotheses linking oceanographic features to potential mechanisms driving both the ingress and egress (i.e., recruitment) of *Illex* to the southern stock component of the fishery. The following five general hypotheses informed the selection and spatial scale of covariates considered in the multivariate statistical models used in this study:

a) Frontal dynamics may create areas of high productivity (implications for abundance/distribution/growth/aggregation)

b) Warm core rings may serve as a transport/retention mechanism for larval stage/pre-recruits (implications for immigration, mortality, emigration)

c) Strength and location of warm core rings may contribute to increased primary productivity due to upwelling of nutrients and provide a mechanism to concentrate food sources for juveniles and adults (implications for aggregation, abundance, growth, distribution)

d) Bottom temperature may influence (optimal) habitat selection for managing metabolic demands of juveniles and adults (implications for emigration, growth, aggregation)

e) Changes in slope water composition may have profound impacts on Illex distribution (implications for immigration/emigration)

The identification of oceanographic drivers of *Illex* catch in space and time is an important first step in increasing our understanding around the mechanistic processes influencing the availability of *Illex* on the northeast U.S. continental shelf. Understanding the movement of *Illex* into and out of the ecosystem and fishery is highly relevant in reaching future stock assessment and management goals.

Methods

Fishery dependent catch data

This work uses estimates of the nominal *Illex* catch per unit effort (CPUE) calculated from two high resolution datasets maintained by the Northeast Fishery Science Center's (NEFSC) Study Fleet program and Observer program from 2008-2020. The CPUE estimates used for this study were derived by Lowman *et al.* (2022) and resulting values were summed across weeks and fishing locations. The Observer data consists of catch data collected onboard commercial fishing vessels by professionally trained biologists (observers) at the tow level. The Study Fleet data is voluntary self-reported catch and effort data from individual tows collected by captains on participating vessels. The Observer data is collected from approximately 10% of the *Illex* fishing trips annually, with lower coverage rates in recent years. The Study Fleet data is collected from approximately ~ 40% of fishing trips annually, with higher coverage in recent years. The Study Fleet and observer datasets were for this study due to their fine scale spatiotemporal data on *Illex* catch and effort, which is required for exploring potential oceanographic indicators. Specifically, these datasets include detailed fishing trip location start and end points via GPS coordinates (see Lowman *et al.* 2021, 2022 and Jones *et al.* 2020), which was instrumental in identifying co-located environmental conditions.

Models run in this study utilize catch from both 'targeted' and 'untargeted' trips, in effort to reduce the biases implicit in using fishery dependent catch and effort data as an index of abundance. Combining all available tow data where catch comprises greater than 10% *Illex* (and more than 100 pounds landed), previously described as the 'comprehensive data set' by Jones *et al.* (2020) allowed for the examination of a larger number of trips over a greater range of space and time and the ability to capture instances of both low and high catch throughout the region. The resulting catch data was subset into two fishing fleets based on vessel hold type (Freezer Trawlers and 'Wet Boats'). This decision follows work by Lowman *et al.* (2022) as well as correspondence via *Illex* WG meetings and industry conversations, where clear differences in fishing behavior and capacity were noted between fleets (Mercer *et al.* 2022). These differences stem from the highly perishable nature of this species and differential processing capacity of the two fleet types (Mercer *et al.* 2022, Lowman *et al.* 2021, 2022). The particular set of constraints imposed by 'wet boats' makes them more likely to reflect real-time responses to oceanographic conditions and more likely to pick up an environmental signal as opposed to freezer trawlers which have a 'ceiling' or limit to the amount of squid they can take on board, even during instances of high squid availability. Therefore, only wet boats (vessels with refrigerated sea water or ice holds) were considered for this study, excluding all freezer trawlers.

Oceanographic Covariate Data

The majority of the environmental covariates were either direct observations via remotely sensed satellite data or metrics derived from remote sensed products. Satellite remote sensors are an ideal data source for assessing dynamic marine ecosystems because they provide long-term synoptic, near real-time coverage of near-surface oceanographic conditions at high spatial (1-4 km) and temporal (daily) resolutions. To understand subsurface conditions, weekly bottom temperature and salinity time series were derived from a daily GLORYS12V1 global ocean reanalysis model data (CMEMS 2018) that was subset over the northwest Atlantic and averaged to create weekly products. This modeled product has a gridded 8-km horizontal resolution, up to 50 fixed vertical depth bins, and the data are available from 1993 to 2020.

Remote sensing data

Daily Level 3 (L3) mapped (4km resolution, sinusoidally projected) satellite ocean color data (version 5.0; Sathyendranath *et al.* 2021) were obtained from the European Space Agency's Ocean Colour Climate Change Initiative (OC-CCI) project (Sathyendranath *et al.* 2019). The OC-CCI dataset comprises of globally merged SeaWIFS, MERIS, MODIS-Aqua, VIIRS and Sentinel3A-OLCI data. The L3 OC-CCI products include chlorophyll a (CHL-CCI), remote sensing reflectance ($Rrs(\lambda)$), and several inherent optical property products (IOPs). The CHL-CCI blended algorithm attempts to weight the outputs of the best-performing chlorophyll algorithms based on the water types present, which improves performance in nearshore water compared to open-ocean algorithms.

Daily sea surface temperature (SST) data (gridded 1km resolution) were acquired from the Group for High Resolution Sea Surface Temperature (GHRSST) Multiscale Ultrahigh Resolution (MUR, version 4.1) Level 4 (L4) data (JPL MUR MEaSUREs Project 2015). The MUR analysis ingests the Moderate Resolution Imaging Spectroradiometer (MODIS) retrievals and seeks to capture small scale SST structures wherever available. The MODIS data are combined with lower resolution SST data from satellite infra-red and microwave sensors as well as *in situ* measurements (Chin *et al.* 2017).

The global CHL and SST products were spatially subset to the U.S. East Coast (SW longitude=-82.5, SW latitude=22.5, NE longitude=-51.5, NE latitude=48.5). Weekly statistics (minimum, maximum, mean, standard deviation and coefficient of variation) were calculated for both CHL and SST. Climatological weekly means were calculated from the entire time series (1998-2020 for CHL and 2003-2020 for SST) to generate the anomalies. CHL in the NES are log-normally distributed, thus to calculate the CHL anomaly (CHL_{anom}) the data are first log-transformed before taking the difference between the weekly mean (CHL_i) and the climatological mean (CHL_{ci}), which results in a unitless CHL anomaly ratio (Eq 1.).

$$CHL_{anom} = EXP(log_{ln}(CHL_i) - log_{ln}(CHL_{ci})) \quad \text{(Eq 1.)}$$

The SST anomaly (SST_{anom}) is just the difference between the weekly SST (SST_i) and the climatological mean (SST_{ci}) (Eq 2.).

$$SST_{anom} = SST_i - SST_{ci} \qquad \text{(Eq 2.)}$$

Oceanographic fronts

Oceanographic fronts are narrow zones of enhanced horizontal gradients of water properties (temperature, salinity, chlorophyll, etc.) that represent major biogeographical/ecosystem boundaries and are often associated with zones of elevated primary and secondary productivity and can be "hot spots" of marine life and fishing (Belkin *et al.* 2009). For the frontal data, daily high resolution (1km) MODIS imagery from the Aqua and Terra satellites were acquired from the NASA Ocean Biology Processing Group (OBPG). The Level 1A MODIS-Aqua ocean color files (NASA 2018) were processed using the NASA Ocean Biology Processing Group SeaDAS software version 7.4. All MODIS imagery were spatially subset to the U.S. East Coast (SW longitude=-82.5, SW latitude=22.5, NE longitude=-51.5, NE latitude=48.5) using L1AEXTRACT_MODIS. SeaDAS's L2GEN program was used to generate Level 2 (L2) products including chlorophyll a (CHL) using the default settings and optimal ancillary files. MODIS-Aqua SST (4µm night and 11µm day images; NASA 2019) and MODIS-Terra CHL (NASA 2018) and SST (4µm night and 11µm day images; NASA 2019) were downloaded from OBPG as L2 files. The SeaDAS L2BIN program spatially and temporally aggregated the L2 files to create daily Level 3 binned (L3B) files. The daily files were binned at 2 km resolution that are stored in a global, nearly equal-area, integerized sinusoidal grids and the CHL files use the default L2 ocean color flag mask.

Daily CHL and SST frontal gradients were calculated using the Belkin and O'Reilly (2009) algorithm. CHL fronts are more diverse and complex than SST fronts and thus this algorithm uses a contextual median filter to preserve the main features of the CHL field, namely CHL enhancement on hydrographic fronts and CHL blooms. Prior to running the algorithm, the CHL data were log-normally transformed to account for the log-normal distribution of CHL. Because the gradient data are normalized differences between pixels, data from the Aqua and Terra sensors were merged into daily files, which were then used to create weekly frontal metrics.

Derivation of frontal metrics

In order to isolate prominent frontal features, a threshold of 0.4°C (SST) and 0.06 mgm^{-3}(CHL) was applied to the frontal gradient data (Miller 2009, Suberg *et al.* 2019). Following methods by Suberg *et al.* (2019), the number of valid frontal pixels (*Fvalid*) was identified for each satellite image and summed across a seven-day period. The metric calculated by summing the number of times a pixel exceeded the frontal threshold in a given week. For example, if a pixel was identified as frontal on days 1, 3, 4, and 5 of a given week, it would have a *Fvalid* value of 4. This metric was used as a covariate for this study by determining the proportion of valid frontal pixels in a given area per week (see Table 2.28 and Figure 2.37 for details on areas of data extraction).

Warm core rings

Warm core rings (WCRs) are anti-cyclonic mesoscale eddies that break off from the Gulf Stream (GS), after it detaches from the coast around Cape Hatteras. Once detached from the stream, these mesoscale eddies move in a west-southwestward direction carrying the entrapped warm GS water through the slope sea to the US continental shelf region (Gangopadhyay *et al.* 2020, Silva *et al.* 2021). When a WCR impinges on the shelf slope, its inherent anti-cyclonic properties (clockwise movement of surface waters) create differential water characteristics on opposing sides of the ring (Morgan and Bishop 1977, Gawarkiewicz *et al.* 2001, Cenedese *et al.* 2013). On the eastern edge of the ring, cooler shelf water is entrained and exported from the shelf into the slope sea creating a streamer of shelf water (Gawarkiewicz *et al.* 2001). These shelf water streamers may interact with the Middle Atlantic Bight (MAB) Shelfbreak Jet resulting in an area of increased upwelling (Ryan *et al.* 1999, Forsyth *et al.* 2020, Forsyth *et al.* 2021). Conversely on the western edge of the ring, there is a steepening of the shelf-break front combined with an onshore flow, resulting in warmer, more saline water intrusions (Gawarkiewicz *et al.* 2001). Recent years have seen a significant increase in the number and frequency of these mesoscale eddies (Gangopadhyay *et al.* 2019) which potentially play a key role in the changing dynamics of the Northwest Atlantic shelf and slope waters (Gawarkiewicz *et al.* 2018, Harden *et al.* 2020, Chen *et al.* 2021; Gawarkiewicz *et al.* 2022).

Derivation of warm core ring metrics

Ring tracking census

A Gulf Stream ring tracking dataset of weekly ring size and location was generated from Jenifer Clark's Gulf Stream Charts for the years 2011 through 2020. These charts have been previously used to create a 38 year WCR census (Gangopadhyay *et al.* 2019, 2020). Following the same methodology as Gangopadhyay *et al.* (2020), location and ring area were verified using a QGIS framework. Several different ring indices were created from this dataset.

Ring occupancy

Ring Occupancy is an index created to calculate the number of "ring days" on the Northeast continental shelf. A ring was considered to 'occupy the shelf' if the approximate radius (calculated from ring area assuming the ring was a perfect circle) was longer than or equal to the distance from the ring center to the nearest point of the 100m isobath. The number of ring days was calculated by combining the total number of rings on the shelf and the number of days they remained there. For example, in a given week, if ring A spends 3 days on the shelf, and ring B spends 7 days on the shelf, the ring occupancy would be equal to 10 (ring days). This index was calculated on weekly, monthly and annual time scales.

Ring Footprint Index

The Ring Footprint Index (RFI) accounts for both the amount of time a ring spends in a given area as well as its size, where: RFI = ring days per ring area / (total area of region * total time period). This index was adapted from the RFI calculated in Gangopadhyay *et al.* (2020). The numerator, ring days per ring area, multiplies the time a ring is in a given region (zone) by the area of the ring. This term is then divided by a second term, which multiplies the total area of the zone by the total time period of interest. This was calculated at a weekly time scale across 4 different longitudinal zones binned by 5° increments (Zone 1: 75-70°W, Zone 2: 70-65°W, Zone 3: 65-60°W, and Zone 4: 60-55°W, see Figure 2.38).

Ring Orientation

Ring Orientation is a metric derived in effort to better understand the relationship between the physical properties of warm core rings and catch locations. Information about the ring angle accounts for the processes that are related to the presence of the ring and the orientation of the ring traveling past a fishing point. This ring orientation metric was calculated by identifying ring and fishing location reference points and calculating the angle between them (Figure 2.39). Specifically, coordinates detailing each ring's northern, western, eastern, southern and center points as well as the location where the ring meets the 100 meter isobath were identified. This series of coordinates was then paired with fishing locations and used to generate two lines and their associated angles (Figure 2.39). Comparison between resulting angles was used to determine the orientation of a given ring to individual fishing locations. For a given week, we calculated the distance between individual fishing points and all rings present. Ring orientation was then calculated between a given fishing point and the closest ring associated with that location.

Generalized Additive Modeling

To examine relationships between *Illex* CPUE and oceanographic covariates, we fit Generalized Additive Models (GAMs) to the combined Study Fleet and Observer datasets. GAMs are a powerful statistical tool and are increasingly used in ecological contexts as they are inherently flexible and thus able to account for nonlinear relationships without compromising interpretability (Pederson *et al.* 2019). This flexibility stems from the additive framework of GAMs, which uses local smoothing functions to fit predictor variables to a response variable.

Here, the response variable (CPUE) was adjusted via a negative binomial error distribution with a log link function to account for positive skew and over dispersion. Explanatory variables consisted of thirty-one candidate oceanographic metrics across multiple spatial scales (Table 2.28). A strength of GAMs is their ability to account for relationships between variables occurring on different scales. We facilitated regular correspondence among experts in the fishing industry, oceanography, fisheries, and management to generate a series of hypotheses describing potential relationships between *Illex* catch and key oceanographic processes. These hypotheses were used to inform and select the spatial scale at which each oceanographic dataset was extracted. GAMs were fit using an iterative variable selection process and the optimal model was chosen based on lowest Akaike Information Criterion (AIC; Burnham and Anderson 2002) and highest deviance explained as in similar work from these datasets by Jones *et al.* (2020) and Lowman *et al.* (2021), for consistency. All GAMs were run in R 4.0.5 (R Core Team 2020) using the *mgcv* package (Wood 2011, 2017).

Results

Generalized Additive Model results identified ten covariates that were significant predictors of *Illex* CPUE, including temporal (year, week), spatial (latitude, longitude, and NAFO subareas) and environmental (bottom temperature, ring footprint index, ring orientation, salinity at the 222 meter isobath, chlorophyll frontal activity, and standard deviation in sea surface temperature) variables (Table 2.29, Figure 2.40). The full model accounted for 69.9 % of the deviance explained. The main temporal trends that emerged in the full model are consistent with findings from Jones *et al.* (2020) as well as Lowman *et al.* (2021), where catch is relatively stable in the beginning of the time series (2011, 2012) experiences a significant drop in year 2013 followed by three consecutive low years (2014, 2015, 2016) and significantly higher catch over the most recent four years (2017, 2018, 2019, 2020, Figure 2.40h). The spatial smoother captured the interacting effects of latitude and longitude and identified hot spots of catch along the shelf break (Figure 2.40a). Fishing locations were categorized by Northwest Atlantic Fisheries Organization (NAFO) subareas, which identified differences in catch between Northern and Southern portions of the southern stock component (Table 2.29, Figure 2.40k).

The ecological predictors revealed some interesting patterns. The most impactful ecological predictor in the analysis was bottom water temperature. Its effects suggest a small range of cooler bottom temperatures (6-10°C) support higher catch with a peak around 6.5°C (Figure 2.40b). Salinity at 222 meters exhibits a multi-modal relationship between salinity and catch with two smaller peaks at 35.45 and a larger peak at 35.73 psu (Figure 2.40c). Important mesoscale features included the presence of rings in the slope sea between 70 and 65°W longitude (i.e. Zone 2), 6 months prior to catch, and Zone 1(between 75-70°W), 3 months prior to catch. Specifically, in a given week, the highest catch was associated with a ring footprint index of 0.3 (Figure 2.40de). Additionally, there was a significant positive effect of ring orientation on *Illex* catch, where fishing locations on the eastern side of rings had significantly higher catch than fishing locations on the western side of a particular warm core ring (Figure 2.40j). There was a bi-modal relationship between catch and the variability in sea surface temperature with peaks at standard deviation values of 0.4 and 0.9, suggesting higher catch associated with more variable surface temperature conditions (Figure 2.40f). Finally, chlorophyll frontal dynamics in fishing areas (i.e. the proportion of area identified as a chlorophyll front) revealed higher catch when greater than 40% of the area is identified as chlorophyll fronts (Figure 2.40g).

Discussion

The results from this study largely support the hypotheses developed by the multidisciplinary research team and industry collaborators. In particular, results suggest a suite of environmental variables which may serve as indicators of *Illex* habitat condition or areas of increased primary productivity. These indicators are of interest due to their implications for identifying potential areas of *Illex* aggregation and better understanding their distribution and availability to the fishery. In particular, bottom temperature and ring footprint index may be useful indicators for habitat conditions relevant to *Illex* juvenile/adult and pre-recruit/larval life stages, respectively, whereas the remaining covariates, ring orientation, salinity, and chlorophyll frontal dynamics are potential indicators of areas of high productivity. Results from GAMs identified low mean bottom temperatures as a strong predictor of CPUE, which is consistent with results from surveys done by Hendrickson (2004), where juveniles were associated with deeper waters (140 - 260 m) and lower bottom temperatures (9.9 °C). Existing hypotheses around habitat conditions explaining the relationship between *Illex* occurrence and cooler bottom temperatures have been attributed to both the selection of cooler temperatures to manage metabolic demands and the use of depth to avoid predation (Benoit-Bird and Moline 2021). Bottom temperatures on the shelf are highly dependent on local processes (e.g.: circulation and intrusions) and variable in space and time (Chen *et al.*, 2021a, b), therefore more research is needed to better understand this relationship. The lagged ring footprint index, a measure of ring occupancy in the slope sea, may serve as an additional indicator of habitat condition for pre-recruit/larval stages. Examining ring footprints in the slope sea at 6 and 3-month lag times was an effort to understand slope water conditions in areas previously identified as important for larval stages of the *Illex* (Bakun and Csirke 1998, Dawe *et al.* 2007) and gain insight into rings as potential transport/retention mechanisms. The significant relationship that emerged between catch and a lagged WCR footprint index in slope sea zones (higher catch at RFI > 0.3 in zone 2 lagged by 6 months, see Figure 2.40c), is an important result that merits further investigation as it may have implications as a pre-season indicator. Recent research conducted by Jones and Hendrickson of the WG, to address TOR 3, has identified two predominant *Illex* cohorts, with one cohort hatching in the winter and one cohort hatching in the summer, with specific hatch times varying inter-annually (Jones and Hendrickson, *unpublished manuscript*). This work extends the findings of Hendrickson (2004) that a winter cohort supports the *Illex* fishery to include a summer cohort that supports the latter part of the fishery. Thus, having an indication of the total area of the slope sea occupied by WCRs during the winter hatch months (January - March) may provide greater understanding of the habitat conditions (salinity, temperature, productivity) under which newly hatched *Illex* are exposed. Increased characterization of the presence and timing of mesoscale oceanographic features in areas occupied by newly hatched *Illex* may also provide insight into the habitat characteristics that are favorable to newly hatched *Illex*, which has the potential to improve our ability to forward-project availability of mature squid to the fishery.

The remaining covariates can be summed up as indicators of areas of high productivity. Namely, the significance of the eastern orientation of a warm core ring to a fishing point supports our hypotheses that that *Illex* abundance is likely to be higher or more concentrated on the eastern edge of a warm core ring. Specifically, Forsyth *et al.* (2021) have found that as a WCR impinges on the shelf, the interaction between the shelf streamer created on its eastern edge and the MAB Shelfbreak Jet can result in increased upwelling (by a factor of ten) resulting in enhanced productivity in those locations (Forsyth *et al.* 2020, Gawarkiewicz *et al.* 2001, Cenedese *et al.* 2013). Additionally, the strong significant relationship between high catch and sub-surface salinity greater than 35.6 psu (at 222 meters depth) is also an important and informative indicator of productivity, and indicates a meaningful relationship between mid-depth intrusions of Gulf Stream water and *Illex* squid. Near surface salinity measurements are less indicative of a warm core ring because surface salinity is more variable due to the mixing of surface waters, whereas higher salinity at a depth of 200 meters is more indicative of the presence of a warm core ring and also coincident with the near-bottom preference of *Illex* squid. Additionally, the 200 meter isobath is roughly the mean position of the MAB Shelfbreak Jet, where upwelling can reach the 26.0 isopycnal. The interaction of the jet and the highly saline ring water has the potential to support high levels of primary productivity (Forsyth *et al.* 2020, Oliver *et al.* 2021). The two smaller salinity peaks at 35.3 and 35.4 psu are likely signals of older rings that have mixed with surrounding slope water, characterized by smaller diameters and less vertical extent than rings with higher salinity of 35.7-35.8 psu (Gawarkiewicz *et al.* 2001, Silva *et al.* 2020).

The relationship that emerged between higher standard deviations in sea surface temperature and catch is not unexpected as the highest amount of variation in sea surface temperature occurs at the shelf-break front (Linder and Gawarkiewicz, 1998), which is also the location of the majority of the fishing effort. The ecological interpretation of this trend is less clear as the variability in SST may simply be acting as an indicator for capturing heterogeneity in the environment, including bathymetric features (such as high slope). Alternatively, this relationship may serve as a useful indicator of changes in the water composition, where increased standard deviations are related to instances of slope water intrusions onto the shelf. Finally, the peaks in CPUE in areas where 30-50 percent of the surface is identified as chlorophyll fronts support the hypothesis that chlorophyll frontal activity can serve as a near-surface indicator of productivity, with biological implications for benthopelagic species such as *Illex*.

While these results are correlative in nature, they have strong implications for understanding the mechanistic drivers of the distribution of *Illex* throughout the fishery in space and time. More research is needed to identify and verify these potential drivers in order to move towards in-season management and pre-season forecasting. Therefore, it is our recommendation that future research should focus on the following primary areas concerning *Illex* availability, growth, and aggregation to address key uncertainties in current stock assessment models. Specific research initiatives should include a) increased *Illex* sampling efforts throughout the slope sea across multiple life history stages (e.g.: larval, juvenile, adult), b) categorization of environmental conditions/dynamics of proposed nursery habitat (slope water composition), c) isolation and near-real-time monitoring of the shelf break front position via satellite derived metrics, d) standard and continuous categorization of warm core ring trajectories and other mesoscale features, e) real-time monitoring of salinity maximum intrusions along shelf break, f) identification of *Illex* spawning locations, g) cooperative research aboard commercial fishing vessels to quantify *Illex* within and around WCRs during the fishing season, and h) efforts to support fine scale monitoring (both spatial and temporal) including increased fleet participation in fine scale catch reporting, as well as inclusion of new data fields, such as details around location selection, in order to identify if fishing locations are reflective of fishing behavior (gear restrictions, steepness of slope, [mis]matches in trip length/duration with vessel processing abilities) or patterns in squid distribution (aggregation in areas of high productivity).

This work has important implications for the development and understanding of future stock assessments. Having a better understanding of the role of environmental conditions and the mechanistic oceanographic underpinnings driving the productivity and movement of *Illex* is an invaluable part of its stock assessment and management. Specifically, given that multiple cohorts (winter and summer) are likely supporting the *Illex* fishery, it is imperative to have clarity around the core oceanographic processes driving the observed ingress and egress events of *Illex* in order to support and account for the open population assumption (Manderson & Mercer 2022) of this fishery in future stock assessment models.

TOR 3: Utilize the age, size and maturity dataset, collected from the 2019 landings, to identify the dominant intra-annual cohorts in the fishery and to estimate growth rates and maturity ogives for each cohort. Also use these data to identify fishery recruitment pulses.

Squid have a unique life history characterized by rapid growth, primarily sub-annual lifespan, semelparous reproduction with intra-annual cohorts, highly variable inter-annual abundance and rapid growth rates with high plasticity due to their close linkage with environmental conditions (Jackson and O'Dor 2001, Rodhouse *et al.* 2014, Doubleday *et al.* 2016). These traits make squid stocks difficult to assess and manage (Arkhipkin *et al.* 2020), especially transboundary ommastrephid stocks like *Illex illecebrosus* and *Illex argentinus*. Both stocks also have similar assessment and management challenges, for example, they both have extremely broad geographic ranges that extend across the regulatory jurisdictions of multiple Coastal States and a Regional Fisheries Management Organization (Figure 1.1) in the case of *I. illecebrosus* (Arkhipkin *et al*. 2015). *I. illecebrosus* and *I. argentinus* have such similar life histories that they both serve as a life history model for the *Illex* genus (Rodhouse *et al.* 1998).

Illex illecebrosus is a sub-annual, semelparous species for which ageing studies have shown that spawning occurs year-round with seasonal peaks that result in intra-annual cohorts (Dawe and Beck 1997, Hendrickson 2004). The latter study identified the winter cohort and determined that it supported the early portion of the U.S. *I. illecebrosus* fishery. Based on the average lifespan of the winter cohort, a second cohort (identified then as the spring cohort) was inferred and believed to support the latter part of the fishery period (Hendrickson 2004). The same study was the first to identify the spawning grounds and describe the age, growth and maturity of the southern stock component (i.e., the portion of the *I. illecebrosus* stock managed by the U.S.). The spawning grounds for the winter cohort is located in the Mid-Atlantic Bight near the edge of the continental shelf and within the U.S, fishing grounds where mature males and females have been caught in the directed fishery (Hendrickson 2004, Hendrickson and Hart 2006). This is the spawning grounds for the entire stock because mature and mated squid have never been captured in the Slope Sea and only a few mature females have been caught in colder Canadian waters (Hendrickson 2004). The 2019 and 2020 biological datasets described here were collected throughout the U.S. fishing season so they should be useful for confirming the winter cohort identification and identifying the second cohort and determining which months of the fishery that each cohort supports. In addition, the length, weight and maturity data from the 2019 fishery are also characterized.

Due to the time-consuming nature of processing and reading daily increments on cephalopod hard structures, there are few studies that have investigated population structure based on age analysis in this species (Morris and Aldrich 1984, Dawe *et al.* 1985, Dawe and Beck 1997, Hendrickson 2004). However, age rather than length data must be used to identify intra-annual cohorts and to estimate growth rates because squid growth rates show high plasticity, so individuals of the same mantle length can be from different intra-annual cohorts (Pierce and Guerra 1994, Arkhipkin *et al.* 2000, Arkhipkin *et al.* 2020). Without time-consuming population age studies to reveal the cohort structure, cohort assignment based on modal lengths may be misleading (Caddy 1991).

Cohort assignment itself is crucial for the sustainable management of squid stocks because differences in growth and maturation rates between cohorts require each cohort to be assessed separately as if it were a separate stock (Arkhipkin *et al.* 2020). A good reminder of the need for cohort-specific management of squid stocks is the collapse of the northern stock component (NAFO Subareas 3+4) of *I. illecebrosus* (Rodhouse *et al.* 1998) in 1982, following record high catches during 1976-1981 (Figure 1.2). The collapse subsequently led to a 36-year period of low productivity during 1982-2017 that could not support a fishery on this stock component (Hendrickson and Showell 2019).

Objectives of the 2019 and 2020 studies were to use statolith-based age analysis to identify the intra-annual cohorts that support the U.S. *I. illecebrosus* fishery and to summarize the biological data (i.e., DML, body weight and age) collected from the 2019 fishery samples. The 2020 study was conducted with grant funds awarded to Hendrickson after the Terms of Reference (TORs) for the *Illex* Research Track Assessment were established. This funding allowed a postdoctoral squid ageing and Trace Element Analysis (TEA) expert, Jessica Jones from the Falkland Islands, to conduct this research at the NEFSC. Thus, two additional objectives of the 2020 study were to improve the temporal resolution of the biological dataset through biweekly sampling of the fishery and to combine the age analysis with trace element analysis (TEA) of the statolith microstructure to determine whether the intra-annual cohorts have unique elemental signatures and to identify the ontogenetic migration patterns of the sampled individuals throughout their lifespans. However, for the reasons described below, only the former objective could be addressed in time for inclusion of the results in this report. For the same reasons, much of the biological data analyses focus on the age analyses.

BIOLOGICAL SAMPLING

Methods

Biological data were collected from unculled samples of *Illex* catches from the U.S. *Illex* fishery during 2019 and 2020. Each sample was collected from a known vessel, trip date and fishing location. The samples were provided by two *Illex* processors, Lunds Fisheries (Cape May, New Jersey) and The Town Dock (pack-out facility located in New Bedford, MA). Upon arrival at the processing plant, catches were randomly sampled, packed in boxes with trip identifier information, and then flash frozen. Samples were provided for June to October 2020, but May and September samples were not available due to COVID-19 pandemic-related issues. The samples were obtained from the catches of both fleet types, RSW boats and FT boats that did not cull their catches, were from trips conducted on both the northern and southern fishing grounds, in Southern New England and the Mid-Atlantic Bight regions, respectively (Figure 3.1). The frozen samples were later provided for two studies, referred to here as the 2019 and 2020 studies, although most of the dissection and ageing work occurred during 2020 and 2021, respectively.

The COVID-19 pandemic severely delayed analysis of the 2020 data because Jones was prevented from entering the U.S. when planned. This delayed Hendrickson's stock assessment analyses because she had to conduct most of the biological data collection and statolith extractions. Closure of the London laboratory where the TEA equipment was located forced Jones to make alternative plans to accomplish this research. These delays prevented Jones from completing her TEA research as planned. However, she and Hendrickson will complete this research and publish it following the *I. illecebrosus* Management Track Assessment process. However, the results of analyses that could be completed in time, including a preliminary analysis of one of the trace elements, strontium, is presented.

Biological data for both years were collected in the laboratory from thawed specimens using the methods described in Hendrickson (2004). Dorsal mantle length (DML, mm), body weight (g), sex and sexual maturity stage were recorded for all specimens. Sex and maturity stage were assessed according to Mercer (1973) for males (stages 1-4) and Durward *et al.* (1979) for females (stages 1-5). Statoliths were extracted from all specimens and stored in 96% ethanol. For the 2019 samples, the MAFMC retained marine biologists from a consulting firm to collect the biological data following in-person training by Hendrickson and with her daily oversight. Age determinations were conducted by a European consultant with *Illex illecebrosus* ageing experience. Biological data collection and statolith extractions for the 2020 samples were conducted by Hendrickson and Jones. Age determinations were conducted by Jones, whose statolith-based squid ageing experience is extensive. Specimens subsampled for age analysis were representative of the sex ratios. The 2020 age subsamples were subsampled a second time to select individuals for TEA to ensure that biweekly samples, both sexes and a range of sexual maturity stages were represented.

Results

The *Illex* samples provided by the squid processors for biological data analysis are representative of the 2019 and 2020 directed fisheries (Figure 3.1). The samples are also temporally representative of the fisheries during both years, although sampling months differed between years due to different temporal sampling objectives and sample availability during the 2020 pandemic. During 2019 and 2020, the numbers of squid sampled for DML, body weight, sex and sexual maturity totaled 951 (during May-June and August-October) and 1,269 (during June-August and October), respectively (Table 3.1). The numbers of aged individuals for the same months (except for the 2019 October samples, which were not aged) totaled 400 in 2019 and 325 in 2020 (Table 3.1), which represent large sample sizes relative to many other statolith-based squid ageing studies.

AGEING

Methods

Squid ageing is extremely labor intensive and requires mounting, grinding and polishing both sides of the statolith prior to counting the daily growth increments. Daily increment periodicity has been validated in *I. illecebrosus* using two different chemical markers (Dawe *et al*. 1985, Hurley *et al*. 1985), therefore the total number of growth increments was considered to represent the post hatching age in days, with the nucleus (natal ring) representing the date of hatching (Balch *et al.* 1988).

For the 2019 samples, preparation of statoliths for increment counts involved mounting one statolith from each pair on a microscope slide with Crystalbond™ 509 mounting adhesive, with the anterior concave side uppermost. Statoliths were ground first on the anterior surface and then on the posterior surface. Grinding of both surfaces in the sagittal plane was done to produce relatively thin statolith sections that improved the visibility of growth increments. Increments were counted by eye along the axis of maximum statolith growth with a Nikon compound microscope at 400x magnification. In statoliths of the oldest individuals, when the increments were not clear enough to see (especially at the edge of the statolith or near the nucleus due to statolith crystallization), the number of unclear increments was estimated by extrapolation from the adjacent area. Observed age was the average of two sets of increment counts conducted on separate dates.

For the 2020 *Illex* age samples, one statolith per specimen was mounted for both elemental and age analysis, concave side up using Crystalbond™ 509 mounting adhesive (Aremco Products Inc.), then ground using wet waterproof silicon carbide grinding paper (P1200 followed by P2400 grit, Buehler) and polished (Buehler polishing cloth) on one side to expose the nucleus (Arkhipkin and Shcherbich 2012). Statoliths were then flipped and ground on the other side, embedded in mounting media (Canada Balsam™) and covered with a cover glass for observation (Arkhipkin and Perez 1998; Arkhipkin and Shcherbich 2012). Growth increments were counted manually, under the transmitted light of an Olympus BX60 compound microscope at 400x magnification. Increments were counted from the nucleus to the edge of the dorsal dome using an eyepiece reticle (Morris and Aldrich 1984; Arkhipkin and Laptikhovsky 1994; Arkhipkin *et al.,* 2000). Observed age was the average of two increment counts per statolith, conducted on separate dates.

Results

Linear regression models run on the two sets of statolith increment counts for each year were statistically significant ($p < 0.0001$) and explained model variance was high ($r^2 = 0.89$) and the same for both models. Residual standard errors were 6.9 and 7.9 for the 2019 and 2020 models, respectively. The residuals plot showed a slight bias in the age estimates of individuals older than 200 days, but the sample sizes for that age range were small for both years. Ages for 2019 and 2020 ranged between 107 and 221 days for 2019 and between 78 and 217 days for 2020. Although the maximum ages were similar, the minimum age for the 2020 data was about 30 days younger, mainly due to the smaller individuals from the summer cohort that recruited to the fishery in October (Table 3.2). The mean ages of males and females from the winter cohort were similar within each catch month during both years, with mean ages ranging between 147 and 178 days. However, females were larger than males, in both mantle length and body weight, as has been shown in other studies (Dawe and Beck 1997; Hendrickson 2004). The exception was June of 2020 when both males and females averaged 95 g and were only half the weight of the 2019 June samples. Recruitment of the summer cohort to the fishery primarily occurred during October, but a small portion also occurred in September of 2019. Mean ages for the summer cohort were about 104 days and 116 days, for females and males, respectively (Table 3.3). Mean DML and body weights for each sex were similar between the winter and summer cohorts.

Catch length and age compositions

Catch length and age compositions were computed for each year. Catch length frequencies were computed by multiplying the numbers-at-length pooled across all length subsamples by a length expansion factor. The length expansion factor was computed as the catch weight of *I. illecebrosus* pooled across all trips divided by the subsample weight of the length samples pooled across all trips. Catch length frequencies were then binned by 10-mm intervals. The same procedure was used to compute catch age frequencies for each year, but instead numbers-at-age pooled across all subsamples were expanded to the combined catch from all trips using the same length expansion factor. The hatch month frequency distributions for each year were computed as proportions of the pooled catch across all trips. To do so, catch numbers-at-length for all trips combined (computed as previously described) were multiplied by the proportions at length by hatch month.

Catch length and age compositions were unimodal for 2019 and bimodal for 2020 (Figure 3.2). The 2020 bimodalities were attributable to recruitment of the summer cohort to the fishery in October. Modal lengths and ages for 2020 occurred at 80 and 180 mm and 12 and 24 weeks. The 2019 modal length of the catch (210 mm) was slightly larger and the modal age was slightly younger (22 weeks).

Maturity

No juveniles were caught in the 2019 fishery samples. Modes of female maturity Stages 1, 2 and 3 (immature and maturing) occurred in the catches during May, June and September, respectively. Modes of male maturity Stages 1-3 (immature and maturing) occurred during May, June and August, respectively. The mode for mature males occurred during September. However, there were only 16 mature females in the samples, only six of which were aged. The low percentage of mature females was attributable to low sampling of the spawning grounds south of Hudson Canyon (Hendrickson 2004) during May and June.

INTRA-ANNUAL COHORT IDENTIFICATION

Methods

Intra-annual cohorts were identified from the 2019 and 2020 catch age frequency data pooled by hatch month. The age frequency distribution of each subsample was scaled up to the *I. illecebrosus* catch of the respective trip and binned by hatch month. The numbers-at-age in each trip subsample were multiplied by ratio of the trip catch weight of *I. illecebrosus* to the subsample weight of the aged specimens sampled from each trip. Trace element analysis (TEA) of the statolith microstructure, specifically the strontium sigantures of the winter versus summer cohorts, was used to confirm the cohort assignments that were based on the age frequency data by hatch month.

As reiterated in Arkhipkin *et al.* (2020), squid cohorts must be identified with age data because, due to high individual growth rate plasticity, squid of the same mantle length can be of different ages and from different intra-annual cohorts. Intra-annual cohorts that support the U.S. fishery, were identified from catch age frequency data that are shown as proportions of the age frequencies of the catch by hatch month. Ages were estimated from counts of statolith daily growth increments.

Results

As determined from a previous aging study (Hendrickson 2004), spawning occurs continuously during the U.S fishing season, so monthly fishery catches are comprisesd of a mix of individuals from two to four different hatch months (Figure 3.3). The results of the subject study confirmed the findings of Hendrickson (2004) that the winter cohort supports the early fishery period and a second cohort supports the remainder. The 2019 and 2020 age data allowed identification of the second cohort as the summer cohort, comprised of individuals hatched during May-July (Figure 3.4). September was a cohort transition month because the summer cohort recruited to the fishery in September of 2019, but most of the catch consisted of the winter cohort. The two datasets also showed that the winter cohort, comprised of individuals hatched during November-April, actually supported most of the fishery period, from May through September, which is a longer period than previously thought.

Proportions of the catch age frequency distribution differed by hatch month between the two years, in part, because of differential sampling between years; May-June and August-September (with no July or October samples) during 2019 and June-August and October (with no May or September samples) during 2020. For example, in 2019, the low proportions of individuals hatched in February and June and July were due to the lack of samples during July and October, respectively. Due to these temporal sampling differences, when the catch age frequency distributions of the two years are viewed together, it is clear that the modal hatch months of the winter and summer cohorts are February and June, respectively (Figure 3.4).

TRACE ELEMENT ANALYSIS

Age rather than mantle length data must be used to identify intra-annual squid cohorts and to estimate their growth rates because their growth rates show high plasticity and individuals of the same length can be from different seasonal cohorts (Arkhipkin *et al.,* 2020). As a result, the biological data analysis sections of TOR 3 focus on age analysis and identification of cohorts entering the U.S. *Illex illecebrosus* fishing grounds. The winter cohort was identified using statolith-based age analysis (Hendrickson 2004) as the primary cohort that supports the early part of the fishery period. However, the second cohort (now defined as the summer cohort, given the new information within this assessment), which supports the latter end of the fishery period, was inferred based on the average lifespan of the winter cohort (Hendrickson 2004).

In recent years, the use of trace elemental signatures as natural tags has been shown to have applications in determining population structure. Calcified structures including fish otoliths (Campana 1999), gastropod (Zacherl *et al.* 2003), jellyfish (Morrissey *et al.* 2020) and squid statoliths (Semmens *et al.* 2007, Avigliano *et al,* 2020) have been used to elucidate a variety of life history characteristics. Analogous to fish otoliths, statoliths are hard structures that grow continually throughout life and are formed by the deposition of calcium carbonate, principally in aragonite crystal form, within a protein matrix (Radtke 1983). As material is accumulated, trace elements are incorporated into the statolith microstructure (Arkhipkin 2005). Uptake of elements into the statolith microstructure is considered to reflect the environmental conditions at the time of incorporation, as well as reflecting physiological and genetic factors. They essentially act like a "black box" recording an individual's ecological history (Arkhipkin 2005). Statolith microchemistry has proven to be an effective stock (Green *et al.* 2015, Avigliano *et al.* 2020) or cohort tag (Jones *et al.* 2018, Ching *et al.* 2019) in other species of squid, but trace element analysis has never been undertaken on *I. illecebrosus*.

This study aims to generate temporally resolved elemental chronologies of the 2020 statolith samples as a complimentary method to confirm the assignment of the winter and summer cohorts from the 2019 and 2020 age data.

Methods

Fishery samples were collected in 2020 as described above in the ageing methods section. A total of 551 individuals had their statoliths removed and stored in 96% ethanol. Of these, a subsample of 252 individuals were selected for trace element analysis to ensure that biweekly samples, both sexes and a range of maturities were represented (Table 3.4). These statoliths were mounted on microscope slides then ground and polished on one side to expose the nucleus following Arkhipkin and Shcherbich (2012).

Statoliths were analyzed for trace elements using laser ablation inductively coupled plasma mass spectrometry (LA-ICP-MS) at the Natural History Museum in London, UK. Statoliths were remounted onto shared slides of 30 to reduce the need to expose the ablation cell to external air sources, with contaminants removed from the ground surfaces using ethanol prior to analysis. Because the estimated elemental concentration can be substantially affected by instrumental drift, the analysis sequence was randomized so that the order of analysis for any one sample group was spread over the entire analysis sequence (Kerr and Campana 2014). Elemental concentrations were obtained using an ESI New Wave NWR193 laser ablation system coupled to an in-situ Agilent 7700 ICP-MS. Values for limit of detection (LOD) were calculated as 3 standard deviations (SD) of the background signal.

The following trace elements were quantified; Na, Sr, Mg, B, Li, Ba, Al, Mn, Fe, Zn, Cu, Cd and Pb, with Ca used as an internal standard to account for variation in ablation yield. A transect (25 µm in diameter) continuously acquired sample from the core (representing early ontogeny) to the edge of the dorsal dome (representing date of sample collection) at a rate of 3 $\mu m\ s^{-1}$, in the same direction as the ageing was undertaken (Figure 3.5).

The glass reference materials NIST-610 and NIST-612 (National Institute of Standards and Technology, USA) were used for external calibration. Both standards were ablated between every 5th statolith with NIST-610 used to calibrate elemental concentrations and assess changes in instrumental sensitivity and NIST-612 treated as an unknown sample to assess measurement accuracy.

Following trace element analysis, ablated statoliths were flipped and ground on the other side, embedded in mounting media (Canada Balsam™) and covered with a cover glass for observation

(Arkhipkin and Shcherbich 2012). Statoliths were read under the transmitted light of an Olympus BX60 compound microscope at x400 magnification according to protocols outlined above in the Ageing section. Aged specimens were binned by month based on hatch date (hatch date = date of capture - mean of the last two age counts) and then assigned to a cohort based on the frequency distribution of all sampled specimens, by hatch month, after expanding them to the total catch per trip. As previously discussed, squid hatched between November and April comprised the winter cohort and those hatched between May and July comprised the summer cohort.

All analyses were undertaken in R V.4.0.2 (R Core Team 2021). Elemental concentrations (ppm) were converted into molar concentrations ($\mu mol.mol^{-1}$, or $mmol.mol^{-1}$ for Sr and Na given the high concentration of each element within the statolith microstructure) and standardized to calcium (element: Ca). Prior to analysis, data were post-processed to remove outliers given the noisy nature of the data. Values ±5 SD of the mean for each individual marker were considered outliers and removed from any subsequent analysis according to protocols described in Kerr and Campana (2014). As increments were counted every 25 µm using an eyepiece reticule during the ageing process, data were prepared for compatibility between datasets by binning the trace element data into 25 µm increments and calculating their average.

This analysis focuses on Sr:Ca, which is the most frequently analyzed element in hard biogenic structures. The data set consisted of multiple time observations for each statolith. Mixed modelling was therefore applied with Sr:Ca as the response variable, with the random intercept *slide number* (a unique identifier for each individual) used to model a dependency structure among Sr:Ca observations from the same squid. The random intercept was assumed to be normally distributed with mean 0 and variance σ^2. A Gaussian GAMM (identity link, to ensure positive fitted values) was used to determine whether Sr:Ca ratios were distinct for each assigned cohort and how they changed throughout ontogeny (Equation 1, below). Fixed categorical covariates available were *sex* (two levels), *cohort* (two levels), *location* (geographic location of sample collection, seven levels) and *maturity* (maturity stages 1-3 were coded as immature and stages 4-5 as mature for both sexes, two levels). Preliminary analysis indicated non-linear effects for hatch day and age. The variable *hatch* (day within the year, a continuous variable ranging from 1 to 365) had a smoother fitted using cyclic cubic regression splines, which are penalized cubic regression splines whose ends meet up to avoid discontinuity between December and January. The remaining fixed covariate, *age* (number of days post-hatching), is continuous and a smoother was fitted using thin plate regression splines, with one smoother fitted for each *cohort*. Several models were fitted, with Akaike Information Criterion (AIC) used in conjunction with a backwards model selection procedure, to identify the optimal model according to the ten-step protocol described in Zuur *et al.* (2009) using "REML" estimation for the final model. Given that autocorrelation plots indicated violation of independence during model selection, an autocorrelation structure of order one (AR-1) was fitted for *age* nested within *slide number*, which significantly improved model fit and largely resolved autocorrelation issues. Model assumptions were verified by plotting standardized residuals against fitted values and against all potential covariates (Zuur and Ieno 2016). The optimal model was defined as:

$$Sr\!:Ca \sim f(age)\!:cohort + f(hatch) + location + \ cohort \qquad (1)$$

where $f(age)\colon cohort$ represents one smoother used for each *cohort* and *cohort* fitted as a mean term. All statistical modelling was performed using the R package "mgcv" (Wood 2017).

Results

The candidate models that explored the effects of biological variables on Sr:Ca ratios are given in Table 3.5. The beyond optimal model was fitted, and the optimal random structure was included to model dependency prior to the fixed components being optimized. Maturity was not significant at the 5% level for the beyond optimal model (MN1, Table 3.5) and was removed, which improved the AIC (MN2), but a log-likelihood test indicated that this did not significantly improve model fit ($\chi^2[1] = 3.42$, $p = 0.06$). Sex was not significant at the 5% level in MN2 and was also removed (MN3). This significantly improved model fit ($\chi^2[1] = 4.27$, $p = 0.04$), reduced degrees of freedom and lowered the AIC. Though the smoothers for the effect of age were significant for each *cohort*, *cohort* itself fitted as a mean term was marginally significant at the 5% level ($p = 0.03$) and therefore a model was run without the effect of *cohort* (MN4). This did not improve model fit.

Once the optimal fixed structure was identified (MN3), an autocorrelation plot of the standardized residuals was produced. This plot indicated substantial autocorrelation (Figure 3.6). Several different autocorrelation structures were fitted, but an AR-1 structure fitted for *age* nested within *slide number* provided the best model fit. A total of 5,651 Sr:Ca values were analyzed in the final optimal model (MN5) and model validation indicated no unresolved problems (Figure 3.7). Estimated regression parameters for the optimum model can be found in Table 3.6.

The most parsimonious model included the smoothing term *age* (representing the ontogenetic effect) modelled separately for the winter and summer cohorts. The F-values for both smoothers indicated a substantial effect of both cohorts on Sr:Ca concentration, and the summer cohort had lower expected degrees of freedom than the winter cohort, indicating a less complex trend, closer to linear (Table 3.6). A linear trend would have edf = 1, so substantial non-linear effects were evident for both cohorts. Fitted curves indicated substantial ontogenetic trends for both cohorts (Figure 3.8). Confidence intervals for the summer cohort were wider because the fishery is predominantly supported by the winter cohort and samples were obtained from commercial fishing vessels in-season, therefore a larger sample size of the winter cohort was available for analysis. Error increased in the model towards the latter stages of ontogeny, because those data are only represented by a few of the oldest individuals that have the longest trace element tracks.

Discussion

The ontogenetic trends revealed in this report for Sr:Ca ratios will be further investigated, along with the rest of the trace element concentrations measured in statoliths collected from the 2020 fishery samples, to elucidate migration patterns in *Illex illecebrosus.* However, this research is outside the scope of the current Terms of Reference for this assessment. For now, it is evident that ontogenetic trends are significantly different for each cohort and that removal of the cohort variable within the mixed model significantly impacts model fit. This finding provides additional support for partitioning of the cohorts based on hatch dates for both the 2019 and 2020 datasets.

Sr:Ca ratios have shown great potential to discriminate between population components in other species of squid. Only three species have been analyzed for cohort-specific trace element signals to date. Liu *et al.* (2015) analyzed the multivariate elemental signatures of another ommastrephid squid, *Dosidicus gigas*, and found no significant differences between the spring, fall and winter spawning cohorts. However, this was a preliminary analysis and sample size consisted of just 14 individuals, which substantially reduces the statistical power of the MANOVA applied to these few samples. In addition, this was a solution-based study, which provides an integrated signal over the entire life history of an individual and does not account for ontogenetic changes. The loliginid squid, *Doryteuthis gahi*, has been found to have significantly different elemental signatures between the autumn and spring spawning cohorts within Falkland Islands waters. This has been confirmed using both solution-based (Arkhipkin *et al.* 2004) and laser-ablation-based methods (Jones *et al.* 2018). Cohort specific differences in Sr:Ca and Ba:Ca were also noted for another loliginid squid, *Sepioteuthis lessoniana* (Ching *et al*. 2019).

Differences in Sr:Ca ratios between cohorts has been attributed to the relationship between uptake of strontium into the statolith microstructure and temperature. Arkhipkin *et al.* (2004) found that Sr:Ca ratios among geographic locations were generally consistent with a negative correlation between Sr:Ca and temperature. A second study has shown that the ontogenetic profiles found within statoliths support the hypothesis of a negative correlation with temperature given what is already known regarding their patterns of migration (Jones *et al.* 2018). The only laboratory study undertaken on cephalopods to date failed to establish this relationship between temperature and strontium, but instead found a negative relationship between temperature and Ba:Ca (Zumholz *et al.* 2007). Sample size was also small in that study, with five individuals analyzed per treatment. However, that study was undertaken on cuttlefish which have very different life history traits (e.g., nektobenthic with much smaller ranges) than ommastrephid squids, the latter of which are nerito-oceanic and undergo extensive migrations during their lifespans. Because ommastrephid squid undergo extensive diel-vertical migrations that could mask patterns arising from horizontal migration, it has been suggested that it is more difficult to distinguish a clear strontium pattern in ommastrephid squid (Arkhipkin *et al*. 2004). However, our study indicates that this is not the case if the data are considered at high resolution and are temporally resolved.

In conclusion, the methodology used within our study is novel for ommastrephid squid, and has shown that the summer and winter cohorts have significantly different Sr:Ca ontogenetic signatures. Future analysis of the 2020 trace element data may help elucidate migration patterns to and from the fishing grounds, but for now presents further evidence that the winter and summer cohort assignments presented in this assessment are accurate.

TOR 4: Characterize annual and weekly, in-season spatio-temporal trends in body size based on length and weight samples collected from the landings by port samplers and provided by *Illex* processors. Consider the environmental factors that may influence trends in body size and recruitment. If possible, integrate these results into the stock assessment.

BODY SIZE DATA AND SUMMARIZATION

Mean body weight has been used as a measure of productivity for the *Illex* stock in previous stock assessments (NEFSC 1999; NEFSC 2003; NEFSC 2006; Hendrickson *et al*. 2004). Both annual and weekly *Illex* body weight data were collected from the commercial fishery landings during 1997-2019. The body weight data for 1997-2003 was collected as part of a cooperative research study that involved real-time, fishery-dependent data collection to evaluate changes in stock productivity. Body weight data for 2004-2006 and 2009-2018 were collected from landings of the directed fishery by QA/QC staffs from the two primary *Illex* processors. Data were generously provided by Lunds Fisheries in Excel spreadsheets which required some reformatting for 2016-2019. Data were also provided by Seafreeze Ltd. on their QA/QC sampling forms and required extensive keypunching by staffs from the Population Dynamics Branch. Seafreeze Ltd. provided additional information to identify each trip allow the addition of "date landed" from the Dealer Landings Database to the Seafreeze dataset in order to assign week of the year to the samples from each trip.

Mean body length samples were also collected by NEFSC port samplers, with body weight computed by dividing the sample weight by the number of lengths in the sample. Samples collected by port samplers included 100 squid per market category. These samples were obtained opportunistically with the objective of collecting a target number of monthly samples by market category, fishery region and year. Such samples do not include all market categories from each trip, unlike the Lunds Fisheries/Seafreeze Ltd. samples. As a result of the different sampling protocols, the two mean body weight datasets were summarized separately.

Research survey trends in annual mean body weight are associated with annual trends in *Illex* relative abundance, such that stratified mean body weight is generally lower during year of low relative abundance, and vice versa, on the US Shelf (Hendrickson *et al.* 2004) and Scotian Shelf (Hendrickson and Showell 2019). Annual mean body weights of individuals caught during NEFSC fall bottom trawl surveys decreased substantially in 1982 following the collapse of the northern stock component. Mean body weights then declined and remained below the 1982-2018 average during most years since 1995 (Hendrickson and Showell 2019).

Changes in *Illex* mean body weight represent the combined effects of growth, mortality (both fishing and natural mortality), and emigration and immigration. As is typical for squid species, age rather than body size data must be used for cohort identification because same-sized individuals can be from two different overlapping seasonal cohorts which have different growth rates (Dawe and Beck 1997; Arkhipkin *et al.* 2021b). As documented in previous assessments, mean body weight gradually increases during the fishing season, and for 1997-2019 combined, the peak occurred in week 34 (Figure 4.1). Thereafter, mean body weight decreased through the end of the fishing season as squid migrated back offshore and south. The ongoing *Illex* aging study funded by the MAFMC will be used to identify whether these changes in size involve one or more cohorts.

Body weight data obtained from the squid processors consisted of much larger annual sample sizes than the length-based data obtained by NMFS port samplers (Figure 4.2). Regardless, smooths of both datasets showed a similar W-shaped trend with the presence of larger squid at the beginning, middle and end of the time series (Figure 4.3). Annual mean body sizes of squid sampled by the *Illex* processors ranged between 100 and 200 g, but the mean body sizes of squid collected by the port samplers were larger and ranged between 180 and 480 g. This disparity requires further investigation. However, as described in the Methodology section, other than for trends, the two datasets are not directly comparable due to the differences in sampling protocols. As a result of larger sample sizes and sampling of unculled samples from all RSW and ice boat trips and all market categories from FTs, the processor dataset should be more accurate than the port agent samples. However, further investigation is needed to confirm this conclusion.

When trends between the fishery mean body weight time series and the stratified mean body weight time series from the NEFSC fall surveys are compared, the fishery time series does not show the gradual decrease exhibited by the survey data (Figure 4.3). Body weight data collected from the directed fishery landings represents cluster sampling due to the inherent nature of fishing behavior. When fishing, clusters of tows are conducted in close proximity to one another in areas of high squid abundance and can result in biased fishery-dependent data. For example, *Illex* mean body size increases with latitude (Hendrickson 2004) so if *Illex* body weight samples are predominately obtained from northern fishery areas body size will appear to be larger for that time period. In contrast to the fishery data, the survey's stratified random sampling protocol ensures that these body weight samples are representative of the population that is present on the shelf during the fall. Although the fall survey can be viewed as a post-fishery index because it occurs at or near the end of the fishing season, the gradual decreasing trend in body weight is expected to be present during the fishing season as well. As part of the next steps, a spatial analysis of the fishery body weight data will be conducted to determine its temporal and spatial representativeness.

Graphs of body size by week of the year (Figures 4.4-4.6) show that *Illex* body weight trends do not always follow the characteristic rise-and-fall pattern during the fishing season. Although some of the variability in the weekly trends may be attributable to low sample sizes, body size trends three months prior to survey (June-August) would also be expected to show a decreasing trend if they were representative of the population. For ease of identifying trends, smooths of weekly body size data are shown and they indicate that squid weighed more during years of high landings (1998, 2004 and 2017-2019) and less during years of low landings (Figure 4.7).

ENVIRONMENTAL FACTORS, BODY SIZE, AND RECRUITMENT

See OCEANOGRAPHIC INDICATORS FOR *Illex* section *(*Salois *et al.* 2022) in TOR 2.

TOR 5: Develop a model that can be used for estimation of fishing mortality and stock biomass, for each dominant cohort that supports the fishery, and estimate the uncertainty of these estimates. Compare the results from model runs for years with low, medium and high biomass estimates.

INDIRECT ESTIMATION METHODS (Rago 2020, 2021)

Introduction

This work summarizes the decisions of the MAFMC Scientific and Statistical Committee (SSC) in 2020 and 2021 regarding *Illex* squid quotas, updates the analyses with revised data, and attempts to integrate various approaches for developing logical bounds on population biomass and fishing mortality rates, and are therefore relevant for TOR 5. For the WG the approaches were further modified to include solving for F in the catch equation and examining the effects of uncertainty in the ranges of catchability, availability and natural mortality. A Latin hypercube sampling design is used to explore the full range of parameter space by convolving their underlying distributions for catchability, availability and natural mortality. In this exercise, all three parameters are assumed to be uniformly distributed. The analyses generate sampling distributions of biomass, fishing mortality, and escapement for data from 1997-2019, excluding 2014 and 2017 due to missing data. The model is implemented in R and code is available upon request. The results are further extended to consideration of an alternative quota of 33,000 mt for 2022, and therefore relevant for TOR 9. Fishery independent surveys, total landings, and Vessel Monitoring System summary data are the primary bases for these analyses.

One of the most fundamental issues in stock assessment is trying to discern whether a realized catch is the result of a high rate of fishing applied to a small population or a low rate of fishing applied to a large population. In the former instance, rapidly falling catches over time and reduced economic viability are pretty good signs that overfishing was occurring. In the latter instance, persistence of catches over time might be attributable to sound management or luck. When basic assumptions are met and the underlying data are sound, most fisheries assessment models can help distinguish between these alternatives. When they are not, a variety of data poor methods have been used. Even these methods fail to adequately address problems of open populations. The techniques applied herein are designed to illustrate the logical consequences of the intersections of alternative hypotheses about survey and catch observations. Where possible, independent experiments and analyses and values from the literature are used to inform and refine critical model parameters and the effects of revised estimates of q and v are illustrated. The various approaches employed in this work may ultimately form a basis for an integrated assessment model. The conceptual basis for that integration, however, remains to be developed and the uncertainties of the multiple perspectives applied herein seem appropriate.

Realistic ranges of biomass and fishing mortality estimates are developed by first examining the implications of a broad range of feasible, but not necessarily likely, parameter values for gear efficiency, availability, and natural mortality and fishing mortality. The resulting ranges from one set of assumptions are then compared to ranges derived from another set of assumptions. Logical bounds on biomass are based on upper and lower ranges constrained by excluding values that lie outside the bounds of extreme values from alternative assumptions. In other words, a feasible range of biomass estimates is deduced from estimates that satisfy the joint effects of alternative bases of population abundance. Key parameters include estimates of NEFSC research bottom trawl survey gear efficiency, availability of the population to the shelf area sampling region, potential ranges of M and hypothesized ranges of F, and a variety of parameters related to relative density of *Illex* squid in areas fished vs unfished.

Traditional **Leslie-Davis depletion models** do not work very well for Illex because key assumptions for model application are violated. A **Mass Balance Model** illustrates the magnitude of migration, growth and recruitment effects necessary to offset the differences in relative abundance between the NEFSC spring and fall bottom trawl indices. An **Envelope Model** approach is used to establish logical bounds on biomass based on assumed ranges of catchability, availability, and fishing and natural mortality rates. The basic constructs of the Envelope Model and the Mass Balance Model can be used to establish potential ranges for an **Escapement Model** for existing and hypothesized ABC values. Escapement is defined as the ratio of the observed abundance estimate to the abundance that would have been present in the absence of fishing mortality. Finally, **Vessel Monitoring System** data are analyzed to estimate effective fishing mortality rates over the entire population (see also Rago 2021).

Interrelationships among the various approaches are shown in Figure 5.1. Data inputs and other information sources are summarized in the boxes on the left column. The center column defines the various models (boxes) and the input parameters (ovals). Outputs are summarized in the boxes on the right column. The arrows denote the flow of information and identify the dependencies among models. No single model is considered sufficient to capture the within season dynamics of the Illex fishery. Instead, each model identifies a different facet of the relationships among state variables. Model outputs can also be used to further refine inputs for other models (dashed lines). At best this array of models can be used to provide bounds for the likely range of biomass and F estimates that a more sophisticated comprehensive model might estimate.

The various models identify the potential magnitude of processes not accounted for in the models. For example, the previous failure of the Leslie-Davis Depletion models for *Illex* suggests that migrations into the fishing area, variations in growth, and recruitment overwhelm the depletions associated with the fishery (Rago 2020). The Mass Balance model illustrates the potential magnitude of the combined effects of these processes. The Envelope model compares the upper and lower bounds of biomass estimates derived from assumed ranges of fishing mortality and catchability. The indeterminacy of the catch equation provides a basis for assuming a range of F values to estimate the biomass necessary to support the observed catch. In simple terms, an observed catch can be the product of a lightly fished large population or a heavily fished small population. Hence an assumed range of extreme fishing mortality rates can be used to estimate minimum and maximum biomass estimates. Similarly, survey biomasses are assumed to be proportional to true biomass via the catchability parameter that combines the effects of both gear efficiency (i.e., probability of capture given encounter) and availability of Illex within the survey domain. The true biomass is the observed survey biomass divided by product of gear efficiency and availability. By assuming a plausible range of these parameters, informed by knowledge of empirical gear comparisons and analyses of spatial overlap, one can derive high and low biomass estimates. If the biomass of one imputed series exceeds the maximum value of the other then it suggests that assumptions of the first series were too extreme and would need to be reduced. Similarly, if the biomass estimates of a given series, say based on a high F fell below the minimum value of the series created by the maximum feasible value of catchability, then one would conclude that the assumed F was too high. The set of thus constrained biomass estimates now creates an envelope of estimates bound by an internally consistent set of assumptions. An overview of the data sources, input parameters and outputs for the various models is provided in Table 5.1.

The Envelope Model data can also be used to evaluate the risk of overfishing under various assumptions about catchability, F and M. The Escapement Model back calculates the minimum population size necessary to support the observed catch, and then projects that estimate of abundance forward without catch using only the assumed M used to estimate the initial biomass. The ratio of the observed biomass to the forward projection of population size without catch is a measure of the escapement that can be compared to reference points based on some fraction of maximum spawning potential.

Further refinement of the possible range of fishing mortalities on the population is addressed in the VMS Spatial Model. This model estimates the potential magnitude of fishing mortality based on the spatial distribution of fishing effort expressed in terms of swept area. Individual records of VMS tracks where fishing is occurring are linked to estimated net widths. Key external parameters are the ratio of estimated densities of squid inside and outside the fished areas as well as the behaviors of fisherman to move between areas during successive tows. VMS data suggest a high degree of overlap of fishing areas within season which suggests not only predictable fishing sites but replenishment of the stock by migration of squid through the area. Result of the VAST Model application are valuable for refining the parameter estimates of overlap between the fishery and the resource area. The VAST Model also provides refinement of the availability parameter v that in turn can be used to refine the bounds in the Envelope Model. No formal estimation procedures have been estimated for this assemblage of models (or estimators), but some form of Bayesian state-space model may be feasible for the Research Track Assessment.

Leslie-Davis Model

Methods and Results Summary

The Leslie-Davis depletion model approach used Vessel Trip Report data for 1997 to 2018. Catches are reported in catch per trip by vessel and date landed. Estimates of fishing effort include total days absent, and days fished. Days absent is computable to a resolution of one day, whereas finer scale information on days fished is supplied by fisherman reports. Crude measures of CPUE were estimated as the total catch divided by the number of trips, the total days absent over all trips, or the total days fished summed over all trips within a given standardized week (i.e., week 1 = Jan 1 to 7, week 2 = Jan 8-14, etc). The primary fishing season for these analyses was restricted to standard weeks 22 to 44. Historically this window constitutes 95% of the annual landings by weight. Catches in weight were converted to catches in number by dividing the total catch by the estimated average weight. When weekly average weight samples were not available, average weights were borrowed from the next available week. Capture probabilities are applicable to individuals rather than biomass. All quantities in the Leslie-Davis model were expressed in terms of numbers of individuals.

The Leslie-Davis model is written as

$$CPUE_t = qN_0 - q\sum_{i=1}^{t-1} C_i$$

which is a simple linear regression $CPUE_t = a + b\ K_{t-1}$ where K_{t-1} is equal the sum of catches up to t-1. In theory, the estimated total number of individuals in the population occurs when all of the individuals are captured. This corresponds to CPUE=0, so that the estimate of N_0 is simply equal to -a/b.

The preferred method for estimating the parameters of the Leslie Davis model is to use maximum likelihood estimation because the variance of CPUE changes with each observation (Gould and Pollock, 1997). In practice, a simple linear regression of CPUE vs cumulative catch is sufficient to get estimates fairly close to the ML estimates. For the purposes of this work, the simple linear regression was judged sufficient.

A detailed summary of the results for the various depletion models may be found in Rago (2020). The expected pattern of continuous linear depletion and tight fit (r2>0.7) occurred in only 4 of the 19 years examined (1998, 2010, 2017 and 2018). Three of these years had been judged by fishermen to be excellent harvest years (1998, 2017, and 2018). The proportion of variance in CPUE explained by total removals was about 50% in 2011 and 2016 but in all other years the value of r2 was less than 0.2. From a broad overview, the model would be judged statistically significant in 4 of the 19 years, marginal in 2 and unacceptable in the remaining 13 years. In 7 years the Leslie Davis depletion model had positive slopes for at least one of the CPUE measures.

The MAFMC SSC noted in a 2020 review that "Leslie-Davis depletion models have been used in some assessments worldwide but violations of underlying assumptions suggested that this methodology did not reliably detect the influence of catch on LPUE. Commenters noted that the absence of significant results was an indirect indicator of likely low fishing mortality" (MAFMC 2020, Rago 2021). The lack of the Leslie-Davis model fit *per se* suggests low fishing mortality relative to other processes.

Mass Balance Model

Methods

The NEFSC conducts research bottom trawl surveys in the Northeast U.S. The spring survey typically begins about March 1 and continues for 8 to 10 weeks with 4 separate cruises with sampling progressing from south to north. The fall survey is similarly executed but begins in first week of September. In terms of *Illex* migrations, the spring survey ends well before the bulk of the offshore population arrives in the sampling domain. The fall survey begins after much of the catch has been taken and *Illex* are thought to be moving out of the sampling area. The commercial fishery is prosecuted primarily between May and September in most years, although catches can occur well into fall in some years. These concerns, and the inconsistent and often infeasible results of the simple depletion models used by Rago (2020) and reviewed by the MAFMC SSC in 2020 (MAFMC 2020) beg the question—what are the implications of large catches in the summer for the amount of biomass that much be produced to support it?

Consider a simple mass balance problem wherein the biomass in the fall B_F in any year is equal to the initial biomass in the spring B_S less the losses from the fishery C and natural mortality L. These losses are offset by growth in average weight over the course of the fishery G, net migration of squid Mig into the stock area and new recruits R. The mass balance equation is

$$B_F = B_S - C - L + G + Mig + R \qquad (1)$$

Natural mortality is poorly known but modeling results (Hendrickson and Hart 2006) suggest it is high relative to fishing mortality. One way of exploring the implications of this premise is to express losses due to natural mortality as a function of the observed catch. From Baranov's catch equation we know that

$$C = (F/Z)\ (1-\exp(-Z))\ B \qquad (2)$$

Since F+M = Z, the comparable equation for natural mortality losses is

$$L = (M/Z)\ (1-\exp(-Z))\ B \qquad (3)$$

If we assume that M is some scalar multiplier of F, say M=αF, then we can get a handle on the magnitude of unseen losses as

$$L = (\alpha F/Z)(1-\exp(-Z))\ B = \alpha C \quad (4)$$

The terms G, Mig and R summarize the processes necessary to offset the losses from the fishery but there is precious little data to estimate the individual components. Instead, consider the them as a pool X such that

$$X = G + Mig + R \qquad (5)$$

Plugging Eq. 4 and 5 into Eq. 1 gives

$$B_F = B_S - C - \alpha C + X \ (6)$$

With a little algebra this becomes

$$X = B_F - B_S + (1+\alpha)\ C \quad (7)$$

The final consideration is that the BF and BS are estimated quantities based on minimum swept areas in the spring and fall surveys. Two factors affect these quantities: gear efficiency q and availability v. Using conventional assumptions let IS=BS / (qv) and IF=BF / (qv). Plugging these values into Eq. 7 gives

$$X = (I_F - I_S) / (qv) + (1+\alpha)\, C \qquad (8)$$

Thus X represents amount of production necessary to offset the sum of biomass differences between the fall and spring surveys and the total removals, both seen C and unseen L, written as a function of qv and α.

Results

The results of the Mass Balance modeling suggest a substantial lack of understanding of the movement inshore and offshore, growth and recruitment of *Illex* in the survey and fishing area of the U.S. The magnitude of the uncertainty increases with catch as it is the primary driver of the disparity between the estimates of relative abundance between the spring and fall surveys. The average X factor increases as qv decreases and as the ratio of F to M decreases (Table 5.2). The Mass Balance model is indicative of the potential magnitude of the missing production, but it does not have immediate utility for assessment. Instead, it may be useful for diagnosing the behavior of a more complicated two area model informed by estimates of both growth and oceanographic factors possibly influencing migrations.

Envelope Model

Methods

Let I_t represent observed index of biomass at time *t* and C_t represent the catch at time *t*. The estimated swept area total biomass consistent with the index is

$$B_t = \frac{I_t}{q}\frac{A}{a} \qquad (9)$$

where the catchability or efficiency **q**, is an assumed value. The average area swept per tow is **a** and the total area of the survey is **A**. To account for the fact that a sizable fraction of the Illex population lies outside of the survey area, an additional parameter **v** is introduced which represents the fraction of the resource measured by the survey. If the population is closed **v** is set to one and all of the population is assumed to be in the survey areas. Eq. 9 can be modified to account for this by dividing the right hand side by **v** such that:

$$B_t = \frac{I_t}{q}\frac{A}{a}\frac{1}{v} = \frac{AI_t}{qav} \qquad (10)$$

The NEFSC fall bottom trawl survey occurs after most of the fishery occurs and therefore can be considered a measure of post-fishery abundance. In order to account for the potential swept area biomass that existed at the start of the season, it is necessary to add the total landings removed from the fishery. Thus, the estimate of abundance at the start of fishing season is what was left plus what was extracted. Since the removals take place over a period of time and the squid are subject to natural mortality during that period, it is further necessary to inflate those removals.

To “back up” the abundance estimate to what it would have been at the start of the season, one needs to adjust the actual catch for natural mortality and add it back into $\mathbf{B_t}$. The natural mortality adjustment factor is approximated as exp (M/2 * fishery duration). The virtual swept area estimate of abundance at the start of the fishery can be written using Pope’s approximation (Lassen and Medley, 2001) so that

$$B_0 = B_t \ e^{M\,t} + C_t \, e^{\frac{M}{2}t} \qquad (11)$$

Where $\mathbf{B_t}$ is defined by Eq. 10.

The initial biomass consistent with observed catch can be obtained from the Baranov catch equation as

$$B_0 = \frac{C_t}{\frac{F}{F+M}\left(1-e^{-(F+M)}\right)} \qquad (12)$$

In this expression **F** and **M** are unknown.

Thus, biomass can be written as a function of arbitrary scalars **v, q, M,** and **F.** These equations can be generalized and written as

$$\begin{aligned}
\hat{B}_{1,t} &= B(I_t, q_{Low}, v_{Low}, M_{High}) \\
\hat{B}_{2,t} &= B(I_t, q_{High}, v_{High}, M_{Low}) \\
\hat{B}_{3,t} &= B'(C_t, F_{Low}, M_{High}) \\
\hat{B}_{4,t} &= B'(C_t, F_{High}, M_{Low}).
\end{aligned}$$

By inspection it is evident that $B_{1,t}$ and $B_{3,t}$ constitute an upper range, and $B_{2,t}$ and $B_{4,t}$ constitute a lower range. Upper and lower bounds consistent with these estimates are

$$\begin{aligned}
\hat{B}_{upper,t} &= \min(B_{1,t}, B_{3,t}) \\
\hat{B}_{lower,t} &= \max(B_{2,t}, B_{4,t}) .
\end{aligned}$$

Values of biomass that exceed the $\hat{B}_{upper,t}$ imply catchabilities smaller than than q_{low} or fishing mortalities less than F_{low}. Conversely, values of biomass less than $\hat{B}_{lower,t}$ imply catchabilities greater than q_{high} or fishing mortalities greater than F_{high}. These bounds describe a set of feasible options that are consistent with the assumed ranges of q, v, M, and F. In theory, a more sophisticated population model should lie within this feasible range.

Alternatively, by fixing q, v, and M in equations 10, 11 and 12, it is possible to solve for F in Eq. 12. This answers the question of what F is consistent with the range of hypothesized q, v and M parameters. By substituting Eq. 10 into 11 and setting Eq. 11 equal to Eq. 12, one can numerically solve for F in the following implicit equation.

$$\left(\frac{AI_t}{qav} \quad e^{M\,t} + C_t\, e^{\frac{M}{2}\,t}\right) - \left(\frac{C_t}{\frac{F}{F+M}\left(1-e^{-(F+M)}\right)}\right) = 0 \qquad (13)$$

Equation 12 also allows one to further constrain the feasible range of q and v since $C_t<B_0$. Note that this formulation of the Envelope method does not include the bounds on the range of biomasses from the constrained set of equations. Instead, the estimator of F (Eq.13) allows for estimates consistent with the range of assumed q, v, and M. For example, an infeasible estimate of F arises when $C>B_0$ which will occur when the product qv is too high. Values of F are often further constrained to F=3 or 5 in projection models such as AGEPRO to ensure numerical stability. In addition, by estimating F it is possible to compute $F/M= \alpha$ in the mass balance Eq. 8-10.

Results

Details on the parameterization of the Envelope model may be found in Appendix 2 of Rago (2021). The model assumes a 24 week fishery. F and M estimates are the assumed weekly rates times 24. Maximum and minimum survey trawl efficiency estimates are consistent with results of interviews with fishermen and experiments conducted under the guidance of the Northeast Trawl Advisory Panel (NTAP; an industry-cooperative body that advises the NEFSC on trawl survey issues). Min and max estimates of availability are influenced by results of Wright et al (2020). The effects of the consistency constraint can be seen in the following figure of biomass trajectories and by comparison of the average biomass estimates for the period 1997-2019. Note that the range of biomass estimates for the constrained set (Table 5.3, Figure 5.2) is only 2% of the interval defined by the assumed range of qv:

(i.e., 0.021 = (284,301- 56,059) / (10,982,522-55,984)

There does not appear to be a significant trend in any of the biomass estimates.

Escapement Model

Methods

For the purposes of this work, escapement is defined as the ratio of the observed end of fishing season population B_t to that expected if no fishing mortality occurred. The projected population if no fishing occurred can be obtained by projecting B0 in Equation 10 by the fraction surviving natural mortality:

$$B_{t,without\ fishery} = B_0 e^{-Mt} \qquad (14)$$

The "escapement" is now computed as the ratio of the estimated Bt based on the survey divided by the projected biomass that would have occurred in the absence of the fishery.

$$Escapement = \frac{B_t}{B_{t,without\ fishery}} \qquad (15)$$

Equation 16 can be further simplified by plugging Eq. 10 and 11 into Eq. 15 to obtain:

$$Escapement = \frac{\frac{AI_t}{aqv}}{\frac{AI_t}{aqv} + C_t e^{-M/2}} \qquad (16)$$

Where the quantity (A/a) I_t is the minimum swept area assuming qv=1.

A nearly equivalent way of estimating Escapement can be obtained by using the mass balance approach in Eq. 8. If we let $B_{S(t)}$ represent the initial population size when the fishery is present, we can simply estimate what would be left in the hypothetical absence of the fishery by subtracting the catch. The ratio of population biomass without the fishery to the population estimate with the fishery is the measure of escapement.

Substituting Eq. 5 into Eq. 1 gives $B_F=B_S - C - L + X$ where X = G + Mig + R.

The population size that would occur in the absence of the fishery can now be obtained by letting C=0. When C=0 then F= 0 and the total loss from natural mortality reduces from L=(M/Z)(1-exp(-Z)) B_0 to L'=(1-exp(-M)) B_0. Thus the escapement derived from the mass balance approach is simply $B_f/(B_s\text{-}L' + X)$. Expressed in terms of the input data and assumed parameters, escapement is expressed as

$$Escapement.2 = \frac{\frac{AI_{f,t}}{aqv}}{\frac{AI_{s,t}}{aqv} - L' + X} \qquad (17)$$

Stochastic Methods for Mass Balance, Envelope and Escapement

For a given set of assumed parameters {q, v, M} and fixed inputs for survey estimates and catch {$I_{f,t}$, $I_{s,t}$, C_t} it is possible to estimate $B_{0,t}$, F_t, $Escapement_t$ F/M, X/C and other outputs of possible utility for the assessment. The ranges of these quantities can be established by examining a range of values. In Rago (2021) this was done by bounding estimates of biomass based on ranges of q, v and M as shown below

$$\begin{aligned}\hat{B}_{1,t} &= B(I_t, q_{Low}, v_{Low}, M_{High})\\ \hat{B}_{2,t} &= B(I_t, q_{High}, v_{High}, M_{Low})\\ \hat{B}_{3,t} &= B'(C_t, F_{Low}, M_{High})\\ \hat{B}_{4,t} &= B'(C_t, F_{High}, M_{Low}).\end{aligned}$$

By assuming that each of the parameters is drawn from an underlying distribution of values, it is possible to compute the resulting distribution of $B_{0,t}$, F_t, $Escapement_t$ etc. One way of efficiently sampling over the entire range of values is known as Latin hypercube sampling. In simple terms, one assigns an equal probability to each value drawn from the underlying distribution by dividing the range of the parameter into equal probability intervals. The area under the curve (i.e. the integral) for a probability density function over a define range e.g., (q_1, q_2) is the same for all intervals. Thus each observation, defined as the midpoint of (q_1, q_2) now

has the same probability. For a uniform distribution this just means dividing the domain of the distribution (p_{min}, p_{max}) into equally spaced intervals.
This same principle can be applied to any hypothetical parameter, say r, (r_{min}, r_{max}) to obtain equal probability observations. By looping over the full range of r for every value of p you a measure of the expected value of some function Y for p over every value of r. If there are N_p intervals for parameter p, N_r for r and N_s for s, then the joint probability for any combination {p_i, r_j, s_k} is $(1/N_p)(1/N_r)(1/N_s)$. Looping over all possible combinations yields a probability density function for any function of p, r and s. In this case, various functions of q, v, and M were examined to derive the pdf of biomass, F, X etc. N was set to 40 for each parameter so each plot constitutes 64,000 evaluations of the function. The models were implemented in R and the code is available upon request.

Results

Deterministic

Table 5.4 illustrates application of Eq. 16 to the survey data using a value of 0.25 for qv and M=0.87. Note that the NEFSC spring bottom trawl survey does not enter into the computations in the table. Sensitivity analyses of the historical escapement estimates to a range of qv and M are shown in the Table 5.5.a-c. The average escapement (Table 5.5.a) falls below 40% only when M is relatively low (<0.4, i.e., 0.017/week) and when qv is improbably high (>0.6). Table 5.5.b examines the lowest escapement in the time series as the table entry. This would be the worst case scenario in which at least one year experienced escapement less than 40%. Table 5.5.c examines the fraction of years in which escapement falls below the 40% MSP proxy. As expected, the highest risk occurs when qv is improbably high and M is improbably low. The proportions of overfished status expected can be compared directly with the implied risks of overfishing in the ABC control rule developed by the SSC. Integration of the results from the spatial overlap and VMS data can provide some additional insights.

Stochastic

The stochastic versions of the mass balance and escapement models were applied to each available year (1997-2019). Result for 2019 are presented (Figures 5.3-5.11) in detail to illustrate the effects of the F constraint for assumed ranges of q = [0.01, 0.5], v = [0.01, 0.8], and M = [0.01, 0.06]. M is expressed as weekly rates over an assumed 25 week fishery. The feasible combinations of q and v for 2019 are depicted in Figure 5.3. The resulting response surface for B.o for these combinations (Figure 5.4) illustrates the highest values when both q and v are lowest. The overall distribution of feasible biomasses (Figure 5.5) shows the bulk of the distribution between $e^{11.5}$ and e^{13} mt (98 kt to 442 mt). Since F is inversely related to B for a fixed value of catch, the response surface for F (Figure 5.6) is the inverse of the biomass. The marginal distribution of F for the entire fishing season (Figure 5.7) over all values of q, v, and M suggests a maximum weekly rate of 0.024 (=0.6/25). The response surface for Escapement (Figure 5.8) and overall marginal distribution (Figure 5.9) are based on Eq. 17. There appears to be little chance that the 2019 catch of 30,000 mt resulted in escapement under 50%. The predicted distribution of F/M is illustrate in Figure 5.10. Although a reference point has not been defined for *Illex* in terms of F over M, the methodology could be used to illustrate the relative risks for various catch levels. Finally, the relationship between escapement and F/M (Figure 5.11) highlights not only the expected inverse relationship between these variables, but also the effect of increasing M. The bands in the plot represent different natural mortality rates with the lowest values on the left (M=0.01) and highest (M=0.06) on the right. The time series of biomass, fishing mortality, F/M and escapements for 1997-2019 are shown in Figures 5.12-5.15. Surveys were missing for 2014 and 2017. The black line represents the median and the straight red line is the median of the annual medians. Empirical interquartile ranges are shown in blue. The orange dashed lines and dotted red lines represent the 80% and the 90% percentile intervals.

VMS Spatial Model

Methods

Vessel Monitoring System (VMS) data provide a rich database for exploring the spatial patterns of fishing effort and its potential consequences for fishing mortality. A working paper presented to the MAFMC SSC in 2020 (Rago 2020b) described the patterns of fishing concentration for 2017-2019. The VMS data for this working paper were kindly provided by L. Hendrickson and A. Miller of the NEFSC. VMS data from 2017 to 2019 for May through October were filtered for putative towing speeds of 2.6 to 3.3 knots. Each VMS ping represents an interval censored observation since speed is derived from the distance between successive pings divided by the time between pings (one hour). Hence the average speed at a ping can reflect a mixture of steaming at higher speeds and actual towing, as well as processing time at lower speeds. (See Palmer and Wigley 2009 for more details).

Locations were binned into 3-minute squares of latitude and longitude. As distance between longitude degrees varies as a function of latitude, it was assumed the average fishing latitude was 39 degrees. At this latitude the average 3 minute square is cos (39^o) x 3 minutes longitude x 3 minutes latitude ~6.99 nm^2. This approximation is used for all computations of swept area.

L. Hendrickson also provided estimates of average net width for each permit using records from the Northeast Fisheries Observer Program (NEFOP) database. By linking these data to permit number and vessel speed for each ping it was possible to compute nominal estimates of swept area per ping (i.e., hour fished). The total area swept in any cell and time interval was computed as the sum of the vessel-specific swept area estimates. Vessel permits without information on net width were assigned the average width for the measured set of permits. No vessel names were included in the database and no permit numbers are reported herein. Since the focus of this analysis is the spatial pattern of effort, expressed as swept area, differences among vessel types (freezer, RSW, ice) are not considered. The working paper (Rago 2020b) revealed a high degree of spatial concentration with a Gini index =0.822 across all years and even higher rates for individual years. The intense concentration of fishing effort in a relatively small number of cells provides insights about potential effects on overall fishing mortality and movement of squid from adjacent cells.

To begin, consider a population in a 3 minute square of size **A** (6.99 nm^2) that does not mix with adjacent 3 minute squares and is uniformly mixed within that square. Assuming that a trawl tow of size **a** is 100% efficient (i.e., **q**=1.0) in capturing everything in its path, then each tow would represent a proportional reduction in the remaining population. The fraction **f** of a cell's population removed can be defined by the efficiency **q** times the ratio of the tow area **a** to the total cell area **A** is defined as

$$f = q\frac{a}{A} \qquad (18)$$

By definition the fraction of the population remaining after one tow is **1-f** = **(1-q a/A)** Applying the removal process recursively, the fraction remaining after n tows is

$$(1-f)^n = \left(1-\frac{q\,a}{A}\right)^n \qquad (19)$$

As the fraction **q a/A** becomes small, the above equation can be expressed using instantaneous rates so that the fraction of the population remaining after n tows is

$$\left(1-\frac{q\,a}{A}\right)^n = e^{\left(-\frac{q\,a\,n}{A}\right)} \qquad (20)$$

Note that the product **a** x **n** is simply the total swept area (**TS**) if all of the tows are of equal size **a**. Building on this concept, then the total swept area after **n** tows of varying size $\mathbf{a_i}$ is

$$TS = \sum_{i=1}^{n} a_i \qquad (21)$$

Note that this generalization allows us to examine the fraction of the population remaining after it has been exploited **n** times by a gear with efficiency **q** and a swept area per tow of $\mathbf{a_i}$.

$$e^{\left(-\frac{q\,TS}{A}\right)} \qquad (22)$$

Thus the fraction of the population remaining after an area swept of **TS** or a ratio of **TS/A** times is given by Eq. 22. In the most heavily fished cells, the implied reductions in abundance are equivalent to the implied reductions in catch per unit effort. For the top 50 cells where fishing was concentrated the "implied" depletion, i.e., the average fraction of the initial population remaining is predicted to be 0.064 in Rago (2020b). These depletion ratios would occur ONLY if the population was static and did not depend on a flux of squid from other areas. Although a firm criterion for continuation of fishing activity during a season is not possible to estimate, one might safely assume that depletions of more than 90% do not occur during the course of the season. Clearly an individ ual vessel would move to another cell well before this type of reduction occurred.

Let γ represent the ratio of CPUE that induces a movement of a vessel into a new area. Conceptually, this might be related to an economic incentive related to the profitability and an expected profitability of the next tow. Conversations with fishermen suggested that this may not be a hard and fast rule since many different factors can affect the decision to move to another fishing area. Let $CPUE_o$ represent the initial CPUE and $CPUE_t$ represent the CPUE after time t has elapsed. The ratio of $CPUE_t/CPUE_o=\boldsymbol{\gamma}$ such that a new area is fished when the ratio falls below γ. For economy this ratio can be called a "move along" criterion.

Using the swept area notation from Eq. 22 the CPUE ratio can be written as

$$\gamma = \frac{CPUE_t}{CPUE_o} = e^{(-q\frac{TS}{A})} \quad (23)$$

Where q is the gear efficiency, TS is the total area swept in time step **t** and **A** is the area of the cell. Equation 23 can be rearranged to solve for A such that

$$A_V = \frac{-q\,TS}{ln(\gamma)} \quad (24)$$

If we assume that abundance in a cell is replenished by transfer of squid from adjacent areas, then the estimate of **A** can be called a virtual **A** or $\mathbf{A_V}$ which implies the total area of all cells that would be impacted by a total swept area TS by a gear with efficiency **q** and a "move along" criterion of $\boldsymbol{\gamma}$. As the acceptable ratio of CPUE decline becomes smaller, the virtual area the population that replenishes the cell fished becomes smaller.

Consider a few examples. Suppose that the estimated total swept area for a cell is 3 times the total area of the cell or **TS/A**=3.0. Assuming that the gear was 50% efficient (**q**=0.5), then the predicted depletion ratio from Eq. 22 is exp (-0.5 *3) = 0.22. This is what would occur if the population were closed to immigration. Clearly, fishing activity would move to another area if higher yields were available elsewhere. If a vessel "moves along" when the CPUE ration drops by only 10% then $\boldsymbol{\gamma}$ = 0.9 and ln ($\boldsymbol{\gamma}$) = -0.105. By Eq. 24 the virtual area of the cell increases by a factor of 9.49 (= 1/0.105). Thus, a fleet that moves along when fishing declines by 10% and yet returns to fish such that it covers the entire area 3 times over the course of the season, is in fact fishing a virtual area 9.49 times greater than the size of the cell. For a three-minute square this is 66.34 nm^2. Alternatively, a fleet that moves along when the CPUE ratio is 0.5 will have a virtual fishing area that is 1/ln (0.5) = 1.44 times higher than the cell size.

The concept of virtual area fished can now be expanded to compute an area weighted fishing mortality rate. For each cell it is possible to compute the virtual area swept from Eq. 24. When the virtual area fished exceeds the actual cell size the magnitude of the fishing mortality in a given cell **i** is constrained by the defined threshold parameter $\boldsymbol{\gamma}$. This can be expressed as

$$F_i = min(-\,ln\,ln\,(\gamma)\,, q\,TS_i/A\,) \quad (25)$$

The area weighted average F ($\mathbf{F_{ave}}$) over the entire set of cells fished in a given year can now be estimated as

$$F_{ave} = \frac{\sum_i^n \; F_i A_{Vi}}{\sum_i^n \; A_{Vi}} \quad (26)$$

The estimates of $\mathbf{F_{ave}}$ in the area fished are, of course, inadequate to estimate the fishing mortality on the entire stock. The magnitude of fishing mortality on the stock depends on the overlap of the area that is fished to the total habitat and the fraction of the population in the area that is fished. High fishing effort on high concentrations of the resource induce a higher total fishing mortality than if the population was uniformly distributed. It is probably safe to assume that Illex are not uniformly distributed over all areas of habitat. Otherwise fishing would not exhibit the high degree of concentration observed. One can further assume that fishing is most likely to occur in preferred habitats, or at least in areas where Illex temporarily aggregate prior to a more general movement onto the shelf. The distributional patterns of abundance that define the overall F on the population are unknown, but the available data from the VMS and the fishing vs habitat overlap estimates of Wright *et al.* (2020) are sufficient to at least bound the problem. Wright *et al.* (2020, Table 3) estimated that availability, defined as the proportion of habitat that overlaps spatially with fishing effort, ranges between 0.9% to 9.6% depending on year (2000-2019) and the probability threshold (40-80%) used for habitat definition.

With a little algebra, the joint effects of overlap of fishing effort with habitat and the differences in abundance in the fished and unfished areas can now be addressed. Beverton & Holt (1957, p 148-151) were perhaps the first to introduce the concept of an "effective F" for fishing over spatially distributed population.

Let **A** represent the total habitat area of Illex and $\mathbf{A_f}$ and $\mathbf{A_u}$ denote the areas were fishing does and does not occur, respectively. Thus

$$A = A_f + A_u \quad (27)$$

Further, let $\mathbf{D_f}$ and $\mathbf{D_u}$ represent the densities of Illex in the fished and unfished areas, respectively. Density can be expressed in either numbers or weight per unit area without loss of generality as long as average weights per individual are the same in each habitat area. The total population size **P** is thus defined as

$$P = A_f D_f + A_u D_u \qquad (28)$$

Beverton and Holt defined effective fishing mortality as the product of the fishing mortality times catch per unit effort summed over all spatial units, divided the sum of catch per unit effort over all spatial units. This is equivalent to a biomass weighted **F**. If we let $\mathbf{F_f}$ and $\mathbf{F_u}$ represent the fishing mortality rates in the fished and unfished areas, then the effective **F**, defined as $\mathbf{F_{eff}}$ is

$$F_{eff} = \frac{F_f A_f D_f + F_u A_u D_u}{A_f D_f + A_u D_u} \qquad (29)$$

Equation 29 can be simplified by letting $\mathbf{D_u = \varphi\ D_f}$, $\mathbf{A_f = \theta\ A}$, $\mathbf{A_u = (1-\theta)\ A}$ and noting that $\mathbf{F_u}=0$ by definition. Substituting these expressions into Eq. 29 gives

$$F_{eff} = \frac{F_f \theta A\, D_f + 0\,(1-\theta) A \phi D_f}{\theta A D_f + (1-\theta) A \phi D_f} \qquad (30)$$

Canceling out the relevant symbols leads to

$$F_{eff} = \frac{F_f \theta}{\theta + (1-\theta)\phi} \qquad (31)$$

Thus the effective **F** on the entire population $\mathbf{F_{eff}}$ is a function of the **F** in the area fished $\mathbf{F_f}$, the relative density ratio in the fished and unfished areas $\boldsymbol{\varphi}$, and the fraction of the total habitat in the fished area $\boldsymbol{\theta}$. As a starting point one can assume that the density in the unfished habitat area is less than or equal to one and that the Wright et al range of values for $\boldsymbol{\theta}$ is between (0.01 and 0.2). The upper bound of 0.2 is roughly twice that estimated by Wright *et al.* (2020) under any scenario.

Parameters for VMS Spatial Model

"Move along rule" parameter γ (Eq. 23)

The "move along" rule might be amenable to a survey questionnaire of fisherman's general behaviors with respect to repeat tows within small areas. Preliminary discussions with fishermen reveal a wide variety of factors underlying such behaviors. Alternatively the actual behavior of vessels was used to estimate an empirical basis for a "move along rule" = $\boldsymbol{\gamma}$. VMS records were ordered by permit and day. With any given calendar day, the number of unique cells visited were summarized for each trip. The frequency of visits to each unique cell were also tallied. The range of g can be estimated as the potential range of depletion that occurs with the 3 nautical mile square cell. Equation 20 can be used to define a range of potential in cell depletions by a given vessel on a given day. Using the average net width and a speed of 3 knots, the fraction of area swept in a single pass is 0.0975 square nautical mile. If the gear efficiency is 1.0 a single pass would reduce the population by 0.0975/6.99 = 0.01395. In this case $\boldsymbol{\gamma}$ is 1-0.01395=0.986. For a two pass scenario, the depletion is $(1-0.01395)^2$ =0.972. Summary statistics for 1,886 permit day trips (text table below) revealed that the average cell was "pinged" 1.94 times with a range of 1 to 12 times. For those cells that were pinged most frequently with a permit day, the average number of pings was 3.27. In other words, preferred cells were fished an average of 3.27 times per day giving an average maximum depletion of $(1-0.01395)^{3.27}$ =0.955. For the most heavily fish cell (n=12 pings), the maximum depletion ratio is 0.844.

As noted above, the average cell was pinged 1.94 times. Could this be due to chance alone owing to the size of the cell and the vessel velocity, e.g., pinged after entry to cell and before exit? A small simulation was done to evaluate the likelihood of falling outside the cell give the speed at the time of the ping. Starting locations were defined on a 13 x 13 grid within the 6.99 nautical mile square cell. The total distance traveled was equal to the initial speed at the time of the first ping times a one hour duration. To evaluate the effect of random directions, the vector was rotated 360 degrees in 2.5-degree increments. The end point of the vector was then evaluated with respect the boundaries of the cell. Finally, to account for different initial velocities, the above simulation was evaluated at vessels speeds of 2.6 to 3.3 knots. The overall average fraction of points outside the cell was weighted by the frequency distribution of vessel speeds. Under these conditions, the overall fraction of times that a cell would be expected to have two consecutive pings is 0.077. Hence, the observation of an average of 1.94 pings per cell within a given day is not due to chance alone and indicates a high probability that multiple tows within cells are the result of fishermen's decisions.

This table summarizes the total number of cells hit within a trip during a given day. The range of depletion depends on the number of hits per cell.
Fishermen behavior is inferred from the maximum number of hits per cell per day. This assumes that the last tow was sufficiently low to result in a "move along" rule. Fishing removal is estimated by assuming an average net width and area swept = 0.097549 nm sqr.
Dividing the average area swept per hour by the total area of a 3 min sqr (6.99 nm sqr) gives an average fraction swept = 0.013955
If the net is 100% efficient, then the reduction in biomass is proportional to the fraction of area swept.

	max # Pings per cell	Total Pings per Day	ave # pings/cell	#Cells	Maximum Depletion Fraction	Average Depletion Fraction
min	1	1	1	1	0.0140	0.0140
max	12	37	7	17	0.1552	0.0937
average	3.27	10.26	1.94	5.19	0.0445	0.0268
Std Dev	2.03	6.80	0.94	2.79	0.0269	0.0128

Ratio of densities inside and outside fished area φ (Eq. 30)

The ratio of densities of Illex in fished and unfished areas during the period of peak fishing activity is not known because there are no fishery independent surveys coincident with the fishery. However, the NEFSC fall survey overlaps with the fishery in some years and can be used as a first approximation of the parameter **φ** (Eq. 30).

Georeferenced NEFSC survey data for 2008 to 2019 were partitioned into observation inside and outside areas where fishing occurred. Areas fished were defined by the resolution of VTR data with 5 min sqr cells. Data for this exercise were kindly provided by John Manderson, Open Ocean Inc. In nearly all years the tows with the stratified random design were allocated proportional to stratum size (PPS) such that a stratum is twice as large as another would have twice as many tow locations. This suggests that the differing inclusion probabilities for tows can be assumed to be equal as a first approximation. From this the average catch per tow in the areas inside the fishing area $\mathbf{D_f}$ is simply the arithmetic average of all tows. Average density in the unfished areas $\mathbf{D_u}$ can be computed similarly. Computations for 2008 to 2019, excluding 2017, are summarized below:

	Ave weight/tow			
Year	*outside D_u*	*inside D_f*	*ratio IN:OUT*	*phi*
2008	5.00	45.28	9.06	0.1103
2009	14.06	105.50	7.50	0.1333
2010	12.20	153.14	12.55	0.0797
2011	15.68	83.85	5.35	0.1870
2012	9.39	127.21	13.55	0.0738
2013	4.97	67.74	13.63	0.0734
2014	10.29	91.68	8.91	0.1123
2015	10.48	37.00	3.53	0.2833
2016	14.20	132.24	9.31	0.1074
2017				
2018	25.57	59.32	2.32	0.4310
2019	10.66	41.81	3.92	0.2550
Grand Total	**11.59**	**87.38**	**7.54**	0.1326
Average	12.05	85.89	8.15	0.17
SD	5.65	39.77	4.03	0.11
min	4.97	37.00	2.32	0.07
max	25.57	153.14	13.63	0.43

On average, Illex density inside the areas where fishing occurred were 8 times higher than in the unfished areas.

Ratio of Area Fished to Total Habitat Area (parameter θ, Eq.30)

The analyses of Lowman *et al.* (2021) were revised by J. Manderson to include additional habitat areas surveyed by the NEAMAP, MA DMF, and DFO Canada (NAFO Area 4VWX) surveys. Summary data for this exercise for the fall surveys were kindly provided by J. Manderson are summarized below. Details on the methodology used to estimate overlap are provided in Manderson *et al.* (2021). The different methods result is relative little differences between methods and surprisingly low variations across years. The overall range of **θ** is 0.27 to 0.48.

	Ratio of Fishing area to habitat (theta)	
Year	Overlap: Method 1	Overlap: Method 2
2008	0.30381	0.36934
2009	0.27681	0.36109
2010	0.28897	0.34653
2011	0.34128	0.34622
2012	0.41122	0.38100
2013	0.44802	0.43115
2014	0.48467	0.45846
2015	0.46423	0.44658
2016	0.40276	0.40538
2017	0.34940	0.36314
2018	0.31333	0.35189
2019	0.31620	0.35108
average	0.36672	0.38432
min	0.27681	0.34622
max	0.48467	0.45846

Results

Actual values for gear efficiency **q** and move along thresholds **γ** are unknown, but their consequences can be evaluated for the observed fishing patterns for 2017-2019. Table 5.6 illustrates the effect of assumed gear efficiency and the depletion ratio threshold on estimated virtual area swept. The virtual area swept ranges from 124 km^2 to 45,755 km^2. Wright *et al.* (2020, their Table 2) independently reported fishing areas 12,993 to 15,313 km^2 for 2017 to 2019. These estimates were derived by binning the data into 5 minute squares (roughly 19.42 nm^2 or 2.8 times larger than the 3 minute square used herein.) The Wright *et al.* (2020) method provided estimates of presence/absence in a given cell rather that estimates of swept area but are useful for comparison. If the Wright *et al.* (2020) average of 14,315 km^2 is used, the feasible range of **q** and **γ** parameters range from 0.3 to 1 for **q** and 0.95 to 0.8 for **γ**.

Estimates of spatially weighted average F (Eq. 26) for 2017-2019 by year are given in Table 5.7. As expected, the average F is greatest under the assumption that gear efficiency **q** is 1.0 and that the depletion ratio threshold **γ** is small. The lowest estimates of average F occur when gear efficiency is assumed to be low and the depletion ratio is large (Table 5.5).

To address the potential range of effective fishing mortalities, $\mathbf{F_{eff}}$ I chose the maximum value of $\mathbf{F_f}$ from Table 5.7 for various combinations of assumed gear efficiency **q** and depletion ratio **γ**. By inspection, it is clear that $\mathbf{F_{eff}}$ reaches its maximum value when **θ** =1(i.e. all of the habitat is fished) or when **φ** = 0 (i.e., no fish are in the unfished area). Under either of these conditions, the effective F over the whole area is equal to the fishing mortality in the area where fishing occurs. For all other combinations of **φ (0,1)** and **θ (0,1)** the effective F will be less than the F in the fishing area because some fish are protected from fishing. Over the assumed range of parameter values, the maximum F in the area fished (=1.2765 from Table 5.7) is reduced to a maximum value of 0.912 in Table 5.8. Based on these calculations and examination of the results for 2017 to 2019 individually it appears unlikely that the overall F on the population exceeds 1.2 in any of the recent 3 years (Rago 2021, Appendix 1).

Integration of Indirect Estimation Method Results

As described in the Schematic (Figure 5.1) the range of biomasses, Fs and risks can be refined by combining information from the various models. Notably, the VMS data provides a way of refining the seasonal effective F estimate based on the spatial patterns of fishing effort and the derived parameters as described above. Using the derived bounds on feasible Fs and likely ranges of survey gear efficiency, the Envelope analyses can be refined as well as the Escapement risks.

At the May 2020 MAFMC SSC meeting analyses of the potential effects of a 30,000 and 33,000 mt quotas were conducted (MAFMC 2020). For those scenarios, it was assumed that the quotas were taken in all years (Tables 5.9-5.12). The Escapement Model results indicate that an ABC of 33,000 mt would pose a high risk of falling below a 40% escapement rate only if qv exceeded 0.2 and M was less than 0.6

Effects of Refined Parameter Ranges on Estimates of Stock Biomass and Fishing Mortality

The preceding analyses have been based on a broad range of parameter estimates, often nearly spanning the entire feasible range. An example would be catchability ranging from 0.05 to 0.95. Various empirical results noted herein and literature values suggest more likely ranges summarized below.

Parameter	***Symbol***	***Equation Number***	***Min Value***	***Max Value***	***Source/Comment***
Catchability (Survey)	**q**	9	0.2	0.5	NTAP experiments, fishermen interviews
Availability	**v**	10	0.27	0.48	Manderson *et al.* 2021
Catchability x Availability	**qv**	10	0.054	0.240	Min and max value products
Move Along Threshold	**γ**	23	0.01	0.15	VMS Analyses herein
Ratio of Average Density outside to inside	**φ**	30	0.07	0.43	VMS Analyses herein. Post stratified NEFSC fall survey: inside vs outside fishing cells. Mean for 2008-2019 =0.017
Ratio of fishing area to survey area	**θ**	30	0.014	0.363	Lowman *et al.* 2021.
Natural Mortality	**M**	11	0.87	3.92	Hendrickson and Hart 2006

The consequences of these revised ranges of parameters can be evaluated within the Envelope, Escapement, and VMS models to derive updated ranges of key output parameters. Using the minimum and maximum values above, the minimum and maximum values the envelope biomass estimates increase from (56,000 mt, 284,000 mt) to (138,000 mt, 652,000 mt) owing to the lower estimates of qv and the narrower range of F derived from the VMS analyses (0.082, 0.167)(see Text Table below). These analyses suggest a large, lightly-fished stock. The escapement analyses examine the estimated average escapement levels over all years under the simple assumption that the initial biomass can be derived in a VPA like approximation, using only the observed end of season biomass (i.e., rescaled fall survey biomass), and the M adjusted value of landings (See Eq. 11). When the refined estimates of M and qv are applied the results suggest that average escapement range is 0.66 to 0.97. Over this range of parameters the maximum number of years in which escapement fell below 40% MSP was 1 (i.e. 1/22 =0.04545).

This historical range of fall survey biomasses for 1997-2019 can be evaluated against hypothesized 30,000 mt and 33,000 mt ABCs. This counter factual exercise provide some insights into the potential consequences for average escapement and the fraction of years in which escapement fell below 40% MSP. For a 30,000 mt ABC the minimum average escapement was 0.45 and the maximum average escapement is 0.93. Over the entire parameter space, the average of all computed average escapements was 0.72. The maximum fraction of years in which escapement fell below the 40% MSP threshold was 0.45. Over the full joint range of parameter space for qv and M, the average fraction of years falling below the threshold was 0.04 when ABC = 30,000 mt.

The same counterfactual scenario was repeated for an assumed quota of 33,000 mt. For the original range of parameters, the average escapement spans the interval 0.17 to 0.87. For the revised range of input parameters, the average escapement estimates span the interval 0.42 to 0.93. Over the joint range of qv and M the overall average escapement is expected to be 0.70. The range for fraction of years in which escapement is below 40% MSP is 0.0 to 0.5. Hence none of the scenarios fell below the threshold more than 50% of the time. The average percent escapement over the joint parameter space of M and qv was 0.054. In fact, the maximum value of 0.5 occurred in only one of the 168 scenarios evaluated.

Comparison of original outputs with outputs based on revised ranges of parameters

			Original Output Range		***Revised Output Range***	
Model	***Output Variable***	***ABC***	***Min Value_orig***	***Max Value_orig***	***Min Value_rev***	***Max Value_rev***
Envelope	Average Biomass (1997-2019) mt	NA	56,059	284,301	137,961	652,468
Escapement	Average Escapement	Observed Landings	0.3598	0.94574	0.6618	0.9715
	Fraction Yrs <40% MSP	Observed Landings	0	0.6364	0	0.04545
	Average Escapement	30,000 mt	0.17961	0.87598	0.44548	0.93184
	Fraction Yrs <40% MSP	30,000 mt	0	0.95455	0	0.45455
	Average Escapement	33,000 mt	0.16676	0.86572	0.42404	0.92570
	Fraction Yrs <40% MSP	33,000 mt	0	0.95455	0.	0.5
VMS	Spatially Weighted F (24 wk)	NA	0.0436	1.2765	0.0098	0.1455
	Effective F (24 wk) on population.	NA	0.0130	0.9120	0.0820	0.1670

Discussion

The analyses herein systematically explore the uncertainties of key parameters that influence *Illex* stock dynamics. The basic principle underlying these analyses is consideration of a broad range of potential parameters on the estimation of abundance and fishing mortality, followed by a refinement of the parameter range to a more plausible set of values. “Plausible” values are informed either by inconsistencies among initial parameter ranges or by external information derived from empirical studies. Inconsistencies can arise when abundance estimates derived on the basis of an assumed extreme range of F lie outside of a range generated by an assumed extreme range of gear efficiency and availability. The mismatch suggests that as least one of the parameter combinations are “too extreme” such that a constraint is appropriate.

An attempt has been made here to focus on parameters that can be derived from empirical studies such as gear comparison experiments or deduced from detailed analyses of harvester behaviors (e.g., study fleets). The Lowman *et al.* (2021) study illustrates the value of empirical constraints that can be used to refine the plausible range of availability. Similarly, various studies supported by the NTAP can be used to develop a narrower range of possible gear efficiencies. The derived Effective F ranges based on VMS in the text table above (0.082-0.167) compare favorably with the distribution of F estimates derived from the Envelope method (Figure 5.16). Finally, the spatial patterns of fishing activity can be used to infer potential fishing mortality rates. Spatial analyses in particular proved to be valuable for defining ranges of fishing mortality on the stock present in US waters.

There are no approved Biological Reference Points (BRP) or proxies for *Illex* in US waters. The work of Hendrickson and Hart (2006) suggests a range of fishing mortality rates consistent with estimated rates of natural mortality in this semelparous species. The 24-week F estimates based on VMS data are about an order of magnitude lower than the reference points in Hendrickson and Hart (2006).

The Escapement model, which uses a VPA approximation to estimate the size of the population necessary to support the observed catch, relies heavily on a range of possible Fs for the entire season taken from Hendrickson and Hart (2006). The escapement ratio is also a virtual concept since the denominator is a quantity that is deducible from first principles but unlikely to be estimable for the foreseeable future. The hypothetical evaluations of potential escapements for constant quotas of 30,000 mt and 33,000 mt do suggest that over the range of observed post-fishery fall survey indices, there is a low likelihood that either ABC level would induce a significant fraction of escapements below a 40% MSP threshold.

Indirect Methods Main Conclusions

1. The overall *Illex* population is likely to be large.
2. Observations suggest relatively low chances of high fishing mortality rates over a broad range of assumed parameter extremes.
3. Spatial analyses of survey and fishery footprint suggest high escapement (Lowman *et al.* 2021, Manderson *et al.* 2021)

4. None of the estimates of area wide fishing mortality suggest fishing mortality rates greater that life history-based biological reference point proxies.
5. Increases of quotas to 33,000 mt create risks to falling below F40% but the risk is lower than the risks of overfishing associated with current Harvest Control Rules used by the MAFMC SSC and the risk policy adopted by the MAFMC.

WG CONCLUSION ON THE INDIRECT ESTIMATION METHODS

The WG concluded that when considered together, the Indirect Estimation Methods suggest that the overall *Illex* population is likely to be large and relatively low chances of high fishing mortality rates over a broad range of assumed parameter extremes. However, the point estimates of stock biomass and fishing mortality were not accepted as a basis for stock status determination.

GENERALIZED DEPLETION MODEL (GDM; Manderson & Mercer 2022)

Introduction

Depletion models can use short time steps (days to months) in the analysis of fishery catch and effort to estimate the abundance of the vulnerable portion of a population required to support fishery catches. The approach is used in many parts of the world to assess cephalopod populations because the time scale of the analyses can be made to match the dynamics of short lived, semelparous, and environmentally controlled populations that are typically not well sampled by fishery independent surveys and with respect to age composition (see Arkhipkin *et al.* 2020). Depletion modeling does not provide a full stock assessment of population abundance, productivity and condition relative to fishery reference points. Instead, depletion models develop minimal assessments of species catchability by the fishery, the abundance of the population vulnerable to the fishery (N_o), fishing mortality (F) with respect to the vulnerable population, and natural mortality (M). The results of intra-annual depletion analysis can used in a hierarchical manner to inform assessment models that develop a full suite of fishery reference points (e.g. Roa-Ureta *et al.* 2021)

Depletion models can also be used to estimate fishery escapement (H) relative to sustainable biomass targets by calculating the proportion of the vulnerable stock (N_0) remaining at the end of the fishing season (see Roa-Ureta 2012, Arkhipkin *et al.* 2008, Lin *et al.* 2017, Maynou *et al.* 2021). This is an important application in assessments of squid that have sub-annual life cycles and therefore lack portfolios of age classes that can buffer populations from recruitment failure (Beddington *et al.* 1990). Depletion modeling is considered useful for in-season assessment and management of cephalopod fisheries (Robert 2010). Since the early 1990s, depletion based methods have been discussed in U.S. *Illex illecebrosus* assessments as potentially useful for developing flexible, responsive strategies of in-season fishery management (NEFSC 1992, 1994, 1996, 1999, 2003, 2006).

Classical depletion models combine submodels for the harvested population and the fishery observation process. In the simplest case (Leslie model) the population submodel is:

$$1.\ N_t=N_0-K_{t-1}$$

where N_t is population size at time t, N_0 is the initial size of the population just before the fishery begins and K_{t-1} is cumulative catch prior to time t.

The observation submodel is:

$$2.\ X_t=qN_t$$

where X_t is observed catch per unit effort and q is catchability of the stock per unit effort in the fishery and N_t is the latent population size at time t.

Substituting the submodel of the harvested population into the observation model yields

$$3.\ X_t=q(N_0-K_{t-1})$$

or

$$4.\ X_t=qN_0-qK_{t-1}$$

This linear expression applied to data yields estimates of the catchability coefficient of the fishery (-1*slope=q) and initial population abundance before the fishery begins (intercept/q). In real world applications, depletion models account for losses of individuals resulting from natural morality (M) during the fishing season using Pope's (1972) recursive relation (Chapman 1974). Classical depletion models make the following assumptions:

1) The population is physically and demographically closed to processes of immigration and/or recruitment that increase abundance or emigration that results in losses of animals from the fishing area during the fishing season independently of the fishing process and natural mortality,

2) Losses due to natural mortality are constant over the fishing season,

3) Fishery catch and population abundance are linearly related by the catchability (q) parameter which can therefore be used to estimate vulnerable population abundance (N_0) from the fishery catch,

4) Catchability (q) is constant over the period of fishery removals. A large pool of animals in the population does not have a refuge from the fishery and therefor a q=0,

5) Units of fishing effort are independent and do not compete with each other,

6) Fishing capacity is sufficiently large to deplete the vulnerable portion of the stock at levels required to estimate of output parameters; at a minimum q and N_0, and

7) Assumptions of linear regression are met including random sampling, error free measurement of catch and effort, and independent and normally distributed errors.

Recently, Rago (2021) applied classical Leslie-Davis depletion analysis to weekly U.S. catches of and fishing effort for *Illex illecebrosus* during 19 of the years from 1997 through 2019. Landings per unit effort (LPUE) decreased continuously to produce significantly negative regression slopes as required by classical depletion modeling in only 4 of the 19 years. In 7 years, LPUE increased substantially over fishing seasons, regressions produced positive slopes, negative qs, negative x axis intercepts and thus negative initial population size estimates. Rago (2021) concluded *"the failure of the Leslie-Davis depletion models suggests that migrations into the fishing area, variations in growth, and recruitment overwhelm depletions associated with the fishery" (i*.e. violations of the open population assumption [#1 above] and possibly assumptions of sufficient fishing capacity in the fleet [#6 above]*)*.

Roa-Ureta (2012, 2015, 2020) and others (Paya 2009, 2016, McAllister 2004, Robert 2010) have modified the Leslie-Davis method to develop a Generalized Depletion Modeling approach (GDM) that relaxes the closed population and linear catchability assumptions. GDM relaxes the closed population assumption by modifying the population submodel to account for successive perturbations in catch associated with immigration or recruitment into the fishery, or emigration out of the fishery that reset and restart the depletion process. The method has been successfully applied to a catadromous fish stock (glass eels, *Anguilla japonica*) with transient dynamics on fishing grounds that are completely controlled by immigration and emigration (see Lin *et al.* 2017). GDM also modifies the fishery observation submodel to allow nonlinear relationships between fishery catch and effort and fishery catch and the abundance of the vulnerable population (*assumption #3 above*). Multiple fleets in a fishery can be modeled explicitly and multiple years can be analyzed in a Multi-Annual Generalized Depletion modeling (MAGD) framework (Roa-Ureta 2015, Maynou 2015, Maynou *et al.* 2021), or results of intra-annual GDM can be used as inputs to inter-annual stock recruitment models (e.g. Pella-Tomlinson surplus production model; Roa-Ureta 2020, Roa-Ureta *et al.* 2021). The method, originally developed for the assessment of Patagonian longfin squid (*Doryteuthis gahi*), has been successfully applied to data-limited fisheries for spanish mackerel (Roa-Ureta 2015), glass eels (Lin *et al.* 2017), sand eels (Maynou *et al.* 2021), octopus (Roa-Ureta *et al.* 2021) and to evaluate the degree to which the establishment of artificial reefs led to increases in fish production or increased fish aggregation (Roa-Ureta *et al.* 2019). The method can be implemented using the R package *CatDyn (*Fishery Stock Assessment by Catch Dynamics Models CatDyn version 1.1-1 2018-12-18).

More specifically, GDMs describe the true fishery catch in numbers of individuals (C_t) as a function of observed fishery effort (E_t) and the size of the vulnerable portion of the population (N_t) such that

$$5.\ C_t = f(E_t, N_t) = f_E(E_t)f_N(N_t) = kE^{\alpha}{}_tN^{\beta}{}_te^{-M/2}$$

where t is the time step, C, E and N are as defined above. Effort (E) is assumed to be observed without error, while population size, N, is unobserved and latent. M is natural mortality per time step and is assumed to be constant over the time steps. Parameters associated with catchability are k, a constant scaler (similar to q where CPUE=C/E=qN); α, an effort response parameter; and β, an abundance response parameter. The effort response (α) modulates the output of catch so that it can be saturable $\alpha < 1$ (fishing gear catches proportionally less with additional effort), proportional $\alpha \sim 1$ (catch is proportional to effort), or synergistic $\alpha > 1$ (additional effort yields a disproportionate increase in catch). The abundance response (β) reflects the degree to which fishers perceive true population abundance where $\beta<1$ indicates hyperstability and a stable catch rate when population abundance declines, while $\beta >1$ indicates hyperdepletion and a catch rate that declines faster than population abundance. Spatial aspects of the fishing process are implicit in the approach.

GDM uses Pope's (1972) recursive equation to make abundance manifest by including N_0 and M. It can also include in-season perturbations of catch abundance $\{P_j\}$ (immigration, recruitment or emigration) that reset and start the depletion process within the fishing season. A multi-fleet (*f*) GDM with abundance perturbations associated with immigration and emigration is specified as follows:

$$6.\ C_t = \sum_f C_{t,f}$$

$$= \sum k_f E^{\alpha f}_{f,t}\, m(N_0 e^{-Mt} - m[\sum^{t-1}_{i=1} C_{f,i} e^{-M(t-i-1)}] + \sum^{j=P}_{j=1} I_j P_{j,f} e^{-M(t-\tau_{j,f})} - \sum^{j=P}_{j=1} J_j P_{j,f} e^{-M(t-v_{j,f})})^{\beta f}\, e^{-M/2},\ v_j>\tau_j$$

where $_f$ indexes fleet, $_j$ indexes abundance perturbations, P is the total number of perturbations. N_0 and M per time step are as described above. $m = \exp(-M/2)$ and is an adjustment that makes all catch occur instantaneously during the middle of the time step. The term in the square brackets in equation 6 accounts for losses due to fishery catch. The summation following losses to the fishery accounts for perturbations associated with immigration events (I) at time steps τ detectable by each fleet. Emigration events (J) have time steps of v for each fleet and are accounted for in the last summation. Note that natural mortality M of emigrants as well as immigrants is accounted for. If no perturbations of emigration are specified are specified and J=0, the GDM resolves to a model with perturbations associated with only with immigration. If no in-season abundance perturbations are specified at all, GDM resolves to a pure depletion model with a closed population assumption, but the possibility of a nonlinear catchability assumption (e.g. equation 5). Expected catch in numbers (C_t) at each time step is assumed to be a random variable with a known distribution. The discrete time equation is formulated so that survivorship is calculated for the middle of each time step using exponential terms.

The nonlinear regression can be solved using maximum likelihood statistical inference in CatDyn for a variety of candidate distributions for the time series of observed catch ($C_{t,f}$;Poisson, negative binomial, as well as normal, lognormal, gamma; Roa-Ureta 2020). The package optimx (Nash and Varadhan 2011) is called for the optimization. The parameters M and N_0 are common to all fleets in a fishery. Fleet specific parameters include observation (~ fishery catchability) parameters k_f, α_f, and β_f as well as perturbations to abundance P_f and their timings (τ_f,v_f). It is assumed that fleet effects that are additive and provide complementary information about the fish population. Competition between fleets is not accounted for. Fishing mortality per time step is also estimated from abundance, natural mortality and catch using a numerical resolution of the Baranov equation (Roa-Ureta 2020). In a complex GDM with multiple fleets and perturbations of abundance due to immigration or emigration the number of free parameters is 2(M and N_0) + 3*f(k_f, α_f, β_f) + 2*P*f (the magnitude and timing of abundance perturbations that can be fleet specific). It is important to note that the method requires at least ~ 3 times more data than the number of parameters, for parameters to be estimated accurately and with sufficient certainty

(Roa-Ureta 2012, 2015, 2020). A multi-fleet GDM with abundance perturbations as specified above requires data with a short time step and high temporal resolution.

To develop GDM based hypothesis related to immigration, recruitment, or emigration during the fishing season Roa-Ureta (2012) developed a fleet specific catch spike statistic (S_t) using fishery dependent data that accounts for spikes in catch that are independent of by variations in fishing effort (E_t). Lin *et al.* (2017) developed a complementary parametric catch spike and used fishery independent information about environmental drivers of glass eel migration to develop alternative start values for the timing of abundance perturbations. Calculation of the parametric and nonparametric spike statistics are described in the methods section. Spikes in catch can result when animals migrate onto or off of fishing grounds or when fishing fleets shift to more productive fishing grounds or when forced to poorer grounds by fishery regulation (Roa-Ureta 2015). It is therefore important to inspect the spatial dynamics of fishing fleets to understand whether catch perturbations are the result of movements of animals or of fishing fleets.

While GDM relaxes the closed population assumption (# 1); the linear catchability assumption (#3), and allows greater flexibility in the choice of error distributions, several assumptions are made about the migration process when the method is applied to fisheries for fully transient stocks on fishing grounds (e.g. Lin *et al.* 2017).

These include:

8) immigrants mix well with and have the same catchability as the stock on the fishing ground, and

9) abundance added by an immigration pulse at time τ_j is removed from fishing ground when it emigrates at time v_j.

It is important to note that like other catch-only methods, GDM assumes inferences about stock characteristics can be made from fishery catch (Ovando *et al.* 2021). GDMs continue to rely on assumptions #2, #4, #5, #6 listed above. Assumption #4, which posits that the stock does not have refuge from the fishery, is important to consider when making inferences about the *Illex illecebrosus* population in the Northwest Atlantic using GDM. The directed U.S. fishery is a seasonal fishery that operates from May through October on the outer edge of mid Atlantic Bight continental shelf, from Oregon Inlet, North Carolina to Welkers Canyon off southeast Massachusetts. *I. illecebrosus* is believed to produce approximately 4 overlapping cohorts throughout the year and we believe the directed U.S. fishery harvests 1-2 of these cohorts. In the western Atlantic, *Illex illecebrosus* ranges from the Florida Straits northeast to Labrador, the Flemish cap, Baffin Island and Southern Greenland (Trites 1983, Dawe and Beck 1985, Jereb and Roper 2010), so only a small part of the species range is vulnerable to the fishery (Manderson *et al.* 2022). Market forces, technical aspects of processing squid and fisheries regulations also strongly influence fishing effort and catch in US Illex fishery (see Mercer *et al.* 2022).

If, as Rago (2020) suggests, the principle cause of the failure of classical depletion analysis when applied to the U.S. *Illex illecebrosus* fishery is the violation of the closed population assumption (assumption #1 above*),* the GDM approach may more successfully applied to *Illex* to provide information useful for assessing the risk of overfishing for the stock. In this work the application of GDM is evaluated using the R library CatDyn (Fishery Stock Assessment by Catch Dynamics Models v1-1.1) to five years of landings, effort, and individual squid weight data collected in the U.S. *Illex illecebrosus* fishery, aggregated to a weekly time step. Intra-annual models were developed for 2 years (2012, 2016) in which fishery performance was evaluated as poor and three years (2012, 2018, 2019) in which performance was evaluated as good, based on statistical and qualitative industry based assessment of fishery performance (Mercer *et al.* 2022). The steps needed to develop a "best" GDM with an open population assumption for a single year are described and the precision of parameter estimates are presented, and quantities of interest to fishery assessment are calculated. The precision and accuracy of parameter estimates and quantities produced by "best" GDMs are developed for the 5 years. Finally, recommendations are provided for the next steps required to determine whether GDM can be operationalized in the assessment, including in-season assessment, of the risk of overfishing in the U.S. *Illex illecebrosus* fishery.

Fishery Data

Landings and effort data

To assessed the utility of generalized depletion modeling to produce information useful for assessment of the risk of overfishing in the Illex fishery we analyzed 5 years of weekly landings data including years of poor (2013, 2016) and good fishery performance (2017, 2018, 2019) as described in (Mercer *et al.* 2022).

The cumulative landing biomass of squid in kilograms was calculated for ISO 8601 standardized weeks (Monday-Sunday). Several metrics of fishing effort were developed from vessel trip reports (VTR) including number of days fishing (DF), number days absent (DA), and numbers of unique fishing permits responsible for weekly landings. Days absent (DA) is the difference between date-time landed and date-time sailed and includes time steaming between ports and fishing grounds and between fishing grounds. Days fishing (DF) eliminates steaming times and was used here as the preferred effort metric. Effort metrics could only be developed for landings for which there was a 1-to-1 match in dealer reports and VTR records. Fishing effort was curtailed by fishing regulations and seasons closed early in 2017 (09-17; week 37), 2018 (08-14; week 33) and 2019 (08-21; week 34).

We partitioned weekly landings and effort amongst two fleets; vessels that process and freeze squid at sea ("freezer trawlers") and vessels that store squid in recirculating seawater systems (RSW) or on ice and deliver them to shore side plants for processing and freezing onshore (hereafter called "wet boats"). We developed two fleet GDM models for the following reasons. a) Freezer trawlers that process squid at sea can search larger areas for longer times (as long as 14 days) but have longer prey handling times than wet vessels that catch squid and must transport them quickly to nearby shoreside processing plants before the squid spoil (usually within 72 hours; see Mercer et al 2020 for more details). As a result, we expected the scaling, effort and abundance response parameters (k, α, β) as well as timings of detection and magnitudes of pulses of ingressing or egressing squid catch to be different in the two fleets. b) An examination of historical fishery data indicates the ratio of fishing effort in the two fleets fluctuates with fishery performance. In the years landings were low freezer trawlers dominated the fishery and there were sometimes much fewer wet boats. During years of "good" fishery performance wet boats are dominant while many of the freezer trawlers continue to operate in the fishery (Table 5.13). Since 2016, fishery performance has been "exceptional" and some freezer trawlers have been converted to wet boats.

Fishery weigh-out data

Depletion analyses require landed biomass to be converted to number of individuals captured in the fishery for the analysis. We used weights of squid in grams collected for the purposes of inventory and marketing by the two primary processor/dealers in the fishery: Lunds Fisheries, Cape May, New Jersey and Seafreeze Ltd. Davisville, Rhode Island. Whole body weight samples (g) are routinely collected from every trip because the product is marketed by body weight size category. Seafreeze Ltd. primarily inventories squid caught on fishing grounds both north and south of the Hudson Shelf valley that have been frozen at sea on freezer trawlers. Squid from 69 to 100% of trips are thawed and measured in a given year and sample sizes of freezer trawler body weights are typically very high.

Generally landings from fishing grounds south of the Hudson Shelf Valley (~39.5 N) are delivered to Lunds Fisheries which primarily accepts unculled squid for shoreside processing and freezing from wet boats. Weight sampling of the wet boat fleet is less comprehensive. The weight data were provided with the date of measurement but without attribution to fishing ground or the type of vessel responsible for the landing. These data were used in the evaluation of the GDM. The operationalization of the method will require squid weight data that are more representative the fleets, fishing grounds and the time step of analysis.

Greater than 10,000 weights were available for each year and a median of 1690 measurements were available during most weeks of the fishing seasons (5% and 95% quantiles =100 and 4573 wk^{-1}). To develop mean weights of squid (grams) for each week, local polynomial regression (loess) with R defaults (span=0.75; fitting by weighted least squares) was applied to describe the relationship between the weight of squid in grams and day of the year within each fishing year for the fishery as a whole. The loess regressions were then used to predict mean weights (and standard errors) of squid for the day falling in the middle of each week for which landings were reported. This approach has been applied in other studies developing GDMs for data limited fisheries (e.g. Roa-Ureta 2015, Mayou 2021).

GDM Modeling

Strategy for intra-annual generalized depletion model development using CatDyn

The GDM was applied to catch data for the two fishing fleets independently for each fishing year. It is possible to develop Multi-Annual Generalized Depletion models (MAGD; see Maynou *et al.* 2021) but they assume levels of strengths of stock-recruitment relationships and inter-annual autocorrelation in natural mortality not justified for *Illex illecebrosus*. It is also possible to use the results of intra-annual generalized depletion models to inform assessment models in a hierarchical manner and more formally develop biological reference points (Roa-

Ureta 2020, Roa-Ureta *et al.* 2021). This type of hierarchical analysis is beyond the scope of this work. Here, the potential utility of the GDM for the assessment the Illex fishery is evaluated by developing intra-annual GDMs using data with a weekly time step for recent years classified as good (2017-2019) and poor fishing years (2013, 2016).

Intra-annual GDMs are developed in three steps: 1) the development and selection of model variants for hypothesis about movements of squid onto and off of fishing grounds during the fishing season beginning with a pure depletion model (Null Model) that assumes the fishery is closed, 2) the selection of the "best" hypotheses about in-season movements of squid from the suite of hypotheses developed for the specific fishing season, and finally 3) the use of the "best" model variant reflecting the "best" hypotheses to develop parameter estimates and derived quantities useful for stock assessment in a given year.

Step 1. Development and selection of GDM variants for closed and open fishery hypotheses

Generalized depletion models representing closed and open fisheries were developed for each fishing season using 12 different likelihoods assumptions. Eight model variants applied the same likelihood and distribution assumption to freezer trawler and wet boat fleets [normal (n), adjusted profile normal (apn), lognormal (ln), adjusted profile lognormal (apln), poisson (p), negative binomial (nb), and gamma (g)]. Four additional models were developed for each model hypothesis that applied different likelihoods to the two fleets (freezer trawler: wet boat fleet, apn:apln; apln:apn; n:ln; ln:n). Each of these 12 "likelihood" model variants were fit using four different numerical optimization methods ("spg", "CG", "Nelder-Mead", "BFGS"). Thus, 48 possible model variants were produced for each model hypothesis in each season.

Reasonable initial starting values for parameters are required for fitting GDM model variants to data using maximum likelihood through calls from CatDyn to the optimx function in the R package optimx. Initial values for M, N_0 as well as the fleet specific parameters k, α, β are required for fitting pure depletion models (H0). Model variants with an open population assumption also require starting values for the timing and magnitudes of in-season pulses of squid. Starting parameters were refined before model fitting based on the visual inspection plots generated with the *CatDynExp* function that allows visually exploration of initial parameter values. We selected starting values that minimized the difference between observed and predicted catch, and temporal trends in deviance residuals. The ranges for starting parameter values are reported in the following text table.

Ranges for initial starting values for fitting model variants that were refined using the CatDyn exploratory tools and plots of observed and predicted catch, and temporal trends in deviance residuals.		
Initial Starting Parameter	Value or equation	Logic
M (weekly)	0.01-0.15	Literature values from Roa-Ureta & Arkhipkin 2007; Arkhipkin *et al.* 2021b; Hendrickson 2004, Hendrickson & Hart, 2006; Hoenig 2005 as described in text below. Adjusted on the basis of weekly trends in observed vs predicted catch. Lower threshold relaxed in null models or those missing pulses evident in catch perturbation analysis.
$N_{0,a}$ *(M unaccounted for)*	Total Annual Catch * 1/0.25 pure depletion models Total Annual Catch * 1/0.33 when pulses evident	Industry estimates of industry net efficiency ~0.25 (Mercer *et al.* 2022; Manderson *et al.* 2022) Reduced when vulnerable population open and in-season pulses are probable
$N_{0,b}$ *(M accounted for)*	Total Annual Catch * 1/0.25 + (Total Catch * 1/0.25) * 1-exp(-M*number of fishing weeks)/2 As above but with M accounted for when pulses evident	Account for net efficiency as well as losses due to natural mortality over ½ of fishing season
Fleet specific start values		
k_f	1/total days fished by fleet /n	n ~100-350. Often different for the fleets
α_f Effort Response	0.8-1	Assume close to linearity
β_f Abundance Response	1-1.3	Assume close to linearity
P_f (Sign, timing)	Determined on the basis of catch perturbation analysis described in text below	Assumes that inferences about in-season immigration/emigration can be developed soley on the basis of rom perturbation analysis of fishery dependent data.
$P1_f$ magnitude	¼ of N_0 * proportion of cumulative catch caught by fleet	Assumes that size of incoming pulses is smaller than the size of the vulnerable fraction before the fishery began. This assumption is probably not valid.
multiplicative dispersion parameter	0.25*sd(log(total catch))^2	When the likelihood is lognormal, negative binomial, gamma
additive dispersion parameter	0.25*sd(total catch)^2	When the likelihood is the normal distribution

Probabilistic model selection criterion (AIC, BIC, MDL) can only be used to compare models that assume the same likelihood and numerical optimization method. As a result, GDM variants of model hypotheses were selected using a set of criteria associated with statistical properties and biological realism. Statistical criteria included the selection of converged models that produced numerical gradients for parameter estimates < |1| (Thorson *et al.* 2015, Roa-Ureta *et al.* 2021). Remaining models were compared with respect to their ability to produce asymptotic standard errors, %CVs for parameter estimate, and multi-collinearity among parameter estimates.

Models (usually ≤ 4) that produced standard errors for most estimates, relatively small standard error/ parameter ratios, and relatively small parameter inter-correlations were compared with respect to biological realism criteria, placing greatest weight on natural mortality, M wk^{-1} estimates. Unrealistic values of M were identified based on the literature (Roa-Ureta & Arkhipkin 2007, Arkhipkin *et al.* 2021b, Hendrickson 2004, Hendrickson & Hart 2006, Hoenig 2005). Weekly M estimates generally exceed 0.01 wk^{-1} for Ommastrepid squid. It has recently been shown with GDM that natural mortality for *Illex argentinus* (Argentinian shortfin squid) and *Doryteuthis gahi* (Patagonian longfin squid) in the Falklands island is ~ 0.092 wk^{-1} (Roa-Ureta & Arkhipkin 2007, Arkhipkin *et al.* 2021a). Hendrickson (2004) reported a maximum age of 215 days for squid captured on US fishing grounds. For animals with this max age, the Hoenig (2005) age based equation predicts M wk^{-1} ~ 0.134 (SE=0.017). Therefore, models producing M wk^{-1} estimates between 0.01 and 0.15 were considered plausible. A relatively conservative approach was adopted that did not include the higher M wk^{-1} values estimated for mature squid by Hendrickson and Hart (2006). M wk^{-1} estimates > 0.1 were rarely estimated in the more than 750 GDM model variants examined in this work. M wk^{-1} estimates <0.01 were often estimated in pure depletion model variants and variants that did not include in-season pulses evident in catch perturbation analysis. The lower bound to M wk^{-1} was relaxed under these circumstances.

Generalized depletion modeling is an exercise in multi-model inference; the selection and evaluation of hypotheses about the timing and magnitudes in-season pulses of animals onto and off of fishing grounds. Typically these hypotheses are developed from catch perturbation analysis of fishery dependent data sources because fishery independent data describing stock movements are unavailable. This is indeed the case with *Illex illecebrosus* in U.S. waters. The perturbation analyses conducted in this work summarized 4 lines of evidence:

1) Development of pure depletion models (H0) that assumed the fraction of population vulnerable to the fishery was closed to immigration or emigration during the season; identified weeks when observed catch was higher or lower than predicted catch and tallied these residuals (e.g. Figure 5.17).

2) Use of fleet specific catch nonparametric and parametric spike statistics to identify weeks when catches in the fleets were disproportionally high or low when compared to fishing effort (e.g. Figure 5.18). The nonparametric spike statistic $S_{l,t}$, internally generated in CatDyn, was developed by Roa-Ureta (2012) to identify spikes in observed catch (X_t) unexplained by variations in fishing effort (E_t). Such that

$$7.\ \ S_{l,t} = 10(X_{l,t}/\max(X_{l,t}) - E_{l,t}/\max(E_{l,t}))$$

We also computed the complementary parametric residual catch spike statistic developed by Lin *et al.* (2017) that uses plots of residuals from the regression

$$8.\ \log (X_t) = A + \alpha \log (E_t)$$

where the intercept,

$$9.\ A = \beta \log (Nt) - M/2$$

3) We examined plots of gridded weight frequencies of squid landed in the fishery to identify weeks of the season when weight classes of squid may have entered or exited the fishery (e.g. Figure 5.19)

4) Finally, to determine if pulses of squid evident in statistics above reflected the in-season movements of squid into or out of the fishery or movements of the fleet to different fishing grounds, we examined spatially explicit plots of the relative magnitudes of catches of squid reported by NOAA observers, and self-reported by fishers on vessel trip reports VTR and the NOAA study fleet program (e.g. Figure 5.20).

These lines of evidence were entered in a perturbation summary table (e.g. Table 5.14) and synthesized into a set of alternative hypotheses about the timings of in-season movements of squid onto or off of the fishing ground. Hypotheses were only developed for timings when two more indicators recorded in the perturbation summary table coincided in time.

Model variants were developed and selected for each open population hypothesis using methods described above. The "best" model variant (distribution assumption, numerical method) for each hypothesis was selected using the statistical and biological realism criteria described above.

Step 2) Selection of the "best" hypotheses about in-season movements of squid

We used statistical and biological realism criteria described above as well as the protocol of Lin *et al.* (2017) who used the Akaike information criterion (AIC) to objectively select the "best" hypothesis for a fishing season. This required selecting likelihood and numerical optimization algorithms resulting in convergence for all model hypotheses including the pure depletion model (H_0). In most cases several combinations of likelihood and numerical method could be found, but this was a compromise since one or more of the model hypothesis failed to meet the criteria described in the previous section. We selected the hypothesis with the lowest AIC, from a consensus of the likelihood and numerical method combination that could be used to compare the hypotheses. Once the "best" hypothesis was selected, the "best" model variant meeting statistical and biological realism criteria in step 1 representing "best" hypothesis was used in step 3, to develop final parameter estimates and derived quantities useful for stock assessment.

Step 3) Develop parameter estimates and derived quantities useful for stock assessment using "best" model variant reflecting the selected hypothesis

The best model variant (step 1) reflecting the selected hypothesis (step 2) was used to produce final estimates of fishing and population parameters, including N_0, M wk^{-1}, fishing mortality (F wk^{-1}), exploitation rate, the magnitude and timing of in season pulses of squid into the fishery and escapement biomass at the end a fishing season. All of these quantities are computed within CatDyn software or can be developed from computed quantities.

The results section proceeds as follows. We describe the development of a "best" general depletion model with an open population assumption for a single the fishing year of 2016. We selected 2016 because the final model was relatively well behaved with respect to the statistical and biological realism criterion described above. Models were constructed in the manner described in all years. We then discuss parameter estimates and their uncertainties from the "best" GDMs developed for all 5 years before presenting quantities that could be of use in assessments. We discuss the potential role of model time step and sample size in determining parameter uncertainties and suggest next steps that may lead to use of generalized depletion models in the operational assessment, including in-season assessment if necessary, of the risk of overfishing in the US *Illex illecebrosus* fishery.

GDM Model Results

Development of GDM with open population assumption for the 2016 fishing year

Statistical and qualitative industry based assessments of fishery performance indicated that the 2016 fishing year was relatively poor (Table 5.13). The fishery landed 7,004,000 kg of squid during the season. Overall fishing effort was relatively low and 12 vessels were responsible for the landings (J. Didden personal communication). Only 5 of vessels landed more 226 mt. While the freezer trawler fleet accounted for 68% of total landings and 56% of total landings, no effort was recorded for freezer trawlers in 6 of the 19 weeks of the season. This probably occurred because the duration of most freezer trawler trips was longer than 7 days. Nevertheless since there were 19 weeks in the season, 38 datum were available to estimate the population parameters N_0 and M, while 19 datum were available to estimate fleet specific parameters (k, α, β) and the timings (τ, or v) and magnitudes of perturbations (P_j) associated with in-season ingress or egress of squid.

Seven of 48 pure depletion model variants converged, had numerical gradients less than 1, and 2 or fewer incalculable standard errors (Table 5.15a). Natural mortality estimates (M wk $10^{-3} – 10^{-7}$) were much lower than the lower bound indicating that squid may have moved onto the fishing grounds during the fishing season. The pure depletion model variant with the smallest CVs (Table 5.15b, others not shown) and parameter correlations (Figure 5.21) assumed a normal distribution for freezer trawler catches, a lognormal distribution for "wet boats" and was optimized with the CG algorithm.

In the catch perturbation summary table (Table 5.14) we recorded residuals from the time series plots of observed vs predicted catch for the freezer trawler and wet boat fleets (Figure 5.17) developed from the "best" pure depletion model. We also tallied high positive and low negative values for nonparametric and parametric catch spike statistics (Figure 5.18), weeks of appearance for weight classes of squid (Figure 5.19), along with the weekly positions where the majority of catches were relative to the Hudson Canyon (Figure 5.21) in the catch perturbation summary table used to develop hypothesis about in-season ingress or egress of squid for the 2016 season.

Using the multiple lines of evidence in the 2016 catch perturbation summary table (Table 5.14) we framed 3 hypothesis for the development and evaluation of GDM model variants with an open population assumptions. Hypothesis H1, posited ingress of squid into the fishery detected by the wet boat fleet landing in week 33 and in the freezer trawler fleet in week 34. Hypothesis H1 was supported by weight frequencies, residuals of the pure depletion model, and spike statistics in the freezer trawler fleet, and spike statistics in wet boat fleet. Hypothesis H2 added a second pulse of ingress detectible in landings in in weeks 37 (freezer trawlers) and 38 (wet boats). H2 was supported by the parametric and non-parametric catch spike statistics. Hypothesis H3 added early season egress in both fleets to Hypothesis H2a that was a post hoc modified the H2 inference. H3 posited that the second pulse of ingress was only detectible in the wet boat fleet. Some model variants with input perturbation parameters reflecting H1, H2 and H2b converged when fit to the data using maximum likelihood. Model variants for H3 did not converge. H3 had 9 fleet specific parameters for the wet boat fleet with a parameter to data ratio of 0.67 (9/19; 7 parameters in the freezer trawler fleet) and a total of 18 parameters and parameter to data ratio of 0.47 (18/38).

Model variants best reflecting H1 and H2 and H2b were selected on the basis of statistical and biological realism criteria described in the methods and demonstrated for the pure depletion model H0 above. For the sake of brevity only parameter estimates of "best" model variants reflecting the 4 (H0-H2b) hypotheses are presented here (Table 5.15b-d). The H1 model with a single ingress of squid into the fishery produced an M falling within the bounds of biological realism criteria and %CVs for parameter estimates that were less than 57% except for the catch-ability scaler for wet boats (k CV=168%) and the magnitude of the relatively of ingresses into the freezer trawler fleet (CV >5000%, 4c) which was 0.24% of the magnitude of the pulse detected in the wet boat fleet. Parameters associated with the fishing process (k, α, β) for the H1 model variant appear unrealistic. Developing H2 by adding the second in-season pulse of squid ingress to both fleets increased CVs for nearly all the parameters including M which fell below the lower bound unless the error is considered (Table 5.15d). Model variants for H2b with the first ingress event detectible in both fleets and the second detectible only in the wet boat fleet were developed in response to statistical properties of the best H2 variant and further inspection of the perturbation summery (Table 5.14). This scenario was supported by more lines of evidence in catch perturbation analysis, including weight frequencies (Table 5.14). M Fell within the bounds and parameter CVs for the best H2b variant were somewhat smaller than for the H2 variant (Table 5.15e). However fewer standard errors were produced in the H2b variant. Parameter estimate correlations were also higher for the best H2b variant than the H2 variant.

The H1 model variant (apln apln BFGS) appears to best explain the weekly fishery dependent data available for the 2016 season compared with the other hypothesis variants based on most of the statistical and biological realism criterion. This is supported by the AIC comparison of hypotheses H0-H2b made by holding constant distribution assumptions and numerical operationalization method constant for all the hypothesis developed for the 2016 fishing season (Table 5.16).

The “best” H1 model variant had a single squid ingress event detectable by the freezer trawler fleet in week 35 and in wet boat fleet in week 33 (Figure 5.23). Deviance residuals did not show a temporal trend for either fleet. However plots of predicted vs observed catch indicate that the wet boat fleet was fit better than the freezer trawler fleet that did not land trips in 6 of the 19 weeks of the fishing season.

Quantities derived from the best H1 GDM variant in 2016 and useful for assessing the risk of overfishing are shown in Figure 5.24. The weekly natural mortality estimate was 0.026 (SE=0.015). The median weekly F for the fishery was 7.75E-5 (2.5 and 97.5 quantiles: 1.00E-09, 4.22E-04) with a cumulative F over the season of ~0.0023 (Table 5.20, Figure 5.24a). The median observed exploitation rate (F/Z) for the fleet was estimated to be 8.96E-07 (7.46E-08, 4.87E-06; Table 5.20, Figure 5.24b). Cumulative F/M was ~0.005 well below the value of 0.667 proposed by Patterson 1992 as biological reference point appropriate for small pelagic fish (Table 5.20, Figure 5.24c). The GDM model predicted escapement biomass at the end of the fishing season to be 3,889,492 metric tons (Table 5.0, Figure 5.24d). This value fell at the 96^{th} percentile of values developed using the Rago (2021) Indirect Estimation Methods approach to developing plausible bounds using spring and fall NEFSC trawl surveys on the continental shelf (Figure 5.25).

Caution is warranted in interpreting some of these quantities given the uncertainties for some parameter estimates, specifically those related to the fishing process and the small in-season pulse of squid in 2016. However, the small Fs and large escapement value are not out of the realm of possibility given the small size of the fleet and its fishing effort.

Review of modeling results for final models for all years 2013, 2016-2019 fishing years

Hypothesis selection

Models that included in-season pulses of squid into the fishery and an open population assumption generally better explained Illex fishery catches than pure depletion models with a closed population assumption (Table 5.16). In 2 years (2016, 2017), models with a single pulse of squid ingress detected in landings by both fishing fleets had the lowest AICs. In 2019, the “best” model had 1 in-season pulse into both fleets followed by a second positive pulse detectible in the wet boat fleet. In 2018 a pure depletion model with a closed population assumption had the lowest AIC; 2018 had the shortest fishing season (12 weeks), the smallest sample size, and AICs for the three 2018 model hypotheses developed were very similar. There was not strong evidence for an in-season pulse of ingress in the 2018 perturbation summary (not shown). Furthermore, the pure depletion model variant that passed statistical criteria produced reasonable estimates of M wk^{-1} (0.045-0.093). In the seasons for which open population assumption GDMs better explained catches, pure depletion model variants with a closed assumption produced mortality estimates orders of magnitude lower than the plausible bounds (0.01-0.15).

There was no evidence for significant in-season pulses of squid emigration from the fishery in the week fishery landings data analyzed in this work. There were no model variants meeting statistical criteria that produced M wk^{-1} estimates greater than 0.1. High values for M wk^{-1}

would be expected for model variants that did account for substantial pulses of in-season emigration. However, weight frequency plots suggested that in some years larger squid leave the fishery by emigration or mortality (e.g. Figure 5.19). Fishers also observe squid moving off of continental shelf fishing grounds response to weather and oceanographic events (Mercer *et al.* 2022). In addition *Illex* are known to move off the continental shelf in a sex specific manner during the fall (O'Dor & Dawe 2013).

We believe the hypotheses about the number in-season pulses of ingress were limited by the weekly time step since ratio of the number of parameters to be estimated to the amount of data was high and increased for open population models. Pure depletion GDMs with 2 fleets (P0P0) that assumed the fishery "closed" during the season estimated eight parameters (N0, M wk^{-1} as well as k, α, β for each of the two fleets; Table 5 & 10). The timings and magnitudes of each in-seasons pulse of squid into or out of the fishery are detected in the landings in a fleet specific manner. Four additional parameters are estimated when a single in season pulse is detected in landings in both fleets for a total of 12 parameters. Sixteen parameters are estimated in models with two perturbations in each fleet. The longest season (2016) produced only 19 data points per fleet. Even in that year the best GDM with a single pulse in each fleet produced a parameter to data ratio of 0.316. Generalized depletion modeling requires a parameter to data ratio less than 0.333 (Roa-Ureta 2012, 2015, 2020). Sample sizes in the weekly Illex fishery data fell as low as 24 in 2018 when the pure depletion model best explained the data.

Models best representing supported hypotheses

GDM variants best representing the hypotheses and chosen on the basis of numerical quality, statistical quality, and biological realism criteria described in step 2 were fit with using the Broyden–Fletcher–Goldfarb–Shanno (BFGS) numerical optimization algorithm. The best variants assumed a variety of data distributions, but with the same distributions applied to both fleets (Table 5.17). The normal distribution best explained the data for both fleets in two years (2017, 2019) while adjusted profile lognormal, negative binomial, and gamma models were also represented.

Parameters describing the fishing process (k, α, β) were extremely variable and difficult to estimate with GDM using data with a weekly time step (Table 5.17). Asymptotic standard errors could not be estimated for all fishing parameters except for 2016 that had the largest sample size and 2018 when the pure depletion model best explained the available data.

Estimates for the scaling parameter k (~q) varied by 13 orders of magnitude for freezer trawlers and 11 orders of magnitude for the wet boat fleet (Table 5.17). The standard errors for k could not be computed for freezer trawlers in 2017 and 2019 and for wet boats in 2013 and 2019. The pure depletion model for the 2018 season produced a k that had particularly low precision (CV=4524%).

Estimates for the effort response parameter were variable for both fleets; saturable ($\alpha < 1$, gear catches proportionally less with additional effort) in some years and synergistic ($\alpha > 1$, additional effort yields a disproportionate increase in catch) in others (Table 5.17). While patterns were not consistent among the fleets, asymptotic standard errors were produced in all cases and CVs for α estimates were < 45% for freezer trawlers and < 64% for wet boats.

Estimates for the abundance response parameter were also variable, standard errors frequently inestimable, and when they were estimable, they were often quite high (Table 5.17). β estimates for the wet boat fleet were less than <1 in 4 of the years (2016-2019; hyperstability: stable catch rate when the vulnerable fraction of the population changes). However, standard errors could not be produced in 2 years (2013, 2019) and the CV for β was 256% in 2018. β estimates for the freezer trawler fleet were greater than 1 in 3 years (2016-2018, β >1, hyperdepletion: catch rate changes faster than abundance of the vulnerable fraction of the population) less than 1 in 2 years. In 2013 the freezer trawler β estimate was 0.005 and the CV, 1500%.

GDM makes inferences about in-season pulses of squid into or out of fishing areas based on their detectability in landings made by the individual fleets. In a two fleet model half the total sample size is used to estimate the timings and magnitudes of pulses along with the catch-ability parameters. Like catchability parameter estimates, the magnitudes of in-season pulses of squid were very imprecise; probably again a result of the small sample sizes (Table 5.18). The CVs for pulses were greater than 3000% for pulses in the freezer trawler fleet which were more than 400 times smaller than estimates in the wet boat fleet. However, the CVs for pulse magnitudes also exceeded 400% for the wet boat fleet except in one case (2016, CV=22%).

Natural mortality (M wk^{-1}) and the numerical abundance (N_0* 1000) of the vulnerable fraction of the population before the fishing season appeared to have been better estimated with the GDMs (Table 5.19). This is to be expected because the entire datasets (2 fleets * length of the season) are used to estimate population parameters. M wk^{-1} ranged from 0.26 (SE=0.015) to 0.97 (SE=0.012) and CVs were less than 58% in 3 seasons (2016, 2017, 2018). CVs for M wk^{-1} were greater than 100% in 2013 and 2019. It is also important to acknowledge that M wk^{-1} served as a diagnostic criteria for biological realism in our model selection process. However, M wk^{-1} fell into a range between 0.02 and 0.1 in all model variants meeting statistical criteria if in-season pulses evident in the perturbation summaries had been specified. Error estimates for N_0 were produced in all years except 2018. CVs for N_0 were greater than 400% in 2013 and 2019; CVs were less than 75% 2016 and 2017.

Derived quantities of interest for assessing the risk of overfishing and sample sizes

Quantities derived from the final GDM useful for assessing the risk of overfishing (M, F, Exploitation rate, F/M, Escapement biomass) are reported in Table 5.20. Weekly Fs generally fell below 0.027 and observed exploitation rates fell below 3.25E-04 in all years. F/M ratios ranged from 3.89E-08 to 4.08E-01, with seasonal means ranging from 0.002 to 0.115. Finally, in all years except 2013, escapement biomass predictions from the GDMs exceeded 1,000,000 metric tons. These values fell near the upper bounds (>85th percentiles) of escapement estimates develop by Rago (2022) using fishery independent survey estimates and ranges plausible values for survey gear efficiency q and availability v and ratios of F/M.

The uncertainty of the parameter estimates is too large to make a reasonable conclusion about the risk of overfishing for every year analyzed in this work except 2016. Even for 2016, the uncertainty of the estimated fishing process parameters is large. The overall lack of precision in this analysis might be eliminated by moving from a weekly to a daily time step and increasing sample sizes. Moving to a daily time step would reduce the ratio of parameters to data in the models specified here from an average of 38% to %11 (Table 5.21). This could dramatically increase the precision of fleet specific parameters associated with the fishing process and in-season pulses of squid. However, it is also the case that catch data with a daily time step will be noisier due to the influence of nuisance variables (holidays, stormy weather, etc.).

Conclusion

Generalized depletion modeling appears to be a very useful technique providing historical and in-season assessments of the risk of over fishing for stocks that are transient on fishing grounds during the fishing grounds. The technique is used to estimate the abundance of the fraction of the population vulnerable to the fishery (No), natural mortality (M), fishing mortality (F), and fishery escapement (H) in a manner that accounts for in-season migration that confounds the estimation of those parameters. While we believe that some parameters had reasonable precision in some years, overall the GDM analysis indicates that a weekly time step is not sufficient in the U.S. *Illex* fishery to support the precision required for operational stock assessment. This is very much the case during years when the fishing is good and the fishery is closed early upon achieving the quota. We recommend, in order of priority, 4 steps that could allow generalized depletion modeling to be operationalized for the assessment of the U.S. *Illex* fishery in the future:

1) Use analysis of existing landings and weight data along with data simulation to determine the effects of moving to a daily time step on the accuracy and precision of parameter estimates developed using GDM. In the simulations, test the effects of variations in data quality and quantity on parameter estimate accuracy and precision under different and realistic scenarios of in-season ingress and egress of squid onto fishing grounds.

2) Refine existing catch and landings reporting programs to meet requirements determined in #1.

3) Determine the requisite frequency of sampling of squid weights representative of the fishery, its fleets and its fishing grounds required to estimate mean daily weights of squid (and errors) accurately at the time step required for GDM. Co-create with the fishing industry a sampling program based on those findings that is mutually beneficial to fishing businesses as well as fisheries science.

4) Develop a research program investigating the in-season movements and migration of squid through fishing grounds including roles played by oceanographic processes and variations in structure. Develop from this research fishery independent indicators that can supplement fishery catch perturbation analysis used to inform plausible open population hypotheses for GDM.

WG CONCLUSION ON THE GDM

The WG believes GDM approach is promising but requires further research. The GDM results suggest in a qualitative way that F was lower than M (from internal GDM F to M ratios results) and that stock biomass was lightly fished in 2019 (from comparison of the estimated range of annual biomass to the Rago (2021) Mass Balance bounds). The WG concludes that the GDM (as currently configured with weekly fishery landings data) does not provide an adequate quantitative basis for stock status determination using any of the candidate BRPs, including Mass Balance bounds, F to M ratios, or previously published estimates of biological reference points for the stock (i.e., Hendrickson and Hart 2006).

TOR 6: Describe the data that would be needed to conduct in-season stock assessments for adaptive management and identify whether the data already exist or if new data would need to be collected and at what frequency.

In-season stock assessments to facilitate adaptive management for the southern component of the *Illex illecebrosus* stock (i.e., the portion of the stock managed by the U.S.) has been discussed and recommended in stock assessments since at least 1996. Described below are the data, analytical tools, and management tools that the WG recommends as needed for in-season assessment and adaptive management for *Illex illecebrosus*.

Below in tabular form are the WG recommendations of data needs for in-season assessment and adaptive management of *Illex illecebrosus*, identification of where needed data or tools currently exist, and identification of where further development is needed prior to the implementation of in-season assessment and management.

Needs for In-season Assessment and Management	Status of In-season Assessment and Management Needs	Are Existing Data or Resources Sufficient to Meet In-season Assessment and Management Needs?	Approaches for Meeting In-season Assessment and Management Needs
Data collected within a fishing season to inform an assessment model that is run in real time. The data used for the in-season assessment of the *Illex argentinus* and *Dory teuthis gahi* stocks in the Falkland Islands, which are used in a GDM, were reviewed in this assessment (Jones & Hendrickson 2022). The utility of the Generalized Depletion Model (GDM) with open population assumption and multiple pulses into fishery was reviewed in this assessment (Manderson & Mercer 2022).	GDM was evaluated with weekly landings data in this assessment and it was found that samples sizes were too low with a weekly time step to estimate parameters useful for management with sufficient precision and accuracy (Manderson & Mercer 2022). Daily landings could be sufficient but that is not known.	Is there sufficient expertise and resources to support evaluation of GDM using historical data and simulation? Yes, with sufficient staffing and resources in READ PDB to conduct the work over an extended period (i.e., one year or more).	Further evaluate the utility of GDM by: 1) Apply GDM to existing historical data using a daily time step, 2) Simulate *Illex* fishery data with a daily time step and evaluate parameter estimation sensitivities using likely scenarios of in-season squid migration. If a functional GDM does not exist and resources are not sufficient to pursue further development, efforts to enhance data sources, as described below, would not be fruitful.

Comprehensive and precise fishing location data available on a daily time scale.	Positional (Lat-Lon) fishing location data (one location per subtrip) reported through electronic Vessel Trip Reports (eVTR) for all *Illex* trips. Precise fishing location (tow tracks) data through Study Fleet but only start and end of tow for Observer program data, which cover between 10% and 50% of the *Illex* trips annually. Hourly vessel position data (hourly Lat-Lon) via Vessel Monitoring Systems (VMS) for all *Illex* vessels.	Data: By-tow (VMS), Generally by-tow (Study Fleet, Observer), By sub-trip (eVTR) Process: VMS data requires processing to ID fishing locations. Study Fleet and observer data processing takes approximately 6 months.	1) Develop automated routine for processing VMS data to identify fishing locations, 2) Incentivize industry participation in research programs, such as Study Fleet, to collect haul-level fishing location data on a daily time scale, 3) utilize eVTR in a manner to maximize utility of acquired data.
Comprehensive and precise fishing effort/duration data (minutes spent fishing per trip) available on a daily time scale	Sub-trip level effort data (days absent is computed from date and time landed minus date and time sailed, days fished is computed from number of tows x average tow duration) reported through eVTRs for all *Illex* fishing trips; By-tow effort data (tow times in minutes) through Study Fleet and Observer program, which cover between 10% and 50% of the *Illex* trips annually.	Data: Sub-trip in eVTR, Generally by-tow in Study Fleet and Observer Process: Study Fleet and Observer data processing takes approximately 6 months.	1) Incentivize industry participation in research programs, such as Study Fleet, to collect haul-level fishing effort data, 2) Evaluate utility of the scale of fishing effort data (minutes, days, trips) in the directed fleets from eVTR.
Total weight of *Illex* catch reported on a daily time scale, or since discards are low, use landings as a proxy for total catch	Total *Illex* landings reported through eVTRs for all *Illex* trips; Precise tow-level catch weights for the subset of vessels participating in the Study Fleet or with Observer coverage, which includes between 10% and 50% of the *Illex* trips annually	Data: Yes (eVTR, Study Fleet, observer) Process: Yes (assuming eVTR processing occurs within 48 hours)	Amendment 20 includes daily VMS reporting of Illex landings by the directed fishery, and is expected to begin during the 2023 fishing year.

Body weight, length, sex, and maturity of *Illex* throughout the fishing season, with metadata regarding the precise fishing location and fishing effort from which squid were sampled. Representative (fleet, time, and space) daily mean weight data is required if a technique like GDM is applied.	Individual *Illex* body weights and lengths collected by processors through Illex Electronic Size Monitoring Project (ILXSM) which was piloted in 2021; *Illex* mantle lengths collected by observer program; *Illex* mantle lengths and weight of the subsample collected by Northeast Port Biological Sampling Program (samples allocated by month)	Data: Length/weights through ILXSM in 2021; lengths, weights, sex, and maturity through Observer sampling program in 2021-2022 Process: ILXSM data processing requires eVTR matching, which takes >48 hours	1) Automation of ILXSM and eVTR data, 2) Additional Observer data collection of individual *Illex* size, weights, and sexual maturity, 3) Additional Northeast Port Biological Sampling Program data collection of individual *Illex* size and weights, 4) Paired length-weight samples from NEFSC seasonal trawl surveys
Oceanographic drivers of *Illex illecebrosus* distribution, abundance, and movement	Oceanographic indicators of the timing of inshore-offshore *Illex* migration would be valuable for identifying potential waves of migration for GDM. Salois *et al.* 2022 identifies several oceanographic drivers of *Illex* catch and provides hypotheses that can be tested experimentally. Sea Surface Temperature and Chlorophyll indices (mean, standard deviation, anomalies) and frontal dynamics are available in near real time and work is underway to fully automate their processing and make them available on a public database.	Data: Remotely sensed data available but specific products require significant processing; sub-surface oceanographic data minimally available Process: Concrete oceanographic drivers, mechanisms, and indicators not currently defined	Requires automation and validation of current and updated data streams (bottom temperature, salinity, warm core ring tracking, ring shelf occupancy calculations, ring footprint index, ring orientation, precise fishing locations). Also needs collaborative research program embedded in the fishery to identify relevant oceanographic drivers.

Embed industry-science cooperative research in the active fishery. Develop healthy and continuously open channels of communication between fishers, fish processors and scientists.	There is cooperative work being done by government, academic, industry sectors of the fishery, as exemplified by the Study Fleet. This is a work in progress.	Process: Some	High frequency qualitative information about the status of the fishery and catch is valuable for developing and evaluating the accuracy of any in-season assessment model.
Management Approach	No real time management process currently in place	Process: No	Needs development of processes by MAFMC & GARFO

Additional descriptions of the needs for the in-season assessment and management of *Illex illecebrosus* are provided below.

- In-season assessment and management approach
    - Generalized Depletion Model (Manderson & Mercer 2022)
        - Traditional depletion modeling with a closed population assumption cannot be used for the assessment of the risk of overfishing for *Illex* because of the frequency of in-season migration into and out of the fishery (Rago 2021). Roa-Ureta (2015) has developed a generalized depletion modeling (GDM) approach, called CatDyn, that relaxes the closed population assumption, and linear relationships between fishery catch and population size of traditional depletion modeling by explicitly accounting for a) waves of immigrants into or emigrants out of the fishing areas that reset depletion, and b) nonlinear relationships between fishing effort, catch and size of the fraction of the population vulnerable to the fishery. The method allows multiple fleets to be specified in a single analysis. GDM may be appropriate for *Illex illecebrosus* that is on US fishing grounds during the fishing season. Like traditional depletion modeling, GDM is a data-limited method for minimal stock assessment based on high frequency records of fishery catch, effort, and minimal information about catch composition (weights of individuals caught in the fishery). It does not rely on information rich fishery dependent and fishery independent data sources describing catch and catch composition at the extent of the entire population. GDM estimates of the abundance of the portion of a population vulnerable to the fishery, natural mortality (M), some aspects of species catch-ability by the fishery, fishing mortality (F), exploitation rate as well as escapement (H) from the fishery at the end of the fishing season. Research performed during the 2022 assessment indicates that fishery dependent data aggregated to a weekly time step, produces sample sizes that are too small to estimate quantities of interest to fisheries management with sufficient precision and accuracy using GDM (Manderson 2022). Parameter to data ratios ranged from 0.32 to 0.5 using weekly data. Data with a daily time step would provide 7 times the sample size of weekly data, parameter to data ratios of 0.04-0.07 and GDM applied with a daily time step could provide sufficiently accurate and precise estimates. However, the data would also be more variable and this remains to be tested.
        - If the generalized depletion modeling method is appropriate for in-season quota adjustment in the *Illex* fishery, trip level catch and effort data with a daily time step may be sufficient. This, however, has not been tested. Thus, additional data are required for a successful application of the

approach. This includes: representative individual weights of squid representative of the catch in fleets designated in the modeling measured as frequencies that allow landings biomass to be translated to number of individuals and for weight frequencies to be useful for making inferences about in-season pulses of squid into and out of the fishing areas. Data collected in the Illex electronic Size Monitoring program (ILXSM) discussed below would be sufficient.

        - Inferences about the timing and magnitudes of pulses of immigration and emigration are typically made using fishery dependent catches and body sizes exclusively. Fishery independent information derived from studies of the mechanisms and drivers of offshore-onshore movements of squid and pulses into and out of the fishery to supplement fishery dependent information would be extremely valuable.

        - GDMs are spatially implicit but they require explicit data about fishery dynamics to understand whether pulses of squid in fishery CPUE reflect the movements of squid onto and off of fishing grounds or movements of fleets to new fishing grounds

- Precise fishing locations

    - The full *Illex* fleet reports the center of their fishing location for every subtrip through eVTRs, but the precision of these data are insufficient to support in-season assessment and management.

    - All *Illex* vessels are required to run Vessel Monitoring Systems that collect spatial data every hour. An automated routine for processing VMS data to identify precise fishing locations could be developed.

        - Daily catch reporting via VMS is anticipated in 2023.

    - Approximately 40% of *Illex* wet boat fleet (RSW and ice boats) participates in the Study Fleet and record precise fishing locations. Incentivizing more of the *Illex* fleet, including participants in the freezer trawler fleet, to participate in collaborative research programs such as Study Fleet could produce valuable data to support in-season management.

    - The observer program covers between 4 and 10% of Illex fishing trips annually and collects precise fishing location data.

- More precise catch and effort data (daily at a minimum, tow-level preferred)

    - The full *Illex* fleet reports subtrip-level catch and effort data through eVTRs. It may be possible to use these high frequency data using an in-season depletion modeling method. But the method has not been identified and data needs evaluated.

- Approximately 40% of *Illex* wet boat fleet participates in the Study Fleet and records tow-level catch and effort data. Incentivizing more of the *Illex* fleet to participate in collaborative research programs such as Study Fleet could help support data needs for in-season assessment and management.
- The observer program covers between 4 and 10% of Illex fishing trips annually and collects tow-level catch and effort data.

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- Individual *Illex* mantle length,, weight, sex and maturity data throughout the fishing season by fleet (freezer and wet boat)
  - Prior to 2021, processors collected individual *Illex illecebrosus* body weights from each fishing trip landed at their facilities. These data were collected for marketing purposes and hard copies of the data were shared with the NEFSC after the fishing season ended.
  - The Illex electronic Size Monitoring program (ILXSM) program was launched in July 2021, with the goal of producing a standardized data stream of individual *Illex illecebrosus* size and weights throughout the fishing season. The NEFSC Cooperative Research Branch partnered with the six major *Illex* processing facilities across the region to pilot the use of electronic measuring boards, scales, and tablets for collection of individual *Illex* size and weights. The data collected through this program is uploaded directly into the NEFSC BIOSAMP database and matched with vessel trip report data. The data collected through ILXSM is also directly accessible to the processors who collect the data. ILXSM was piloted in 2021 and will be further refined in 2022.
  - If ILXSM is operationalized, near real-time (within 60 days) length and body weights of individual *Illex* would be available from six processing facilities throughout the fishing season going forward.
  - The Northeast Fisheries Observer Program and Northeast Port Biological Sampling Program collect individual *Illex* mantle lengths, but no individual weights. Expanding these programs to collect paired *Illex* size, weight, sex, and sexual maturity could help fill data needs for in-season management.
    - Enhancements of the port sampling program would require additional resources, which are currently not available.
    - In 2021, fishery observers on *Illex* trips collected body weight, mantle length, sex and sexual maturity data required for any in-season model. However, individual body weight data could not be collected due to the resolution of the observer's scales (in lbs), so the subsampled weight of

similarly sized groups of squid are divided by the number of squid in each subsample to compute mean weight per haul. Similar sampling by observers is planned for 2022.

- Oceanographic indicators
    - *Illex* squid is highly sensitive to its environment, both biologically (growth rates) and ecologically (aggregation, movement). Thus, oceanographic indicators can provide a valuable tool for predicting the productivity and availability of *Illex* squid during the fishing season.
    - Salois *et al.* (2022) identifies several oceanographic drivers of *Illex* catch and provides hypotheses that can be tested experimentally. Developing mechanistic understandings of the oceanographic features and conditions that are driving the productivity, ingress, egress, and availability of *Illex* squid is critical for supporting in-season assessment and management.
        - Requires automation and validation of current and updated data streams
            - Bottom temperature and salinity used in Salois *et al.* (2022) are reanalysis modeled products that are not available in near real time, however forecast models exist (though would need to be validated) that could serve as a potential new data stream for these indicators
            - Warm core ring tracking and associated metrics (ring shelf occupancy, ring footprint index, ring orientation) are not currently automated or available in near real time
        - SST and CHL indices (mean, sd, anomalies) and frontal dynamics are available in near real time and work is underway to fully automate their processing and make them available on a public database.
        - Metric detailing rationale for location selection is needed to decipher between fishing behavior (e.g. gear restrictions, vessel capacities, etc) and *Illex* aggregations.
    - Oceanographic indicators associated with in-season changes in the availability of squid to the fishery could be useful in the near term in analysis of catch perturbations used to inform generalized depletion modeling if that method was selected.
- In-season management process
    - In order to ensure availability of requisite information for in-season assessments and management adjustments, the data for an in-season process may need to be required (consider what would happen if all of the voluntary data submission

suddenly ceased). Collecting additional data would require Council approval and a rule-making action which could take 18 months or more before implementation.

    - It is recommended that sufficient data needs are met and in place and the assessments completed for at least 1 full fishing year before considering implementing measures that could make an in-season adjustment to the quota.

- For in-season adjustments to the quota, the most practical implementation would be an in-season action similar to the closing of a fishery. These actions can be completed swiftly and within a week to 10 days.

    - An in-season action would require specific parameters set in the regulations in order to avoid a longer rule making process each year. A management change involving a rule making, other than an in-season action, would involve SSC input and public comment. This longer process would negate the feasibility of an in-season approach.

    - An amendment would likely be needed to be approved by the Council in order to set the regulatory parameters for an in-season action. This process would likely take at least 12 months for implementation.

As described here, some of the data, and analytical and management processes that are required for in-season assessment and management of *Illex illecebrosus* are not currently available or in place. Thus, additional research and resources are needed prior to pursuing in-season assessment or management for northern shortfin squid. Furthermore, the real time management approach that is used in the Falkland Islands (Jones & Hendrickson 2022) may not be successful in the Northeast USA because of significant differences in oceanography, ecology, and fishery characteristics (Mercer & Manderson 2022).

As *Illex* is a sub-annual species, assessments should be based on data from the current year. However, stock assessments are prepared for the previous year because data for the current year are unavailable at the time of the assessment and/or the current year's fishery is ongoing at the time of any annual assessment. Consideration of the timing of future *Illex* assessments and the collection of in-season assessment data are might help remedy these issues.

Additional Considerations for Applying In-Season Management for *Illex illecebrosus*

Mercer & Manderson (2022) details the oceanography, ecology, fishery and human social dimensions as they pertain to the *Illex illecebrosus* and *Illex argentinus* fisheries to elucidate challenges and opportunities for applying an in-season assessment and management approach similar to that of the Falkland Islands in the northern shortfin squid fishery in the Northwest Atlantic. The oceanographic system on the continental shelf and in the slope sea in the southwest Atlantic provides consistent and productive nursery, spawning, and feeding grounds that support two spawning contingents of *Illex argentinus*, which in turn support an international fishery that is nearly 40 times larger than volume than the *Illex illecebrosus* fishery in the northwest Atlantic.

A relatively high latitude strong oceanographic front between the western boundary current (Brazil) and subpolar current (Malvinas), along with upwelling in the vicinity of the Falklands Islands concentrates squid and the fishery. The *Illex argentinus* fishery is assessed and managed in-season using a depletion model (Winter 2019), which is supported by high levels of data collection by observers and individual fishing vessels. In the northwest Atlantic shelf productivity is lower than on the South Atlantic Shelf and a single *Illex illecebrosus* cohort uses the highly stochastic Gulf Stream and Slope Sea system as a spawning and larval and early juvenile nursery ground. South of latitude 41°N an unknown fraction of the late stage juvenile and adult portion of the population uses the outer edge of the continental shelf where the US trawl fishery operates. In this lower latitude portion of the species range, *Illex illecebrosus* is transient on the outer shelf fishing grounds that support a much lower volume fishery (Lowman *et al.* 2021, Mercer & Manderson 2022). It has been estimated that the U.S. fishery accesses less than 1.14% of the area occupied by the species on the U.S. and Canadian continental shelf and the all life stages are known to occur in the shelf slope sea that is not surveyed or available to the trawl fishery (Rago 2021). The U.S. component of the *Illex illecebrosus* stock is managed using annual Total Allowable Catch, tracked using coarse data collection on fishing effort and catch. The northwest and southwest Atlantic *Illex* fishery systems differ in important oceanographic, ecological, and sociological ways that may prohibit the successful application of Falkland Island approaches to the US Fishery. These include differences in squid life history and contingent structure that may affect population dynamics, availability to the fisheries including degree of transience on fishing grounds, and scales of the two fisheries. The scientific and industry resources required to support the in-season assessment and management of the *Illex argentinus* fishery are significant. These resources are warranted given the scale of the fishery, and its pivotal role supporting the Falkland Island economy. Given the smaller scale and different social system surrounding *Illex illecebrosus* in the northwest Atlantic, fewer resources have been devoted to assessing and managing the fishery. It would take significant commitments from scientific agencies, management bodies, and the fishing industry to support in season assessment and management of *Illex illecebrosus*, as is conducted in the southwest Atlantic. It is also not clear that there is a method identified appropriate for in-season assessment of the stock or sufficient risk of overfishing justify the commitment to operationalize it.

In-season Assessment Needs Addressed in Previous *Illex illecebrosus* Assessments

The *I. illecebrosus* stock exhibits inter-annual "boom-bust" periods of abundance on the U.S. shelf because, like most squid stocks, recruitment is closely tied to changes in environmental conditions (Boyle and Rodhouse 2005). The portion of the stock that is managed by the U.S. is subject to a TAC that is fixed throughout the fishing season, and though *I. illecebrosus* is a sub-annual species, assessments are not conducted annually. Out of all of the globally fished squid stocks that are assessed, forecasting of annual stock abundance has only been applied to one stock (Moustahfid *et al.* 2021). However, implementing an in-season assessment for adaptive management of the U.S. fishery could allow fishermen to take advantage of otherwise foregone yield during high abundance years and reduce the potential for recruitment overfishing during low abundance years (Arkhipkin et al, 2020; Moustahfid *et al.* 2021), Therefore, the previous three stock assessments, conducted during 1999 (NEFSC 1999), 2003 (NEFSC 2003) and 2005 (NEFSC 2006), focused on the data and modeling needs for in-season assessment.

Following the first early closure of the *I. illecebrosus* fishery, in 1998, the *Illex* fishermen requested that in-season assessment and management be investigated so that increases in the TAC could be considered during years of high abundance. In 1999, most of the fleet participated in the tow-based, at-sea data collection project and these data as well as body weight data from the processors were evaluated in the 2003 assessment (NEFSC 2003). This project was improved upon in 2002 and included real-time, tow-based, electronic data reporting with automated uploading to an e-VTR program containing the same VTR fields in current use (Hendrickson *et al.* 2003). Some of the additional advancements made toward in-season assessment included a pre-fishery *Illex* survey that was used to estimate pre-fishery abundance and growth and maturity parameters (Hendrickson 2004). New LPUE indices were computed using the fishery data collected at sea and vessel types were identified and spatial and temporal fishing behavior was analyzed by fleet. A squid acoustics workshop was held with both fishermen and international scientific experts as speakers. A semelparous-based maturation-natural mortality model and a per-recruit model were also developed to estimate Biological Reference Points for this semelparous species (Hendrickson and Hart 2006). The weekly time-step model that was developed for in-season assessment however was not accepted by the reviewers for management use due to infeasible parameter estimates, additional data needs and more work required on the simulations that were run. In summary, these examples are some of the advances made in previous assessments and which have lain the foundation for the research that was able to be conducted in this Research Track Assessment. Further details regarding these improvements are described below by assessment. Please note that in-season management is referred to in the following paragraphs by the synonym of real-time management (RTM) which is the terminology previously used.

1996 SAW 21

Real-time management (RTM) is particularly desirable for sub-annual stocks such as *Illex* squid because population abundance can be highly variable and a single recruitment failure could result in stock collapse. Stock size is unknown before the start of the fishing season and can only be estimated once the fishing season is underway. In-season adjustments of catch or effort could provide biological and economic benefits such as the preservation of adequate spawning biomass each year, avoidance of overfishing during periods of poor recruitment, and increased landings during periods of good recruitment. Under the existing quota-based management system, the catch limit would have to be set very conservatively in order to avoid reducing spawning biomass to a dangerously low level. Furthermore, currently no advantage can be taken of periods of good recruitment detected during the fishing season.

A real-time management plan which incorporates effort controls has been implemented in the Falkland Islands for the *Illex argentinus* fishery (Basson et al 1996; Beddington et al 1990; Rosenberg et al 1990). Effort controls were selected rather than catch quotas because effort management allows catches to vary with population size, which permits taking advantage of good recruitment. The *Illex argentinus* management plan is based on ensuring that proportional escapement remains at a selected target level which is above a threshold minimum spawning stock biomass. Proportional escapement is defined as the ratio between the number of spawners surviving under a given level of fishing mortality and the number of spawners with no fishing mortality. This spawning stock biomass target (in this case, 40,000 metric tons) was used to set fishing effort limitations prior to the start of the fishing season, which is when population abundance is unknown. For example, the number of licenses was determined via the target fishing mortality using effort and estimates of catchability. Once the fishing season started, catch (in weight) and effort data were reported on a daily basis and weekly biological data were collected from a subset of vessels, by observers at sea, as part of fishing license agreements. The biological data is critical to the conversion of catch weight to numbers, due to the rapid growth of *Illex* during the fishing season and is used to identify recruitment pulses into the fishing zone.

After several weeks of data collection, these data were then incorporated in a Leslie-Delury depletion model to compute in-season estimates of initial population size (or recruitment), current population size and catchability coefficients (Winter 2019). These results were used to project, under different fishing effort scenarios, levels of effort through the end of the fishing season. If the projected absolute escapement was below the threshold, an early closure was considered in collaboration with the industry. If escapement was above the threshold, then in-season adjustments were considered in order to take advantage of good recruitment. The 1996 SAW 21 working group concluded that given the similar life history of *Illex illecebrosus,* a single fishing season, and the relatively small number of vessels participating in the domestic fishery, the U.S. *Illex* fishery would be a feasible test case for implementing a similar real-time management plan. The 1996 SAW 21 concluded that the details of a specific real-time management plan for the U.S. *Illex* fishery would require further research and should be specified prior to implementation.

1999 SAW 29

The 1999 SAW 29 Assessment Subcommittee discussed “real time management” (RTM) as a potential long-term solution to improving data resolution and the assessment of this stock. Fishing industry members present at the SAW 29 meetings were in favor of investigating RTM and 17 captains agreed to participate in a RTM feasibility study beginning on June 1, 1999. Each fishing vessel was to report their catch, effort and fishing location on a daily basis. In addition, squid processors were to submit weekly biological data reports and shipping samples to NEFSC for further biological data analysis. It was noted that through Amendment 6 of the FMP, the MAFMC has the authority to regulate the length of the *Illex* fishing season. It was noted that a delay in the start of the fishing season could result in an increase in fishery yields and the Subcommittee proposed that this possibility should be investigated as an intermediate step in the process of moving toward the implementation of real-time management. In an effort to make this analysis possible, the industry submitted a multi-year data set of *lllex* squid mantle lengths and body weights which were analyzed as part of the SAW 29 stock assessment. Tow-based catch and effort data were also submitted, but these data were not extensive enough to incorporate into a quantitative model to estimate stock size.

2003 SAW 37

The 2003 SAW 37 noted that research recommendations in previous assessments had emphasized the need for improved stock assessment data, particularly since *Illex* lives for less than one year and the U.S. fishing season is of short duration (4-5 months on average). It was further noted that the NEFSC had conducted several cooperative research projects with the *Illex* fishing industry that have resulted in: (1) improved spatial and temporal resolution of fisheries catch, effort and biological data; (2) characterization of the age composition, growth, and maturity of *Illex* inhabiting U.S. waters prior to the start of the fishery; and (3) the collection of fisheries data, in real-time, via electronic logbook reporting, all of which was used extensively in the 2003 SAW 37 assessment.

The 2003 SAW 37 assessment described how during 1999-2001, a large portion of the *Illex* fleet participated in a real-time data collection study that involved recording tow-based catch, effort and fishing location data, in hardcopy form, with weekly submittals of these data to the NEFSC. In addition, squid processors provided mantle length and body weight data from squid collected daily during each trip. In 2002, tow-based data were collected electronically in real-time, via e-mail, and automatically loaded into Oracle tables (Hendrickson *et al.* 2003). Vessel operators were able to log on to secure, personal web sites to edit and confirm their fisheries data collected at sea, and to incorporate additional vessel data required for logbooks. The web site also allowed fishermen to view their personal catch and oceanographic data through the use of an interactive mapping tool and print hardcopy logbooks for their records. The study demonstrated that electronic logbook reporting offers an efficient, cost-effective means of collecting accurate, high resolution fisheries and oceanographic data that can rapidly be made available to fishermen and stock assessments scientists. During May 2000, a pre-fishery bottom trawl survey was conducted with two squid vessels, chartered by the NEFSC, to assess initial stock size and distribution and to collect biological data for age, growth and maturity analyses (Hendrickson *et al.* 2005). The 2003 SAW 37 panel reiterated the need to move towards a scheme of in season stock assessment and management approaches.

2005 SAW 42

The 2005 SAW 42 review noted that within-season depletion models have been found to offer the most promise for assessing ommastrephid and loliginid squid stocks and have been used to assess the Falkland Islands stocks of *Illex argentinus* and *Doryteuthis gahi.* The group determined that some depletion estimation techniques require data consisting of: total catch, mean body weights, an abundance index (e.g., CPUE), spatial information, a recruitment index proportional to the number of recruits, and an estimate of natural mortality. In addition, these data must be of appropriate temporal and spatial resolution, tow-based, and available throughout the fishing season.

The 2005 SAW 42 reviewed the results of the in-season assessment model developed for the 1996 SAW 29 assessment, revised for the 2003 SAW 37 assessment, and further developed and updated for the 2005 SAW 42 assessment. The model, which estimates weekly fishing mortality rates and initial stock size, was run using tow-based catch, effort and fishing location data instead of VTR data and allowed for the possibility of fitting maturity ogive parameters, initial stock size, and fishing mortality. The 2005 SAW 42 review panel concluded that the model formulation was sound but that the model results should not be used to update fishing mortality and stock size estimates because of 1) uncertainty is the use of a May growth curve which underestimates growth later in the fishing season, 2) uncertainty in the method of computing the weekly recruitment indices, 3) the need for sensitivity analyses for various values of initial stock size. The 2005 SAW 42 panel also reviewed results from the reformulated maturation-natural mortality model and the per-recruit models taken from a journal publication (Hendrickson and

Hart 2006) and a previously reviewed (2003 SAW 37) in-season stock assessment model that was further developed and simulation tested as the potential foundation for an in-season assessment modeling approach.

With respect to the data needs for in-season assessment modeling, the 2005 SAW 42 review concluded that: a) All of the models presented in the 2005 SAW 42 review required additional data collection. Maturity and age data should be collected throughout the fishing season to evaluate the effects of differential growth and maturity within seasons and between years. Emphasis should be placed on the collection of weekly data. The in-season model would be improved with tow-based catch, effort and fishing location data, particularly if collected electronically in real-time; b) M_{ns} and M_{sp} for females from each seasonal cohort should be re-estimated with new growth data and a determination made whether estimates for males are similar to those of females; c) Biological reference points for each seasonal cohort should be re-estimated by incorporating seasonal information regarding growth, selectivity, and natural mortality; d) Additional simulation analyses are needed to determine the range of possible responses by the model to input parameters. The simulation analyses should reflect the actual reality of the fishery and data input/output (such as fishery length frequencies for estimating partial recruitment). Length data rather than age data should be utilized in the simulation model so that the simulation formulation is identical to that used in the in-season model; e) Further exploration of relationships between oceanographic conditions and abundance and body size of squid on the US Shelf is needed to determine whether a pre-season predictor variable for abundance or stock productivity can be found; f) A pre-fishery, stratified random survey would be useful to estimate initial stock size.

TOR 7: Update or redefine Biological Reference Points (BRP point estimates for B_{MSY}, $B_{THRESHOLD}$ and F_{MSY}) or BRP proxies, for each dominant cohort that supports the fishery, and provide estimates of their uncertainty. If analytical model-based estimates are unavailable, consider recommending alternative measurable proxies for BRPs. Comment on the scientific adequacy of existing and recommended BRPs or their proxies.

Amendment 8 (MAFMC 1998c) established MSY-based biological reference points. The three stock assessments conducted since 1996 have recommended %MSP-based MSY proxies to reduce the likelihood of recruitment overfishing.

During the most recent assessment conducted in 2005 (NEFSC 2006), an aged-based cohort model that estimates the post-spawning mortality of this semelparous species was reviewed (Hendrickson and Hart 2006). This maturation-natural mortality model estimates maturation rate and post-spawning mortality rate as a continuous function of age for an unfished cohort of females. The weekly model tracks non-mature and mature females separately as they age, become mature, mate and then quickly spawn (due to the lack of a sperm storage receptacle) and die. Model input data included both mature and non-mature females collected during a stratified, random pre-fishery *Illex* survey conducted during late May in 2000. Sampling of the complete US shelf *Illex* habitat during the survey resulted in representative sampling of the on-shelf US stock component during spring and included a large number of mature females (many of which were mated). The spawning mortality estimate from this model was then included in a weekly egg-per-recruit (EPR) model that also accounted for semelparity and was used to estimate %MSP-based BRP proxies. The 2005 SAW 42 assessment review panel (NEFSC 2006) considered both model formulations to be sound, but decided that model sensitivities required additional testing with seasonal maturity and growth rate data other than May because growth rates are likely to increase during the fishing season.

Although new age and maturity data were collected during 2019 and 2020 for the current assessment, the number of mature females in the aged samples were too few to run the Hendrickson and Hart (2006) models to estimate updated values of natural mortality. Despite the fact that these samples were randomly collected from multiple statistical areas, there were only six mature females in the 2019 samples and 10 mature females in the 2020 samples, representing only 3% and 7% of the aged female samples, respectively. In contrast, mature females were more numerous in the pre-fishery May 2000 samples, totaling 37% of the aged female samples. Statolith-based ageing of squid samples is very expensive and there are few squid ageing experts available globally. These facts, combined with the need for an adequate number of mature females, suggest aged-based estimation methods for BRP proxies might not be practical for this southern stock component of the northern shortfin *Illex* stock managed by the US.

An extension (Rago 2022) of the Hendrickson and Hart (2006) was considered by the WG. The extended model recast the continuous time model as a discrete monthly time step model with a seasonal fishery. The model provided useful insights into the magnitude of population compensation necessary to offset the force of fishing mortality and the protective effects of seasonal (vs continuous) fisheries. However, it was not sufficient to redefine an alternative basis for a biological reference points or MSY proxies. The revised matrix model may have utility as a dynamic estimation model for future assessments.

Proportional escapement rates have been used in global squid stock assessments as a biological reference points (Arkhipkin et al 2021b). The Indirect Estimation Methods approach (Rago 2021) can be used to compute the proportional or fractional escapement for all years where estimates of landings and appropriate survey indices are available. This is done by computing the initial biomass prior to start of the fishery by adding landings and expected natural mortality to the end of fishery biomass estimates based on the NEFSC fall survey. The initial biomass is then projected forward using only natural mortality to obtain an estimate of what biomass would have been in the absence of the fishery. The ratio of the observed to the projected biomass estimate is a measure of escapement. The model can be evaluated over a broad range of assumed values of catchability (q), availability (v), and natural mortality (M) to get a distribution of potential values for a given year. The simplicity of the model allows for examination of the effects of alternative landings over a given set of fall survey biomasses. If future biomasses are unknown, but historical patterns provide guidance on the likely range of outcomes, then the risk of falling below any target escapement level any hypothetical catch limit can be estimated by counting the number of times this event occurs. It was noted that the probabilities of escapement levels could be refined if strong autocorrelation patterns in the time series of survey indices were considered.

TOR 8: Recommend a stock status determination (i.e., overfishing and overfished), for each dominant cohort supporting the fishery, based on new modeling approaches developed for this peer review.

The suite of Indirect Estimation Methods (Rago 2021) provides logical bounds on stock biomass and fishing mortality rates based on assumed ranges of survey and fishery catchability and availability and natural mortality. The ranges of the parameters are broad and reflect a feasible range. The approach is also used to evaluate the risks to the stock, given these bounds, of falling below a desired escapement rate for a proposed ABC.

The GDM results (Manderson & Mercer 2022) suggest in a qualitative way that F was lower than M (from internal GDM F to M ratios results) and that stock biomass was lightly fished in 2019 (from comparison of the estimated range of annual biomass to the Indirect Methods biomass bounds). These conclusions are supported by results of the Indirect Estimation Methods wherein the distribution of F/M ratios, based on observed landings and survey indices, potential ranges of catchability and availability, and M are derived.

The WG recommends that the stock status is unknown with respect to reference points-based definitions of overfishing and overfished. However, the scientific evidence examined in the current assessment is sufficient to conclude that the *Illex* stock was lightly fished in 2019.

TOR 9: Define the methodology for performing short-term projections of catch and biomass under alternative harvest scenarios, including the assumptions of fishery selectivity, weights at age, and maturity.

The northern shortfin squid, *Illex illecebrosus*, inhabits the continental shelf and slope waters of the Northwest Atlantic Ocean between Iceland and the east coast of Florida and constitutes a unit stock throughout its range. The species is highly migratory, growth is rapid and the lifespan is short, up to 217 days for individuals inhabiting the US shelf. The WG does not consider the use of traditional multi-age projection methods commonly used in Northeast U.S. finfish assessments to be appropriate for the *Illex* stock on the US shelf. The reason is the stock's life span of less than one year and subsequent lack of multiple age class 'inter-annual memory' in the population that makes such projections useful for multi-age finfish stocks.

If some 'projection' approach is needed to satisfy management requirements, the *Illex* WG proposes the 'PlanBsmooth' approach (NEFSC IBMWG 2021 In prep.; https://github.com/cmlegault/PlanBsmooth) as a guide for forecast OFL/ABC advice. This peer-reviewed approach has been used to set catch advice for Georges Bank cod since the rejection of the 2015 age-based assessment (NEFSC 2015, 2017, 2019 In prep.), and has since been used as the 'Plan B' or 'Alternative' assessment projection approach for other stocks in the Northeast region. The approach can use a single index of stock biomass or averaged multiple indices, with a LOESS smoother first applied to the resulting index (with a span = 0.3). The predicted LOESS smoothed values in the final three years are then used in a log-linear regression to estimate the slope (i.e., trend or rate of change), and this slope (transformed back to the linear scale) is then used to adjust the most recent three year average catch to generate catch advice.

As illustrative examples for *Illex*, the NEFSC FSV Albatross IV equivalent fall trawl survey indices for 1997-2019 (Run 1), the commercial fishery Dealer/VTR nominal LPUE (nominal metric tons landed per day fished) for 1997-2019 (Run 2), and the commercial fishery Dealer/VTR GLM standardized LPUE (nominal metric tons landed per day fished) for 1997-2019 (Run 3) were used to compute the recent trend in biomass to generate potential catch advice (Figure 9.1). An example that combined the fall survey and GLM standardized fishery LPUE was also computed. The PlanBsmooth approach (Run 4) could also be applied to recent years of any time series developed from annual estimates of stock biomass developed from a depletion model approach.

The approach applied to NEFSC fall survey data indicates the rate of change in the recent three years of the smoothed survey indices of biomass to be 0.970 (Figure 9.2). Application to the fishery nominal LPUE data indicates the rate of change in the recent three years of the smoothed LPUE indices of biomass to be 1.026 (Figure 9.3). The fishery GLM standardized LPUE data indicates the rate of change in the recent three years of the smoothed LPUE indices of biomass to be 1.177 (Figure 9.4). The combined NEFSC fall survey and GLM standardized fishery LPUE data indicates the rate of change in the recent three years of the smoothed LPUE indices of biomass to be 1.090 (Figure 9.5). These results indicate that, depending on the identity and number of surveys used and the length of the projection, management agencies might consider a range of catch multipliers from 0.970 to 1.177 in developing catch advice for years after 2019.

TOR 10: Review, evaluate and report on the status of the Stock Assessment Review Committee (SARC) and Working Group research recommendations listed in the most recent SARC- reviewed assessment and review panel reports. Identify new research recommendations.

2021 WG Responses in *italics*.

2005 SAW 42 and previous benchmark assessments

1) Continue model development, with the objective of producing sound statistical models for stock assessment purposes

Analytical population models presented at SAW 37 and SAW 42 were improved upon (i.e., implementation of the Roa-Ureta (2012, 2015, 2020) Generalized Depletion Model with perturbations and a weekly time-step) and tested. Contemporary (2019-2020) seasonal length, weight, age, sex and maturity data, were collected from fishery samples and used to identify the intra-annual cohorts that support the fishery. Median sizes- and ages-at-maturity, and growth rates were also computed for each cohort.

A suite of Indirect Estimation Methods developed through a MAFMC workgroup in recent years have been reviewed by the MAFMC SSC and are now used to set Acceptable Biological Catches for the fishery given the absence of an accepted analytical population model. The Indirect Estimation Methods consider logical bounds on population biomass, fishing mortality rates, and spawner escapement. These approaches were further developed for this assessment.

2) Consider the development of "operating models" which can be used to test the effectiveness of alternative management strategies

No progress to date. This research recommendation cannot be accomplished until a reliable stock assessment model is available.

3) Evaluate the relationship between growth rates and sea temperature to define possible changes in stock productivity associated with environmental conditions.

Contemporary (2019-2020) seasonal length, weight, age, sex, and maturity data were collected and summarized in this assessment. Further investigation of these relationships with respect to temperature and other environmental drivers would be useful.

4) Define biological indicators of low or high productivity regimes. Evaluate seasonal and latitudinal clines in growth rates.

During SAWs 37 and 42, as well as the NAFO Illex assessment, average body weight has been documented as a biological indicator of low and high productivity regimes based on research survey data and fishery data. Annual and weekly mean body weight data were collected from the fishery during the 1999-2002 real-time, at-sea data collection project, and thereafter from industry-supplied body weight data, were updated for this assessment through 2019 (see TOR 3).

Hendrickson (2004) documented a latitudinal cline in relative abundance, body size and median size-at-maturity that is correlated with sea surface temperature.

5) Evaluate and design cooperative research programs with commercial vessels for sampling of size and weight of *Illex* during the fishing season

Contemporary (2019-2020) seasonal length, weight, age, sex, and maturity data were collected from fishery samples and trends in mean body weight data collected by Illex processors/dealers were summarized in this assessment. Starting in 2021, the Illex assessment lead worked with the Cooperative Research Branch and ITD to outfit the major Illex processors with electronic technology (government-issued measuring boards, scales, and tablets) to collect paired body weight and mantle length data throughout the fishing season. If resources for this program are sustained, these data will be available for Illex stock assessments in near real-time in the future.

6) Continue with cooperative ventures for pre-season survey to obtain possible indices of upcoming stock abundance and productivity.

A stratified-random pre-season Illex survey was conducted prior to the start of the fishery during 2000 with two Illex fishing vessels with funds from an external grant and these data were used in the SAW 37 and SAW 42 assessments. Ageing of squid samples from this survey showed that the early portion of the fishery was supported by the winter cohort. External funding would be needed to conduct future Illex pre-season surveys to assess the inter-annual variability of the data. In addition, a better understanding of the movement dynamics of the portion of the stock supporting the fishery is required before a pre-season survey can be designed. Current research suggests that the fishery is supported to a large degree by the migration of individuals from the slope sea and back again and the timing and magnitude of those migrations is related to dynamic ocean properties. Thus, estimation of a precise estimate of pre-season abundance would be informative but not definitive. In addition, careful consideration of the timing of the survey so that sampling occurs immediately after the migration of the "early season" squid group is critical. Much additional research is required to design any pre-season survey and to weight it properly with respect to the dynamics of the stock exploited by the fishery.

7) Evaluate catch rates by vessel by using VTR and Weighout databases to improve procedures for standardization of nominal LPUE.

Multiple independent standardization models of fishery-dependent LPUE were developed for this assessment. These efforts indicated similar trends in standardized LPUE over time. During years when VTR reporting rate has been high (from 2008-2019), LPUE index trends have been similar to NEFSC fall survey biomass index trends.

8) All of the models presented require additional data collection. Maturity and age data should be collected throughout the fishing season to evaluate the effects of differential growth and maturity within seasons and between years. Emphasis should be placed on the collection of weekly data. The in-season model would be improved with tow-based catch, effort and fishing location data, particularly if collected electronically in real-time.

As noted in #3 and #5 above, contemporary (2019-2020) seasonal length, weight, age, sex, and maturity data collected by the Illex processors/dealers are summarized in this assessment.

9) Re-estimate Mns and Msp for females from each seasonal cohort and determine whether Mns and Msp estimates for males are similar to those of females.

The numbers of mature females contained in the 2019 and 2020 biological datasets were too few (i.e., 6 and 10, respectively) to produce reliable Msp estimates from the Hendrickson and Hart (2006) model, so this research recommendation could not be completed for consideration in this assessment.

10) Re-estimate biological reference points for each seasonal cohort by incorporating seasonal information regarding growth, selectivity, and natural mortality.

As explained in #9, the low number of mature females in the 2019 and 2020 biological datasets prevented computing a reliable Msp estimate that is needed for inclusion in Hendrickson and Hart (2006) BRP model for semelparous species. Therefore, this age-based BRP estimation method could not be completed for consideration in this assessment.

11) The in-season assessment model results show a high sensitivity to parameters such as growth and recruitment and additional simulation analyses are needed to determine the range of possible model responses. The simulation analyses should reflect the reality of the fishery and data input/output (such as fishery length frequencies for estimating partial recruitment). Length data rather than age data should be utilized in the simulation model so that the simulation formulation is identical to that used in the in-season model.

Work is in progress but not completed for consideration in this assessment.

12) Further exploration of relationships between oceanographic conditions and abundance and body size of squid on the U.S. Shelf is needed to determine whether a pre-season predictor variable for abundance or stock productivity can be found.

Work is in progress but not completed for consideration in this assessment.

13) It is important to know what fraction of the stock inhabits waters deeper than 185 m, particularly during May and in the fall. It would be useful to conduct some adaptive or fixed stations for determining *Illex* abundance and length composition, during daylight hours, at depths beyond 185 m during May and in the fall.

No progress to date, although a deep water (> 400 m) survey along the shelf edge has been proposed multiple times for documenting the abundance of Illex and butterfish, as well as additional assessed species, using NEFSC's research survey vessel with the addition of a deep water strata set.

14) A pre-fishery, stratified random survey would be useful to estimate initial stock size.

Refer to the response to #6 above.

15) Evaluate the utility of relative abundance and biomass indices from the NEFSC winter survey.

The NEFSC winter survey relative abundance and biomass indices have been compiled and included in this assessment with the other series of survey indices (TOR 2) and as part of the "Indirect Estimation Methods' approach. However, the winter survey indices are not reliable estimates of Illex abundance or biomass because 1) Illex catchability is low due to the low headrope height of the survey net and the different type of ground gear, 2) only a subset of strata are sampled and the strata set varies by year and 3) winter is a time when Illex squid are least available to a bottom trawl survey conducted on the U.S. shelf.

MAFMC SSC May 2020 and May 2021

1) Evaluate stock assessment methodologies with a sub-annual time step, undertaking cooperative research with the fishing industry. Such assessment methodologies should seek to support in-season management.

Refer to the response to #1 above.

2) Collect demographic information on growth, maturation, mortality, and reproduction by sex, season, and cohort to estimate and evaluate the level and changes in stock productivity.

Contemporary (2019-2020) seasonal length, weight, age, sex, and maturity data were collected from squid samples donated by Illex processors/dealers and summarized in this assessment.

3) Evaluate the potential to collect real-time spatial and temporal data on catch and biological characteristics of the catch to support in-season management.

The necessary data and their sources were summarized in this assessment under TOR 6.

4) Undertake fishery-independent surveys covering the distribution of *Illex* in both fished and unfished areas of their distributions.

Refer to #13 above regarding previous requests for NEFSC research vessels to conduct such surveys.

5) Continue work to evaluate factors controlling the availability of *Illex* squid to the fishery.

Work is in progress but not completed for this assessment.

6) Landings time series show evidence of strong autocorrelation. As a result work should evaluate the impact of climate and environmental factors on recruitment, growth and understanding of *Illex* squid dynamics.

Work is in progress but not completed for consideration in this assessment.

7) Evaluate the benefits of a post-season, industry run survey to provide additional information on squid growth, distribution and dynamics.

No progress to date.

8) Explore the influence of market factors, including price, on fleet activity and its relationship to squid abundance.

The influence of market factors, including price and global production of ommastrephids, on Illex fleet LPUE was considered in GAM standardization models (Lowman et al. 2021). Price was found to significantly influence LPUE in both the wet boat and freezer fleets. Qualitative information related to market and other social factors influencing the Illex fishery has been synthesized in the working paper titled "Technical and economic aspects of northern shortfin squid (Illex illecebrosus) harvesting, processing and marketing essential for interpreting of fishing effort and catch as indicators of population trend and condition" (Mercer et al. 2022).

9) Include the approach explored in the Rago working paper (2021) in the Research Track Assessment so that it receives more complete peer review. Currently, results are available for only two levels of ABC (30,000 MT and 33,000 MT), and these preclude an assessment of how risk changes as ABC varies.

The Rago (2021) Indirect Estimation Methods approach that the SSC has recently been using to assess the stock, with advances made since May 2021, has been included as a model option in responding to TORs 5 and 11 of this assessment.

***Illex* RTA WG 2021**

The research recommendations proposed by the WG are listed below in order of priority. The WG reached consensus on the 11 research topics and used a survey polling tool facilitate prioritization. Expanded background details in *italics*.

1) Develop a standardized data set of *Illex* body weights and mantle lengths throughout the fishing season from the freezer and wet boat fleets. This includes an industry-science collaboration to collect paired *Illex* weights and lengths at processing facilities with a standardized sampling protocol. This sampling should be balanced across fleets, space, and time. This would also include enhanced sampling of individual *Illex* size and body weights by the Northeast Port Biological Sampling Program and Observer Program. Specifically, the Observer Program should continue the existing program that incorporates collection of individual *Illex* size and weights and sexual maturity on *Illex* fishing trips, with an effort to ensure samples reflect total landings by fleet (freezer and wet boats).

The Illex Electronic Size Monitoring Pilot Program (ILXSM) was developed by the NEFSC Cooperative Research Branch, Information Technology Division, and Population Dynamics Branch in 2021. The program developed an electronic data collection system that is being used *by Illex processors to collect paired Illex mantle length and body weight data throughout the fishing season. These data are loaded into the NEFSC's biological sample database and are matched with VTR data to identify the statistical area where the samples were caught. ILXSM piloted the electronic data collection systems during the 2021 fishing season and will continue to pilot the systems during the 2022 fishing season.*

2) Continue to investigate the utility of an open population generalized depletion model (GDM), such as CatDyn (Roa-Ureta 2015), that allows for immigration and emigration and produces estimates of and uncertainties for M, F, escapement biomass and other parameters used to estimate stock status. Research associated with the 2022 assessment indicated that catch data from the U.S. *Illex illecebrosus* fishery with a weekly time step does not provide sample sizes large enough in GDM to develop estimates accurate or precise enough for use as a stock assessment. Future research should therefore investigate whether landings, effort, and body size data with a daily time step in GDM produces estimates sufficiently accurate and precise for stock assessment. The research should assess whether a) existing data collected by government and the fishing industry can be used to develop estimates of sufficient accuracy and precision, and b) use simulated data in GDM to evaluate parameter sensitivities to variations in data quality and quantity under different scenarios of in-season immigration/emigration of squid onto/off of fishing grounds.

3) Develop an R Library to run the Indirect Estimation Methods approach (Rago 2021).

4) Further research on the oceanographic and environmental drivers of *Illex* distribution, abundance, productivity, and body size. This includes, but is not limited to coincident *Illex* fishing and environmental monitoring, satellite derived indices, and mechanistic experiments for ground-truthing working hypotheses. This research requires precise fishing locations as well as spatially-explicit *Illex* size distributions, which ties to research recommendations 1 and 2 detailed above. The ultimate goal of this research should be to identify a pre-season or in-season indicator (or suite of indicators) of *Illex* productivity and distribution (e.g. availability). In the near term an understanding of mechanisms underlying in-season variations in squid availability can be used to inform generalized depletion modeling.

In particular, research aims should focus on the identification of spawning locations, characterization of oceanographic conditions (habitat) for different life stages, as well as efforts to ground truth and expand upon recent research presented in Salois et al. (2022).
Specific research to pursue includes: Increased Illex sampling efforts throughout the slope sea across multiple life history stages (e.g.: larval, juvenile, adult); Categorization of environmental conditions/dynamics of proposed nursery habitat (slope water composition); Isolation and near-real-time monitoring of the shelf break front position via satellite derived metrics; Standard and continuous categorization of warm core ring trajectories and other mesoscale features; Real-time monitoring of salinity maximum intrusions along shelf break; Identification of Illex spawning locations; Cooperative research with the fishing industry to sample for Illex within warm core rings during the fishing season; and Increased efforts to support fine scale monitoring (both spatial and temporal) including increased fleet participation in fine scale catch reporting inclusion of new data fields, such as details around location selection in order to identify if fishing locations are reflective of fishing behavior (gear restrictions, steepness of

slope, [mis]matches in trip length/duration with vessel processing abilities) or patterns in squid distribution (aggregation in areas of high productivity).

5) Given the high cost associated with ageing squid, further research regarding the development of Biological Reference Points that are not age-based, and that also account for the species' sub-annual, semelparous life history is needed.

6) Three types of at-sea storage/processing of *Illex* catch occur in the directed fishery; sorting, packing and freezing (freezer trawlers) and catch storage on ice (ice boats) or in refrigerated seawater (RSW boats). Knowing which vessel type is associated with each *Illex* and longfin squid permit is imperative for accurate LPUE standardization and research involving fishing behavior. However, such data are not available in any NEFSC or GARFO databases. This "vessel type" data must be collected annually because vessels have been converted from one type to another. Previous recommendations to resolve this important data gap have not been addressed so it is being reiterated here and consists of adding a "vessel type" field to the annual permit renewal form for both *Illex* and longfin squid permits so that "vessel type" data will be available in the GARFO Permit Database.

7) As recommended in previous *Illex* assessments, fleet-wide high resolution data collection should be investigated to improve spatial analyses of catch, effort and biological data. This information would be useful in the near term for depletion modeling with open population assumptions. This could be accomplished through several mechanisms, including daily catch and effort data collection for the full fleet, participation in the NEFSC Study Fleet, or development of an automated routine for identifying fishing activity from Vessel Monitoring System data. Study Fleet data could be used to ground truth fishing patterns identified via VMS data. There may be legal impediments to automated processing and use of VMS data for *Illex* assessment and management that should be considered.

8) One of the challenges of the 2021 *Illex* Research Track Stock Assessment was data access by WG participants who are not federal employees. A data portal for external researchers working on shortfin squid (including landings, catch, effort, size/weight, etc.) should be pursued for future *Illex* Research Track Stock Assessments.

9) The NEFSC's stratified random bottom trawl surveys cover the largest area of *Illex* habitat on the U.S. shelf and upper slope. Therefore, these surveys are the best available survey platform for representative sampling of paired *Illex* body weight and length data. Like the other assessed species, body weight data could be collected at the time of length sampling, the latter which currently occurs. Other research surveys cover smaller areas of *Illex* habitat but paired weight-length sampling during these surveys would also be beneficial for stock assessments.

10) Better refine the catchability of the *Illex* fleet (freezer boat, wet boat [RSW and ice boats]) and availability of *Illex* to the fishery and to NEFSC surveys to inform and refine the mass-balance approach.

11) Explore *Illex* distribution, abundance, and body size in the slope sea throughout the year to better estimate *Illex* biomass and body size outside of fishing areas as well as immigration into,

emigration out of, and escapement from the fishery. Note that current bottom trawl fishing and survey technology are not capable of fishing in the depths of the slope sea. Access to the slope sea by the trawl fishing industry is currently prohibited by fishery regulation, and fishery independent surveys do not currently sustain a seasonal presence in the slope sea. Additional technologies, such as acoustics or remotely operated survey vehicles, would need to be explored.

TOR 11: Develop a "Plan B" alternate assessment approach to providing scientific advice to managers if the analytical assessment does not pass review.

As noted in the Introduction of this report, the previous benchmark assessment review for *Illex* (2005 SAW 42; NEFSC 2006), concluded that "More and better data are needed to underpin the analyses" that had been attempted to estimate stock size and mortality rates. The review therefore also concluded that stock status could not be determined because model results were not available to estimate fishing mortality rates and absolute stock size. The 2005 SAW 42 assessment instead simply provided information on trends in research survey indices, fisheries catch and LPUE data, and biological data collected during prior cooperative research projects.

Since the 2005 SAW 42 assessment, the NEFSC has provided annual fishery and survey data updates to the MAFMC to inform the specification of the annual Overfishing Limit (OFL) and Acceptable Biological Catch (ABC). Given unusually high landings in 2017-2018, in 2019 the MAFMC formed a work group to consider approaches for setting ABCs. For reference, the history of those how those approaches were developed and used is provided below.

The current work seeks to advance the assessment in terms of the WG response to the relevant TORs, with considerable effort put into improving age determination, standardization of landings per unit effort, assessment of environmental variation as it relates to stock productivity and availability, and further development of in-season and per-recruit analytical models. This TOR requests that the WG develop a "Plan B" alternative assessment approach if these analytical results are deemed insufficient for use in evaluating the status of the stock and providing catch advice.

The WG recommends that the stock status is unknown with respect to reference points-based definitions of overfishing and overfished. However, the scientific evidence examined in the current assessment is sufficient to conclude that the *Illex* stock was lightly fished in 2019. The WG recommends that the MAFMC and NMFS continue to use the current Indirect Estimation Methods approach (Rago 2021) to guide establishment of future ABC recommendations.

An annual approach aligns with the biology of *Illex* and should be considered by the Northeast Region Coordinating Council (NRCC) and Assessment Oversight Panel (AOP) as assessments schedules are developed.

Illex **Quota History and Procedures**

Early History

The original squid FMP was adopted in the late 1970s. A preliminary Maximum Sustainable Yield (MSY) of 40,000 mt was based on biological considerations such as yield-per-recruit, growth rate, survey abundance, and assuming a moderate to strong stock-recruitment relationship (Anderson 1976). An optimum yield (OY) of 30,000 mt was set to provide for "cautious development" of the fishery. The MSY value was still 40,000 mt with an OY of 30,000 mt through Amendment 5 to the subsequent Mackerel Squid Butterfish (MSB) FMP in 1995. Amendment 6 (1996) indicated that the then most recent assessment (1996 SAW 21; NEFSC 1996) evaluated biological reference points and settled on a F50% target of 19,000 mt, believed to be sustainable over a wide range of stock sizes. A proposed rule for the 1997 specifications indicated that an F20% for *Illex* was being implemented in Amendment 6, with a resulting maximum OY of 24,000 mt, but specified 19,000 mt based on F50% as an appropriate *target* harvest level per SAW 21. The 1998 specifications specified a maximum OY of 24,000 mt and an allowable biological catch of 19,000 mt.

Amendment 8

The MAFMC submitted Amendment 8 to the MSB FMP in 1998, to bring the FMP into accord with the Sustainable Fisheries Act. The new overfishing definition for *Illex* squid in Amendment 8 included a target yield associated with 75 percent of the fishing mortality at maximum sustainable yield (FMSY), initially calculated to be 18,000 mt. However, upon review of the overfishing definition, the NEFSC discovered an error that target yield had been calculated as 75 percent of MSY, rather than being based on a 75 percent of FMSY calculation. Further, the overfishing definition had inadvertently cited a draft version of the 1996 SAW 21 assessment. The NEFSC determined that the actual yield associated with FMSY should be set at 22,800 mt, and so that was the final allowable biological catch specification for 1999, although maximum OY remained at 24,000 mt.

1999 SAW 29 and 2000-2018 Specifications

The 1999 SAW 29 (NEFSC 1999) concluded that the stock was not in an overfished condition and that overfishing was not occurring. Due to a lack of adequate data, an estimate of yield at FMSY was not updated. However, an upper bound on annual F was computed for the U.S. exclusive economic zone (EEZ) portion of the stock based on a model that incorporated weekly landings and relative fishing effort and mean squid weights during 1994-1998. These estimates of F were well below relevant biological reference points. Current absolute stock size was unknown and no stock projections were done. Since data limitations did not allow an update of yield estimates at the threshold and target F values, maximum OY and allowable biological catch were specified at 24,000 mt, and remained there through the 2018 specifications. Beginning in 2009 the MAFMC SSC began setting Acceptable Biological Catches (ABC) for *Illex*, which create a ceiling on the catches that can be specified by the MAFMC. The MAFMC's original risk policy prohibited ABC increases when an OFL could not be defined, but subsequent modification of the risk policy allowed increases if the SSC could determine that stock biomass appeared stable or increasing, and that the recommended increase would not be expected to result in overfishing.

2019 Specifications

Despite rejecting the basis of a MAFMC ABC remand (which requires stringent criteria for revisiting an ABC recommendation), the SSC discussed the basis of its previous ABC specification. The SSC considered whether there were any changes in knowledge of the biology of *Illex* squid, the information on the recent catches, and information presented to it on catches of

Illex squid in the NEAMAP survey. The SSC concluded that raising the ABC to 26,000 mt in 2019, and perhaps 2020 as well, would most likely not cause overfishing. The SSC encouraged the Council and industry to pursue collaborative endeavors to address questions such as:

- If an OFL can be estimated given current information
- What alternative squid management might look like?
- Identifying a feasible approach for in-season management
- Data that are needed to support a stock assessment that estimates an OFL or in-season management
- Who does the work, costs, and requirements
- What has been done in the past here, and in other regions?
- Signals that the SSC should be looking for to adjust ABC

2020 Specifications

In May 2020, the SSC considered a number of analyses of a workgroup intended to address short-term catch/quota setting, given the timing of the upcoming Research Track Assessment (intended to be available in 2022). The research topics considered by the workgroup included CPUE, availability, biomass/mortality envelope bounding, and real-time condition determination. The SSC recommended an ABC for *Illex* squid for 2020 of 30,000 mt, as the evidence reviewed by the SSC lead it to believe that harvests in the range of 18,000-30,000 mt would be unlikely to result in overfishing. Catches above 30,000 mt had not been previously analyzed in the National Environmental Policy Act documents required as part of the management process, thus constraining the range of practical ABC options at the time.

2021 Specifications

For the May 2021 SSC meeting, and given the timing of the research track assessment, Dr. Paul Rago was asked to evaluate an additional 10% increase in catch relative to the biomass and fishing mortality bounding approaches considered in 2020. Updated availability and net efficiency information was also reviewed. Based on evidence presented to it, including patterns that suggested an increase in stock abundance, low levels of exploitation, and catches that have been constrained by existing ABCs for the last four years, the SSC continued to believe that the *Illex* stock was at a high level of abundance and experiencing a low exploitation rate. While the SSC requested that in the future they be consulted about catch ranges being analyzed, the SSC increased the ABC recommendation to 33,000 mt for 2021-2022.

ACKNOWLEDGEMENTS

The WG is especially grateful to the owners of Lund's Fisheries and The Town Dock for donating the *Illex* samples that allowed us to conduct the biological data analyses and to Jason Didden (MAFMC Atlantic Mackerel, Squid, Butterfish FMP staff lead), who facilitated obtaining MAFMC funding for the 2019 biological data collection and ageing work. In addition, the assessment would not have been possible without the body weight data collected over the years by staffs at Seafreeze Ltd. and Lunds Fisheries as well as the many NEFSC fishery observers, survey scientists and crews and survey database managers, GARFO port samplers and port agents, and our state partners who collected and provided the NEAMAP and state survey indices. Finally, there are many *Illex* fishermen who have participated in previous in-season assessment-related pilot studies and have provided the assessment lead with important knowledge about what they observe when fishing for *Illex*, and to them, the WG is truly grateful.

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