# Improving Management and Conservation of Cusk (Brosme brosme): Habitat Distribution, Bycatch Interactions, and Conservation Practices 

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# IMPROVING MANAGEMENT AND CONSERVATION OF CUSK (BROSME BROSME): HABITAT DISTRIBUTION, BYCATCH INTERACTIONS, AND CONSERVATION PRACTICES 

By<br>Jocelyn Runnebaum<br>B.S. Stephen F. Austin State University, 2006<br>A DISSERTATION<br>Submitted in Partial Fulfillment of the<br>Requirements for the Degree of<br>Doctor of Philosophy<br>(in Marine Biology)<br>The Graduate School<br>The University of Maine

August 2017

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# IMPROVING MANAGEMENT AND CONSERVATION OF CUSK (BROSME <br> BROSME): HABITAT DISTRIBUTION, BYCATCH INTERACTIONS, AND CONSERVATION PRACTICES 

By Jocelyn Runnebaum<br>Dissertation Advisor: Dr. Yong Chen

An Abstract of the Dissertation Presented in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy<br>(in Marine Biology)

August 2017

Cusk (Brosme brosme) are a National Oceanic and Atmospheric Administration species of concern, currently under internal status review for the Endangered Species Act, but are considered data limited. Current concerns for cusk include: decline in abundance, increase in fishing mortality relative to survey biomass, increased patchiness in habitat, and lack of management ( 72 FR 10710). Future management will require an improved understanding of cusk distribution, habitat use, spatial distribution of bycatch interactions, and the impact of bycatch on the population. This study set out to evaluate changes in cusk distribution and habitat, locations and levels of bycatch, and the feasibility of implementing conservation measures to reduce discard mortality of cusk bycatch.

Data limited approaches were developed to map cusk habitat and potential areas of bycatch. A spatio-temporal delta-Generalized Linear Mixed Model (GLMM) was used to combine observations from the Northeast Fisheries Science Center (NEFSC) spring and fall research bottom trawl survey with the NEFSC western Gulf of Maine (GOM) co-operative
research longline survey. The resulting density estimates were then used to develop model-based habitat suitability index (HSI) maps for cusk with increased data resolution.

The American lobster (Homarus americanus) fishery is thought to be a significant source of mortality for cusk, as such bycatch of cusk within this fishery was evaluated. Bycatch 'hotspots' were predicted based on the overlap of cusk and American lobster high quality habitat. Field studies were conducted in collaboration with Maine lobster fishermen to evaluate the ability of cusk to survive incidental catches within the lobster fishery. These studies resulted in an estimated $75 \%$ survival rate in the medium-term (4-14 days) if recompressed. To evaluate the impact of implementing the recompression of cusk as a conservation measure throughout the Maine lobster fleet stock assessment simulations were conducted. Cusk bycatch was first estimated for the Maine lobster fishery to develop the simulation scenarios. These estimates indicate $2-9$ cusk are caught per 10,000 trap hauls, depending on location. Life history parameters were also estimated for cusk for the simulations. The stock assessment simulations indicated that a decrease in fishing mortality would be beneficial to the population, but only decreasing mortality from the Maine lobster fishery would not be enough to significantly improve the population status.

## DEDICATION

The journey was long, the road was hard, but the support of my loved ones kept me moving forward. To my wonderful family, thank you for the support you have provided from the very beginning. To my friends near and far, you have touched my life in so many ways and changed the way I see the world. Thank you for the unconditional love and support of my rock.

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Fishermen collected data on the survival rates of cusk when recompressed within lobster traps used in Chapters 4 and 5. Jason Alley, Tim Alley, Arney Gamage, Brian McClain, Jeremy McLellan, Steve Train, and Eben Wilson provided an incredible learning environment for me and supported the cusk barotrauma project despite the contentiousness of the research. Their dedication to science and the resulting friendship is greatly appreciated. Thank you to Patrice McCarron and the Maine Lobstermen's Association for providing a platform to discuss cusk bycatch with the industry and for the support to fishermen carrying at-sea observers.

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## CHAPTER 1

## AN INTRODUCTION TO CUSK (BROSME BROSME)

### 1.1. Habitat

Cusk (Brosme brosme) are a demersal species preferring complex bottom types in relatively deep waters. The depth range for cusk has been documented between 20 to 1000 m (Collette and Klein-MacPhee, 2002), with preferences for moderately deep waters of 120 to 140 m (Hare et al., 2012). Within the Gulf of Maine cusk, historically, have rarely been caught below 180 m and in less than 18 m (Collette and Klein-MacPhee, 2002). Cusk are thought to prefer hard, rocky substrate that provides structure for hiding (Husebo et al., 2002; Rountree and Juanes, 2010; Hare et al., 2012). Remotely operated vehicle (ROV) experiments on Stellwagen Bank National Marine Sanctuary showed cusk tended to be common around boulders (Rountree and Juanes, 2010) but are occasionally found on gravel and mud (Bergstad et al., 1998; Harris and Hanke, 2010). Cusk are a dominant finfish species in deep-sea coral reefs in the Northeast Atlantic, with a preference for coral habitats over non-coral habitats (Husebo et al, 2002). Norwegian fishermen reported reduced cusk catches in areas on the continental shelf in the Northeast Atlantic that were once dominated by coral reefs but have since been reduced by bottom trawl fishing (Husebo et al., 2002).

Cusk are thought to prefer bottom water temperatures between $9^{\circ}$ and $10^{\circ} \mathrm{C}$ and are inhibited by water colder than $4{ }^{\ominus} \mathrm{C}$ (Oldham, 1972). In the face of climate change and warming ocean temperatures, cusk habitat could be impacted (Hare et al., 2012). A decrease in preferred habitat and increased patchiness of habitat has been predicted for cusk under high emission climate change scenarios (Hare et al., 2012). The Gulf of Maine is at the southern extent of the
range for cusk in the Northwest Atlantic (Oldham, 1972), thus warming bottom temperatures over the next $50-100$ years could be detrimental to cusk in this region (Hare et al., 2012).

Cusk are a rare species with low catch rates in seasonal surveys in the Northwest Atlantic and in commercial fisheries (Beacham, 1981; Harris and Hanke, 2010). Many basic biological questions remain for cusk because of the limited data available. Habitat use of adult and juveniles has not been well documented (Harris and Hanke, 2010; Rountree and Juanes, 2010). Maximum age and age at maturity has yet to be validated (DFO, 2014). No spawning aggregations have yet to be found for cusk, indicating this is not part of their reproductive strategy (Harris and Hanke, 2010).

Available diet studies show cusk are opportunistic predators. Their diet in the deep-sea corals off Norway were dominated by unidentified decapods, fish, and polychaetas (Husebo et al., 2002). Forty-nine cusk sampled from the NEFSC bottom trawl survey conducted from Cape Fear, North Carolina to Nova Scotia from 1977 to 1980 had a decapod crustacean dominated diet followed by bivalves, mollusks, gastropods, echinoderms, cnidarians, urochordates, and fish (Bowman et al., 2000).

### 1.2. Range and Population Structure

Cusk are found throughout the North Atlantic Ocean. They range from Newfoundland to Cape Cod in the Northwest Atlantic (Oldham, 1972; Hare et al., 2012) to the European Shelf in the Northeast Atlantic (Hare et al., 2012). Cusk are found throughout the Gulf of Maine but have declined in abundance by $75-80 \%$ in the NEFSC spring and fall trawl survey (1963 to 2009; Hare et al., 2012).

The population structure of cusk is affected by bathymetry. Genetic samples were taken from eight locations throughout the North Atlantic from 2004 to 2008 to determine the impact of the physical environment (i.e., depth, bathymetry, and ocean circulation) on cusk population structure (Knutsen et al., 2009). Successful genetic samples were scored for at least five of seven microsatellite loci for 764 specimens (Knutsen et al., 2009). Genetic differences were detected among individuals that were separated by distinct bathymetric features and individuals in habitat close together were more similar (Knutsen et al., 2009). Differences were most notable between areas that were divided by deep ocean ridges and basis (> 1000 m ), indicating cusk are not inhabiting these deep ridges (Knutsen et al., 2009). These results prompted ongoing discussions for the Northwest Atlantic population to be considered a distinct population segment (Hare et al., 2012).

### 1.3. Known Life History

Cusk spawn in the late spring and early summer in the Gulf of Maine and Georges Bank (Berrien and Sibunka, 1999) with no known spawning aggregations (Oldham, 1972). Similar to other gadids, cusk are highly fecund with an estimated 100,000 to 3 million eggs produced by females between 56 and 90 cm (DFO, 2014). There is discrepancy in the aging of cusk, some estimates found cusk to be sexually mature by age five or six (approximately 50 cm total length), with a generation time estimated at nine years, and a maximum life expectancy of twenty years (Harris and Hanke, 2010; Oldham, 1972). More recent aging data from Canada found cusk reaching sexual maturity at age 10 , a generation time of fifteen years, and a larger fish ( 82 cm ) estimated to be 39 years old (DFO, 2014; Davies and Jonsen, 2011). Length-at-age studies have been minimal in the Northeast Atlantic, but it is thought that most cusk reach maturity by 40-

45 cm or eight to ten years of age (Harris and Hanke, 2010; Beacham, 1981). Aging cusk using otoliths is difficult due to interpretation problems as 20-30\% of large specimens ( $40-70 \mathrm{~cm}$ ) have unreadable otoliths (Flodevigen et al., 1996).

Cusk eggs are buoyant, between 1.06 and 1.38 mm , with an oil globule and are identifiable based on the pitted chorion (Markle and Frost, 1985). Larvae are approximately 4 mm at hatching and remain pelagic until approximately 50 mm when they migrate to the benthos (Harris and Hanke, 2010; Collette and Klein-MacPhee, 2002).

### 1.4. Biology

Cusk are an elongated fish with a rounded body before the vent and more compressed after the vent, tapering towards the caudal fin (Collette and Klein-MacPhee, 2002). Cusk color vary ranges from a dark gray to brown to green and yellow with a lighter colored belly (Collette and Klein-MacPhee, 2002). Cusk have a single dorsal fin that runs uniformly down the length of the body starting just behind the head and ending at the caudal fin as distinctly separate (Collette and Klein-MacPhee, 2002). Cusk have one anal fin which starts approximately mid-way down the body and ends at the caudal fin, also distinctly separate (Collette and Klein-MacPhee, 2002). The caudal fin and the pectoral fins are rounded in shape, with a fleshy base and the fin rays becoming visible towards the ends (Collette and Klein-MacPhee, 2002). The pelvic fins are elongated with freed fin rays at the ends and are found almost directly under the pectoral fins (Collette and Klein-MacPhee, 2002). Their body and head are covered in small cycloid scales (Collette and Klein-MacPhee, 2002) which makes them appear almost scale-less (Flodevigen et al., 1996). Cusk have a sub-terminal mouth with one barbel under the chin (Collette and KleinMacPhee, 2002).

### 1.5. Swimbladder Physiology

Swimbladders are an energy-efficient method of obtaining neutral buoyancy within the water column (Smith and Croll, 2011). As a hydrostatic organ, the swim bladder is involved in respiration, the production of sound, and in some species sound reception (Helfman et al., 1997). The swimbladder originates from the foregut as a dorsal outgrowth with two general types, physoclistous and physostomous. Physoclistous swimbladders, as found in cusk, are completely closed off from the esophagus. Physostomous swimbladders, as found in salmonids for example, are connected with the pneumatic duct between the swimbladder and the gut, which allows gases to be quickly "exhaled" or "inhaled" (Harden-Jones, 1951a; Harden-Jones, 1951b; Nichol and Chilton, 2006). Physoclistous species lose the connection to the foregut during embryonic development while physostomous species retain the connection (Helfman et al., 1997; Evans, 1998). In some physoclistous species the ductus pneumaticus develops into the resorbing section of the swimbladder while in physostomous species is the ductus pneumaticus is the connective organ (Evans, 1998), which allows for air exchange between the swimbladder and the environment.

Two types of physoclistous swimbladders have previously been identified, paraphysoclistous and euphysoclistous (Steen, 1970). Areas of gas secretion and reabsorption are not distinctly separate from each other in paraphysoclistous swimbladders but are in euphysoclistous swimbladders. Some euphysoclistous species have a diaphragm, a posterior chamber for reabsorption separated from the area of secretion by a membrane with an adjustable opening in the center (Steen, 1970). Other euphysoclistous species do not have a distinct chamber but only have a well vascularized region separated by the rest of the swimbladder mucosa by a muscular sheath called the oval (Steen, 1970). There are other physoclistous species
that do not have a distinct oval or diaphragm and resorption occurs throughout the swimbladder (Hoar, 1970).

Physoclistous swimbladder inflation can take several hours to days (Evans, 1998; Nichol and Chilton, 2006; Campbell et al., 2009). Gases are concentrated by the countercurrent arrangement of arterial and venous capillaries known as the rete mirabile to increase partial pressure of the blood. The increased partial pressure of the gases allows for diffusion into the swimbladder (Evans, 1998). The Root effect reduces the oxygen carrying capacity and the Bohr effect reduces oxygen affinity of hemoglobin in low pH . The Root effect can be thought of as an exaggerated Bohr effect (Evans, 1998). Local acidosis at the rete mirabile reduces the capacity of hemoglobin to bind oxygen, which increases the amount of unbound $\mathrm{O}_{2}$. The unbound $\mathrm{O}_{2}$ creates a pressure gradient and allows for the swimbladder to achieve a high partial pressure of oxygen. The Root effect is found only in fish hemoglobin among species that possess a swimbladder and/or choroid rete (Evans, 1998). The choroid rete maintains ocular partial pressure in species adapted to life at high pressure (Evans, 1998; Wittenbert and Haedrich, 1974). Not all demersal species possess a choroid rete, but many if not all gadoid species are thought to have them (Wittenbert and Haedrich, 1974). Conversely, species with a swimbladder are thought to have rete mirabile; they are well developed in most physoclistous species but only weakly developed in physostomous species (Hoar, 1970).

Organisms are at hydrostatic equilibrium with the environment when at neutral buoyancy (Harden-Jones, 1951a). Swimbladder gases will change volume with changes in pressure and temperature (i.e., the combined gas law; Smith and Croll, 2011). One atmosphere is roughly equivalent to ten meters of the water column. An organisms hydrostatic zone is roughly equivalent to the atmosphere they are in equilibrium with (Harden-Jones, 1951a). A decrease in
hydrostatic pressure causes gases in the swimbladder to be reabsorbed into the blood. Gases diffuse back into the blood per the partial pressure gradient (Hoar, 1970). The elevated $\mathrm{O}_{2}$ blood leaving the area of reabsorption flows directly to the gills where some of the oxygen will be released to the environment due to differences in partial pressure between gill surface and the water (Hoar, 1970). An increase in hydrostatic pressure will require secretion of gases into the swimbladder due to a decrease in gas volume to maintain hydrostatic equilibrium.

Cusk possess a physoclistous swimbladder to maintain neutral buoyancy at high pressure. The exact physiology of the cusk swimbladder is unknown and areas of reabsorption in the cusk swimbladder have not yet been described. The cusk swimbladder does have well developed drumming muscles, like other gadoids, (Hawkins and Rasmussen, 1978), with substantial evidence suggesting the swimbladder is used for sound production (Rountree and Juanes, 2010).

### 1.6. Threats to the Species

On March 9, 2007 NOAA initiated an internal status review of cusk for listing with the Endangered Species Act, citing significant threats to the species: bycatch in commercial fisheries; increasing catches in the recreational fishery; no existing regulatory mechanisms for the fishery; habitat loss and degradation, increasing habitat patchiness (72 FR 10710, 2007). In 2003, the Canadian Committee on the Status of Endangered Wildlife in Canada (COSEWIC) completed a status report for cusk assessing the species as Threatened (Harris, 2010) and updated the status to Endangered in 2012 (DFO, 2014) due to persistent declines in population levels. Cusk have been declined listing on the Canadian Species at Risk Act (SARA) to date (DFO, 2014), which would provide full legal protection to cusk (Harris, 2010), much like the ESA. The evaluation of cusk in Canada partially influenced the U.S. initiating a status review for listing
cusk on the ESA (Tallack, 2012), in addition to the steady decline in abundance in the NEFSC autumn bottom trawl survey since the 1960s (O'Brien, 2006).

Cusk are predominately caught as bycatch in the longline, gillnet, and trawl groundfish fisheries and as bycatch in the lobster fisheries in both the United States and Canada (Harris et al., 2002; O'Brien, 2006). Cusk have been increasingly targeted in recreational fisheries in recent years (Figure 1.1), presumably due to the decline in Atlantic cod (Gadus morhua) in the Gulf of Maine (Tallack, 2012). Cusk are currently unmanaged in the United States which allows recreational anglers to keep all cusk they catch and there is no bycatch quota for any U.S. commercial fisheries.

Cusk are vulnerable to high discard mortality due to their swimbladder physiology. For species that are not targeted commercially nor are economically valuable, incidental catch and discarding can be a significant source of mortality. Cusk experience barotrauma when brought to the surface in fishing gear and remain positively buoyant. Incidental catches, the resulting barotrauma, and discarding are likely significant threats to the cusk population.


Figure 1.1. U.S. commercial and recreational cusk landings, 1946 - 2016 (NEFSC landings data). In recent years, recreational landings (dashed lined) exceed commercial landings (solid line).

### 1.6.1. Barotrauma

Physoclistous teleost are likely to have a defined bathymetric range due to the swimbladder restricting vertical movement (Harden-Jones, 1951a; Brown and Thatje, 2014). Deep-dwelling organisms become adapted to high-pressure environments and are sensitive to perturbations from those environments (Brown and Thatje, 2014). Physoclistous fish adapted to high pressure will experience expansion of the swimbladder when forced outside of their depth range, potentially to the point of rupturing (Harden-Jones, 1951a). The trauma resulting from a reduction in pressure is known as catastrophic decompression (Rummer and Bennett, 2005) or barotrauma (Brown et al, 2009). Physoclistous species are likely to become positively buoyant
when brought to the surface due to gas expansion. Their ability to return to a depth of neutral buoyancy is inhibited and the chance of predation increases during this vulnerable state (Jarvis and Lowe, 2008). The likelihood of being positively buoyant is a function of capture depth and the size of the fish (Hannah et al., 2008b).

Barotrauma causes severe physical external and internal injuries. Observable injuries include stomach eversion, exophthalmia, intestinal protrusion from the cloaca, external hemorrhaging, subcutaneous gas bubbles, and ocular gas bubbles (Rummer and Bennet 2005; Hannah et al., 2008b; Rogers et al., 2008; Campbell et al. 2009; Pribly et al., 2009; Butcher et al., 2012). Unobserved injuries include organ torsion, hemorrhaging in the liver, blood in the peritoneal cavity, and blood in the pericardium (Hannah et al., 2008a). Expansion of the swimbladder is thought to increase its permeability. Gases have been observed to infuse the tissues around the head kidney, heart, and postcranial musculature when a distended swimbladder was present (Hannah et al., 2008a). Gases were observed to move anterio-dorsally through the body and thought to be the cause of ocular gas bubbles, exopthalmia, and other external signs of barotrauma (Hannah et al., 2008a). This research concluded that external trauma can be attributed to the gases from the swimbladder following a path of least resistance within the body and not from fluid gases coming out of solution (Hannah et al., 2008a). However, others perceive observable injuries from barotrauma to be a result of changes in the state and volume of gas filled organs like the swimbladder and bubbles present elsewhere in the fish in addition to gas released from solution in the blood. Brown et al. (2010) attributed the damage of internal organs to the increase in blood pressure in the arteries and veins from increased blood volume from gases being released from solution. Exophthalmia and ocular clouding could arise from gases expanding in the choroid rete.

Barotrauma is not immediately lethal to an animal, but an increase in capture depth can increase the presence of trauma. Pacific rockfish (Sebastes spp.) had an increase in external signs of barotrauma with increasing capture depth (Hannah et al., 2008b). However, an increase in number of physical traumas present in Pacific rockfish is not predictive of survival potential (Hannah and Matteson, 2007; Jarvis and Lowe, 2008). Fish can survive barotrauma if recompressed (Jarvis and Lowe, 2008; Hannah et al., 2008a; Rogers et al., 2011; Butcher et al., 2012). Treating barotrauma by recompressing fish increases the chance of surviving surface predation (Jarvis and Lowe, 2008; Hannah et al., 2008a; Rogers et al., 2011). Rosy rockfish (Sebastes rosaceus) were found to have a higher survivorship if recompressed or returned to capture depth almost immediately after capture (Rogers et al., 2011). Cod swimbladders are likely to rupture but is not lethal; they were able to recuperate from barotrauma in two to seventeen days, depending on the original depth of capture (Nichol and Chilton, 2006). Pacific rockfish behavior was shown to not be severely affected by recompression; most individuals maintained vertical orientation and could quickly swim away (Hannah and Matteson, 2007). Pacific rockfish also had a $68 \%$ survival rate over a two-day period with most of the animals showing no physical symptoms after two days (Jarvis and Lowe, 2008). Barotrauma did not cause mortality in snapper (Pagrus auratus) over a three-day period and individuals could recover in the short term, under the environmental conditions they experienced (Butcher et al., 2012). Red emperor (Lutjanus sebae) could quickly repair the damage to their swimbladders from barotrauma (Brown et al., 2010).

Investigations into alleviating barotrauma have been well documented (Jarvis and Lowe, 2008; Hannah et al., 2008a; Rogers et al., 2011; Butcher et al., 2012). However, there is limited data regarding specific protocols for alleviation as well as diagnosing the physical condition of
many species that suffer from barotrauma (Butcher et al., 2012). Time at the surface and between capture and release is known to impact the survival of an animal and should be shortened during treatment (Brown et al., 2010). Line-caught red emperor were returned to twenty meters after venting treatment showed improved buoyancy and swimming ability (Brown et al.,2010). It is thought that the speed of pressure release from barotrauma might be the most important factor in deciding which treatment to administer (Brown et al., 2010; Butcher et al., 2012). A quick return to capture depth will lower the probability of predation, oxygen demand, energy expenditure, stress from warm surface water temps, sun exposure, or being hit by boats (Butcher et al., 2012). Treatment experiments on snapper showed venting to provide the quickest release of pressure (Butcher et al., 2012). However, venting only releases air from the swimbladder, not from all tissues, indicating that recompression might be a better method of release, although the longterm consequences of recompression are unknown as is the vulnerability of a disoriented recompressed animal (Butcher et al., 2012). Potential benefits of treating barotrauma might outweigh the negative impacts of that treatment (Butcher et al., 2012).

### 1.6.2. Bycatch and Discard Mortality

Discard mortality is dependent on the individual's physiology, the amount of physical trauma experienced, the environmental conditions experienced, the gear type encountered, and the skill of the fisherman. These factors are variable but contribute to the physiological condition of captured species, making survival dependent on the situation (Cooke et al., 2013). Despite being context specific, these variables can be used to predict what factors influence mortality across the population and in turn used for management decisions (Cooke and O'Connor, 2010).

For instance, regulations in California specify a depth limit for recreational groundfish fishing (California Fish and Wildlife, 2015). Conservation policies could require fishers to release captured fish under the assumption that a certain percentage will survive. Fishermen must make an instantaneous decision as to whether or not they should release a fish and in what manner it should be released. This decision will hinge on the fisherman's previous experience with a particular species and presumptions about a fish's ability to survive given its condition. Despite any discarding policies in place, fishermen will make an instantaneous decision to comply with the law, which will impact the effectiveness of those policies and on population estimates. Physoclistous species that exhibit external signs of barotrauma are likely to be perceived by fishermen as having a reduced ability to survive, potentially leading to reduced discarding of these species.

It has been estimated that the Gulf of Maine lobster fishery accounts for approximately $80 \%$ of all cusk discards on average (Tallack, 2012). Estimates of cusk bycatch in the 2008 Gulf of Maine lobster fishery ( 102 mt ) were double that of 2008 commercial landings ( 54 mt ) of cusk in the United States (Bannister et al., 2013). When examined at the trap level the Maine lobster fishery is estimated to catch an average of two fish per 1000 traps annually (Zhang and Chen, 2015). These interactions are seasonal, as fishermen in the spring and fall experience higher catch rates than in the summer when fishing effort is highest (Figure. 1.2; Chen and Runnebaum, 2014).

## Cusk Bycatch in the Maine Lobster Fishery



Figure 1.2. Cusk bycatch in the lobster fishery by month. Fishing pressure is highest between June and November in the Maine lobster fishery (Maine DMR lobster sea sampling data, 2006 2013).

### 1.6.3. Overview

Cusk biology, distribution in the Gulf of Maine, and bycatch in the lobster fishery is not well understood. This dissertation explores different aspects of the incidental catch of cusk in the Gulf of Maine lobster fishery. Chapter 2 evaluates cusk habitat utilizing the NEFSC spring and fall bottom trawl and bottom longline surveys to improve habitat mapping of cusk. Chapter 3 evaluates the overlap of cusk and lobster habitat to predict locations where bycatch is likely to occur. Chapter 4 evaluates the significant factors that influence cusk surviving recompression.

Chapter 5 uses a computer simulation to assess possible impacts of not including cusk bycatch on the stock assessment with different survival rates survival rates if recompressed.

The systematic study conducted in this dissertation provides valuable information that fills knowledge gaps in our understanding of cusk population dynamics and provides insights on the conservation of this species that is at historically low levels. The framework developed in this study can also be applied to other species with similar life history and status. The significant policy implications of this study are discussed throughout.

## CHAPTER 2

## HABITAT SUITABILITY MODELING OF CUSK IN THE GULF OF MAINE BASED ON A SPATIO-TEMPORAL MODEL

### 2.1. Introduction

Habitat suitability indices (HSI) are a method of assessing relative habitat quality for a species based on abundance at associated environmental conditions for a given location (Brooks, 1997; Chen et al. 2009). These models have been extensively applied to evaluate potential habitat for aquatic species utilizing abundance indices derived from survey catch data (e.g., catch per unit effort, CPUE) (Terrell, 1984; Terrell and Carpenter, 1997; Morris and Ball, 2006). The predicted HSI can be projected spatially, providing valuable representation of habitat quality and potential locations of essential fish habitat (Chen et al., 2009). Habitat use and distribution is a critical aspect in the management and conservation of species that are in decline. Conventional HSIs that are based on survey data with declining catch rates for a species are not able to account for changes in catch rates over time, catch rates that are not reflective of species density, or missed sampling of a species' habitat. These factors need to be accounted for in order to produce an unbiased understanding of habitat quality for a species.

HSIs assume that high density of a species indicates high quality habitat and that the absence or low density of a species indicates habitat of low value to the species. The use of catch data as a proxy for density assumes that sampled catches truly reflect the density or absence of a species at a given location and are not confounded by stock status, sampling inefficiency and bias. This assumption may be reasonable for species that have relatively constant and high survey catchability over space and time. However, for species that have low abundance and are
poorly sampled (e.g., low survey catchability or reside in habitat that is not well covered by the survey program), or for which survey catchability has changed over time, conventional HSIs may perform poorly or even produce biased results.

Conventional HSIs use available data from sampled locations, hereinafter referred to as sample-based HSIs, which are often restricted to the locations of occurrence and typically processed to assume that the samples are representative (i.e., the species is effectively sampled) and are comparable through time (i.e., no changes in sampling distribution and efficiency). Therefore, the sample-based HSIs might not be appropriate in at least the following two situations: 1) the survey misses a significant portion or type of the species' habitat; and 2) sampling efficiency (i.e., catchability) changes over space and/or through time due to densitydependent processes. Density-dependent habitat selection is a likely mechanism for species in decline (MacCall, 1990). When a species population is high, individuals move into previously marginal habitat because high quality habitat is saturated; thus, the overall suitability of all occupied habitat declines on average (MacCall, 1990). Conversely, as populations decline, individuals retreat to the highest suitable habitat as it becomes less densely occupied and available (MacCall, 1990; Hare et al., 2012).

Another limitation of sample-based HSI arises when data from multiple surveys are available for a species. Attempts to combine data from multiple surveys face serious difficulties, including quantifying the relative differences of catchability among different sampling gear (i.e., trawl and longline). Such complications often result in discarding data by trimming the survey data to common surveyed areas and time periods with consistent survey methods or utilizing only one data set. This is often unsatisfactory due to losses in spatial coverage given that different surveys of different gear types usually sample different areas or habitats. For example,
trawl surveys likely do not sample rocky habitat as well as longline surveys. If rocky bottom is one of a species' preferred habitat types, using only trawl surveys for developing HSIs could bias the results.

Cusk (Brosme brosme) in the Gulf of Maine is one species facing difficulties with using conventional HSIs. It is a data-limited species, with low abundance, and low catchability. Cusk populations are monitored by two different multispecies survey programs, the Northeast Fisheries Science Center (NEFSC) spring and fall research bottom trawl survey (BTS) and more recently by the NEFSC cooperative research bottom longline survey (LLS) in the Western Gulf of Maine. These two survey programs differ in sampling efficiency, spatial coverage, and duration. Rocky, complex habitat, thought to be utilized by cusk, is not well sampled by the BTS. Cusk catchability is believed to have declined in the BTS time series due to declines in stock abundance (Davies and Jonsen, 2011; Hare et al., 2012). Additionally, changes to the survey protocols over the time series could impact the catchability of cusk in the BTS. In 2009, the BTS changed the sampling vessel, net type, and tow duration (Politis et al., 2014). The protocol changes in 2009 required conversion coefficients to be estimated for all species to allow for the data to be combined into a continuous time series (Miller et al., 2010). However, low catch numbers and low frequency of occurrence of cusk during the calibration study prevented conversion coefficients to be estimated for cusk (Miller et al., 2010). Catch declines of groundfish species within the BTS prompted the development of a bottom longline survey (LLS) to enhance monitoring efforts for data poor and depleted stocks residing in rocky habitat (Hoey et al., 2013). Both survey programs are stratified by depth and overlap in the Western Gulf of Maine (Figure 2.1). The LLS is able to sample rocky, complex bottom types more effectively than the BTS covering the same region, due to the nature of the gear.


Figure 2.1. Gulf of Maine and Georges Bank study area for habitat suitability mapping. All analyses were restricted to this region. The open circles represent positive catches of cusk in the NMFS spring and fall bottom trawl survey (1972 - 2015), and the gray circles represent all sampled locations for the bottom longline survey (2014 - 2015).

The BTS has shown a decline in the survey abundance index and mean size of cusk within U.S. waters of the Northwest Atlantic (Sosebee and Cadrin, 2006; Hare et al., 2012). The GOM and Georges Bank (GB) are the southern extent of the range for cusk and account for the majority of habitat within U.S. waters. Concerns regarding overfishing of the population, climate change, and increased patchiness of cusk habitat prompted a National Marine Fisheries Services (NMFS) internal status review of cusk for the Endangered Species Act (72 FR 10710, 2007). To implement effective management and conservation for cusk an understanding of their habitat distribution and use is necessary (Brooks, 1997; Hare et al. 2012).

Traditional HSIs use empirical data from one survey to evaluate habitat quality (Tanaka and Chen, 2016), and model performance is dependent on the quality and quantity of input data (Jowett and Davey, 2007). In the case of cusk, the BTS would likely not provide a realistic evaluation of habitat quality because of catch declines over the time series and poor sampling in rocky habitat. This study proposes a modeling framework for data limited species, like cusk, by combining the bottom trawl survey and the bottom longline survey data to derive model-based density estimates to improve spatial resolution of data for use in HSIs. An independent spatiotemporal model (Thorson et al., 2015) is used to derive spatially explicit density estimates from the bottom trawl and bottom longline surveys combined. The spatio-temporal model estimates a grid-based, season-specific cusk density over the entire study area, controlling for catchability. Grid-based density estimates are then used to develop season-specific HSI models, predicted over the same grid. The spatio-temporal model includes catchability, to account for the 2009 BTS gear changes, and allows for data from different gear types to successfully be combined by accounting for differences in gear catchability. The results from the model-based HSI are contrasted with those derived from sample-based HSI to test the hypothesis that HSI
performance would improve with the use of higher resolution spatial information from combining multiple surveys and imputing values for un-sampled locations.

### 2.2. Methods

### 2.2.1. Survey and Environmental Data

Cusk data are available from the NEFSC spring and fall bottom trawl survey (1980-2015) and the NEFSC spring and fall bottom longline survey (2014-2015). The BTS is a demersal, multispecies, depth stratified random survey synoptic of the GOM and GB. The NEFSC developed a depth stratified random longline survey in the western and central GOM to better sample species that primarily reside in complex habitat (Hoey et al., 2013). Six survey strata were selected for the LLS from ten offshore and four inshore strata from the BTS. This survey also samples in the spring and fall to coincide with the BTS and randomly samples hard bottom sites within each stratum (Hoey et al., 2013). The LLS follows the tidal cycle, with gear deployed one hour before slack tide and fished for two hours. The longline gear is one nautical mile long, with 1000 semi-circle hooks baited with squid set within a three-nautical mile grid (Hoey et al., 2013).

Environmental variables known to impact cusk habitat are depth, temperature, and sediment type (Hare et al., 2012). Cusk have been documented between 18 m and 1000 m and are thought to tolerate temperatures between $0^{\circ} \mathrm{C}$ and $14^{\circ} \mathrm{C}$, with the majority of cusk occurring between $6^{\circ} \mathrm{C}$ and $10^{\circ} \mathrm{C}$ in the GOM (Cohen et al., 1990; Collette and Klein-MacPhee, 2002). Cusk are thought to prefer rock, gravel, or pebble sediment but are known to inhabit mud areas in the GOM, but not smooth sand (Cohen et al., 1990; Collette and Klein-MacPhee, 2002). These three environmental variables were used to develop HSIs for the GOM and GB (Figure 2.1).

Simulated bottom temperature data (1980-2013) were obtained from the Northeast Coastal Ocean Forecast System (NECOFS) integrated atmosphere-ocean model forecast system for the GOM, GB, and New England Shelf regions. The simulated temperature data were generated from an unstructured Finite-Volume Community Ocean Model (FVCOM) grid for these regions (Beardsley, Chen, and Xu, 2013; NECOFS, 2013) and averaged over the primary two months when the surveys were conducted.

For sample-based HSIs, depth data from the BTS were used. For model-based HSIs depth was extracted from the General Bathymetric Chart of the Oceans (GEBCO) 30 arc-second interval grid. Sediment data were extracted from the United States Geological Survey (USGS) East-Coast Sediment Texture Database (Poppe et al., 2014) using Geographic Information System (GIS). The study area was divided into 5710 cells $\left(0.05^{\circ} \times 0.05^{\circ}\right)$ for developing a modelbased abundance index and to predict grid-based HSIs by season. Simulated environmental variables were assigned to the beginning of the trawl survey location for sample-based HSIs and to the center of $0.05^{\circ} \mathrm{x} 0.05^{\circ}$ grid cells for model-based HSIs.

### 2.2.2. Spatial-Temporal Model for Predicting Abundance

A spatio-temporal delta-generalized linear mixed model (delta-GLMM) developed by Thorson et al. (2015) was applied (using the VAST package in R; Thorson et al., 2017) to data collected from both NEFSC BTS and LLS to estimate cusk density fields from 1980-2015. This is a two-stage model that ultimately infers population density throughout the study area. Sample data is fit in two stage by: (1) estimating the probability of encountering and catching cusk (i.e., presence/absence) then (2) estimating catches (C) when cusk are present (Thorson et al. 2015).

The first model component estimates the probability $(p)$ of catching at least one of the target species:

$$
\begin{equation*}
\operatorname{Pr}[\mathrm{C}>0]=p \tag{2.1}
\end{equation*}
$$

The second stage of the model approximates positive catches (c):

$$
\begin{equation*}
\operatorname{Pr}[\mathrm{C}=\mathrm{c} \mid \mathrm{C}>0]=\operatorname{Gamma}\left(\mathrm{c}, \sigma^{-2}, \lambda \sigma^{2}\right) \tag{2.2}
\end{equation*}
$$

The probability density function $\operatorname{Gamma}(c, x, y)$ is evaluated at $c$ given a gamma distribution, where $\lambda$ is the expected catch if encountered, and $\sigma$ is the coefficient of variation for positive catches (Thorson and Ward, 2013; Thorson et al., 2015).

Spatial autocorrelation is incorporated into the model as a random effect to account for the spatial dependence of species density. Spatial $(\omega)$ and spatio-temporal $(\varepsilon)$ autocorrelations are, two Gaussian Markov random fields are included in both stages of the model as a random effect (Thorson et al., 2015). The random fields are approximated at 250 pre-specified knots that are generated based on the proportional density of survey data over the defined domain (i.e., the $0.05^{\circ} \times 0.05^{\circ}$ grid; Thorson et al., 2015). The spatial ( $\omega$ ) and spato-temporal ( $\varepsilon$ ) random effects were used in both spring and fall density estimates.

Encounter probability $p$ and positive catch rates $\lambda$ are approximated using linear predictors (Thorson et al., 2015):

$$
\begin{align*}
& p_{i}=\operatorname{logit}^{-1}\left(d_{T_{(i)}}^{(p)}+Q_{i}^{(p)}+\omega_{J_{(i)}}^{(p)}+\varepsilon_{J_{(i)}, T_{(i)}}^{(p)}\right)  \tag{2.3}\\
& \lambda_{i}=w_{i} \exp \left(d_{T_{(i)}}^{(\lambda)}+Q_{i}^{(\lambda)}+\omega_{J_{(i)}}^{(\lambda)}+\varepsilon_{J_{(i)}, T_{(i)}}^{(\lambda)}\right) \tag{2.4}
\end{align*}
$$

where $p_{i}$ and $\lambda_{i}$ are the expected probabilities of an occupied habitat and positive catches given occupied habitat for sample $i$ at a given location; $d_{T_{(i)}}$ is the average reference density (encounters/positive catch rates) in year $T_{(i)}, Q_{i}$ is catchability for each survey; $w_{i}$ is the area
swept for sample $i, J_{i}$ is the nearest knot to sample $i, \omega_{J(i)}$ is a random field accounting for spatially correlated variability at knot $J_{i}$ that is persistent among years; $\varepsilon_{J(i), T(i)}$ is the random field accounting for spatio-temporal correlation at knot $J_{i}$ in year $T_{(i)}$; (Thorson et al., 2015). Spatial and spatial-temporal random fields were used in all models for both seasons.

A design matrix with indicator variables for each survey is used to estimate $Q_{i}$. This study assumes the need to estimate three catchability parameters due to the BTS protocol changes in 2009 and the inclusion of the LLS. A three-column design matrix was built using ThorsonUtilities with as many rows as observations and reduced to a two-column matrix for identifiability. The 2009 protocol changes cause the intercepts of $Q_{i}$ and $d_{T_{(i)}}$ to be collinear due to a lack of variance in $Q_{i}$ in a given year as a result of two non-overlapping time-blocks in the BTS. To resolve this issue, year effect was modeled via a temporal autocorrelation structure:

$$
\begin{align*}
& \beta_{1}(t+1) \sim \operatorname{Normal}\left(\rho *_{\beta 1}(t), \sigma_{\beta 1}^{2}\right)  \tag{2.5}\\
& \beta_{2}(t+1) \sim \operatorname{Normal}\left(\rho *_{\beta 2}(t), \sigma_{\beta 2}^{2}\right) \tag{2.6}
\end{align*}
$$

where $\rho_{\beta 1}$ and $\rho_{\beta 2}$ are defined as a random walk and specified as one in the model (Thorson, 2017).

Catchability is then removed from the model and the underlying species density is predicted at each knot. Grid cells are assigned the density of the nearest knot based on closest Euclidean distance calculated using the Voronoi tool in the PBSmapping package in R (Schnute et al., 2013). This also estimates the area associated with each knot that can be used to estimate total abundance across the domain is then calculated as:

$$
\begin{equation*}
\hat{b}_{t}=\sum_{j=1}^{n_{j}} a_{j} \log ^{i t} t^{-1}\left(d_{T_{(i}}^{(p)}+\omega_{J_{(i)}}^{(p)}+\varepsilon_{J_{(i)}, T_{(i)}}^{(p)}\right) \exp \left(d_{T_{(i)}}^{(\lambda)}+\omega_{J_{(i)}}^{(\lambda)}+\varepsilon_{J_{(i)}, T_{(i)}}^{(\lambda)}\right) \tag{2.7}
\end{equation*}
$$

Full model details can be found in Thorson et al. (2015).

Within the delta-GLMM, catch rate was estimated as catch number by area swept (Thorson et al., 2015). Area swept for the BTS tows in the GOM have been standardized as $0.024 \mathrm{~km}^{2}$ for the Bigelow, and $0.038 \mathrm{~km}^{2}$ for the Albatross IV and the Delaware II (NEFSC, 2013). The area fished $\left(A_{i, y} \mathrm{~km}^{2}\right)$ for the LLS is calculated as the distance between the beginning location of the longline and the end of the longline set in $\mathrm{km}(L)$ times an estimated bait plume (b) along the length of the longline for each sample site $(i)$ in a given year $(y)$.

$$
\begin{equation*}
A_{i, y}=L_{i, y} b \tag{2.8}
\end{equation*}
$$

The bait plume (b) is assumed to be a fixed constant $(=0.28 \mathrm{~km})$ for all years and all locations. Evaluation of the impact of varying bait plume sizes on density estimates can be found in Appendix I.

In summary, the delta-generalized linear mixed model is a variation on the standard generalized linear model. This is a two-stage model that first estimates the probability of presence then estimates positive catch rates in the second stage. To account for the spatial dependence of species density within the model, spatial autocorrelation is incorporated into the model as a random effect. Positive catch rates in the model are a function of area swept. However, this study is combining two types of surveys with two different concepts of area swept. The bottom trawl survey area swept is considered a standardized volume that is a function of the width of the doors and trawl speed. Longline surveys do not have a standardized area fished. The area impacted by the bait plume is a function of current speed, water temperature and density, and hunger of the fish, the hungrier a fish is the further away it can detect bait.

The number of knots are user defined and derived over the spatial domain based on the relative sampling density. The first and second stage of the model is fit using the survey data. The first stage of the model is fit as a function of annual average density, catchability, and spatial
and spatial temporal random effects estimated from the nearest knot. The second stage of the model is fit given all of the same parameters as a function of area swept. Catchability is then removed and the underlying species density is predicted at each knot. Density is then assigned to each grid cell, generated for the entire domain, based on the closest grid (closest by Euclidean distance).

### 2.2.3. Habitat Suitability Indices

HSIs quantify the overall habitat quality for a species by evaluating species density associated with each selected environmental variable. Suitability Indices (SI) quantify the relationship between an environmental variable and species abundance at a given location (Terrell, 1984; Terrell and Carpenter, 1997; Morris and Ball, 2006). SIs are then combined either through a geometric mean or an arithmetic mean to derive an overall habitat suitability index to quantify habitat quality from relatively good (1) to relatively bad (0) (Chen et al., 2009; Tanaka and Chen, 2016). HSIs assume that locations with the highest abundance have the highest quality habitat for that organism.

Season-specific HSIs were developed for 1980-2013 mean conditions using two different types of abundance indices to compare the performance of model-based HSIs relative to sample-based HSIs. CPUE (i.e., catch number per area swept) from the BTS was used as the abundance index for the sample-based HSIs. Model-based density estimates derived from both the BTS and LLS were extracted for each cell and used in the model-based HSIs. All abundance indices were divided into spring (i.e., April - May) and fall (i.e., October - November). The time series for cusk used in this study is from 1980 to 2015, however simulated monthly mean temperature data were only available up to 2013 at the time of writing. All data (i.e., observed

CPUE and model-based density) were trimmed to 1980-2013 and averaged for the entire time series. NECOFS simulated bottom temperatures (Chen et al., 2006) were averaged for the indicated seasons for the time series. Mean environmental data (i.e., bottom temperature, depth, and sediment type) were extracted for the beginning latitude and longitude for each trawl haul and for each grid center using GIS.

Fisher natural breaks were used to bin the continuous environmental variables of depth and bottom temperature (Bivand, 2013; Tanaka and Chen, 2016). Sensitivity analyses were conducted to determine both the most appropriate number of bins for each model and the minimum bin size ( $5-8$ bins). Categorical sediment data were extracted from the USGS sediment layer, the nine defined sediment types from the layer were used as bins (Poppe et al., 2005).

For the sample-based HSIs, CPUE for cusk was calculated as catch number at station (i), in season $(s)$, and year $(y)$ per area swept for each vessel ( $v$ ) (Chang et al., 2012; Tanaka and Chen, 2015; Tanaka and Chen, 2016).

$$
\begin{equation*}
\text { CPUEi }_{\text {sy }}=\frac{\text { Catch Number }_{\text {isy }}}{\text { Area Swept }_{v}} \tag{2.9}
\end{equation*}
$$

where catch number is the total number of cusk caught per tow and area swept is standardized for each of the three vessels used in the BTS (NEFSC, 2013). For model-based HSIs, mean abundances estimated from the spatio-temporal model were used for each $0.05^{\circ} \times 0.05^{\circ}$ grid cell. The suitability index for $\operatorname{bin}(b)$ of environmental variable $(k), \mathrm{SI}_{\mathrm{j}, \mathrm{k}}$, was calculated on a 0.0 to 1.0 scale (Chang et al., 2012; Tanaka and Chen, 2015 and 2016):

$$
\begin{equation*}
\mathrm{SI}_{b, k}=\frac{\overline{C P U E}_{b, k}-\overline{\mathrm{CPUE}}_{k, \min }}{\overline{C P U E}_{k, \text { max }}-\overline{\mathrm{CPUE}}_{k, \text { min }}} \tag{2.10}
\end{equation*}
$$

where $\overline{C P U E_{b, k}}$ is the average CPUE over all sampled stations within bin $b$ for each environmental variable $k$ (Tanaka and Chen, 2015 and 2016). These SI values were then averaged by an arithmetic mean (AMM) and a geometric mean (GMM).

$$
\begin{align*}
H S I_{A M M} & =\frac{\sum_{i=1}^{n} S I_{k}}{n}  \tag{2.11}\\
H S I_{G M M} & =\prod_{i=1}^{n} S I_{k}{ }^{1 / n} \tag{2.12}
\end{align*}
$$

where all $\mathrm{SI}_{\mathrm{i}}$ represent equally weighted SI values for the $k^{\text {th }}$ environmental variable for and $n$ is the number of environmental variables included.

The sample- and model-based HSIs were based on different datasets. Due to the limitation of sample-based HSI, the CPUE used was restricted to only the spring and fall BTS survey. However, model-based HSIs incorporated density estimates derived from both the BTS and LLS. Density estimates are extrapolated over the grid cells based on the abundance estimates for the nearest knot. The $0.05^{\circ} \times 0.05^{\circ}$ grid size was used to increase spatial resolution for environmental variables over the entire survey area.

### 2.3. Results

### 2.3.1. Spatial-Temporal Model for Predicting Abundance

Four model-based abundance indices were derived using only the BTS (spring and fall) then combing the BTS and LLS (spring and fall). Two catchability coefficients were defined for before and after the 2009 protocol changes to the BTS, treating the survey as two surveys within each season with no temporal overlap. Therefore, models with data from both survey programs estimated three catchability parameters and models that included only the BTS estimated two. The resulting abundance estimates do not vary in relative trend from the abundance estimates using the combined surveys. Abundance was high in 1980 - 1981 with a decline to persistent low levels since 2005 (Figure 2.2). However, there is a difference in the two most recent years of the time series (2014-2015) when the longline survey is added. Abundance estimates based only on the BTS show an increase from 2014 to 2015, while the abundance estimates based on both
survey programs show a decrease from 2014 to 2015 (Figure 2.2). All model-based abundance indices show a decrease in cusk abundance over the time series (1980-2015) for both seasons. Varying estimates of area fished for the LLS were tested to evaluate their impact on abundance estimates but were shown to have no impact because the catchability coefficient could account for differences in catch rate (Appendix I). This makes it possible to combine two different gear types without needing to know the size of the bait plume for the longline survey.

Density plots for annual species distribution indicate that the cusk population is densest in the central GOM, with annual variability (Figure 2.3). Cusk density has constricted over the time-period, with lower densities predicted inshore in both seasons later in the time series (Figure 2.3). From 1980 to 1993 cusk density is highest in the time series, with a slight decrease in density particularly in the offshore regions that are the most yellow and red (Figure 2.3). Cusk population density from 1994 to 2007 remains relatively constant in the spring and the fall. Starting in 2008 to the end of the time series shows low density levels particularly in the inshore regions. Over the time series density around Georges Bank (i.e., the southernmost extent of the plots) shows a steady decline in cusk abundance, predominately in the spring and somewhat in the fall, over the entire time series (Figure 2.3).


Figure 2.2. Brosme brosme model-based abundance indices. Derived from the both the NEFSC bottom trawl survey and longline survey combined ( $a$ and $b$ ) and the NEFSC bottom trawl survey only ( $c$ and d). The spring ( $a$ and $c$ ) and fall ( $b$ and d) model based abundance indices accounted for spatial and spatio-temporal randomness. Error bars are standard deviations from the annual mean.
(a) Spring
(b) Fall


Figure 2.3. Density field plots from the delta-generalized spatio-temporal model. Red
indicates areas of higher abundance, blue indicates areas of lower abundance.

### 2.3.2. Habitat Suitability Index Models

### 2.3.2.1. Sample-Based HSI

Sample-based SIs were derived from observed CPUE from the BTS using simulated temperature and sediment data and observed average depths. Simulated seasonal mean bottom temperatures were compared to observed instantaneous bottom temperatures from the BTS when available (Figure 2.4). The instantaneous observed temperatures were more variable (spring: $1.35^{\circ} \mathrm{C}$ to $12.30^{\circ} \mathrm{C}$; fall: $4.47^{\circ} \mathrm{C}$ to $19.20^{\circ} \mathrm{C}$ ) compared to simulated temperatures (spring: $4.29^{\circ} \mathrm{C}$ to $7.64^{\circ} \mathrm{C}$; fall: $6.66^{\circ} \mathrm{C}$ to $14.09^{\circ} \mathrm{C}$; Figure 2.4).


Figure 2.4. Linear regression of simulated and observed mean, seasonal bottom temperature. NECOFS simulated, seasonal mean temperatures (x-axis) compared to instantaneous observed bottom temperature from the NEFSC BTS (y-axis), when recorded on the survey.

Assuming the simulated temperature represents mean conditions that cusk would experience during each season, the preferred mean temperatures for cusk were between $7.05^{\circ}$ to $7.63^{\circ} \mathrm{C}$ in the spring and 8.14 to $8.72^{\circ} \mathrm{C}$ in the fall (Figure 2.5). Cusk preferred depths between 189 m to 224 m in the spring and 192 m to 227 m in the fall (Figure 2.5). Bedrock was the most preferred sediment type followed by a combination of sand, silt, and clay in the spring samplebased HSI (Figure 2.5) and combinations of clay, silt, and sand in the fall sample-based HSI (Figure 2.5).

HSIs assume that habitat quality increases with density. A simple linear regression between abundance and HSI was used to test this assumption. Sample-based HSIs for the spring and fall did not show a clear relationship between density and habitat quality (Table 2.1). Linear regressions between CPUE and sample-based HSIs in the spring showed a significant relationship (p-value < 0.01) but the models failed to fit the data well (e.g., spring AMM, CPUE $\mathrm{R}^{2}<0.072$; fall AMM, CPUE $\mathrm{R}^{2}<0.05$ Table 2.1).


Figure 2.5. Comparing model-based and sample-based suitability index curves for cusk. For these comparisons (a) all model-based abundance suitability indices (SIs) derived from both BTS and LLS; (b) sample-based abundance SIs derived from the BTS. Sediment types include: bedrock (br), gravel (gr), gravelly sediment (gr-sd), sand (sd), $33 \%$ sand, silt, and clay (sd/st/cl), $25 \%-50 \%$ sand with clay and silt (sd-cl/st), > $75 \%$ sand with silt and clay (sd-st/clay), 50-75\% clay with silt with sand (cl-st/sd), clay (cl) (Poppe et al., 2003).

Table 2.1. HSI model comparisons. Linear regression results between abundance and arithmetic mean (AMM) and geometric mean (GMM) HSI results and Pearson's correlation coefficient (estimated in R).

| Model | $\mathbf{R}^{2}$ | Correlation <br> Coefficient | p-value of t- <br> test for slope <br> coefficient |
| :---: | :---: | :---: | :---: |
| Spring AMM, model-based HSI | 0.38 | 0.62 | $<0.01$ |
| Spring GMM, mode model-based HSI | 0.44 | 0.66 | $<0.01$ |
| Spring AMM, sample-based HSI | 0.07 | 0.27 | $<0.01$ |
| Spring GMM, sample-based HSI | 0.08 | 0.29 | $<0.01$ |
| Fall AMM, model-based HSI | 0.29 | 0.54 | $<0.01$ |
| Fall GMM, model-based HSI | 0.30 | 0.55 | $<0.01$ |
| Fall AMM, sample-based HSI | 0.04 | 0.21 | $<0.01$ |
| Fall GMM, sample-based HSI | 0.04 | 0.20 | $<0.01$ |

### 2.3.2.2. Model-Based HSI

Model-based SIs were derived from density field estimates from the delta-GLMM (spring and fall, $b=0.28 \mathrm{~km}$ ). Model-based bottom temperature SI curves found $6.87^{\circ}$ to $7.25^{\circ} \mathrm{C}$ as the most suitable temperatures in the spring and $8.07^{\circ}$ to $8.68^{\circ} \mathrm{C}$ in the fall (Figure 2.5). SI depth curves for abundance indices derived from both data sets, showed that 161 m to 208 m was the most preferred depth range in both the spring and fall. For all spring and fall model-based HSI models, the most preferred sediment type was a combination of sand, silt, and clay in both the spring and fall (Figure 2.5).

### 2.3.2.3. Comparison Between Sample- and Model-Based HSI

The model-based SIs and sample-based SIs have similar results in habitat use for both the spring and the fall, except for sediment use. Both the model-based and sampled-based bottom temperature SI curves indicate cusk were caught in slightly warmer waters in the fall but prefer temperatures around $7^{\circ} \mathrm{C}$ in the spring and $8^{\circ} \mathrm{C}$ in the fall (Figure 2.5). The model-based depth SI curves showed cusk were associated with depth ranges between 2 m and 877 m in the spring and fall compared to BTS observed depth ranges in the spring (22 to 368 m ) and fall (20 to 412 m ). Both model-based depth SI curves showed 161 m to 208 m as the most preferred depth ranges in the spring and fall (Figure 2.5). These preferred depth ranges are shallower than the preferred depth ranges estimated ( 189 m to 224 m in the spring and 192 m to 227 m in the fall) by the sample-based depth SI, but show the same pattern of preferring deeper depths in the spring and shallower depths in the fall (Figure 2.5).

The model-based sediment SI histograms derived for both the spring and fall indicated a mixture of sand, silt, and clay to be the most preferred sediment (Figure 2.5). Most of the cusk
catches in both the spring and fall BTS were in these sediment types (Figure 2.6). For samplebased sediment, SI histograms indicated that bedrock was the most important sediment type in the spring and gravel the third most important for the fall (Figure 2.5). However, for the entire time series (1980 - 2013) one cusk was caught in bedrock and two in gravel in the spring, and in the fall zero were caught in bedrock and six were caught in gravel (Figure 2.6).

The model-based GMM HSIs had higher $\mathrm{r}^{2}$ and correlation coefficients for both seasons in all the models except in the fall sample-based HSI (Table 2.1). Model-based HSIs derived only from the BTS were statistically significant ( $\mathrm{p}<0.001$ ) with an $\mathrm{R}^{2}$ of 0.3836 (AMM) and 0.4366 (GMM) for the spring and 0.2927 (AMM) and 0.3041 (GMM) for the fall (Table 2.1, modeled BTS only). Model-based HSI models predicted habitat quality well relative to survey catch rates (Figure 2.7).


Figure 2.6. Spring and fall BTS positive catches of cusk by sediment type. Low catch rates of cusk at complex sediment types is likely to lead to biased sediment suitability index (SI) estimates. Sediment histograms are ordered from coarsest sediment (bedrock) to the finest sediment (clay). Sediment types include: bedrock (br), gravel (gr), gravelly sediment (gr-sd), sand (sd), $33 \%$ sand, silt, and clay (sd/st/cl), $25 \%-50 \%$ sand with clay and silt (sd-cl/st), > 75\% sand with silt and clay (sd-st/clay), 50-75\% clay with silt with sand (cl-st/sd), clay (cl) (Poppe et al., 2003).


Figure. 2.7. Cusk habitat suitability maps. These HSI maps were derived from the modelbased density estimates using data from both the bottom trawl and longline surveys. High habitat quality (red) is mostly offshore for both the spring and fall and lower habitat quality (dark blue) is mostly inshore and around Georges Bank. Positive catch rates from the BTS (circles) and the LLS (triangles) are used to validate model predictions of cusk habitat quality. The size of the circle or triangle indicate catch rates, with smaller circles/triangles indicating lower catch rates compared to the larger circle/triangle.

### 2.4. Discussion

Model-based abundance indices were used to develop HSI models for cusk in the GOM and GB. HSIs commonly used in fisheries rely on catch rates from survey data as a measure of density to determine habitat quality (Guan et al., 2016; Tanaka and Chen, 2016 and 2015; Chen et al., 2011). Abundance estimates, for a given location, derived from observed survey data for HSIs are dependent on 1) whether or not the location was sampled by the survey, and 2) if the survey was able to catch the species of interest. The spatial and spatial-temporal random effects in the model in the delta-GLMM can account for changes in spatial distribution over time and predict density distribution of a species over the study area (Thorson et al., 2015). This provides high resolution spatial data for species with low catch rates or experiencing decreased catchability in surveys. These data can better inform HSIs, which in turn are better able to explain variance in abundance at different levels of habitat quality with an increase in spatial resolution. The ability to utilize multiple data sets to inform local abundance can overcome the sampling bias of BTS for species like cusk that associate with complex habitats. Fully utilizing all available survey data changed the perception of depth and sediment preferences of cusk because of the imputed estimates for un-sampled locations. HSIs were better able to predict an increase in habitat quality with increasing density with the use of model-based abundance estimates (i.e., spring AMM r${ }^{2}=0.38$, fall AMM r ${ }^{2}=0.3$ ) compared to sampled-based HSI models derived from the spring (i.e., spring $A M M r^{2}=0.07$ ) and fall only (i.e., fall $\mathrm{AMM} \mathrm{r}^{2}=$ 0.04; Table 2.1).

### 2.4.1. Spatial-Temporal Model for Predicting Abundance

Annual abundance estimates based only on the BTS are likely biased due to densitydependent and time-varying catchability of cusk. Bottom trawl surveys are likely to produce biased estimates of abundance if the species' spatial distribution has changed over time and if gear performance varies by the habitat that the target species associates with over time (Thorson et al., 2013). Catchability of cusk in the BTS is thought to be a density-dependent process (Hare et al., 2012). The decline in cusk abundance is thought to have reduced the catchability of cusk in the BTS due to the population constricting to rocky habitat not accessible to the BTS (Davies and Jonsen, 2011; Hare et al., 2012). Cusk catches in the BTS are likely subject to changes in catchability over the time series because of these density-dependent processes. Although the delta-GLMM (Thorson et al., 2014) accounts for the changes in catchability before and after 2009, finer temporal changes, (e.g., year-specific changes) were not considered. The inclusion of the random year effect accounts for time varying catchability for the BTS before and after 2009 and for the LLS.

The LLS was incorporated into the model-based abundance estimates in an attempt to compensate for density-dependent processes. Density-dependent processes cause systematic biases in BTS CPUE estimates which can lead to large error in estimating species' spatial distribution (Thorson et al., 2013; Kotwicki et al., 2014). Including the longline survey when deriving density estimates changes the abundance estimates in the most present years (Figure 2.2). As the LLS time-series increases, the perceived systematic bias in abundance estimates from the BTS can be tested and addressed. The LLS would need to be conducted at the same locations as the BTS tows to compare catch rates from the two surveys to fully understand the consequences of spatially varying catchability (Thorson et al., 2013).

Accounting for differences in catchability has been shown to produce estimates with reduced variability when multiple vessels are involved (Thorson and Ward, 2014). Differing values for the bait plume were tested for their impact on abundance estimates (Appendix I). This essentially served as a test of the sensitivity of the model to catchability estimates for the LLS (Appendix I). Varying values of area fished had no impact on the abundance indices and estimated catchability in the model accounted for differences in area fished (Appendix I).

### 2.4.2. Habitat Suitability Index Models

Overall, the model-based HSIs were better able to account for variance in abundance at different levels of habitat quality compared to sample-based HSIs. The increased spatial resolution of density estimates (Figure 2.3) can provide information for a species' use of habitat without perfect sampling coverage or low catch rates. Utilizing model-based abundance indices changes the perception of habitat use through two mechanisms. First, inclusion of the LLS provides data for the model outside of where the BTS sampled. The use of two gear types within the model-based density estimates provides increased data on habitat use because of the ability to sample in different sediment types. By utilizing all available data, the subsequent HSIs were better informed than both the sample-based HSIs and model-based HSIs that only used the BTS to predict abundance. Second, the estimated density fields by grid provides information where the LLS and/or BTS did not sample. Increasing the spatial resolution of density estimates and the interaction with environmental variables is believed to be the primary driver in improving the HSIs.

The sample-based SI sediment curves are likely biased due to low catch rates in more complex sediment types (Figure 2.5). Few cusk were caught in bedrock (1 in spring, 0 in fall) and in gravel (2 in spring and 6 in fall) between 1980-2013 (Figure 2.5). The model-based HSIs provide abundance estimates for areas not directly observed in the survey, allowing for an improved understanding of how cusk might be utilizing different sediment types. Model-based abundance estimates associated cusk with bedrock (20 times in the spring, 21 in the fall) and gravel ( 95 times in the spring, and 88 times in the fall). Cusk are thought to predominately reside on hard bottom (i.e., bedrock and gravel; Collette and Klein-MacPhee, 2002), making the modelbased abundance estimates associated with hard bottom more realistic with regard to presumed cusk behavior. The LLS could provide catch data for sediment types that the BTS is not able to provide consistent data for, which improves the spatially explicit density estimates over the time series. Model-based abundance estimates that incorporate the LLS are thought to improve data quality for use in habitat mapping by better informing the model in areas not well sampled by the BTS.

HSI models are a relative index traditionally built from empirical data. These models are not able to account for uncertainty in their estimates. Using model-output as model-input can incorporate unaccounted uncertainty that can be magnified within the second model (Brooks and Deroba, 2015). However, the HSI model used in this study is not able to account for uncertainty no matter if modeled or empirical data are used. Future research should focus on: 1) using the delta-GLMM to evaluate habitat preference and/or 2) using model-based abundance estimates that have an associated uncertainty in abundance to account for uncertainty within habitat modeling.

This study did not assume that cusks' preferences for sediment, depth, and temperature change on an annual basis. The relationship between mean abundance and each of these variables was assumed to be constant during 1980 to 2013. HSI models are typically used to understand a species' response to changes in habitat (Terrell and Carpenter, 1997). Many HSI models assume that an organism's habitat preference does not change on an annual basis; distribution might, but the underlying relationship does not (Chen et al., 2011; Tanaka and Chen, 2015; Guan and Chen, 2016). For the HSI models in this study to provide such insight, annual predictions would need to be made. The aim of this research was to test the use of model-based abundance indices to improve habitat modeling, the next phase of this research will evaluate annual changes in habitat use based on modeled abundance.

This study does not evaluate age or size dependent processes in habitat selection. Cusk caught in the LLS had a larger median size ( 57 cm ) and narrower length range ( $30-84 \mathrm{~cm}$ ) compared to the median size cusk ( 50 cm ) caught in the spring and fall BTS, which had a much wider length range (11-94 cm). These size differences are expected given the two gear types have different selectivity. The average size at maturity for cusk in the Scotian Shelf area is 50 cm for males and females combined (COSEWIC, 2003). These two gear types catch predominantly mature individuals; a quarter of the catch is below 4 cm . Based on these size distributions, it is assumed that the habitat suitability indices represent adult habitat.

### 2.5. Conclusion

The delta-generalized spatio-temporal model provided a means of generating modeled abundance that reflects spatial heterogeneity in species density. This model also provides a method of utilizing all available survey data for a species. The incorporation of different gear types to estimate abundance can, in part, overcome systematic density-dependent sampling biases that are seen in trawl surveys when a species' abundance contracts to habitat that is not effectively sampled by the survey. Spatially explicit abundance estimates provide a means of evaluating the habitat suitability, by providing estimates in areas that were not directly sampled by the survey. The increased spatial resolution of abundance data improved the habitat suitability models in this study. A delta-GLMM offers a method of providing abundance information for areas not sampled by survey programs and for species caught in low numbers.

## CHAPTER 3

## PREDICTING BYCATCH HOTSPOTS USING HABITAT MODELS DERIVED FROM A SPATIO-TEMPORAL MODEL

### 3.1. Introduction

Bycatch remains a serious threat to the conservation of rare, endangered, or overfished species (Alverson et al., 1996; Crowder and Murawski, 1998; Morgan and Chuenpagdee, 2003; Harrington et al., 2005). A variety of mitigation measures are used to reduce bycatch including gear modifications, effort reduction, area/time closures, total allowable catch for bycatch species, levies on incidental takes, or incentive programs to reduce bycatch (Wilcox and Donlan, 2007; O'Keefe et al., 2014). Implementing a variety of bycatch mitigation measures is often thought to be the best approach for conservation of bycatch (O'Keefe et al., 2014). However, record of the spatial extent and timing of bycatch is necessary for many of these management strategies to be developed (Lewison et al., 2009).

Fisheries-dependent data (e.g., observer or logbook data) is typically used to understand the spatial-temporal patterns of bycatch (Lewison et al., 2009; Sims et al., 2008). However, not all fisheries require reporting of bycatch through logbook data nor have extensive observer coverage to effectively understand the spatial-temporal distribution of bycatch. Accurate spatiotemporal distribution of bycatch cannot be estimated without explicit times and locations of bycatch interactions from fishery-dependent data. Similarly, the spatio-temporal distribution of bycatch is difficult to assess if bycatch observations are not randomly obtained across the fishery.

The underlying ecological process of bycatch is an overlap in presence of the target and non-target species. Concurrent presence of both the target and non-target species indicates shared habitat use. The spatio-temporal patterns of habitat overlap can be used to understand the spatial extent of potential locations for bycatch interactions (Eguchi et al., 2017). The overlap in habitat use of the target and bycatch species can be used to understand persistent areas of bycatch (Lewison et al., 2009) or bycatch "hot spots". Potential bycatch "hot spots" can be spatially analyzed based on habitat maps for both the target and non-target species (Sims et al., 2008). These potential "hot spots" can then be incorporated in fisheries management to implement spatially explicit bycatch avoidance measures. Mapping the spatial extent of target and nontarget species overlap can also be used to fine tune monitoring programs for the species of conservation interest.

A habitat suitability index (HSI) offers a method of assessing relative habitat quality for a given location (Brooks, 1997; Chen et al., 2009). These models typically utilize abundance indices (e.g., catch per unit effort, CPUE) derived from fisheries-independent surveys to evaluate the quality of habitat in a step-wise process (Terrell, 1984; Terrell and Carpenter, 1997; Morris and Ball, 2006). The HSI is then spatially projected to visualize areas of suitable habitat (Chen et al., 2009). These spatially projected indices can be used to explore species habitat distribution and changes over time (Guisan and Zimmermann, 2000). The HSI is derived from suitability indices estimated for each environmental covariate (i.e., depth, bottom temperature, sediment type, and salinity) to rank binned habitat variables as relatively high or low quality based on mean species abundance for each bin (Tanaka and Chen, 2016). This provides a ranking approach to evaluate preference based on available data.

HSIs are generally derived from a single survey which limits the spatial distribution of observations. Using modeled-abundance, instead of observed abundance, has been shown to improve HSI models by increasing the spatial resolution of density estimates (Chapter 2). The spatial-temporal delta-generalized linear mixed model (delta-GLMM) allows for multiple surveys to be incorporated into abundance estimates, allowing for all data to be fully utilized when combining multiple surveys (Thorson et al., 2015; Chapter 2). Multiple surveys with different gear types are able to be combined because of the ability to estimate catchability for each survey within the delta-GLMM (Thorson et al., 2017; Chapter 2).

The objective of this research is to develop an ecological framework for predicting areas where cusk bycatch in the American lobster fishery is most likely to occur based on species habitat use. American lobster (Homarus americanus) is a key commercial species in the US, with the highest landings value from 2005 - 2014 (NMFS, 2016). Cusk are a NOAA species of concern and currently under internal status review for the Endangered Species Act (72 FR 10710,2007 ) and seasonally caught as bycatch within the American lobster fishery (Chen and Runnebaum, 2014). Bycatch reporting for the inshore Maine lobster fishery is not required, unless the fisher owns a federal permit for another fishery that requires bycatch reporting. Cusk bycatch within the American lobster fishery is an ideal case study for evaluating the utility of the ecological modeling framework that estimates species abundance given available survey data that can be used to develop habitat suitability maps to evaluate potential bycatch "hot spots."

This study utilizes the delta-GLMM to estimate spatially explicit density estimates for cusk and utilizing multiple surveys for each species (Thorson et al., 2014) following the methods in Chapter 2. These density estimates are then used to generate habitat suitability indices following the methods of developed by Tanaka and Chen (2016). First, seasonal density is
estimated for each species using a delta-GLMM. Using these density field estimates, seasonal species suitable habitat is mapped for all study years for both species. Next, the overlap in high quality habitat is evaluated on an annual basis. The overlap of high quality cusk and lobster habitat were mapped using habitat suitability index models to test the assumption of spatially explicit occurrence of bycatch. Density field estimates were mapped for both cusk and American lobster over the defined stock area for cusk. The validated HSI models were used to calculate the proportion of annual and mean overlap. The model results were validated from nominal bycatch estimates derived from the Maine lobster sea sampling program and from the NEFSC observer program.

### 3.2. Methods

### 3.2.1. Survey and Environmental Data

Abundance estimates for cusk and American lobster were derived from multiple survey programs (Figure 3.1). For cusk, data are available from the Northeast Fisheries Science Center (NEFSC) spring and fall research bottom trawl survey (BTS; 1980-2015) and the NEFSC bottom longline survey (2014-2015). For American lobster data are available from the NEFSC spring and fall BTS (1980-2015), the Maine-New Hampshire (ME-NH) BTS 2001-2015), and the Massachusetts (MA) BTS (1982-2015). The NEFSC BTS is a demersal multispecies, stratified random survey operating from Cape Hatteras, North Carolina to the Scotian Shelf in the Gulf of Maine (GOM). The NEFSC stratified random longline survey operates in the western and central GOM to better sample demersal species in complex, rocky habitat not well sampled by the NEFSC BTS (Hoey et al., 2013). Six survey strata were selected for the LLS from ten offshore and four inshore strata from the BTS. The bottom longline survey also samples in the spring and
fall to coincide with the BTS and randomly samples both smooth and hard bottom sites within each stratum (Hoey et al., 2013). The ME-NH inshore, stratified random bottom trawl survey is conducted in the spring and fall by Maine Department of Marine Resources (Sherman et al., 2005). The ME-NH BTS has four depth strata and extends to approximately twelve miles off shore, covering state waters. The Massachusetts BTS, conducted by the Division of Marine Resources (MADMR) in the spring and fall, is stratified by five biogeographic regions and six depth zones (King et al., 2010). The Maine lobster sea sampling program provides spatially explicit fisheries-dependent data about the Maine lobster fishery (MDMR,2016), but is not a randomly-designed survey program. This program began sampling bycatch in 2006, when possible. The Maine lobster sea sampling program has inherent biases due to the lack of a random-design for the survey program and inconsistency in recording bycatch. The NEFSC observer program provides catch rates of cusk by statistical area and year. Both the MDMR lobster sea sampling data and the NEFSC observer data are used to partially validate the overlap hotspots.


Figure 3.1. Study area and survey data for overlap of cusk and American lobster. The Maine-New Hampshire (ME-NH), Massachusetts (MASS), and North East Fisheries Science Center (NMFS BTS) are the bottom trawl surveys used for developing a model-based abundance index for American lobster. The NEFSC bottom trawl (NMFS BTS) and longline surveys were used for developing the model based abundance index for cusk.

Cusk habitat use is strongly influenced by depth, bottom temperature, and sediment type (Hare et al., 2012). Environmental variables known to impact lobster habitat use are temperature, salinity, and depth (Tanaka and Chen, 2016). In recognition of these abiotic factors having influence on habitat choices for both species, all four variables (i.e., depth, temperature, sediment, and salinity) were used to model habitat. Cusk have been documented between 18 m and 1000 m and are thought to tolerate bottom temperatures between $0^{\circ} \mathrm{C}$ and $14^{\circ} \mathrm{C}$, with most cusk occurring between $6^{\circ} \mathrm{C}$ and $10^{\circ} \mathrm{C}$ in the GOM (Cohen et al., 1990; Collette and KleinMacPhee, 2002). Cusk are thought to prefer rock, gravel, or pebble sediment but are known to inhabit mud areas in the GOM, but not smooth sand (Cohen et al., 1990; Collette and KleinMacPhee, 2002).

American lobsters are found in temperatures ranging from $0^{\circ} \mathrm{C}$ to $25^{\circ} \mathrm{C}$ and salinity ranging from 15 to 32 ppt (Reynolds and Casterlin, 1979; Crossin et al., 1998; ASMFC, 2015). American lobsters reside in a wide variety of sediment types; juvenile and adult lobsters can be found in mud, cobble, bedrock inshore and in similar sediment types offshore as well as in clay (Lawton and Lavalli, 1995). However, specific sediment preference is dependent on life history and molting stages (Lawton and Lavalli, 1995). American lobsters are thought to be mainly found in depths up to 50 m but have been fished along the continental shelf in waters up to 700 m (Lawton and Lavalli, 1995).

Monthly mean bottom temperature and salinity data (1980-2013) are simulated for the American lobster stock area from the Northeast Coastal Ocean Forecast System (NECOFS) integrated atmosphere-ocean model forecast system for the GOM and Georges Bank (GB) regions. NECOFS data are generated over an unstructured Finite-Volume Community Ocean Model (FVCOM) G3 grid for these regions (Beardsley et al., 2013; NECOFS, 2013; Li et al. 2017). Seasonal means were taken for the predominate three months when bottom trawl and longline surveys for cusk and American lobster were conducted. Modeled depth data were extracted from the General Bathymetric Chart of the Oceans 30 arc-second interval grid (GEBCO, 2014). Sediment data were extracted from the United States Geological Survey (USGS) East-Coast Sediment Texture Database (Poppe et al., 2014) using Geographic Information System (GIS). Simulated environmental variables were correlated to the center of $0.5^{\circ} \times 0.5^{\circ}$ cells.

### 3.2.2. Species Density Estimates

This study is an extension of previous habitat modeling efforts for cusk in the GOM that combined the NEFSC bottom trawl and longline surveys to estimate density fields for cusk to use in habitat mapping (Chapter 2). Previous density field plots were developed for the cusk stock unit (i.e., statistical areas $464-465,511-515,521-522,551,561$ ). However, this study is examining where cusk are likely to interact with the American lobster fishery. The spatial domain (i.e., grid cells) needs to match for both American lobster and cusk to compare habitat. For these reasons, density field estimates for both cusk and American lobster are estimated for the American lobster GOM and GB lobster stock unit (i.e., statistical areas 464-465, 511-515, 525-526, 521-522, 551-552, 561-562).

A delta-GLMM was used to estimate abundance indices for American lobster and cusk (Thorson et al., 2015). Multiple surveys were combined to improve spatial-temporal coverage for both species (Chapter 2). Following the methods of Chapter 2, data from the NEFSC bottom trawl and longline surveys were combined to produce location specific density estimates for cusk. Following the methods used for cusk, lobster density field plots were estimated by combining the NEFSC bottom trawl survey, the ME-NH inshore bottom trawl survey, and the Massachusetts bottom trawl survey.

The delta-GLMM is a two-staged model that estimates catch in numbers by (1) estimating the probability of encountering the target species (i.e., presence/absence)

$$
\begin{equation*}
\operatorname{Pr}[\mathrm{C}>0]=p \tag{3.1}
\end{equation*}
$$

then (2) estimating species density given the presence of a species (i.e., positive catches; Thorson et al. 2015).

$$
\begin{equation*}
\operatorname{Pr}[\mathrm{C}=\mathrm{c} \mid \mathrm{C}>0]=\operatorname{Gamma}\left(\mathrm{c}, \sigma^{-2}, \lambda \sigma^{2}\right) \tag{3.2}
\end{equation*}
$$

The second stage of the model assumes that positive catches follow a Gamma distribution for both cusk and American lobster, where $\lambda$ is the expected catch if encountered, and $\sigma$ is the coefficient of variation for positive catches (Thorson and Ward, 2013; Thorson et al., 2015).

Both stages of the model include two Gaussian Markov random fields to account for spatial ( $\omega$ ) and spatio-temporal ( $\varepsilon$ ) autocorrelations (Thorson et al., 2015). The random fields are approximated at a pre-specified number of knots that are generated over the defined domain (i.e., the $0.05^{\circ} \times 0.05^{\circ}$ grid; Thorson et al., 2015). In this study, 250 knots were preselected for both species and subsequently generated based on the proportional density of survey data over the study area for all years. Knot locations were determined by applying a $k$-means algorithm to survey location data. The area $a_{j}$ of each knot $j$ was then calculated using the Voronoi tool in the PBSmapping package in R (Schnute et al., 2015).

Encounter probability $p_{i}$ and positive catch rates $\lambda_{i}$ are approximated using linear predictors (Thorson et al., 2015):

$$
\begin{align*}
& p_{i}=\operatorname{logit}^{-1}\left(d_{T_{(i)}}^{(p)}+Q_{i}^{(p)}+\omega_{J_{(i)}}^{(p)}+\varepsilon_{J_{(i)}, T_{(i)}}^{(p)}\right)  \tag{3.3}\\
& \lambda_{i}=w_{i} \exp \left(d_{T_{(i)}}^{(\lambda)}+Q_{i}^{(\lambda)}+\omega_{J_{(i)}}^{(\lambda)}+\varepsilon_{J_{(i)}, T_{(i)}}^{(\lambda)}\right) \tag{3.4}
\end{align*}
$$

where $p_{i}$ and $\lambda_{i}$ are the expected probabilities of an occupied habitat and positive catches given occupied habitat for sample $i$ at a given location; $d_{T_{(i)}}$ is the average reference density (encounters/positive catch rates) in year $T_{(i)}, Q_{i}$ is catchability for each survey; $w_{i}$ is the area swept for sample $i, J_{i}$ is the nearest knot to sample $i, \omega_{J(i)}$ is a random field accounting for spatially correlated variability at knot $J_{i}$ that is persistent among years; $\varepsilon_{J(i), T(i)}$ is the random field accounting for spatio-temporal correlation at knot $J_{i}$ in year $T_{(i)}$; (Thorson et al., 2015). Abundance estimates were extrapolated over a prespecified survey area grid with $0.05^{\circ} \times 0.05^{\circ}$
grid cells, resulting in a density estimate for each grid cell. The prespecified grid for both cusk and lobster follows the GOM and GB defined lobster stock unit (ASMFC, 2015)

Model settings for cusk follow those outlined in Chapter 2. To account for differences in catchability between surveys a design matrix is needed to estimate $Q_{i}$ as an intercept. For cusk, this study assumes catchability needs to be estimated for the bottom trawl survey before and after the 2009 protocol changes. The protocol changes resulted in different catchabilities which could not be estimated for cusk due to low catch numbers and low frequency of occurrence during the calibration studies, preventing the estimation of conversion coefficients (Miller et al., 2010). To account for these differences the NEFSC BTS is considered to be two separate surveys. The three-column design matrix for cusk was built using the R package ThorsonUtilities with as many rows as observations and reduced to a two-column matrix for identifiability. The estimated intercepts for $Q_{i}$ and $d_{T_{(i)}}$ are collinear when both are estimated in the model. To resolve this issue, a structure on temporal variation was defined for both stages of the cusk delta-GLMM. A random walk process was defined for $d_{T_{(i)}}$ for the first stage and second stages of the cusk deltaGLMM. The random walk process can also account for time-varying catchability (Wilbert et al., 2010).

The lobster delta-GLMM also required a three-column design matrix for the three surveys included (i.e., ME-NH, MA, NEFSC BTS). A random walk process was defined also for $d_{T_{(i)}}$ for the first stage and second stages of the lobster delta-GLMM. The random walk process is also necessary to account for time-varying catchability in American lobster, but for the opposite reason to cusk. While cusk population abundance has declined (Hare et al., 2012), the American lobster population abundance has steadily increased (ASMFC, 2015).

### 3.2.3. Habitat Suitability Indices

HSI models evaluate species abundance at selected environmental variables to quantify habitat quality at a given location. Suitability indices (SI) are calculated for each environmental variable to quantify the optimal range of environmental conditions (Terrell, 1984; Terrell and Carpenter, 1997; Morris and Ball, 2006). This provides a ranking approach to evaluate preference based on available data. SIs are then averaged (i.e., geometric mean or an arithmetic mean) at each location to determine relative habitat quality from suitable (1) to unsuitable (0) (Chen et al., 2009; Tanaka and Chen, 2016). Locations with the highest abundance are assumed to have the highest quality habitat for that organism.

Seasonal HSI models were derived for cusk and American lobster to estimate habitat overlap in the defined stock unit for American lobster from 1980-2013. The time-series was truncated for the HSI models due to a lack of NECOFS modeled-temperature being available at the time of writing. The HSI model algorithm was developed by Tanaka and Chen (2016) for American lobster that previously utilized standardized catch-per-unit-effort from the ME-NH inshore bottom trawl survey (Tanaka et al., 2016). Density estimates derived from the deltaGLMM were used in the HSI models in place of sample-based abundance estimates for both species. Utilizing model-based abundance provides spatially explicit abundance in areas that were not directly sampled and has shown improvement in HSI modeling frameworks (Chapter 2).

Mean density was estimated for each cell from the annual cell density derived in the delta-GLMM. The suitability index for bin $(k)$ of environmental variable $(j), \mathrm{SI}_{\mathrm{j}, \mathrm{k}}$, was calculated on a 0.0 to 1.0 scale (Chang et al., 2012; Tanaka and Chen, 2015 and 2016):
where $\overline{D_{J, k}}$ is the mean density over all the entire study area within bin $k$ for each environmental variable $i$. These SI values were then averaged as an arithmetic mean (AMM) and a geometric mean (GMM) for each cell.

$$
\begin{align*}
& H S I_{A M M}=\frac{\sum_{i=1}^{n} S I_{i j k}}{n}  \tag{3.6}\\
& H S I_{G M M}=\prod_{i=1}^{n} S I_{i}^{1 / n} \tag{3.7}
\end{align*}
$$

where all SI $_{\mathrm{i}}$ represent equally weighted SI values associated for the $i^{\text {th }}$ environmental variable for calculating HSI values and $n$ is the number of SI values included (i.e., the number of environmental variables).

HSI models were cross validated using a subset of the data to test the HSI models built from a training set. The HSI models for the cross validation were built using $80 \%$ of the original data. To test how well the model performs when not built using all the data, $20 \%$ of the original data were used to run the 'predicted HSI'. The HSI values estimated from the training data were regressed against the HSI estimates from the test data. The cross validation was conducted for both the $H S I_{A M M}$ and $H S I_{G M M}$ were conducted for both species.

The change in habitat suitability over the time series was then evaluated for both species. HSI was estimated for each year (1980 - 2013). The vector of HSI values for each grid cell was linearly regressed by year to estimate the slope, or change, in habitat relative to the mean habitat for the time series. Slope was then extracted for each grid cell and mapped over the study area to evaluate where habitat for cusk and American lobster had changed positively or negatively over time for a given location (Tanaka and Chen, 2016). A positive slope is interpreted to mean an increase in habitat quality available while a negative slope is interpreted to mean a decrease in habitat quality available (Tanaka and Chen, 2016).

### 3.2.4. Overlap of Cusk and American Lobster

Seasonal HSI maps for both species were developed from the HSI models. Low quality habitat $\left(H S I_{A M M}<0.3\right)$ were removed for each species to evaluate the overlap of moderate to high habitat quality. Areas with moderate to high habitat quality for cusk were subtracted from areas with moderate to high habitat quality for American lobster (eq. 3.8). Mean areas of overlap $\left(\overline{O_{y, l}}\right)$ were estimated utilizing mean cusk and American lobster HSI maps for areas with moderate to high habitat quality $\left(H S I_{A M M}>0.3\right)$ :

$$
\begin{equation*}
\overline{O_{y, l}}=\overline{H S I_{\text {Lobster }, y, l}}-\overline{H S I_{C u s k, y, l}} \tag{3.8}
\end{equation*}
$$

Negative areas of overlap (i.e., -0.3) (see Figure 8 below) indicate higher quality cusk habitat suitability while positive values (i.e., 0.3 ) indicate areas of higher lobster habitat suitability. Values close to zero indicate similar cusk and lobster habitat, either both moderate or both high.

Annual overlap maps were made for each season to extract the annual proportion of habitat suitability overlap. Grid cells with an $H S I_{A M M}>0.3$ were summed across the entire study area and extracted as a proportion of the total number of grid cells in the study area for each species. The changes in annual proportion of overlap were then correlated to NECOFS simulated bottom temperature to evaluate the relationship of temperature to the proportion of habitat overlap, using the cross-correlation function in R. Temperature variability from year to year is hypothesized to drive the proportion of habitat suitability overlap for these two species with strong temperature preference and dependence.

To validate median predicted locations of overlap in habitat for cusk and American lobster, the positive catches from the Maine DMR lobster sea sampling program were mapped on top of the median overlap maps. This allows for a qualitative evaluation of where the median overlap predictions worked and did not work.

### 3.3. Results

### 3.3.1. delta-GLMM Density Estimates

The best model fit for both seasons and both species were produced with a random walk process defined for $d_{T_{(i)}}$ for the first and second stages of the models. The resulting annual abundance indices in spring and fall show a decrease in cusk abundance and an increase in American lobster over the time series (1980 - 2015; Figure 3.2).

Density field estimates for cusk show a contraction of the population further offshore while American lobster showed an expansion of the population throughout the GOM and GB region with a predominant increase in the inshore area (Figure 3.3).


Figure 3.2. Lobster and cusk abundance indices. Abundance estimates for both seasons for cusk (a and b) and American lobster (c and d).


Figure 3.3. Density field plots for American lobster and cusk. Estimated from the delta-
generalized spatio-temporal model. Red indicates areas of high abundance, blue indicates areas of low abundance.

### 3.3.2. Habitat Suitability Index Models

Seasonal HSI models for cusk and lobster were compared to determine the best method for estimating habitat quality. The AMM HSIs performed better for both cusk and lobster based on cross-validation analyses (Table 3.1). Cross-validation for cusk indicated marginal differences in model performance between the AMM (i.e., cusk spring AIC -7848.04.15, $\mathrm{R}^{2} 0.99$ ) and GMM (i.e., cusk spring AIC $-4051.97 .15, \mathrm{R}^{2} 0.93$; Table 3.1) HSIs, with the AMM having slightly less variability in predictive performance (Figure 3.4). However, the cross-validation analyses showed greater variability in predictive performance for American lobster using the GMM HSI compared to the AMM HSI (Figure 3.4). Seasonal HSI maps for both species were based on AMM HSIs.

Mean seasonal HSI maps indicate that American lobster suitable habitat is predominately inshore on the northern and southern coastal shelfs and on portions of Georges Bank and Browns Bank (Figure 3.5). The most suitable habitat for cusk is offshore in the central Gulf of Maine, outside of the prominent basins in the region and on the edge of Georges Bank (Figure3.5). Mean habitat suitability maps for cusk and American lobster are almost the inverse of each other with lobster preferring inshore habitat and cusk preferring offshore habitat.






Figure 3.4. Cross validation of habitat suitability index models. Estimated using modeledabundance from the delta-GLMM for both cusk ( $a$ and $b$ ) and American lobster ( $c$ and d).

Table 3.1. Evaluation of model fit. AIC and mean $R^{2}$ values for all models to evaluate model performance.

| Model | AIC | Mean $\mathbf{R}^{2}$ |
| :--- | :---: | :---: |
| Cusk AMM Spring | -7848.04 | 0.99 |
| Cusk GMM Spring | -4051.97 | 0.93 |
| Cusk AMM Fall | -7884.21 | 0.99 |
| Cusk GMM Fall | -5468.06 | 0.97 |
| Lobster AMM Spring | -6940.84 | 0.98 |
| Lobster GMM Spring | -6932.78 | 0.96 |
| Lobster AMM Fall | -4716.21 | 0.94 |
| Lobster GMM Fall | -7129.45 | 0.92 |



Figure 3.5. Habitat suitability maps for cusk and American lobster for the spring and fall.
The most suitable habitat for cusk is in the offshore Gulf of Maine while the highest suitability of habitat for lobster is in the inshore Gulf of Maine on the coastal shelfs.

Change in habitat suitability over the time series was evaluated for both species over the study area. Spring habitat suitability for both cusk and American lobster had a positive change over most of the study area, with the most pronounced changes occurring in portions of Georges Bank for cusk and in the central Gulf of Maine for lobster (Figure 3.6). In the fall, habitat suitability for cusk had a negative change in quality in most of the Gulf of Maine except for a few patches where it positively changed in Georges Bank (Figure 3.6). Habitat suitability for American lobster in the fall had a positive change in the Gulf of Maine and Georges Bank during the time-period (Figure 3.6).


Figure 3.6. Changes in habitat suitability for cusk and American lobster (1980 - 2013). Blue indicates a negative change in habitat quality and red indicates a positive change in habitat quality.

### 3.3.3. Overlap of Cusk and Lobster

There is inter-annual variability in the proportion of overlap for both seasons with an overall increase in the proportion of overlap in the spring and fall (Figure 3.7). Time-series analysis indicate the proportion of overlap in habitat suitability is negatively correlated with temperature in the spring and positively correlated in the fall with a slight time lag for both (Figure 3.8). In the Spring, temperature two years before have a significant negative correlation on the proportion of overlap, while in the fall temperatures seven years before have a significant positive correlation with the proportion of overlap (Figure 3.8). Salinity is significantly negatively correlated in both the spring and fall, more so in the spring though (Figure 3.9).


Figure 3.7. Proportion of habitat overlap for cusk and American lobster. The proportion in overlap of moderate to high quality habitat $\left(H S I_{A M M}>0.3\right)$ has increased over the time series.


Figure 3.8. Proportion of habitat overlap correlated to temperature. Proportion of overlap (solid line) relative to seasonal mean temperatures dashed line for spring (a) and fall (b) with associated cross-correlations between proportion overlap and seasonal mean temperatures.

Dashed blue lines on the time-series analysis (bottom plots) indicates a significant relationship.


Figure 3.9. Proportion of habitat overlap correlated to salinity. Proportion of overlap (solid line) relative to seasonal mean salinity dashed line for spring (a) and fall (b) with associated cross-correlations between proportion overlap and seasonal mean salinity. Dashed blue lines on the time-series analysis (bottom plots) indicates a significant relationship.

Mean areas of overlap of moderate to high quality habitat $\left(H S I_{A M M}>0.3\right)$ for cusk and lobster in mostly in the near shore regions along the norther coastal shelf (Figure 3.10). Mean overlap (Figure 3.10) provides evidence of persistent areas of habitat overlap along the edge of the northern and southern coastal shelf, in the central Gulf of Maine where cusk habitat is highest, and on the southern portion of Georges Bank in both the spring and fall (Figure 3.3.10). The mean overlap maps indicate higher proportion of overlap in the fall than in the spring (Figure 3.10). Mean overlap maps were partially validated by overlaying known locations where cusk bycatch in the Maine lobster fishery has occurred from 2006-2013, combined (Figure 3.10). Aggregated NEFSC observer data indicate that the higher catches of cusk (i.e., reported presence of cusk) are in statistical areas 464,515 , and 561 for all seasons combined due to data aggregation requirements (Figure 3.11).


Figure 3.10. Mean habitat overlap of cusk and American lobster. Spring (a) and fall (b) for HSI values greater than 0.3 to capture marginal $(0.3-0.6)$ and high quality $(0.6-1.0)$ habitat. Negative areas of overlap (i.e., -0.3 ) in indicate higher quality cusk habitat (blue) while positive values (i.e., 0.3) indicate areas of higher lobster habitat (yellow). Values close to zero (red) indicate similar cusk and lobster habitat, either both moderate or both high.


Figure 3.11. Positive catches of cusk observed in the NEFSC observer data from the federal lobster fishery.

### 3.4. Discussion

### 3.4.1. Delta-GLMM Density Estimates

This study developed a modeling framework to predict where cusk bycatch is most likely to occur given habitat quality of the target and non-target species. This framework incorporates a method of increasing spatial resolution of density estimates for use in HSIs for each species using the delta-GLMM. Having density estimates on the same grid allows for habitat suitability indices to be directly compared at each cell across the study area to evaluate mean (Figure 3.9) and annual proportion of overlap in habitat suitability.

Using model-based density estimates in habitat mapping offers a method of overcoming the limitations encountered when using observed data (Becker et al., 2016). The use of modeledbased density estimates allowed for multiple surveys to be combined (Thorson et al., 2016) and for habitat to be directly compared over the same grid. The use of model-based density has also been shown to improve habitat mapping for species with low encounter rates (Becker et al., 2016). Using modeled-density allows for estimates to be made in locations that are not directly sampled by the survey program, offering insight into how a species is interacting with the environment in locations where species are not directly observed or where surveys may not be able to sample well.

The model-based density estimates for American lobster show the population distributed predominately inshore with the highest density in Massachusetts waters until the late 1990s (Figure 3.3). American lobster density increased steadily over the time series, with offshore densities increasing in the most recent years (2010-2015; Figure 3.3). Density estimates show a clear increase inshore in 2000, which happens to coincide with the start of the ME-NH bottom trawl survey. Density estimates were generated without the ME-NH bottom trawl survey to evaluate how much of an impact that survey had on the 2000 population increase (results not shown). Without the ME-NH survey there was still a large increase in the inshore population of American lobster just west of Penobscot Bay. However, without accounting for temporal autocorrelation using a random walk the ME-NH survey had significant influence (results not shown). To reduce the perceived impact from temporal autocorrelation with the incorporation of a survey with a shorter time series than that of the other two surveys, a random walk autocorrelation was used for $d_{T}$ (Thorson et al., 2017), resulting in a better model fit when all three bottom trawl surveys were incorporated in the model.

Model-based density estimates for cusk in this study were expanded to include the GOM and Georges Bank lobster stock unit, which expands beyond the cusk stock unit. The density estimates for cusk in the Georges Bank region are low compared to the GOM, indicating catch rates from the trawl survey are low in that area. However, cusk HSI maps indicate portions of Georges Bank to be of high habitat quality (Figure 3.5).

### 3.4.2. Habitat Suitability Index Model

American lobster is predominately an inshore species with high habitat quality along the coast of Maine on the Northern Coastal Shelf. Habitat quality is higher in the fall than the spring (Figure 3.5), consistent with the findings from Tanaka and Chen (2016). The Southern Coastal Shelf, i.e., inshore waters around Massachusetts, also have high habitat quality. This area was not evaluated in the previous study by Tanaka and Chen (2016) that quantified habitat for American lobster, but the mean HSI maps indicate it has been important habitat for lobster over the time series.

The high habitat quality for American lobster in the Maine inshore waters is also consistent with where most of the Maine lobster fishery occurs, less than twelve miles off the coast (ASMFC, 2015). More than 50\% of Maine landings comes from the mid-coast region (ASMFC, 2015) where the habitat quality is highest in Maine, particularly in the fall (Figure 3.5). Massachusetts has the second highest landings, but $\sim 71 \%$ of the landings have come from Georges Bank since the early 1990s (ASMFC, 2016). Federal permits allow fishers to harvest in federal water ( $>3$ miles offshore); the number of these permits increased by $41 \%$ in 1988 from the previous year and have remained relatively stable since (ASMFC, 2015). Habitat quality for

American lobster increased in offshore Gulf of Maine (>12 miles offshore) and portions of Georges Bank in the spring and fall (Figure 3.6). In pursuit fisheries, fishing behavior often mirrors stock abundance (Pelletier and Magal, 1996). As a pursuit fishery (Scheirer, 2003), the increase in habitat for American lobster in offshore waters suggests federal license holders would be fishing further offshore for lobster, thus they are more likely to encounter cusk.

Cusk seasonal HSI maps indicate offshore central GOM and GB as favorable cusk habitat (Figure 3.5), consistent with findings in Chapter 2. Habitat maps for cusk were developed for a larger area in this study to evaluate potential overlap with the entire GOM and GB American lobster stock. By extending the study area, it is evident that there is a significant proportion of cusk habitat on Georges Bank (Figure 3.5) even though density estimates for much of this area are low (Figure 3.3). Cusk habitat is believed to be negatively impacted by warming temperatures in the Gulf of Maine (Hare et al., 2012). Cusk habitat on Georges Bank increased in quality in the spring over the study years (Figure 3.6), indicating this region could be of increasing importance for cusk and an area where the American lobster fishery could encounter cusk as bycatch.

### 3.4.3. Overlap of Cusk and Lobster Habitat

Mapping the overlap in habitat of target and non-target species is an indirect method of estimating where bycatch is likely to occur. Spatially explicit bycatch data from the American lobster fishery currently available is limited (ASMFC, 2015), and what does exist in the Maine lobster seas sampling data is biased due to non-random sampling of the fleet. This modeling framework provides a method of evaluating where high risk areas of bycatch are likely to be without having direct observations.

The mean overlap maps with specific locations of cusk bycatch match well in some locations and not well in others (Figure 3.10). Areas of habitat overlap are broader in the spring than the fall, which matches with our understanding of bycatch in the lobster fishery. Cusk bycatch in the Maine lobster fishery is highest in the spring (Chen and Runnebaum, 2012). Cusk bycatch interactions have been presumed to be highest in the spring because of the Maine lobster fishery increasing interaction with the species by predominately occurring offshore in the spring (Chen and Runnebaum, 2012). This study suggests that the proportion of overlap in the spring is also higher (Figure 3.7), which would also increase the probability of bycatch interactions.

The general trends in overlap matches with the current understanding of where bycatch interactions occur (i.e., offshore in the Gulf of Maine and portions of Georges Bank) given the limited documented bycatch in the Maine lobster sea sampling program (Figure 3.10) and federal observer program (Figure 3.11). Cusk bycatch data from the federal observer program did not have spatially explicit or seasonal bycatch information to identify specific areas of bycatch due to data confidentiality. However, understanding the number of cusk caught per statistical area from this data can help interpret the predicted areas of overlap. The mean overlap map predicts statistical area $511,512,513,515,464$, and 465 to have high overlap in habitat for cusk and American lobster in the spring and fall (Figure 3.10). Based on the NEFSC observer data, there have been several cusk caught in statistical areas 512, 513, 515, and 464 but not 511 or 464 .

American lobster distribution has been shown to be positively correlated with temperature and negatively correlated with salinity (Chang et al., 2010; Tanaka and Chen, 2016). The results of this study indicate that the annual proportion of overlap is negatively correlated with temperature in the spring and positively correlated in the fall. It is unclear if American lobster habitat preference or cusk habitat preference is driving this relationship. Temperature is
an important environmental variable for cusk and is thought to have a significant impact on habitat loss for this species (Hare et al., 2012). Climate projections for cusk indicate a $50-80 \%$ loss of habitat due to warming ocean temperatures (Hare et al., 2012). From 1980-2013 cusk habitat has increased in the offshore areas around Georges Bank (Figure 3.6), indicating a shift to cooler waters within their optimal thermal range ( $8-10^{\circ} \mathrm{C}$; Collette and Klein-MacPhee, 2002). Previous habitat suitability analysis indicated that cusk prefer temperatures around $7^{\circ} \mathrm{C}$ in the spring and $8{ }^{\circ} \mathrm{C}$ in the fall (Chapter 2). American lobster in the Gulf of Maine also prefer slightly warmer temperatures in the fall $\left(\sim 11^{\circ} \mathrm{C}\right)$ than the spring ( $8{ }^{\circ} \mathrm{C}$; Tanaka and Chen, 2016). A decrease in water temperatures in the spring results in an increase in proportion of overlap within a one degree temperature range ( $5.5-6.5^{\circ} \mathrm{C}$; Figure 3.8). Lobster density has been shown to increase in the Gulf of Maine when temperatures are over $5^{\circ} \mathrm{C}$ (Chang and Chen, 2010).

The proportion of overlap is negatively correlated with salinity in both seasons. American lobster's affinity for specific salinity ranges is likely driving the negative correlation in proportion of habitat overlap. American lobster has limited ability to adapt to variability in salinity (Jury et al., 1994) and pulses of fresh water in the inshore areas can cause severe mortality in lobster (Thomas and White, 1969). American lobster optimal salinity range is between 31 and 33, with preference towards slightly lower salinity in the spring than the fall (Tanaka and Chen, 2016) as seen in the proportion of habitat overlap correlated to salinity (Figure 3.9).

### 3.4.4. Model Limitations

The analysis does not capture the overlap of cusk and lobster habitat suitability in inshore western GOM as well as the central and eastern inshore Gulf of Maine (Figure 3.9). The Maine lobster sea sampling data indicates several areas where cusk were caught as bycatch, but those locations fall outside of the predicted overlap area (Figure 3.10). The NEFSC bottom trawl survey likely does not have many observations of cusk in that area, so there are few data points to inform the model-based density estimates for cusk. As more data are available for cusk in inshore areas, there may be better predictive capacity for the model-based density estimates to inform the HSI models.

These spatially explicit locations should be interpreted as areas likely to experience bycatch during the spring and fall but not as absolute locations of bycatch. HSI models do not model species distribution, they only provide data on habitat quality relative to species density at a given location (Terrell, 1984; Terrell and Carpenter, 1997; Morris and Ball, 2006). While these models are useful in understanding habitat distribution and shifts, they are limited by the input data available (Guisan and Zimmermann, 2000). Although the model-based HSIs improve the spatial distribution of data available for use in the HSIs, these estimates are also limited by the data availability.

### 3.5. Management Considerations

This study developed a modeling framework that can be used as a method of predicting locations of potential bycatch for non-target species in commercial fisheries with limited to no bycatch data. The mean overlap in habitat maps can be interpreted to be the most persistent areas of potential bycatch across all study years. There is a larger proportion of overlap in habitat in
the spring compared to the fall, consistent with the current understanding of cusk bycatch. Cusk bycatch is thought to be predominately in the spring because the Maine lobster fishery is mostly offshore during that time (Runnebaum and Chen, 2014).

Evaluating the change in American lobster and cusk habitat suitability in relation to changing ocean temperatures will be important in understanding where the bycatch is most likely to occur. This study indicates that both American lobster and cusk habitat suitability is increasing in the offshore Gulf of Maine and Georges Bank regions (Figure 3.6). These changes will be extremely important in the management of all bycatch species in the American lobster fishery as the fishery continues to move offshore in pursuit of lobster.

## CHAPTER 4

# EVALUATING THE EFFECTIVENESS OF RECOMPRESSING CUSK (BROSME BROSME) IN LOBSTER TRAPS, THROUGH COLLABORATIVE RESEARCH, AS A CONSERVATION 

 MANAGEMENT STRATEGY
### 4.1. Introduction

Bycatch is a significant issue facing global fisheries (Davies et al., 2009). Approximately $8 \%$ of all fish caught in commercial fisheries around the world are discarded (Kelleher, 2005), typically due to fisheries regulations or low economic values (Harrington et al., 2005; Rochet and Trenkel, 2005). The survival rates of these discarded individuals depend on the physiology of the species, type of gear used, handling practices, and environmental conditions (Benoit et al., 2010). Understanding how these factors might influence post-release mortality under realistic fishing conditions can lead to a better understanding of discard mortality, a significant source of uncertainty in fisheries stock assessments (Alverson et al., 1994; Davis, 2002; Chen et al. 2007; Benoit et al., 2010).

Species with swimbladders often experience barotrauma, injury or mortality when caught as bycatch due to change in pressure. The reduction in barometric pressure causes air to expand in the swimbladder, forcing the stomach to evert (Smith and Croll, 2011). Other physical traumas can include exophthalmia, subcutaneous gases, and external hemorrhaging (Campbell et al., 2009; Pribly et al., 2009; Butcher et al., 2012). Releasing positively buoyant fish at the surface is often fatal because of predation or suffocation due to the inability to return to depth quickly (Brown et al., 2010).

Treating barotrauma has been shown to successfully increase the rate of survival for physoclistous species. For example, Pacific rockfish (Sebastes spp.) have been shown to have higher survivorship over two days if recompressed in wire cages almost immediately after capture and the physical symptoms of barotrauma were reversed (Jarvis and Lowe, 2008). Snapper (Pagrus auratus) are also able to survive over a three-day period after recompression in bathy cages (Butcher et al., 2012). Cod (Gadus morhua) recuperation from barotrauma took between two and seventeen days depending on the original depth of capture when surface released after tagging (Nichol and Chilton, 2006), and individuals could survive in the short-term if they could re-submerge (i.e., swim away) on their own (Ferter et al., 2015).

This research is focused on cusk (Brosme brosme) bycatch in the Gulf of Maine American lobster fishery, highlighting the use of collaborative research to evaluate the ability of cusk to survive barotrauma. Cusk are classified as a National Marine Fisheries Services' (NMFS) "Species of Concern" and currently under NMFS internal status review for the Endangered Species Act (ESA). Concerns for this species include increased patchiness in habitat, habitat loss and degradation, incidental catch in commercial fisheries, recreational catches, and lack of management (72 FR 10710). Cusk are caught as bycatch in the Maine lobster fishery, currently reported to account for approximately $80 \%$ of all cusk discards on average (Tallack, 2012). Estimates of cusk bycatch in the 2008 Maine lobster fishery ( 102 mt ) were double that of 2008 commercial landings ( 54 mt ) of cusk in the United States (Bannister et al., 2013). These estimates suggest a cumulative impact on the cusk population, but when examined at the trap level the Maine lobster fishery is estimated to catch an average of two fish per 1000 traps annually (Zhang and Chen, 2015), with an estimated 2.7 million trap tags sold in 2015 (Maine DMR, 2017). These bycatch interactions are seasonal. They are highest in the spring and fall
when fishermen are fishing offshore in deeper water as opposed to summer when fishing effort is highest and predominately inshore (Chen and Runnebaum, 2014). Additionally, sampling programs specifically targeting cusk have had challenges in the past resulting in zero catches of cusk over a dozen sampling trips (Maine DMR, 2011). Given the low frequency of occurrence in the lobster traps and challenges in targeting cusk catch, it is currently difficult to predict timing and location of cusk bycatch.

Collaboration with stakeholders is a cost-effective method of increasing sample sizes over large spatial scales (Fairclough et al., 2014; Sorensen and Jordan, 2016). Participants in collaborative research are concerned individuals from the public (Conrad and Hilchey, 2011) that might be impacted by the outcomes of the research (Silver and Campbell, 2005). The use of volunteers in the data collection process not only decreases the cost of data collection, but increases the quantity and spatio-temporal coverage of data (Fairclough et al., 2014).

Collaborative research as increasingly been utilized in all aspects of fisheries research, from design to data gathering and analysis (Hartley and Robertson, 2009). Fishermen's observations have improved the quality of data collected, how it is analyzed, and resulting management decisions (NRC, 2004; Silver and Campbell, 2005). Fishermen have significantly contributed to knowledge of fish behavior, schooling and migration patterns, spawning grounds, and habitat preference (Johnson and van Densen, 2007). Fishermen can provide reliable, finescale fisheries information that will allow for better quality data (Johnson, 2010).

Fishermen participating in a 2011 cusk conservation workshop proposed recompressing cusk with lobster traps instead of using descending devices as have been suggested by scientists for other species (Tallack, 2012). This study used data collected by fishermen to determine survival rates of cusk using lobster traps as descending devices. This sampling program uses
fishermen to collect data and their knowledge to direct the timing of sampling trips for a rare bycatch species in the Maine lobster fishery. The specific objectives of this research are to 1) determine if cusk can survive barotrauma if recompressed and 2) evaluate if lobster traps are a suitable mechanism for recompression.

### 4.2. Methods

In 2013, the Maine Department of Marine Resources (DMR), Maine Sea Grant, and local lobster cooperatives recommended fishermen that were thought to catch cusk as bycatch and would potentially be interested in participating in this research. Those fishermen were approached individually with the opportunity to participate through data collection on their own, taking the author as an observer, or both.

### 4.2.1. Field Experiments

Fishermen collected data by conducting on-board observations to evaluate cusk survival by utilizing lobster traps as recompression mechanisms. Typical lobster traps have two to three distinct compartments called the 'kitchen' and the 'parlor(s)'. The kitchen is the baited entrance of the trap that allows for free entry and exit of the trap. The first and second parlors have one way entrances that allow organisms in but not out. In 2011, fishermen that participated in a cusk conservation workshop proposed placing cusk back into the 'kitchen' to recompress them, giving them the opportunity to escape (Tallack, 2012). This research set out testing fishermen's hypotheses.

When fishermen caught a cusk during normal fishing activities they recorded the latitude, longitude, depth, and sediment type of the catch location. They t-bar tagged cusk with a unique identification number, recorded the types of trauma present (i.e. stomach eversion, exopthalmia,
subcutaneous gases), then they replaced the fish in the front part of the trap to be recompressed. Traps were returned to the same fishing locations at approximately the same depth. On average, traps would fish six days, but ranged between four and fourteen days, before they were hauled again, at which time fishermen recorded if the cusk was alive, dead, or gone after recompression. Data were collected from 2013 to 2016 from eight fishermen.

In 2014 and 2015, one fisherman conducted surface release experiments, providing useful information about the immediate outcome for surface releases. Cusk were observed for 30 seconds after release at the surface and documented as either "swam away" or "floated" at the surface. These surface release experiments were not conducted by other fishermen but provided preliminary analyses to compare to other surface release experiments.

The author accompanied fishermen on selected fishing trips to validate this data collection method and to collect video data of cusk being recompressed. The observer was advised by the fishermen when they would be fishing in locations where cusk were likely to be caught. The observer collected the same data fishermen collected for the comparison. All observed trips were conducted in locations where cusk had previously been seen by fishermen.

Cusk that were video recorded by the author were photographed and tagged for identification purposes, and evaluated for trauma type prior to recompression. Cusk were then returned to an experimental trap with mounted video monitoring equipment to assess behavior in the traps and, whether the cusk could escape the trap. A GoPro camera in a CamDo deep water housing was used with a CamDo LED autonomous dive light in a deep-water housing was mounted to an un-baited, research lobster trap. Both time lapse ( 5 seconds) and continuous videos were taken.

### 4.2.2. Analysis of Logbook Data using Random Forest

Random forest (RF) models were used to identify the most important factors in classifying the outcome of recompression. This is a method of machine learning to derive classification trees for determining the relative importance of predictor variables (Breiman, 2001; Liaw and Wiener, 2002; Hochhalter, 2012). Generally, the data are divided into training and test data sets to build the classification trees. RF models are built through a multistage process, starting with bootstrapping (i.e., 500) samples from the training data and developing a classification tree from each randomly selected sample (Hochhalter, 2012). Each node of the tree is built by randomly selecting predictor variables, then determining which of those variables results in the most effective split (Goldstein et al., 2010). Trees are continuously added until there is one variable per node and repeated until the specified number of trees are built (Goldstein et al., 2010). Using a larger number of trees generally results in stability of variable importance (Goldstein et al., 2010), for this reason 500 trees were selected as the RF tuning parameter.

Data for this study are limited, with fifty-two observations of cusk survival in the medium-term and eleven in the short-term. For this reason, the relative importance of depth, time at the surface, stomach eversion, subcutaneous gases, exopthalmia, and days between hauls were determined for the medium-term only using the full data set to build classification trees. Preliminary analyses indicated that the starting number for randomly selecting data for bootstrapping (i.e., set seed) impacted the outcome of variable importance (results not shown). To overcome this variability, the set seed was randomly selected and RF algorithm was run iteratively 500 times, randomly changing the starting position each time to estimate mean decrease in accuracy. The mean decrease in accuracy of each variable was recorded for each run,
and is interpreted to be variable importance (VI). VI was then averaged for each factor to estimate mean variable importance $(\overline{V I})$. The reported variable importance indicates the percentage in decrease of accuracy of classifying the outcome if that variable were removed. Preliminary analysis also indicated the data set for short-term survival (11 observations) was too small for reliable classifications using RF. The RF models were built using the randomForest package (Liaw and Wiener, 2002) for R statistical software.

### 4.3. Results

From 2013 to 2016, a total of 211 cusk were reported by eight fishermen and the author from an estimated 14,000 trap hauls. The number of traps hauled were not recorded the first year of the project, therefore trap hauls were estimated based on the average number recorded in previous years. Cusk were caught between 16 m and $156 \mathrm{~m}, 96 \%$ were alive when first captured in the traps (nine came up dead when first caught). Exopthalmia was reported in $55.6 \%$ of cusk, stomach eversion in $48.3 \%$, and subcutaneous gases in $10.7 \%$, with $23.9 \%$ of cusk caught experiencing no observable symptoms of trauma (Figure 4.1). Some fish had multiple trauma types present, $9 \%$ were reported to have both subcutaneous gases and exopthalmia, $29.8 \%$ had both exopthalmia and stomach eversion, $7.3 \%$ had stomach eversion and subcutaneous gases, and $4.7 \%$ had stomach eversion, exopthalmia, and subcutaneous gases reported (Figure 4.1). Fishermen reported 163 cusk from approximately 10,000 trap hauls: 59\% $(n=97)$ were recompressed, $31.9 \%(\mathrm{n}=52)$ had definitive survival observations reported at the next haul, and $27.6 \%(n=45)$ were released overboard and observed to "float" or "swim away." The cusk that were recompressed but did not have observed outcomes of survival reported $(\mathrm{n}=45)$ were either left blank by the fisherman $(\mathrm{n}=9)$ or there were multiple cusk in the trap with no tag number
reported and varying outcomes documented $(\mathrm{n}=36)$. For the university observer, eleven cusk were recompressed with observed outcomes, out of forty-eight caught on observer days, in approximately 4,000 trap hauls.

There were forty-five cusk released at the surface by a fishermen to determine their ability to return to depth on their own. Of those released overboard, $58 \%(n=26)$ immediately swam down while the remaining $42 \%(\mathrm{n}=19)$ floated. In general, cusk that swam away came from shallower depths than those that floated at the surface (Figure 4.2). Stomach eversion and no trauma present were the most significant variables for determining classifications in the RF models.


Figure 4.1. Reported symptoms of physical barotrauma. Exopthalmia (EX), stomach eversion (SE), subcutaneous gases (SG), no trauma (NT), and combined presence of physical traumas. Exopthalmia and stomach eversion were the most commonly reported symptoms of barotrauma in cusk in this study.


Figure 4.2. Evaluating capture depth relative to surface release discarding and recompression. Depth was not a significant factor in cusks' ability to immediately swim away ( $\mathrm{p}>0.05$ ), but significant for medium term survival after recompression ( $\mathrm{p}<0.01$ ).

The two most important variables in categorizing recompressed cusk as alive, dead or gone based on the mean relative importance $(\overline{V I})$ were stomach eversion $(15.51 \% \overline{V I})$ and no trauma $(15.25 \% \overline{V I})$. Time at the surface $(11.39 \% \overline{V I})$ and the combination of exopthalmia and stomach eversion $(9.09 \% \overline{V I})$ were the next two most important variables. The least important variables were days between haul $(4.39 \% \overline{V I})$, exopthalmia $(3.77 \% \overline{V I})$, all three trauma types reported $(0.94 \% \overline{V I})$, subcutaneous gases and exopthalmia $(0.94 \% \overline{V I})$, stomach eversion and subcutaneous gases $(0.94 \% \overline{V I})$, subcutaneous gases $(0.93 \% \overline{V I})$, and depth $(-1.76 \% \overline{V I})$ (Figure 4.3).

## Surface Release



Figure 4.3. Relative importance of variables for cusk released at the surface. Random forest models were used to determine the most important factors in categorizing if a cusk could swim away or not. Stomach eversion and no visible presence of trauma were the two most important factors for surface releases.

Fifty-two fish were recompressed by fishermen were observed after 4-14 days with 38\% $(\mathrm{n}=20)$ reported to have medium-term survival (i.e., reported alive), $37 \%(\mathrm{n}=19)$ were reported gone, and $25 \%(\mathrm{n}=13)$ were reported dead. For short-term survival ( 2 and 8 hours), $82 \%(\mathrm{n}=9)$ of cusk were reported alive, $9 \%(\mathrm{n}=1)$ gone, and $9 \%(\mathrm{n}=1)$ dead. These findings support the hypothesis that cusk can survive if recompressed. The RF model found depth and time at the surface to consistently be the first and second most important variables for constructing classification trees (Figure 4). The relative importance of physical trauma (i.e., exopthalmia, stomach eversion, and subcutaneous gases), the combinations of those trauma types, lack of trauma (i.e., no trauma), and days between hauls varied in importance. The results in Figure 4 are the averages of mean decrease in accuracy for five-hundred runs. Based on these averages, depth $(18.85 \% \overline{V I})$ is by far the most important predictor variable followed by time at the surface $(13.20 \% \overline{V I})$. The combination of stomach eversion and subcutaneous gases $(10.42 \% \overline{V I})$, all three major reported trauma types $(10.38 \% \overline{V I})$ no reported trauma $(10.29 \% \overline{V I})$ and exopthalmia $(9.83 \% \overline{V I})$ are the next most important variables. The least important variables are subcutaneous gases $(5.7 \% \overline{V I})$ presence of both subcutaneous gases and exopthalmia $(5.57 \% \overline{V I})$ stomach eversion $(4.58 \% \overline{V I})$ and the presence of both exopthalmia and stomach eversion $(3.71 \% \overline{V I})$ (Figure 4.4).

## Medium-Term



Figure 4.4. Relative importance of variables for recompressed cusk. Random forest models were used to determine the most important factors in categorizing the outcomes of recompression. Depth and time at the surface were the two most important factors for categorizing if a cusk survive, died, or was reported gone.

A total of eleven videos were attempted, with six being successfully recorded (Table 4.1).
Length of videos ranged from 2 to 3.5 hours, depending on the battery life in cold, deep water. Soak times for cusk placed in traps with video equipment ranged from 2 to 8 hours. Short soak-times resulted in videos only capturing a short period of recompression for some cusk. Some observer trips resulted in no videos because of logistics or lack of catching cusk.

The videos provide insight into the initial behavior after recompression. Two cusk appear upside down for almost an hour and then flip over (right side up). One cusk seen to lay still in the traps after recompression until the video ran out (about 2.5 hours) but was alive after being hauled to the surface shortly thereafter. One cusk was more lively in the videos and appeared to not need a recovery time. One cusk escaped the trap before the trap even hit the bottom because of jerking as other traps it was connected to landed on the bottom.

Table 4.1. Outcomes for videoed recompression. Dates and depths of attempted video monitoring, * indicates successful video recorded.

| Date | Depth | Outcome |
| :--- | :--- | :--- |
| $6 / 5 / 2013$ | 187 ft | Died |
| $11 / 17 / 2013^{*}$ | 348 ft | Survived |
| $5 / 24 / 2014^{*}$ | 290 ft | Survived |
| $5 / 29 / 2014^{*}$ | 222 ft | Survived |
| $6 / 3 / 2014^{*}$ | 282 ft | Survived |
| $6 / 11 / 2014^{*}$ | 193 ft | Survived |
| $11 / 11 / 2014$ | 90 ft | Survived |
| $5 / 25 / 2015$ | 180 ft | Survived |
| $6 / 12 / 2015$ | 70 ft | Survived |
| $7 / 23 / 2015^{*}$ | 90 ft | Gone |
| $5 / 12 / 2016$ | 100 ft | Survived |

### 4.4. Discussion

This research suggests that cusk are able to survive barotrauma with an estimated $38 \%$ survival rate. The $37 \%$ of cusk reported as gone from the traps are believed to have escape, as opposed to dying and being eaten, because there was no indication of fish remains in the traps. Fishermen were asked to record if fish were dead upon re-haul or if there were any remains, for those fish to be recorded as dead. Cusk caught within the traps were between 45 cm and 75 cm , so were large enough to likely leave behind bones that would be too big to fall through the traps or be carried off by lobsters. Based on this available evidence, there is potential that medium term survival is $75 \%$ instead of the observed $38 \%$, but this cannot be validated with the available data.

This research suggests that recompression is likely a better discarding practice than surface discarding for increasing medium-term survival. Of the forty-five surface-released cusk in this study, $42 \%$ were observed to float on the surface immediately after release. The ability to overcome positive buoyancy at the surface is thought to be the most important aspect of surviving discarding (Hannah et al., 2008a). In some cases, the ability of a fish to return to depth on their own diminishes with capture depth (Hochhalter, 2012). Submergence success is thought to improve short-term survival (Hannah et al., 2008a), indicating the longer a discarded fish remains at the surface the higher the probability of mortality. Given that $42 \%$ percent of cusk did not have immediate submergence success in this study suggests that the morality rate of surface discarding is likely similar.

While recompression appears to be an effective method of increasing discard survival of cusk in the medium-term, replacing cusk back inside the lobster trap is likely not the best method of recompression. Only $37 \%$ of recompressed cusk were noted as gone from the lobster traps at
the next haul. The authors consider this to be a low percentage of escapement relative to the ability of cusk to survive (i.e., assumed $75 \%$ survival). Instead of replacing cusk in the head of the trap, descending devices could be attached externally to the trap to retain cusk long enough to reach capture depth, giving them the ability to easily escape the recompression device. However, when cusk are recompressed inside the lobster traps it appears as if there is a recovery period directly after recompression based on video data. It is unclear if the recovery period is a result of the cusk being jarred when the trap hits the bottom or if it is related to the physical traumas of decompression, time at the surface, and subsequent recompression. Hannah and Matteson (2007) found that the frequency of behavioral impairment increases with capture depth.

Depth and time at the surface were the two most important variables in categorizing the outcome of recompression in the medium-term (4 to 14 days). Depth had a significant impact on excess buoyancy and internal trauma for Pacific rockfish caught at 20 m but not at 5 m (Butcher et al., 2012), likely indicating fish caught at deeper depths sustain more trauma. Time at the surface was significant in predicting mortality within two days for Pacific rockfish (Jarvis and Lowe, 2008). Although RF models do not provide direction and statistical significance of relationships, there is the potential that depth and time negatively impact survival when evaluated within the context of other barotrauma studies.

The next most important variables in categorizing the outcome of recompression were the combination of stomach eversion and subcutaneous gases; the combination of exopthalmia, stomach eversion, and subcutaneous gases; no trauma present; and exophtlamia (Figure 4.4). Barotrauma studies on Pacific rockfish did not find specific combinations of trauma as a significant predictor of survival (Jarvis and Lowe, 2008). However, this study found that the presence of the aforementioned trauma type combinations are relatively important in classifying
recompression outcomes. Exopthalmia was considered non-informative in determining mortality in Pacific rockfish (Butcher et al., 2012). However, exopthalmia was an important variable in determining the outcome of recompression for cusk and the only physical symptom of barotrauma to do so alone (Figure 4.4). Several species of gadoids have a choroid rete to maintain the partial pressure of the eye (Wittenberg and Haedrich, 1974) and is susceptible to changes in barometric pressure, as found in swimbladders (Parker et al., 2006). Cusk likely have a choroid rete, like other genera in the family, and the cause of exopthalmia in cusk as well as increasing the potential of injury around the head and brain. Pacific rockfish with everted stomachs had gases infusing the tissues around the head kidney, heart, and postcranial musculature (Hannah et al., 2008b).

Fishermen provided more observations of medium-term survival data but with inconsistencies in their reporting. Fishermen were not as diligent at recompressing cusk or recording signs of cusk at the next haul, but they provided more comprehensive data than could be collected the author on day trips. Several fishermen expressed concerned about the outcomes of this research and the subsequent regulations that might arise. The outcomes reported by fishermen are thought to be their true observations of the outcome of cusk survival. Fishermen were forth coming with information throughout the logbook reporting, some reported instances when cusk were used for bait instead of recompressed for the study. However, there is concern that the lack of reporting outcomes $(\mathrm{n}=9)$ from some fishermen was out of fear of the consequences of the results of this research. This is consistent with findings in other collaborative research (Hall-Arber and Pederson, 1999).

Fishermen provided more data than what could be obtained on day trips by providing medium-term observations after 4 to 14 days. Several cusk observations were reported on the
same day by different fishermen. Capturing this amount of information simultaneously would require a more extensive observer program to provide the same level of observation as the fishermen provided. However, observer coverage is costly (Brooke, 2012), particularly when seeking to observer a single species with low catch rates. Fishermen increased the sampling effort for rare species that are not as easy to capture as opposed to species that are more abundant or that form aggregations such as seen in similar experiments on cod (Gadus morhua; Ferter et al., 2015).

Past studies documenting the survival of physoclistous species experiencing barotrauma rely on hiring fishing vessels to conduct experiments, which can be cost prohibitive for obtaining a large spatial and temporal distribution (Ferter et al., 2015), but more reliable in providing standardized data. However, there is a tradeoff between hiring fishing boats as research platforms and having fishermen independently collect data. Collaborating with the fishing industry is thought to increase fishermen's trust in the data (Johnson and van Densen, 2007). Although this study does not have the same precision in reporting as other barotrauma studies conducted by scientific observers, this study benefitted by having fishermen conduct their own recompression experiments because they shared their observations with fellow fishermen.

The dissemination of research findings by fishermen were witnessed by the author on days when observing at-sea. Participating fishermen were asked about the research being conducted. Often the fishermen summarized the research being conducted, their observations, and the overall findings of the project. Participating fishermen corrected the perceptions of other fishermen who thought that cusk were not able to survive citing their own experience and the video data collected by this research. This behavior was interpreted to mean that participating fishermen were accepting of this scientific research. The author believes other fishermen were
more willing to believe the results of this study when it was reported by their peers. This research was also presented to industry groups by the author over the course of the study. Despite being a contentious issue, this research was well received by those groups with overwhelming support. This reception by industry is believed to be the result of a well-established relationship of the second author with local industry groups and because of the transparency strived for throughout the research process.

The increasing use of cooperative research reflects the growing awareness that stakeholder contribution to the research process leads to higher industry acceptance. Increased acceptance of scientific research has proved to be more effective at generating higher fishermen buy-in to the research, better fisheries management, and increased stewardship of the resources as opposed to traditional scientific research practices (Wendt and Starr, 2009). Collaborative research is believed to make science more relevant to stakeholders (Johnson and van Densen, 2007) by making it more salient, credible and legitimate to the stakeholder (Cash et al., 2002). Scientists and fishermen have different perceptions of what makes research salient, credible, and legitimate (Cash et al., 2002). Extensive involvement of fishermen in this research increased the legitimacy of the research to industry (Cash et al., 2003) but is likely to reduce the perception of credibility by fellow scientists. However, it is necessary to incorporate fishermen in developing appropriate solutions to mitigate bycatch (Hall and Mainprize, 2005) to increase buy-in to the conservation practices.

The use of commercial fishermen to collect data is not a novel approach to increase the spatio-temporal distribution of sampling (Hartley and Robertson, 2009; Fairclough et al., 2014; Masse et al., 2015). However, bycatch data from fishermen's logbooks are not thought to be as reliable as observer data because of misreporting (NOAA, 2011). Similarly, data collected by
volunteers are not treated the same as formal data collection methods by trained scientists (Conrad and Hilchey, 2011). Despite these drawbacks there are three notable benefits to cooperative research: 1) it is a cost-effective approach to increasing the spatio-temporal distribution of observations for rare species (NOAA, 2011); 2) stakeholders view cooperative research as more credible science because of the democratic nature of the scientific process (Hartley and Robertson, 2006); and 3) cooperative research is an effective outreach tool (Conrad and Hilchey, 2011).

### 4.5. Handling Recommendations

Based on our findings and the current barotrauma literature, cusk should be returned to depth as quickly as possible. The amount of time spent at the surface was an important factor in classifying the outcome of recompression in this study. Brown et al. (2010) found that the amount of time at the surface should for red emperor (Lutjanus sebae) should be minimal when providing treatment for barotrauma. The longer the time that a fish with a closed swimbladder is at the surface, the more likely the gases in the swimbladder are to expand. In this study, some cusk did not have an everted stomach when first surfacing but did by the time the traps were redeployed for fishing 5-10 minutes later.

Depth was the most important variable in classifying the results of recompression in the RF models. Pacific rockfish also experience barotrauma (Jarvis and Lowe, 2007; Hochhalter, 2012; Hannah et al., 2013). Regulations in California define a depth limit for recreational fishing for Pacific rockfish (California Fish and Wildlife, 2015) to reduce the likelihood of mortality in recompressed fish. Physoclistous species that exhibit external signs of barotrauma (i.e., stomach eversion and exopthalmia) are likely to be perceived by fishermens as having a reduced ability to
survive the trauma, potentially leading to reduced discarding of these species, based on conversations with fishermen scientists in this study. Avoiding the deepest depths during seasons when cusk are likely to be caught could reduce the capture rate and subsequent mortality of cusk.

Other recompression devices were not tested in this study, but could serve as an important management tool in cusk conservation. Videos collected through this research indicate that some cusk spend time recovering in a vulnerable position directly after recompression. Given that it is unclear if this is from impact of the trap hitting bottom or from being recompressed in general, other recompression tools need to be explored for effectiveness in the long-term (i.e., several months) survival of cusk. Conversely, the empty traps could provide a safe place for cusk to recover in the short-term to avoid predation from larger predators but escapement rates are relatively low (37\%) in this study.

Several management options should be explored for cusk conservation in the future. Two observations were made during this study, through conversations with fishermen: 1) impacted stakeholders (i.e., lobstermen) should be involved in future management discussions and 2) there needs to be incentives for fishermen to participate in conservation of bycatch species. Lobstermen were uneasy about the outcomes of this research and the impact it could have on future regulations for the lobster fishing industry. However, participating fishermen scientists frequently referred to this research as proactive and hoped management decisions would reflect the findings of the study. Participants in this study also suggested incentives to get lobstermen to fully participate in bycatch conservation. Asking one commercial sector to conserve a species for another commercial sector that will likely not have access to in the future, due to closed licenses, could have negative impacts on the relationships between fishermen and managers.

### 4.6. Conclusion

This study found that cusk could survive barotrauma in the medium-term (4 to 14 days). The number of cusk observed to survive was $38 \%$ while the number observed to be gone from the traps was $37 \%$, suggesting a potential $75 \%$ survival rate for recompressed cusk. Given the $37 \%$ escapement rate, lobster traps might not be the most effective recompression tool for cusk. Depth and time at the surface are the most important factors in categorizing recompression outcomes. These findings are interpreted to mean that cusk caught in deeper depths have a higher probability of mortality, and cusk kept at the surface longer also have a higher probability of mortality.

Bycatch research is often contentious in nature, resulting in increased management measures for fishermen. Fishermen compliance with these conservation measures is driven by their perception of the legitimacy of the regulation (Nielsen et al, 2003). This research was centered on a collaborative approach to increase the credibility and legitimacy of these findings with fishermen to increase the likelihood of compliance with any potential future regulations regarding cusk bycatch in the lobster fishery.

## CHAPTER 5

## EVALUATING THE EFFECT OF REDUCING DISCARD MORTALITY RATES ON CUSK (BROSME BROSME) BIOMASS THROUGH STOCK ASSESSMENT SIMULATIONS

### 5.1. Introduction

Bycatch and subsequent discard mortality can be a significant source of unaccounted mortality of fished species, and can result in biased stock assessments (Chen et al., 2007). Discard mortality can be an even greater threat to the conservation of species that are rare, endangered, or overfished (Alverson and Hughes,1996; Crowder and Murawski, 1998; Morgan and Chuenpagdee, 2003; Harrington et al., 2005). Fishing mortality rates (F) are expected to be higher with the inclusion of discard mortality and estimates of F will be biased without inclusion of bycatch, potentially resulting in overestimation of the population size (Breen and Cook, 2002).

Harvest restrictions often require discarding of bycatch of the target and non-target species (Davis, 2002). A key assumption of discarding is long-term survival, but this is not always the case (Cooke et al., 2013). In some instances, additional conservation measures are implemented to ensure reduced discard mortality for species with low population sizes or of significant conservation concern to help the population recover. Assisted recompression of positively buoyant species experiencing barotrauma from decompression has gained momentum as a conservation tool of incidentally caught groundfish species with high susceptibility to barotrauma (NOAAFisheries, 2014; ADFG, 2017; WDFW, 2017). Survival rates are estimated to be high for many species including Pacific rockfish (Sebastes spp.; Hannah et al., 2008; Jarvis and Lowe, 2008; Hochhalter and Reed, 2011; Hochhalter, 2012), snapper (Pagrus auratus;

Butcher et al., 2012), and red snapper (Lutjanus campechanus; Campbell et al., 2010). Ideally reducing discard mortality would help the population to recover. However, this assumption should be tested to evaluate if the estimated survival is greater than the variability associated with bycatch estimates.

Cusk (Brosme brosme) are a physoclistous groundfish species that experience barotrauma, trauma from decompression, when brought to the surface by fishing gear. Catch rates of cusk in the Northeast Fisheries Science Center spring and fall bottom trawl survey have been declining since 1963 (Hare et al., 2012). There is growing concern about the population levels and mortality rates in commercial and recreational fisheries (72 FR 10710, 2007). Cusk are classified as a National Marine Fisheries Services' (NMFS) "Species of Concern" and currently under NMFS internal status review for the Endangered Species Act (ESA).

Cusk are caught as bycatch within the American lobster (Homarus americanus) fishery in the Gulf of Maine, which thought to contribute a significant proportion of total mortality for cusk. There is also concern with a potential increase in interactions between the lobster fishery and cusk due to habitat suitability of lobster increasing in offshore areas where cusk are more likely to be found (Chapter 3). In 2012, lobster fishermen proposed recompressing cusk to reduce discard mortality from barotrauma (Tallack, 2012). Survival rates of cusk caught in the lobster fishery were estimated when treated for barotrauma, a proposed conservation measure for reducing discard mortality (Chapter 4). Cusk were estimated to have a $37 \%$ known survival rate in the medium-term (4-14 days) and 38\% escapement rate (Chapter 4). If recompression of cusk is implemented state wide, before an Endangered Species Act (ESA) listing decision, the conservation measure would likely be taken into consideration during the status review process (Kass, 2015; 68 FR 15100, 2003). Conservation plans for candidate species can alter the formal
assessment of a species status if they are determined to minimize the threat(s) identified for the species (Kass, 2015). Although recompression has evidence of increasing the survival of recompressed cusk (Chapter 4), it is not clear if this conservation would increase the recovery potential of cusk.

Stock assessment simulations provide a method of adjusting varying discard mortality rates and varying bycatch rates to assess the ability of the population to positively respond to conservation practices. However, there is currently not an accepted stock assessment for cusk (NOAA, 2015), a data poor species in this regard (Hare et al., 2012). The lack of an accepted stock assessment prevents an evaluation of these conservation measures using data from the true cusk population. Instead, a simulated population developed from the known population parameters of cusk can be used to estimate the relative impact of conservation measures on the population status.

This study evaluates how varying levels of bycatch and discard mortality rates (DMR) impact the cusk population. This study first simulated a "true" population utilizing available fisheries-independent and -dependent data to derive population parameters. Second, low, median and high cusk bycatch amounts were estimated for the Maine lobster fishery based on fisheries dependent data. Finally, stock assessment simulations were conducted to evaluate the impact of recompression survival at these different levels of bycatch. These simulations provide a method of evaluating if conservation measures to recompress cusk bycatch would have a significant impact on population recovery.

### 5.2. Methods

A simulated population was developed in the NOAA Fisheries Toolbox (NFT) length based population simulator 8.0 (PopSim, NOAA, 2013) to use as input in the NFT Statistical Catch at Length (SCALE) model. Outputs from PopSim used in SCALE include: catch length frequencies, survey length frequencies, recruitment indices, and adult indices (section 5.2.3; Figure 5.1). To evaluate the impact of survival on population recovery, four discard mortality rates (i.e., $25 \%, 50 \%, 75 \%, 100 \%$ ) were applied to three estimated bycatch scenarios (i.e., low, median, high). The true population was held constant for all model runs with variability in total catch for each run for the three bycatch scenarios and four mortality rates.

### 5.2.1. Defining the True Population

Several population parameters were defined for PopSim to generate the true population. These population parameters were estimated from available survey data where possible or defined from the currently available literature. Available survey data for estimating cusk population parameters include the NEFSC spring and fall bottom trawl survey as well as the NEFSC demersal longline survey for groundfish species in the western Gulf of Maine.

### 5.2.1.1. Growth and Aging

The length-based population simulator uses parameters from the von Bertalanffy growth equation to create a growth transition matrix (NOAA, 2013). Mean length at age was estimated by combining data from the NEFSC spring and fall bottom trawl survey (1991-1994) and observer trips for the commercial fisheries (1994 and 1995; unpublished data). These data were fit to a von Bertalanffy growth function (VBGF) in R statistical program package $F S A$ (Ogle, 2013a):

$$
\begin{equation*}
\overline{L_{a}}=L_{\infty}\left(1-e^{-K\left(a-a_{0}\right)}\right) \tag{5.1}
\end{equation*}
$$

Mean length at age $\left(\overline{L_{a}}\right)$ is a function of age (a), relative to the maximum length $L_{\infty}$, growth rate (K), and the theoretical age at length zero $\left(a_{0}\right)$ (Ricker, 1975). Standard deviation of mean length for the initial population was assumed to increase with increasing age.

In PopSim, the probability of being in a given length bin is based on the number of bins between the minimum and maximum lengths and age specific variance defined by the user (Deroba and Schueller, 2013). Growth into the next year $(a+1)$ is defined based on the number of surviving fish in each length bin at each age in the next year and the user defined VBGF parameters, given the probability of being in a given length bin the next year (Deroba and Schueller, 2013). Natural mortality (M) was assumed to be 0.2 and fully selected for both sexes at all ages.

### 5.2.1.2. Length-Weight Relationship

The cusk length-weight relationship was estimated from data collected on NEFSC research bottom trawl survey (2001-2015). Observations with either missing length or weight were removed. Length-weight relationships are generally non-linear relationships; length increases linearly but weight increases three-dimensionally as a volume (Olge, 2013b). Additionally, there is generally an increase in variability of weight for a given length (Olge, 2013b). These generalizations are seen in cusk data from the NEFSC spring and fall bottom trawl. The relationship can be modeled to account for the non-linear relationship and increasing variability in weight at length (Ogle, 2013b):

$$
\begin{equation*}
W_{i}=a L_{i}^{b} e^{\varepsilon_{i}} \tag{5.2}
\end{equation*}
$$

where $a$ and $b$ are constant for all cusk and $\varepsilon_{i}$ is error term for each individual cusk (i). Log transforming length and weight allows for the logistic equation (5.2) to be transformed to a linear model for estimating $a$ and $b$ parameters (Faroese, 2006).:

$$
\begin{equation*}
\log \left(W_{i}\right)=\log (a)+b \log \left(L_{i}\right)+\varepsilon_{i} \tag{5.3}
\end{equation*}
$$

### 5.2.1.3. Maturity

Maturity ogives were derived from the NEFSC spring and fall bottom trawl survey (2001 - 2014) to estimate length at $50 \%$ maturity ( $\mathrm{L}_{50}$ ) and were developed individually for males and females. Ogives were estimated using the R statistical program package sizeMat (TorrejonMagallanes, 2016). The probability of being mature (Burnett et al., 1989) at a given size is estimated with a logistic regression (i.e., GLM with logit link) using bootstrapped samples and allowing for replacement, to estimate median probability and confidence interval (TorrejonMagallanes, 2016):

$$
\begin{equation*}
P_{L}=1 / 1+e^{-\left(\widehat{\beta}_{0}+\widehat{\beta}_{1} X\right)} \tag{5.4}
\end{equation*}
$$

where $\mathrm{P}_{\mathrm{L}}$ is the probability of an individual being mature at length $\mathrm{X}, \hat{\beta}_{0}$ is the slope and $\hat{\beta}_{1}$ is the intercept. $\mathrm{L}_{50}$, the median length at maturity, is estimated as:

$$
\begin{equation*}
L_{50}=-\frac{\widehat{\beta}_{0}}{\widehat{\beta}_{1}} \tag{5.5}
\end{equation*}
$$

### 5.2.1.4 Fishery and Survey Data

Fishing mortality rates (F) were assumed to be combined rates to represent recreational and commercial fisheries. Initial estimates for F are user defined and were assumed to vary between 0.15 and 0.3 at random within the population simulator. One fishing fleet is defined in

PopSim to work in accordance with SCALE (NOAA, 2013). True catch within the population simulator is estimated using the Baranov's catch equation (Deroba and Schueller, 2013) for fishery catches, distinguished by $\theta$ :

$$
\begin{equation*}
C_{\theta, y, l, a}=\frac{F_{y} S_{l}}{z_{y, l}} N_{y, l, a}\left(1-e^{-z_{y, l}}\right) \tag{5.6}
\end{equation*}
$$

where $C_{\theta, y, l, a}$ is the true catch at length $(l)$ and age (a) per year $(y), F_{y}$ is the user defined fishing mortality rate per year, $S_{l}$ is selectivity at length defined by the user, and $Z_{y, l}$ is total mortality at length, the sum of natural mortality $\left(\mathrm{M}_{y}\right)$, defined by the user, and fully selected F for each length class in this study (Deroba and Schueller, 2013; NOAA, 2013). The user provides starting guesses for selectivity which are based on observed commercial length frequencies ( $a=56 \mathrm{~cm}$ and $\beta=0.1$ ). Catch at length per year is a direct input into the SCALE stock assessment model.

This study assumes two surveys are conducted annually (i.e., spring and fall), requiring survey catch at length to be defined for each survey. The true numbers at length $(l)$ are known for each year within the simulated population (Deroba and Schueller, 2013). The true population stock numbers at January $1\left(N_{y, l}\right)$ are multiplied by selectivity ( S ), then summed over all lengths, and a survey catchability (q) and a lognormal error are applied to obtain total number of fish sampled in each survey (Deroba and Schueller, 2013; NOAA, 2013).

Next, an age composition is estimated by converting stock at age into a multinomial distribution between zero and one (Deroba and Schueller, 2013; NOAA, 2013). The user specified number of samples are drawn from the multinomial distribution to estimate the survey catch length frequencies (Deroba and Schueller, 2013; NOAA, 2013).

$$
\begin{equation*}
C_{\vartheta, y}=\sum_{l} N_{y, l} S q e^{\varepsilon_{y}} ; \varepsilon_{y} \sim N\left(0, \sigma_{\vartheta}^{2}\right) \tag{5.7}
\end{equation*}
$$

Adult indices used as input in the SCALE stock assessment model are calculated from age frequencies times $C_{\vartheta, y}$ (NOAA, 2006).

Catch samples of the fishery and the surveys were assumed constant for all years to isolate the effects of varying survival rates on F. Fishery selectivity assumed an $a=55 \mathrm{~cm}$ and $\beta=0.1$. Catch samples from fishery removals were assumed to be 1000 (CV 0.1). Survey samples for the spring survey (survey one) were assumed to be 600 (CV 0.1), catchability 0.1 , and selectivity of 1.0 while catch samples for the fall survey (survey two) was 700 (CV0.2), catchability 0.1 , and selectivity 1.0 .

### 5.2.1.5 Initial Population

The initial starting population size (i.e., in year $\mathrm{y}=1$ ) is user defined within PopSim as numbers at age (Deroba and Schueller, 2013) and was estimated in an iterative process. The initial numbers at age were obtained from the equilibrium population estimated by a preliminary SCALE run that was based on known cusk parameters.

In the first iteration of PopSim, the initial starting population and recruitment that were provided reflected cusk trends in catch. Recruitment in the population simulator is at age one (NOAA, 2013) and the 1983 recruits were set to equal the 1982 age 1 year class. Cusk are highly fecund, producing an estimated three million eggs per female (Collette and Klein-MacPhee, 2002). Recruitment was user defined for the rest of the years to reflect the catch rates estimate for cusk from 1982 - 2013, ranging from 1.3 million to 50,000 age 1 recruits when the population was low. The resulting simulated landings and cusk-like abundance indices from this first PopSim run were used as input into the preliminary SCALE run.

The starting year (1982) equilibrium stock numbers at age outputted from the preliminary SCALE run were then used as input for the initial population at age for 1982 in the final PopSim
run. The second iteration of PopSim, using the same inputs described above and in the previous sections, generated abundance indices reflective of the equilibrium population, and the resulting adult and recruitment indices were incorporated back into SCALE for the base simulation run.

### 5.2.2. Estimating Bycatch Scenarios

Total bycatch of cusk in the GOM lobster fishery is thought to significantly contribute to total removals of this stock. Maine Department of Marine Resources (MDMR) collects some bycatch data through the lobster sea sampling program that started in 2006 (MDMR, 2016a). This is a fisheries-dependent monitoring program with non-random sampling of the fishery. Bycatch is not recorded for every observer trip as the program was designed to evaluate biological characteristics of individual lobsters (MDMR, 2016a). Consequently, these data cannot reliably be scaled up to the fishery for estimating total bycatch using standard (by)catch estimation methods:

$$
\begin{equation*}
C=q E N \tag{5.8}
\end{equation*}
$$

because catch $(C)$ cannot be assumed to be proportional to fishing effort $(E)$ and population density $(N)$.

Bycatch observations from the sea sampling data are recorded per trap from 2006-2013 (after 2013 they are recorded per trawl of multiple traps). These are currently the best data available to evaluate bycatch in the Maine lobster fishery as it is the longest time series with coast wide, year-round spatial coverage (MDMR, 2016a). It is currently the most consistent time-series for bycatch data, but bycatch monitoring efforts by the Northeast Fishery Observer Program recently were reinstated in 2012 for the federal lobster fishery (Brooke, 2015).

The Atlantic States Marine Fishery Commission (ASMFC) lobster stock assessment measures effort in the fishery as the number of traps in an area (i.e., number of trap tags per zone for Maine; ASMFC, 2015). However, a more effective measure of effort would be number of trap hauls (ASMFC, 2015). The lobster sea sampling program provides data on the number, size, and weight of lobsters caught per trap haul as well as the number and type of bycatch, when available (MDMR, 2016a).

Expanding on the efforts of Boenish and Chen (in review), cusk bycatch confidence intervals (CI) are estimated per trap haul to estimate a range of total bycatch in the Maine lobster fishery. Bycatch per month is estimated as:

$$
\begin{equation*}
\text { Bycatch }_{m}=\text { Effort }_{z, m} * \text { BPUE }_{m} \tag{5.9}
\end{equation*}
$$

where effort is number of traps hauled for each zone $(z)$ and month $(m)$, and bycatch-per-uniteffort (BPUE) is estimated for each month, coast wide. Effort is estimated as:

$$
\begin{equation*}
\text { Effort }_{z, m}=\frac{\text { landings }_{z, m}}{C P U E_{z, m}} \tag{5.10}
\end{equation*}
$$

where landings are the reported zonal, monthly landings to the Maine DMR and $C P U E_{z, m}$ is estimated below in section 5.2.2.1 and defined as total weight of legal lobster per trap. BPUE $m_{m}$ is estimated in section 5.2.2.2 and is defined as the total number of cusk per trap. $C P U E_{z, m}$ and $B P U E_{m}$ are estimated through bootstrapped generalized additive models (GAM) and the total amount of cusk bycatch, in numbers, is an estimated range (Figure 5.1).


Figure 5.1. General framework for estimating cusk bycatch. Bycatch estimates are derived from the Maine lobster sea sampling data from Maine Department of Marine Resources using bootstrapped binomial-GAMs to estimate $95 \%$ CIs of the probability of presence (P) or absence (A) of cusk in a lobster trap and delta-GAMs to estimate $95 \%$ CI of trap hauls as a measure of effort in order to estimate a Fieller confidence interval (Fieller, 1954) of low, median, and high bycatch scenarios in numbers of individual cusk per year.

### 5.2.2.1. Estimating Lobster CPUE

GAMs are a common approach to standardizing catch and effort data (Maunder and Punt, 2004). GAMs have also been used to predict fishing effort for unobserved trips and to estimate bycatch (Walsh and Pooley, 2002). Two-stage GAMs (delta-GAMs) are effective for zerodominated data, even when the zeros are caused by missed sampling (Maunder and Punt, 2004). Therefore, a delta-GAM was used to estimate the number of trap hauls per zone per month.

The delta-GAM first estimates the probability of encountering an individual legal-sized lobster $(P)$ using a logit-link function with binomial distribution given spatial-temporal covariates (5.9; Barry and Welsh, 2002; Boenish and Chen, in review):

$$
\begin{equation*}
\operatorname{logit}(P)=\beta_{0}+\sum_{j=1}^{n} s_{j}\left(E_{j}\right)+\varepsilon \tag{5.11}
\end{equation*}
$$

where $\beta_{0}$ is the intercept, $s_{j}$ is the smoothing spline function for covariate $E_{j}$ for continuous covariates, and categorical covariates did not have an smoothing spline applied. The second stage of the model then estimates mean weight of log-transformed legal-sized lobster in kilograms (w) given a log-link and Gamma distribution conditional on the probability of presence in the first sage (Boenish and Chen, in review; Maunder and Punt, 2004):

$$
\begin{equation*}
\log (w)=\beta_{0}+\sum_{j=1}^{n} s_{j}\left(E_{j}\right)+\varepsilon \tag{5.12}
\end{equation*}
$$

Spatial (i.e., latitude, longitude, distance offshore, depth, sediment type) and temporal (i.e., month and year) covariates were used to standardize catch rates of lobsters per trap haul. Stepwise, backwards model selection was used to determine the best model in the first and second stages based on significant models with the lowest AIC.

Catch-per-unit-effort (CPUE) is then defined as the absolute log-transformed lobster weight per trap haul $(\ln (z))$ per zone $(z)$ and month $(m)$ :

$$
\begin{equation*}
\ln (z)=\ln (P)+\ln (w) \tag{5.13}
\end{equation*}
$$

Effective effort in the lobster fishery is then estimated as trap hauls using bootstrapped sampling methods to run 500 iterations of delta-GAMs per zone per month (Boenish and Chen, in review). The lobster delta-GAM estimates the number of lobster landings per trap haul (Lobster $\mathrm{CPUE}_{z, \mathrm{~m}}$; Figure 5.1). To account for the lobster sea sampling data not being from randomly selected vessels, confidence intervals are needed to estimate the range of lobster $\mathrm{CPUE}_{z, \mathrm{~m}}$ (upper and lower). To do this, bootstrapped $95 \%$ CIs are generated by sampling legal lobsters caught and
running the 500 iterations of delta-GAM to generate low, median, and high lobster $\mathrm{CPUE}_{z, \mathrm{~m}}$ (Figure 5.1; Boenish and Chen, in review).

### 5.2.2.2. Estimating Cusk BPUE

Ideally, cusk bycatch rates would be estimated in the same manner. However, a two-stage delta-GAM at the zonal scale was not feasible for developing a standardized bycatch-per-uniteffort (BPUE) for cusk because of low sample rates (303 cusk from 247,314 sampled traps). Instead, the probability of cusk being present in a trap in a given month, for all zones combined, was estimated with a binomial presence/absence GAM, the same as the first stage of the deltaGAM (eq. 5.9), with 500 bootstraps.

Because reliable catch rates could not be predicted with the second stage of the deltaGAM, the mean number of cusk per trap and $95 \%$ CI were estimated through 500 bootstrapped samples from the positive catches of cusk using MDMR sea sampling data (2006 - 2013). The mean number of cusk per trap, when present, was multiplied by the probability of presence from the binomial GAM to get an estimate of the number of cusk caught per trap per month $\left(B P U E_{m}\right)$.

Next, a ratio of mean number of cusk caught per mean weight of lobster was derived ( $\left.B P U E_{m} / C P U E_{z, m}\right)$. Since CPUE and BPUE are mean estimates, it is necessary to look at the range of the number of cusk caught per weight of lobster. However, the ratio of two means, normally distributed, does not result in a normally distributed ratio (Fieller, 1954). Additionally, a ratio with different units cannot have confidence intervals directly estimated (Fieller, 1954). Therefore, it is necessary to use the Fieller method to estimate the ratio of confidence intervals (Fieller, 1954). The standard error of the quotient $\left(\mathrm{Q}=B P U E_{m} / C P U E_{z, m}\right)$ is first estimated:

$$
\begin{equation*}
S E_{Q}=Q \sqrt{\frac{S E_{B}^{2}}{B^{2}}+\frac{S E_{C}^{2}}{C^{2}}} \tag{5.14}
\end{equation*}
$$

where $\mathrm{SE}_{\mathrm{B}}$ is the standard error for BPUE, $\mathrm{SE}_{\mathrm{C}}$ is the standard error for $\mathrm{CPUE}, \mathrm{B}$ and C are Gaussian variables for BPUE and CPUE, respectively (Fieller, 1954). The 95\% CIs are then estimated using the $t^{*}$ statistic for $95 \%$ CIS:

$$
\begin{equation*}
95 \% C I=Q \pm t^{*} \times S E_{Q} \tag{5.15}
\end{equation*}
$$

The ratio $B P U E_{m} / C P U E_{z, m}$ can then be multiplied by the Maine DMR zonal, monthly lobster landings ( kg ) data to get an estimate of the number of cusk bycatch rates per zone and month during 2006-2013. Even though $B P U E_{m}$ is estimated coast wide with the assumption that catch rates are the same in all zones, trap haul is estimated per zone and month, which gives bycatch rates per zone and month. The $5 \%$ and $95 \%$ CIs are the low and high bycatch estimates per zone per month. The low, median, and high bycatch estimates per zone per month are then summed to get total annual bycatch rates.

### 5.2.2.3. Estimating Bycatch Scenarios

Historical bycatch scenarios were back calculated based on the amount of bycatch estimated in 5.2.2.2 by back-calculating bycatch given the abundance of cusk relative to trap density and effort:

$$
\begin{equation*}
B \widehat{P U E}_{y}=\left(s A_{y} * T_{y}\right) * F \tag{5.16}
\end{equation*}
$$

Where $B P U E_{y}$ is the predicted number of cusk caught as bycatch per year, $A_{y}$ is the modelbased abundance derived in Chapter 2, $T_{y}$ the number of traps estimated from the lobster stock assessment report, and F is the fishing mortality rate from the lobster stock assessment report (ASMFC, 2015), $s$ is a scaling factor estimated by minimizing the sum of squared error from 'observed' bycatch quantities from above minus the predicted $B \widehat{P U E}_{y}$.

Table 5.1. Bycatch Scenarios. The resulting bycatch scenarios (low, median, and high) in metric tons and the estimated ladings from PopSim (MT).

| Year | PopSim <br> Landings <br> (MT) | Low <br> Bycatch <br> (MT) | Median <br> Bycatch <br> (MT) | High <br> Bycatch <br> (MT) |
| :---: | :---: | :---: | :---: | :---: |
| 1982 | 1622.88 | 153.4574 | 158.3912 | 181.6126 |
| 1983 | 1047.7 | 124.1831 | 128.1757 | 146.9673 |
| 1984 | 1493.06 | 139.3719 | 143.8529 | 164.9428 |
| 1985 | 1015.91 | 176.6026 | 182.2806 | 209.0043 |
| 1986 | 1307.14 | 174.0105 | 179.6052 | 205.9366 |
| 1987 | 625.21 | 122.3033 | 126.2355 | 144.7426 |
| 1988 | 887.55 | 95.41889 | 98.48671 | 112.9256 |
| 1989 | 976.55 | 87.01187 | 89.80939 | 102.9761 |
| 1990 | 907.36 | 96.49923 | 99.60178 | 114.2042 |
| 1991 | 567.81 | 90.85707 | 93.77822 | 107.5268 |
| 1992 | 425.86 | 60.63065 | 62.57999 | 71.75469 |
| 1993 | 809.6 | 96.86986 | 99.98433 | 114.6428 |
| 1994 | 513.61 | 102.9583 | 106.2685 | 121.8483 |
| 1995 | 410.84 | 75.50634 | 77.93395 | 89.35966 |
| 1996 | 604.71 | 77.64609 | 80.14249 | 91.89199 |
| 1997 | 349.78 | 73.07925 | 75.42882 | 86.48726 |
| 1998 | 243.93 | 68.72372 | 70.93326 | 81.33261 |
| 1999 | 371.64 | 74.0783 | 76.45999 | 87.66961 |
| 2000 | 271.04 | 69.60528 | 71.84316 | 82.37592 |
| 2001 | 389.91 | 75.60234 | 78.03303 | 89.47327 |
| 2002 | 226.4 | 104.2848 | 107.6377 | 123.4182 |
| 2003 | 410.24 | 51.809 | 53.47472 | 61.31452 |
| 2004 | 569.42 | 103.1963 | 106.5142 | 122.13 |
| 2005 | 616.8 | 114.7593 | 118.4489 | 135.8145 |
| 2006 | 406.26 | 71.79 | 74.10264 | 84.552 |
| 2007 | 295.1 | 52.2915 | 55.84236 | 65.25 |
| 2008 | 518.22 | 59.937 | 62.65185 | 71.865 |
| 2009 | 298.5 | 55.179 | 57.16494 | 64.5795 |
| 2010 | 222.38 | 58.5795 | 60.64661 | 69.0885 |
| 2011 | 314.54 | 54.159 | 56.06522 | 63.5325 |
| 2012 | 177.45 | 71.6805 | 73.87775 | 83.718 |
| 2013 | 120.03 | 68.163 | 70.78397 | 80.7015 |
|  |  |  |  |  |

### 5.2.3 Stock Assessment Simulations

In 2009, the NOAA SCALE model was used to estimate cusk biomass for the NOAA Office of Protected Resources for determination of listing (NOAA, 2015). Length-based stock assessment models provide a method of assessment for hard-to-age species (Punt et al., 2013). Statistical-catch-at-length models assign size-classes to age-classes, fundamentally using a statistical-catch-at-age model (Punt et al., 2013). The SCALE model is an age structured model that fits length data, abundance indices, and recruitment-at-age estimated by binning length data from the surveys to the estimated age class (NOAA, 2006).

Simulated data from PopSim were used as input data to SCALE (Figure 5.2). This data includes adult and recruitment indices, catch length frequencies, survey length frequencies, catch rates, and mean length at age. The adult and juvenile indices were estimated from the defined population parameters above: mean length at age, the length-weight relationship, and maturity ogives. Assumed parameters were M equal to 0.2 as natural mortality is unknown and fishery selectivity was fixed at intercept equal to 56 cm and slope equal to 0.1 based on observed commercial length frequencies. SCALE allows for one fleet in the model, requiring estimated landings and discard estimates to be combined. Landings were estimated from PopSim given F and stock biomass.

A total of twelve scenarios were developed for the stock assessment simulations: three bycatch scenarios (i.e., low, median, and high) and four discard mortality rates (i.e., $25 \%, 50 \%$, $75 \%, 100 \%$ ). All the scenarios were compared to the base case scenario that assumed no bycatch (i.e., $0 \%$ discard mortality). Sensitivity analyses were conducted using the same input data to determine the best SCALE model settings for conducting the simulations. The final model settings fit the catch length frequency starting at 15 cm with a defined effective sample size of
1000. The model fit survey length frequency beginning at 15 cm for both the spring (survey 1 ) and fall (survey 2) with an effective sample size of 60 and 70 respectively.

The estimated and back calculated bycatch scenarios were added to the simulated landings for each scenario (Table 5.1). Discards were not estimated within SCALE, instead the bycatch estimate was adjusted to account for the varying discard mortality rates (i.e., $25 \%, 50 \%$, $75 \%, 100 \%$ ). The discard mortality rate of $100 \%$ assumed full mortality of all individuals estimated to be incidentally caught within the Maine lobster fishery, whereas the 25\% discard morality rate assumed that $75 \%$ of the incidentally caught individuals were released alive and were able to survive.

Relative difference (RD) of the bycatch scenarios to the base run were calculated for SSB, recruitment, and fully selected F for each year of the simulation:

$$
\begin{equation*}
R D=\frac{\text { bycatch-base }}{\text { base }} \times 100 \tag{5.17}
\end{equation*}
$$

where bycatch is the bycatch scenario and base is the base run.


Figure 5.2. General framework for the stock assessment simulations. The simulated population is used as model input within the SCALE stock assessment model to evaluate varying levels of bycatch rates and survival rates and the subsequent impact on spawning stock biomass (SSB), recruitment, and fishing mortality (F).

### 5.3. Results

### 5.3.1. Defining the True Population

The true population defined in PopSim directly reflects the population parameters from multiple years estimated for cusk. Initial population (Table 5.2) and recruitment (Table 5.3) numbers were estimated to reflect the current understanding of cusk. Cusk mean weight for the NEFSC spring and fall bottom trawl survey combined was 1.5 kg ( $\pm 1.3 \mathrm{~kg} ; 2001-2015)$. Total landings (not including bycatch) in 1982 was 2281.46 MT. For this study, the initial starting population for cusk in 1982 was 2,711,612 distributed among age classes.

### 5.3.1.1. Growth and Aging

Maximum age for cusk was assumed to be 20 years. Mean length at age was 4.5 cm (SD
3.0) for age 1 fish and 112.9 cm (SD 7.0) for age 20 fish (Table 5.2). The resulting population parameters estimated in the von Bertalanffy growth function (5.1) were $L_{\infty}=126.6, \mathrm{~K}=0.1097$, and $t_{0}=0.6733$.

Table 5.2. PopSim and SCALE inputs. The initial population numbers are for PopSim only.
Mean-length at age and the standard deviation of mean-length at age are for SCALE only.

| Age | Initial <br> Population <br> (numbers) <br> (PopSim) | Mean Length <br> $(\mathbf{c m})$ <br>  <br> SCALE) | Standard <br> Deviation <br> (SCALE) |
| :---: | :---: | :---: | :---: |
| 1 | 1001480 | 4.5 | 3.0 |
| 2 | 819942 | 17.1 | 5.0 |
| 3 | 671310 | 28.5 | 6.0 |
| 4 | 549620 | 38.7 | 7.0 |
| 5 | 449988 | 47.8 | 7.0 |
| 6 | 368414 | 56.0 | 7.0 |
| 7 | 301626 | 63.3 | 7.0 |
| 8 | 246942 | 69.9 | 7.0 |
| 9 | 202170 | 76.0 | 7.0 |
| 10 | 165516 | 81.1 | 7.0 |
| 11 | 135504 | 85.8 | 7.0 |
| 12 | 110934 | 90.0 | 7.0 |
| 13 | 90818 | 93.8 | 7.0 |
| 14 | 74350 | 97.2 | 7.0 |
| 15 | 60868 | 100.3 | 7.0 |
| 16 | 49830 | 105.4 | 7.0 |
| 17 | 40794 | 107.6 | 7.0 |
| 18 | 33396 | 109.6 | 7.0 |
| 19 | 27340 | 111.4 | 7.0 |
| 20 | 22382 | 112.9 | 7.0 |

### 5.3.1.2. Length-Weight Relationships

Cusk demonstrate classic allometric growth (Figure 5.3). Log transformed length and weight (2000-2015) result in $a=-12.4086$ and $b=3.222$ for males and females combined for spring and fall (Figure 5.3).


Figure 5.3. Cusk length-weight relationship. Linear regression of log transformed length and weight to estimate $a$ and $b$ parameters for estimating the "true" population parameters.

### 5.3.1.3. Maturity

Maturity ogives were developed for males and females using 385 samples with known sexual maturity stages out of 404 documented in the NEFSSC spring and fall bottom trawl survey (2000-2015). Based on the maturity classifiers for the NEFSC survey, immature is a single category and mature fish can be classified as either developing, ripe, spent, or resting (Burnett et al., 1989). There were 219 females ( 25 immature, 193 mature, 1 unknown) and 154 males (26 immature, 127 mature, 1 unknown). Size at maturity for females was estimated at $30 \mathrm{~cm}(\mathrm{CI}=22.5-33.8 \mathrm{~cm})$ with a bootstrapped slope $\hat{\beta}_{0}=-5.2822$. Size at maturity for males was estimated at $36.1 \mathrm{~cm}(\mathrm{CI}=31.3-39.4 \mathrm{~cm})$ and a bootstrapped slope $\hat{\beta}_{0}=-6.7591$ (Figure 5.4).


Figure 5.4. Cusk maturity ogives. Maturity ogives for male and female cusk used to define the population parameters in the population simulator to estimate a "true" population.

### 5.3.1.4 Fishery and Survey Data

The population simulator estimated landings for each year given the starting population at age and assumed F for each year (Figure 5.5). Simulated landings followed the general trend of cusk commercial landings in the United States from 1982 to 2013 (Figure 5.5). Fishery selectivity in SCALE is asymptotic (Figure 5.5; NOAA, 2006), therefore, the following selectivity curve (Figure 5.6) was assumed for PopSim fishery selectivity with an intercept of 55 and slope of 0.1 .


Figure 5.5. Cusk landings used in the stock assessment simulations. Observed (solid line) landings for cusk from NOAA and simulated (dashed line) landings from 1982-2013. The simulated landings were used in all the stock assessment simulations.


Figure 5.6. Fishery selectivity assumed for the simulated population. The fishery selectivity is assumed to have an intercept of 55 and slope of 0.1 given observed commercial length frequencies.

### 5.3.1.5 Initial Population

The initial population (Table 5.2) and recruitment numbers (Table 5.3) were estimated to reflect the current understanding of cusk. Starting values for the initial population at age for 1982 are the equilibrium population estimated in the preliminary SCALE and used to develop the true population in PopSim (Table 5.2).

Table 5.3. Recruitment input for PopSim. Assumed user defined recruitment numbers in PopSim to derive simulated catch data similar to observed cusk catch data.

| Year | Recruitment | Year | Recruitment |
| :---: | :---: | :---: | :---: |
| 1983 | 1001480 | 1999 | 1235550 |
| 1984 | 930180 | 2000 | 1391260 |
| 1985 | 888830 | 2001 | 109955 |
| 1986 | 967060 | 2002 | 91365 |
| 1987 | 1076400 | 2003 | 72500 |
| 1988 | 981850 | 2004 | 92895 |
| 1989 | 717800 | 2005 | 117775 |
| 1990 | 326630 | 2006 | 170630 |
| 1991 | 347720 | 2007 | 169955 |
| 1992 | 466900 | 2008 | 71365 |
| 1993 | 278650 | 2009 | 62500 |
| 1994 | 286510 | 2010 | 52895 |
| 1995 | 303890 | 2011 | 57775 |
| 1996 | 283890 | 2012 | 50630 |
| 1997 | 1045630 | 2013 | 54955 |
| 1998 | 1185790 | 2014 | 51365 |

### 5.3.2. Bycatch estimations

### 5.3.2.1. Lobster CPUE and Cusk BPUE

Final models for the first and second stage delta-GAMs for CPUE estimates and cusk binomial-GAM BPUE estimates are outlined in Figure 5.7. Temporal covariates (i.e., year and month) were included in every lobster model and distance offshore was the only spatial covariate excluded in the first stage of the models for zones A and F (Figure 5.7). Sediment type was excluded from the second stage of the models for zones $\mathrm{A}, \mathrm{B}$, and E while longitude was excluded from zone G; the second stages for the rest of the zones included all covariates (Figure 5.7). Number of lobsters were included in every lobster zone model (stage 1 and 2 ) to account for trap density dependent processes. The final model for cusk BPUE (GAM Stage 1) for the entire coastal Maine region included temporal covariates as well as latitude, depth, sediment
type, weight of lobster in the trap, and distance offshore (Figure 5.7). Weight of lobsters was more important than number of lobsters in the cusk binomial-GAM.

Bycatch by zone ranged from 2.9 to 9.1 cusk per 10,000 traps (Table 5.4). The number of cusk caught per 10,000 traps increased from east (zone A) to west (zone G), with zone A having the lowest estimates and zone $G$ having the highest (Table 5.4). Resulting annual cusk bycatch CI estimates varied annually but all years were within an order of magnitude of each other (Table 5.5).


Figure 5.7. Covariates used in bycatch the final GLMs. The models include each lobster zone and cusk throughout the Maine coast. Potential covariates include: Year (Yr), Month (Mo), Latitude (Lat), Longitude (Lon), quantity of Lobster (Lob) in numbers (and in weight for the cusk model) for zones A through G, Sediment Type (S), and Distance Offshore (DS).

Table 5.4. Estimated number of cusk per $\mathbf{1 0 , 0 0 0}$ traps per zone. Estimated in section 5.2.2.2.

| Zone | Low <br> $(\# / \mathbf{1 0 , 0 0 0}$ traps $)$ | Median <br> $(\# / \mathbf{1 0 , 0 0 0}$ traps $)$ | High <br> $(\# / \mathbf{1 0 , 0 0 0}$ traps $)$ |
| :---: | :---: | :---: | :---: |
| A | 2.9 | 3.0 | 3.4 |
| B | 3.7 | 3.9 | 4.5 |
| C | 3.1 | 3.3 | 3.7 |
| D | 4.6 | 4.7 | 5.4 |
| E | 7.3 | 7.7 | 9.0 |
| F | 7.2 | 7.5 | 8.5 |
| G | 7.6 | 7.9 | 9.1 |

Table 5.5. Bycatch estimates for 2006 - 2013. CI of the number (\#) of cusk caught as bycatch per year from 2006-2013 estimated from the Maine Department of Marine Resources lobster sea sampling program.

| Year | Low (\#) | Median (\#) | High (\#) |
| :---: | :---: | :---: | :---: |
| 2006 | 47860 | 49401.76 | 56368 |
| 2007 | 34861 | 37228.24 | 43500 |
| 2008 | 39958 | 41767.9 | 47910 |
| 2009 | 36786 | 38109.96 | 43053 |
| 2010 | 39053 | 40431.07 | 46059 |
| 2011 | 36106 | 37376.81 | 42355 |
| 2012 | 47787 | 49251.83 | 55812 |
| 2013 | 45442 | 47189.31 | 53801 |

### 5.3.2.2. Bycatch Scenarios

The backward projected (back calculated might sound better) estimates of low, med, high bycatch during 1982-2005, based on the observed 2006-2013 median and upper and lower CI values are presented in Figure 5.8. The predicted estimates from the Maine DMR lobster sea sampling data were used for 2006-2013 (solid lines; Figure 5.8). The value of the three bycatch scenarios are of similar magnitude, adding anywhere from 200 to 50 MT to overall catches (Figure 5.8).


Figure 5.8. Bycatch scenarios used in the stock assessment simulations. Bycatch scenarios backward estimated (dashed line) from the 2006-2013 (solid line) bycatch confidence intervals estimated from the Maine Department of Marine Resources lobster sea sampling data. The high bycatch scenarios are in maroon, low are in turquoise, and median are in black.

### 5.3.3 Stock Assessment Simulations

SSB, recruits, and F estimates were compared to the base case SCALE model output that assumed zero incidental catches (Figure 5.9). In each of the three bycatch scenarios, SSB and recruits were estimated to be higher than the no-bycatch scenario in the two highest mortality scenarios (i.e., $75 \%$ DMR, $100 \%$ DMR; Figure 5.9) while the lowest discard mortality rate of $25 \%$ estimated SSB and recruitment closet in value to the no bycatch scenario (Figure 5.9). F would be expected to be lower when biomass is estimated higher because higher total catches
assume higher population give Baranov's catch equation. This holds true for parts of the time series but F is higher at the higher DMRs in 1997 and 2008-2013 (Figure 5.9). Throughout the time series, SSB and recruits are estimated higher in the earlier years but end close to the same value of SSB and recruits for all the scenarios in 2013 (Figure 5.9).

RDs were evaluated between the base case ( $0 \% \mathrm{DMR}$ ) and different discard mortality rates for each bycatch scenario (Figure 5.10). The higher estimates for SSB and recruits for the higher discard mortality rates are evident in the calculated RD. The RD for F shows that fishing mortality rates for the $50 \%$ DMR, $75 \%$ DMR, and $100 \%$ DMR fluctuate higher and lower than the no bycatch catch scenario for the entire time series (Figure 5.10). The $100 \%$ and $75 \%$ DMRs for the three bycatch scenarios have the highest variability in F relative to the other scenarios (Figure 5.10).


Figure 5.9. Stock assessment simulation output. Estimated spawning stock biomass, recruitment, and fishing mortality rates for the three bycatch scenarios (high, median low), four discard mortality scenarios ( $25 \%$ DMR, $50 \%$ DMR, $75 \%$ DMR, $100 \%$ DMR), and the base case (0\% DMR).


Figure 5.10. Relative difference of stock assessment simulation output. Relative differences in estimates for spawning stock biomass, recruitment, and fishing mortality rates relative to the base case for the three bycatch scenarios (high, median low), four discard mortality scenarios ( $25 \%$ DMR, $50 \%$ DMR, $75 \%$ DMR, $100 \%$ DMR), and the base case ( $0 \%$ DMR).

Final model settings were evaluated based on the lowest objective function for the base case scenario. All bycatch scenarios were compared to the no bycatch scenario by the estimated objective function, residual catch weight, and residual length frequency (Table 5.6). The objective function and residuals of the twelve bycatch scenarios were all similar to those of the no bycatch scenario.

Table 5.6. Stock assessment simulation model outputs. Model comparisons for each simulation run for the three bycatch scenarios low bycatch (LB), median bycatch (MB), high bycatch $(\mathrm{HB})$ and four $(25,50,75,100)$ discard mortality rates $(\mathrm{DMR})$ and the no bycatch scenario.

| Model | Obj. Fun. | Resid. Catch Wt. | Resid. Length Freq. |
| :--- | ---: | :---: | :---: |
| No Bycatch | 84.7598 | 0.053476 | 20.6541 |
| LB_25DMR_stitched_bycatch | 84.4885 | 0.0490634 | 20.6058 |
| LB_50DMR_stitched_bycatch | 84.2558 | 0.0453034 | 20.562 |
| LB_75DMR_stitched_bycatch | 84.0557 | 0.0420913 | 20.5221 |
| LB_100DMR_stitched_bycatch | 83.8831 | 0.0393384 | 20.4856 |
| MB_25DMR_stitched_bycatch | 84.4793 | 0.0488991 | 20.6042 |
| MB_50DMR_stitched_bycatch | 84.2400 | 0.0450241 | 20.559 |
| MB_75DMR_stitched_bycatch | 84.0353 | 0.041732 | 20.518 |
| MB_100DMR_stitched_bycatch | 83.8597 | 0.0389293 | 20.4807 |
| HB_25DMR_stitched_bycatch | 84.4447 | 0.0483117 | 20.5973 |
| HB_50DMR_stitched_bycatch | 84.1817 | 0.0440403 | 20.5466 |
| HB_75DMR_stitched_bycatch | 83.9616 | 0.0404959 | 20.5013 |
| HB_100DMR_stitched_bycatch | 83.7766 | 0.0375438 | 20.4605 |

### 5.4 Discussion

This study set out to determine the impact on population biomass of implementing a conservation measure to reduce discard mortality for cusk bycatch in the lobster fishery. The proposed conservation measure is to recompress cusk bycatch within the Maine lobster fishery to increase the probability of survival. Recompressing cusk within lobster traps showed a $75 \%$
survival rate over the medium term (4-14 days; Chapter 4). The impacts of this conservation measure were evaluated relative to estimated SSB , recruitment, and F in twelve bycatch scenarios relative to a base case scenarios assuming no bycatch. To conduct the stock assessment simulations, the population dynamics for cusk were defined based on the most recently available data to reflect the current understanding of cusk. Additionally, cusk bycatch was estimated for the Maine lobster fishery as this is thought to be a significant source of unaccounted mortality for cusk.

### 5.4.1 Defining the True Population

Cusk population dynamics have not been updated in the literature since the 1970s (Oldham, 1972) and cusk is considered data limited with regard to stock assessments (Hare et al., 2012). Many of the population parameters were unknown or have a significant level of uncertainty associated with the available data. The most notable uncertainty for cusk is large discrepancies in estimates for maximum age (DFO, 2014).

For this study, cusk maximum age was assumed to be 20 -years because it is between the lower 15-year maximum life expectance reported by Oldham (1972) and the higher 39-years reported by DFO (2014). Oldham (1972) collected random samples of cusk otoliths from commercial longline vessels, but cusk over nine years were not used in the age estimatesbecause interpretations of marginal rings were unreliable. Newer methods for aging otoliths (i.e., bomb radiocarbon dating; Broecker and Peng, 1982) indicate that an 82 cm cusk is 39 years old (DFO, 2014) while fish of similar length were estimated to be 12 - 13 years by Oldham (1972). Gear selectivity, which excluded smaller cusk ( $<35 \mathrm{~cm}$ ), may have complicated age-at-length estimates potentially skewing the aging interpretations for Oldham (1972). Sizes ranged from

35 cm to 97 cm and estimates for mean length of aged 4, 5, 6, and 7 fish maybe have been biased high (Oldham, 1972). Based on these estimates, cusk were thought to live to age 14 and reach sexual maturity by age 5 or 6 (Oldham, 1972; Collette and Klein-MacPhee, 2002). The bomb radiocarbon dating methods used by DFO have not yet been validated (DFO, 2014), adding uncertainty to the discrepancy in age estimates. These discrepancies have resulted in uncertainty in understanding growth rates for cusk (DFO, 2014), a necessary population parameter and a source of uncertainty in the stock assessment simulations.

Aging errors can be problematic for stock assessments dependent on age data, and may impact all assessment inputs (Reeves, 2003). The underlying population dynamics estimated for the true population are dependent on the mean-length at age estimates. Length based parameters (i.e. survey length frequency, catch length frequency, maturity, and population growth) are converted to age based parameters, using the mean length at age provided to the simulator (Deroba and Schueller, 2013). Errors in the conversions to indices at age will persist from the age-length key (Deroba and Schueller, 2013). The CVs for mean length at age capture the uncertainty in the aging estimates (Deroba and Schueller, 2013), however, errors in the CVs will also persist in defining the true population. These errors will also persist within the stock assessment simulations. These aging errors are not as detrimental to this study as they are to the management of cusk. This study aims to understand the impacts of discard mortality on the population. All the length based processes (i.e., length at maturity) within the population simulator for defining the true population will be biased, but that bias is consistent among scenarios. However, these aging errors do impact our understanding of the length-based population parameters estimated for the stock assessment simulations. Efforts to develop reliable aging efforts for cusk will be necessary to develop a reliable stock assessment for this species.

### 5.4.2. Bycatch Estimations

Standardized bycatch estimates were developed to generate bycatch scenarios for the stock assessment simulations. Standardizing fisheries-dependent data is a method of adjusting catch rates to account for impacts from factors other than abundance (Maunder and Punt, 2004). Effort estimates for the American lobster fishery, defined as trap haul (Boenish and Chen, in review), provided the foundation for being able to estimate the number of individual cusk caught annually. The standardized bycatch estimates from this study differ from similar efforts by Zhang and Chen (2015) that estimated two cusk caught per 1,000 traps also using the Maine DMR lobster sea sampling data. Zhang and Chen (2015) aggregated cusk bycatch data from the lobster sea sampling program (2006 - 2011) by grids throughout coastal GOM, and found that the largest spatial aggregation (900 nautical miles) improved model fitting for standardized bycatch estimates. The present study also found that aggregating at a larger spatial scale was needed (i.e., all zones combined). Aggregating cusk data by zone was first attempted (results not shown), however there were not enough observations of cusk per zone per month for the GAM model predictions to be reliable. Aggregating can reduce the problem of having a high percentage of zero observations, but likely result in a loss of information (Zhang and Chen, 2015). Bycatch rates for cusk were estimated for the entire GOM to increase the number of observations of cusk per month, resulting in the loss of zone specific estimates.

Even earlier efforts by the Marine Stewardship Council (MSC) estimated the amount of cusk bycatch within the Maine lobster fishery using the MDMR sea sampling data as well (MSC, 2013). The MSC assessment report for the Maine lobster trap fishery estimated 0.43 individual cusk caught per fishing trip and estimated a total of 112,387 cusk caught incidentally in 2008 from approximately 260,000 trips in the Maine lobster fishery (MSC, 2013), which are 33\% -

40\% higher than the standardized 2008 BPUE estimates (39,958-47,910) from the present study (Table 5.5). The MSC estimates assume that cusk bycatch is homogenously distributed throughout space and time for the entire fleet because estimates were extrapolated to all estimated fishing trips for 2008. However, cusk have a patchy distribution (Chapter 2; Hare et al., 2012) and the probability of cusk bycatch in the Maine lobster fishery is not homogenous over space and time (Chapter 3).

The bycatch estimates from the present study now make the third attempt to estimate bycatch in the Maine lobster fishery. These estimates range from 0.43 cusk per trip, to 2 cusk per 1,000 traps, to $2.9-9.0$ per 10,000 traps utilizing the same data but from different time periods and with different methods. While standardized bycatch estimates are more reliable (Maunder and Punt, 2004), there is a significant amount of uncertainty surrounding the level of cusk bycatch in the Maine lobster fishery. This adds another level of uncertainty to understanding cusk population dynamics and the total removals of cusk, needed for reliable stock assessments.

Cusk bycatch within the Maine lobster fishery is a function of cusk behavior, fisher's behavior, and to some extent lobster behavior. Trap saturation was taken into consideration for both standardized CPUE and BPUE by either incorporating the number or weight of lobster in the trap at the time of hauling. All lobster models included the number of lobster while the cusk model included weight of lobster (Figure 5.7). Given that cusk are a territorial species, and have been documented to be aggressive towards other species (Roundtree and Juanes, 2010), presumably defending their territory, it is important to take into consideration intraspecies interactions and carrying capacity of the traps when estimating bycatch. Cusk bycatch is seasonal (Chen and Runnebaum, 2014), presumably in part because of fishing behavior. Fishers tend to be in deeper water during the spring and fall when cusk bycatch tends to be highest and more in
shore in the summer when cusk bycatch is the lowest. However, lobster catch rates are lower in the spring (MDMR, 2016b), when cusk bycatch is high. Catch rates for cusk could be higher during this time because density of lobster per trap is much lower than in the summer months.

The 2006-2013 median BPUE and upper and lower CI estimates for cusk were used to back-calculate bycatch estimates (1982 - 2005) based on the cusk abundance index derived in Chapter 2 and annual lobster F estimated from the lobster stock assessment (ASMFC, 2015). The cusk abundance estimate is developed from a spatio-temporal delta-generalized linear mixed model using fisheries-independent data (Chapter 2), which is thought to yield reliable abundance indices (Shelton et al., 2014). Back-calculated bycatch estimates assume that bycatch rates are directly proportional to cusk abundance and effort within the lobster fishery. This assumption assumes that catchability is constant for the entire time-series (Maunder and Punt, 2004). However, catchability of cusk is likely a density-dependent processes changing with declines in the population.

### 5.4.3. Stock Assessment Simulations

Annual abundance is directly proportional to catches, resulting in population estimates that are higher with higher catch rates. Population size in SCALE is estimated based on the numbers at length that survived natural mortality and fishing mortality from the previous year (NOAA, 2006). F is estimated by removing catch from the population using Baranov catch equation (NOAA, 2006). As catch rates increase with each of the DMR scenarios so does SSB, which is not unexpected (Figure 5.9) and F would then be expected to be lower when biomass estimates are higher, all things being equal. The expectations of SSB hold true for all scenarios (Figure 5.9). The expectations of F do not hold true for the entire time series. F is higher than the
base case F at the higher DMRs in 1997-2003 and 2008-2013 (Figure 5.9). These results indicate that fishing mortality rates have increased relative to population biomass and recruitment. From 2008 to 2013, the decline in SSB and recruitment to the lowest levels in the time series is followed by F increasing relative to the no bycatch scenario, in the higher mortality scenarios (Figure 5.10). In 1997 - 2003, when F at the higher DMR rates flips to being higher than F in the base case, SSB is declining and then starts to increase again and recruitment is at an all-time high (Figure 5.9). During this time, the population is dominated by younger fish because SSB is at a low but recruitment is high with the younger age classes dominating for the next few years. The fishery is selecting for the larger individuals, so F is high relative to the number of larger individuals available in the population.

A reduced discard mortality rate of $25 \%$ brought SSB and recruitment levels closer to the base case scenario with no bycatch for all three bycatch scenarios. F in the $25 \%$ DMR scenario in all three bycatch scenarios were of similar magnitude to F in the base case scenario with no bycatch (Figure 5.9). The estimated bycatch levels (MT) for the time series (Figure 5.8) are of similar magnitude to the most recent commercial landings value (Figure 5.5). These simulations show that high discard mortality results in the waste of a resource, a known problem with regulatory discards without reducing bycatch or discard mortality (Harrington et al., 2005). When bycatch rates are similar to the predicted rates of a targeted and commercial fishery, it is critical to reduce discard mortality to reduce wasting the resource.

However, it is not apparent from these simulations that SSB and recruits can recover strictly from reducing discard mortality of bycatch (Figure 5.9). SSB and recruitment estimates ended at almost the same level for all DMRs but with much higher Fs for the higher DMR scenarios (Figure 5.9). Small amounts of bycatch at low population levels can have a significant
impact on population viability (Soykan et al., 2008). Depensation coupled with low levels of removals is of concern for cusk because of their patchy distribution throughout the GOM. Increased patchiness was not thought to lead to depensatory effects for cusk because their eggs and larvae are planktonic and are easily disperse throughout the GOM (Hare et al., 2012). However, if depensation were not a problem, cusk abundance would likely be higher than was estimated in Chapter 2. Historical evidence also suggests that cusk can easily be fished out, within a few years (Goode 1884 in Collette and Klein-MacPhee, 2002) because they are a territorial, long-lived species with high site fidelity, and reach maturity at an older age.

The impact of aging errors on SSB, recruitment, and F estimated within the stock assessment should be acknowledged for cusk given uncertainty in the aging estimates. Aging errors are known to produce biased estimates of SSB, recruitment, and F within stock assessments (Reeves, 2003) and have an impact on all the age based population parameters estimated in this study. Trends for estimates of SSB and F have been shown to be the same when aging errors are present, with varying but not significantly different absolute values estimated (Reeves, 2003). Bias in SSB estimates from aging errors have not been shown to be consistent in one direction or the other, while under-aging tends to result in consistently lower recruitment estimates, and general aging errors tend to under-estimate true mean F (Reeves, 2003). It is likely that F for each of the twelve DMR/bycatch scenarios and one base case in this study was underestimated. The impacts of high F on a small population with low recruitment could exacerbate population decline, and would likely be missed in a stock assessment. Given that the maximum age of cusk is not yet agreed on, further advances will be a necessary step in developing a stock assessment for cusk in the future and to better understand potential biases from aging errors on SSB, recruitment, and F estimates.

When developing a stock assessment for cusk it will also be critical to account for total fishing mortality (i.e., commercial, recreational, bycatch, and discard mortality rates). Commercial removals of cusk are low (Figure 5.5) currently with bycatch estimates equaling close to commercial removals (Figure 5.8). Not accounting for the magnitude of bycatch and discard mortality rates will lead to underestimates of F and result in biased estimates of SSB. Two previous studies using the same data as this study (Zhang and Chen, 2015; MSC 2013), but from different years, have resulted in three different orders of magnitude of bycatch estimates for cusk in the Maine lobster fishery. Determining the most likely bycatch rates for cusk in the Maine lobster fishery is a critical first step to understanding total removals from the population. Chapter 4 indicates that cusk survival when recompressed is between $37-75 \%$, but most likely 75\%.

### 5.5. Management Recommendations

Rebuilding programs for species experiencing a decline in population have been most successful when there is a measurable reduction in fishing mortality at the beginning of the rebuilding phase instead of an incremental decrease in fishing mortality (Brodziak et al., 2008). Cusk are currently an unmanaged species and under NMFS internal status review for the Endangered Species Act, in part because it is not managed and because survey catch rates have declined (72 FR 10710, 2007). With no fisheries management plan in place for cusk, the likelihood of population recovery is low without management intervention. Recompressing cusk bycatch in the Maine lobster fishery was proposed as a potential conservation measure (Tallack, 2012) and was shown to increase survival rates of cusk in the medium-term (4-14 days) in Chapter 4. This proposed conservation measure would focus on reducing the discard mortality
rate of cusk bycatch within the Maine lobster fishery, which is thought to be a significant source of mortality for cusk. However, as a groundfish species, cusk are likely caught as bycatch in other groundfish fisheries (O’Brien, 1998) and have been increasingly targeted by recreational fishers (Hare et al., 2012; Tallack, 2012). Given previous experience, total mortality from recreational and other commercial fisheries would need to be significantly reduced as well in order to have a chance at population recovery. However, some rebuilding programs that have had measurable cuts in fishing mortality have not seen the population recovery anticipated due to incidental catches (Caddy and Agnew, 2004), depensation, loss of habitat from climate effects, predator-prey relationships, or loss of evolutionary resilience (Murawski, 2010). Additionally, moratoriums for late-maturing groundfish species have not been as successful as they have been for short-lived pelagic species (i.e., herring) because there is still incidental take of the species from targeting other groundfish species, and recruitment is low (Caddy and Agnew, 2004).

Reducing total mortality on known cusk locations through time/area closures, especially during the spawning season, could reduce the likelihood of localized depletion. Cusk recovery will likely be impacted by depensation and loss of habitat due to climate effects. Cusk habitat is thought to have become increasingly patchy (72 FR 10710, 2007), which can increase the likelihood of depensation slowing population recovery. Reducing mortality in areas where cusk are known to inhabit will provide this long-lived species opportunity to spawn. Cusk are predicted to be negatively impacted by climate change (Hare et al., 2012), which could also negatively impact population recovery. Cusk have not ever been a widely distributed species because they are sedentary and territorial (Collette and Klein-MacPhee, 2002), therefore management of this species will have to be at a relatively fine scale where they are known to inhabit.

Managing cusk as part of a mixed fishery (i.e., the multispecies groundfish fishery) would be a good first step in population recovery for this species. Rebuilding a mixed fishery may be more plausible than rebuilding specific components of a mixed fishery (Murawski, 2010). Although cusk are not currently considered to be a component of a mixed fishery, they have been caught and landed as part of other groundfish fisheries (i.e., line trawl, otter trawl, gill net, and longline in the Gulf of Maine; O'Brien, 1998). As a demersal groundfish species that have been observed in productive areas, such as coral habitat, with other groundfish species, such as Acadian redfish, (Roundtree and Juanes, 2010), cusk are, in effect, already part of a mixed fishery but without the necessary regulations to ensure sustainable management. The New England Fisheries Management Council (NEFMC) manages groundfish species through the multispecies groundfish fisheries management plan. Incorporating cusk into the NEFSC multispecies groundfish fisheries management plan could allow for rebuilding cusk through mixed fishery management but could also impact commercial and recreational fishermen's access to more robust and lucrative species (Murawski, 2010; Broadziak et al., 2008).

Implementing management plans for cusk and efforts to significantly reduce discard mortality would be a critical aspect to further consider in the ESA status review. ESA listings must consider formalized conservation measures, and their effectiveness, implemented before the review process (Kass, 2015; 68 FR 15100, 2003). This study suggests that reducing discard mortality to $25 \%$ would result in SSB and recruitment estimates to similar levels of no bycatch (Figure 5.9). While reducing discard mortality of cusk bycatch in the lobster fishery to low levels will have a positive impact, it might not be enough to facilitate a population recovery. Requiring lobstermen to recompress cusk as a conservation measure would reduce the discard mortality of cusk (Chapter 4) but compliance with these conservation measures might be low if fishermen do
not agree with the measure. This conservation measure would then be less effective and total mortality would likely be underestimated if $100 \%$ compliance was assumed or overestimated if $0 \%$ compliance was assumed. However, implementing effective measures to reduce discard mortality of cusk may prevent the need for listing cusk under the ESA if the conservation measures are extensive and have been shown to work (Kass, 2015; 68 FR 15100, 2003).

The lack of state and federal management for cusk is likely to reduce the ability of cusk to recover and potentially lead to the need for an ESA listing if population levels continue to decline further. Future management decisions will need to be made for cusk, and there is no ‘silver bullet'. Management decisions will be difficult for this data limited species due to high levels of uncertainty and potential obstacles to a successful recovery. A multipronged approach to significantly reducing total mortality from commercial, recreational, and bycatch fisheries will be necessary, but even a drastic reduction in total mortality will not guarantee population recovery.

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## APPENDIX A: EVALUATING THE IMPACT OF BAIT PLUME SIZE ON DENSITY ESTIMATES

This study, in part, set out to determine if data from two gear types could be combined to develop abundance indices. To test if catchability within the delta-GLMM was capable of accounting for differences of gear types, different estimates of area fished were evaluated for the LLS. The distance between the beginning and end of a longline set were known but the bait plume around the longline was not known. Bait plume is a function of current speed and direction, bait type, and soak duration, which sets the range over which the bait can be detected, as well as factors influencing the range over which fish will respond to detected bait; the fish response factors include length of food deprivation (i.e., hunger), fish size, and swimming speed (Løkkeborg et al., 1995; Zhou et al., 2014). These specifics are rarely known in fisheries surveys, and feeding response to bait plumes has not been measured for cusk. Without knowing the details necessary to estimate the bait plume, three values of $b$ were tested based on the estimates for moderate food deprivation in Løkkeborg et al. (1995). A minimum, medium, and maximum value of $b(280 \mathrm{~m}, 560 \mathrm{~m}, 1121 \mathrm{~m}$ respectively) were used to test the sensitivity of abundance estimates to longline area fished.

A total of six model-based density fields with different configurations of values for $b$ were estimated for spring and fall. Each season had three models that incorporated both the BTS and LLS using the three values of $b$ (i.e., $0.28 \mathrm{~km}, 0.56 \mathrm{~km}$, and 1.12 km ). The resulting estimates for area fished varied by an order of magnitude (less than $0.5 \mathrm{~km}^{2}$ when $b=0.28 \mathrm{~km}$ and up to $2.0 \mathrm{~km}^{2}$ when $b=1.121 \mathrm{~km}$ ). Three catchability parameters were estimated to account for the

2009 protocol changes in the BTS. The estimated abundance index for the three models in the spring and three in the fall were unchanged with changes in the value of $b$ (Figure 2). AICs for all three values of $b$ were unchanged for the different model runs in both the spring (3837) and the fall (3676).

When catchability was not estimated for the LLS, the annual abundance index was inconsistent and highly variable during the exploratory phase of this study (results not shown). The deltaGLMM could account for differences in catchability between the LLS and BTS, indicating this is an effective method of incorporating multiple surveys with different gear types to estimate abundance indices, even without accurate bait plume measures for a longline survey.

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Jocelyn Runnebaum was born in Stillwater, Oklahoma on October 11, 1982. She was raised in Fort Worth, Texas and graduated from Fossil Ridge High School in 2001. She attended Stephen F. Austin State University and graduated in 2006 with a Bachelor's degree in Aquatic Biology. She commercial fished and trained sled dogs in Alaska after receiving her Bachelor's degree. Jocelyn then joined the Peace Corps in Zambia where she worked with small scale aquaculture farmers. Jocelyn entered the School of Marine Sciences graduate program in the fall of 2012. Jocelyn is a candidate for the Doctor of Philosophy degree in Marine Biology from the University of Maine in August 2017.

