

The University of Maine

DigitalCommons@UMaine

Electronic Theses and Dissertations

Fogler Library

Spring 5-10-2019

Developing a Robust Model-Based Framework to Estimate Groundfish Abundance and Understanding Spatial Variability in Life History of Atlantic Cod (*Gadus Morhua*) in the Eastern Gulf of Maine

John A. Carlucci

University of Maine, john.carlucci@maine.edu

Follow this and additional works at: <https://digitalcommons.library.umaine.edu/etd>

Recommended Citation

Carlucci, John A., "Developing a Robust Model-Based Framework to Estimate Groundfish Abundance and Understanding Spatial Variability in Life History of Atlantic Cod (*Gadus Morhua*) in the Eastern Gulf of Maine" (2019). *Electronic Theses and Dissertations*. 3187.
<https://digitalcommons.library.umaine.edu/etd/3187>

This Open-Access Thesis is brought to you for free and open access by DigitalCommons@UMaine. It has been accepted for inclusion in Electronic Theses and Dissertations by an authorized administrator of DigitalCommons@UMaine. For more information, please contact um.library.technical.services@maine.edu.

**DEVELOPING A ROBUST MODEL-BASED FRAMEWORK TO ESTIMATE
GROUNDFISH ABUNDANCE AND UNDERSTANDING SPATIAL
VARIABILITY IN LIFE HISTORY OF ATLANTIC COD
(*GADUS MORHUA*) IN THE EASTERN
GULF OF MAINE**

By

John A. Carlucci

B.S. University of Maine, 2017

A THESIS

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Master of Science

(in Marine Biology)

The Graduate School

The University of Maine

May 2019

Advisory Committee:

Yong Chen, Professor of Fisheries Science, Advisor

Walt Golet, Research Assistant Professor of Marine Sciences

Michael Palmer, Research Fishery Biologist

**DEVELOPING A ROBUST MODEL-BASED FRAMEWORK TO ESTIMATE
GROUNDFISH ABUNDANCE AND UNDERSTANDING SPATIAL
VARIABILITY IN LIFE HISTORY OF ATLANTIC COD
(*GADUS MORHUA*) IN THE EASTERN
GULF OF MAINE**

By: John A. Carlucci

Thesis Advisor: Dr. Yong Chen

An Abstract of the Thesis Presented
in Partial Fulfillment of the Requirements for the
Degree of Master of Science
(in Marine Biology)
May 2019

Over the past several decades, the Atlantic cod (*Gadus morhua*) stock in the Gulf of Maine (GOM) has experienced a steep decline in abundance and exhibited changes in spatial distribution. Although the cod fishery in the Eastern Gulf of Maine (EGOM) remains open to fishing, low stock density and complex bathymetry have resulted in little fishing effort and sparse data collection. In an effort to fill gaps in the available data, the Eastern Gulf of Maine Sentinel Survey is a longline/jig survey that targets groundfish species, such as Atlantic cod, Atlantic halibut (*Hippoglossus hippoglossus*), white hake (*Urophycis tenuis*), and cusk (*Brosme brosme*), to collect fine-scale fisheries-independent and dependent data to improve the existing stock assessments for commercially important groundfish species. This research aims to evaluate the methodology for the jigging portion of the EGOM Sentinel Survey for sources of bias which may skew estimates of relative abundance in addition to developing a robust modeling framework that will produce accurate estimates of abundance for groundfish species in the

EGOM. Statistical models will be used to make inferences about groundfish abundance and assess potential sources of bias from survey methodology. Furthermore, the established Gulf of Maine cod stock assessment/management strategy assumes unit stock structure in which life history parameters are consistent among individuals across the GOM such that any differences would not impede the stock-rebuilding plan. Given the variation in habitat, ecosystem structure, and food availability across the GOM, such simplifying assumptions may inhibit efforts to rebuild the overall cod stock and reduce overfishing across the GOM. This research aims to improve the analysis and interpretation of the fine-scale hook-and-line surveys, provide suggestions to improve fishery survey designs, and provide more information to better inform regional science and management efforts in the Gulf of Maine. In addition to evaluating survey methods and modeled estimates of abundance, age-specific absolute growth (e.g. change in length, weight, and condition factor) will be evaluated for cod in spatially explicit regions of the Gulf of Maine using a non-parametric bootstrap approach to evaluate inter-regional growth rates of Atlantic cod between the EGOM, western GOM, and George's Bank.

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my committee, Dr. Yong Chen, Dr. Walt Golet, and Michael Palmer, for their assistance and support throughout this process. I would like to personally thank Max Ritchie, Cameron Hodgson, Dr. Kisei Tanaka, and Dr. Robert Boenish for their unending help and insight about conducting analyses and writing the R code to execute them; without them this thesis would not have been possible. I would like to thank the fishermen who offered their vessels for this research: Steve Brown, Mattie Thompson, and Bobby Jones. Finally, I owe a very special and sincere thank you to Sammi Nadeau and my family whom, despite involuntarily dealing with the sinusoidal trend in my own personal emotions surrounding this process, have pushed and supported my endeavors of becoming a Marine Biologist.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS **ii**

LIST OF TABLES **viii**

LIST OF FIGURES **xi**

**CHAPTER 1: AN INTRODUCTION TO THE ATLANTIC COD (*GADUS MORHUA*)
FISHERY AND GROUND FISH SURVEY PROGRAMS IN THE EASTERN GULF OF
MAINE** **1**

**CHAPTER 2: EVALUATING SITE-SPECIFIC OCCUPANCY AND DETECTION
PROBABILITY AS A MEASURE OF ASSESSING GEAR CATCHABILITY IN HOOK AND
LINE SURVEYS.** **10**

INTRODUCTION **10**

METHODS **12**

 Survey Methods **12**

 Modeling Methods **13**

RESULTS **14**

DISCUSSION **29**

CONCLUSIONS **33**

**CHAPTER 3: DEVELOPING A ROBUST MODELING FRAMEWORK TO ESTIMATE
GROUND FISH ABUNDANCE FROM HOOK AND LINE SURVEYS.** **35**

I. INTRODUCTION **35**

II. METHODS	37
II-1. Sentinel Survey Sampling Methods	37
II-1-A. Pilot Seasons (2010-2011).....	37
II-1-B. 2012 Addition of Jigging Component.....	38
II-1-C. 2013 Jigging Incorporated at Longline and Fishermen’s Choice Stations.....	39
II-1-D. 2016 Jigging-Only Season	40
II-1-E. 2017 Shortened Longline	41
II-2. Modeling.....	42
II-2-A. Modeling Approaches.....	42
II-2-B. Incorporating Catchability (Probability of detection) into Model- Based Estimates	44
II-2-C. Cross Validation and Model Selection	45
II-3. Calculation of Abundance Indices	47
II-3-A. Design-Based Abundance Index.....	47
II-3-B. Model-Based Abundance Index.....	48
II-4. Standardizing Catch Per Unit of Effort	49
II-5. Allocation of Fishing Effort	50

II-6. 2018 Sentinel Survey Stations	50
III. RESULTS	51
III-1. Estimated Abundance Indices	51
III-1-A. Design-Based Abundance Index – Stratified Random Longline Stations.....	51
III-1-B. Model-Based Abundance Index – Stratified Random Longline Stations.....	52
III-1-C. Design-Based Abundance Index – Stratified Random Jigging Stations.....	59
III-1-D. Model-Based Abundance Index – Stratified Random Jigging Stations.....	59
III-2. Standardized CPUE	64
III-3. Bait Type and Habitat Preference	70
IV. DISCUSSION	83
IV-1. Abundance Indices	83
IV-1.A. Abundance Indices – Stratified Random Longline and Stratified Random Jigging Stations	83

IV-1-B. Selecting the Most Robust Index of Abundance and Comparing Model Types	88
IV-2. Standardization of CPUE	94
IV-3. Bait Type, Habitat Preference, and Seasonal Trends	95
IV-3-A. Bait Preference	95
III-1-B. Depth and Sediment Class	96
III-1-C. Sea Surface and Bottom Temperature	98
III-1-D. Evaluating Seasonal Trends in Catch (Month).....	99
IV-4. Catchability and Non-Target Species	100
IV-5. Data Gaps and Limitations	101
V. CONCLUSIONS	103
 CHAPTER 4: UNDERSTANDING THE SPATIAL VARIABILITY IN LIFE HISTORY PARAMETERS OF ATLANTIC COD (<i>GADUS MORHUA</i>) IN THE EASTERN GULF OF MAINE.	104
INTRODUCTION	104
METHODS	109
Identifying Spatially Explicit Areas in the Gulf of Maine	109
Assessing Inter-Regional Growth Rates	110
Evaluating Temporal Trends in Growth Parameters	113

Evaluating the Statistical Significance of Inter-Regional Growth Differences	114
Limitations	114
RESULTS	115
Seasonal and Temporal trends in Age-Specific Length, Weight, and Condition	
Factor	115
Frequency of Statistically Significant Differences in Age-Specific Growth	
Parameters Between Major Areas and Sub-stocks	160
Major Area Comparison (Eastern GOM, Western GOM, and George’s Bank)	161
Proposed Sub-Stock Comparison (Eastern GOM, Western GOM, Great South	
Channel, George’s Bank).....	166
DISCUSSION	174
CONCLUSIONS	180
CHAPTER 5: A SUMMATION OF CONCLUSIONS.	182
LITERATURE CITED	187
APPENDIX.....	193
Shortened Longline Justification and Evaluation of soak Time (as described by	
Carlucci and Chen, 2017)	193
ABOUT THE AUTHOR.....	195

LIST OF TABLES

Table II-1: Model building process for site-occupancy and site-detection.	14
Table II-2: Output of the occupancy modelling framework in which the top five performing models are reported and organized according to AIC value.	15
Table II-3: Output of the detection modelling framework in which the top five performing models are reported and organized according to AIC value.	15
Table II-4: Model Output to evaluate the significance of the relationship between cod detection, cod occupancy, and each of the environmental covariates.....	16
Table III-1: Annual allocation of fishing effort on the Sentinel Survey from 2012-2018. Longline is abbreviated as LL.	50
Table III-2: Design-based delta mean estimated abundance, standard deviation ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for cod calculated based on stratified random longline data from 2012-2018.....	58
Table III-3: Generalized Additive Model-based delta mean estimated abundance, standard deviation ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for cod calculated based on stratified random longline data from 2012-2018.	58
Table III-4: Boosted Regression Tree model-based delta mean estimated abundance, standard deviation ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for cod calculated based on stratified random longline data from 2012-2018.	58

Table III-5: Design-based delta mean estimated abundance, standard deviation ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for cod calculated based on jigging data from 2012-2018.....	63
Table III-6: GAM-based delta-mean estimated abundance, standard deviation ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for cod calculated based on jigging data from 2012-2018.	63
Table III-7: BRT-based delta-mean estimated abundance, standard deviation ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for cod calculated based on jigging data from 2012-2018.	64
Table III-8: Standardized nominal CPUE, GAM estimated CPUE, and BRT estimated CPUE for survey abundance index based on fisherman’s choice data for targeted groundfish species.....	69
Table III-9: Results of the Tweedie GAM for each target species in the longline data. Asterisks (*) denote levels of significance for each variable (no asterisk means the variable is not statistically significant (p>0.05), (***) represents most significant variable(s) (P<0.05).	80
Table III-10: Results of the Tweedie GAM for cod in the jig data.	81
Table III-11: Results from the BRT models for each species illustrating the average relative influence of each explanatory variable in predicting species abundance.	82

Table III-12: Results from the BRT models for jigging models illustrating the average relative influence of each explanatory variable in predicting cod abundance.	82
Table III-13: Mean squared error of each longline model for each species.....	93
Table III-14: Mean squared error of each jigging model.	93
Table III-15: Intercept, Slope, and R^2 resulting from the cross validation of different model types for each target species caught on the longline.	93
Table III-16: Intercept, Slope, and R^2 resulting from the cross validation of different model types for cod caught in the jigging portion of the survey.	93
Table IV-1: Percent frequency of statistically significant differences in spring length, weight, and condition factor between large areas for each age class.	163
Table IV-2: Percent frequency of statistically significant differences in fall length, weight, and condition factor between large areas for each age class.	164
Table IV-3: Percent frequency of statistically significant differences in combined spring and fall length, weight, and condition factor between large areas for each age class.	165
Table IV-4: Percent frequency of statistically significant differences in spring length, weight, and condition factor between sub-stock areas for each age class.	168
Table IV-5: Percent frequency of statistically significant differences in fall length, weight, and condition factor between sub-stock areas for each age class.	170

Table IV-6: Percent frequency of statistically significant differences in combined
spring and fall length, weight, and condition factor between sub-stock areas for each age
class.....**172**

LIST OF FIGURES

Figure I-1: Top: Map of the Northeast Fisheries Science Center bottom trawl survey data used in the Gulf of Maine Atlantic cod stock assessment as adapted from the NMFS: 2014 Atlantic cod Stock Assessment Update Report.	3
Figure I-2: Map of the 2018 Eastern Gulf of Maine Sentinel Survey area.	5
Figure I-3: Map of proposed Atlantic cod sub-stock areas in the Gulf of Maine (adapted from Pershing 2013) to be used as a template for spatially explicit growth analysis.....	6
Figure II-1: Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in the month of June from 2012-2017.....	17
Figure II-2: Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in the month of July from 2012-2017.	17
Figure II-3: Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in the month of August from 2012-2017.	18
Figure II-4: Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in the month of September from 2012-2017.	18
Figure II-5: Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in the month of October from 2012-2017.	19

Figure II-6: Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in the month of November from 2012-2017.	19
Figure II-7: Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in 2012.	20
Figure II-8: Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in 2013.	20
Figure II-9: Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in 2014.	21
Figure II-10: Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in 2015.	21
Figure II-11: Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in 2016.	22
Figure II-12: Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in 2017.	22
Figure II-13: Map of EGOM Sentinel Survey sampling area displaying probability of site detection in the month of June from 2012-2017.	23
Figure II-14: Map of EGOM Sentinel Survey sampling area displaying probability of site detection in the month of July from 2012-2017.	23
Figure II-15: Map of EGOM Sentinel Survey sampling area displaying probability of site detection in the month of August from 2012-2017.	24

Figure II-16: Map of EGOM Sentinel Survey sampling area displaying probability of site detection in the month of September from 2012-2017.	24
Figure II-17: Map of EGOM Sentinel Survey sampling area displaying probability of site detection in the month of October from 2012-2017.	25
Figure II-18: Map of EGOM Sentinel Survey sampling area displaying probability of site detection in the month of November from 2012-2017.	25
Figure II-19: Map of EGOM Sentinel Survey sampling area displaying probability of site detection in 2012.	26
Figure II-20: Map of EGOM Sentinel Survey sampling area displaying probability of site detection in 2013.	26
Figure II-21: Map of EGOM Sentinel Survey sampling area displaying probability of site detection in 2014.	27
Figure II-22: Map of EGOM Sentinel Survey sampling area displaying probability of site detection in 2015.	27
Figure II-23: Map of EGOM Sentinel Survey sampling area displaying probability of site detection in 2016.	28
Figure II-24: Map of EGOM Sentinel Survey sampling area displaying probability of site detection in 2017.	28
Figure III-1: 2018 Eastern Gulf of Maine Sentinel Survey Stations.	50

Figure III-2: Delta mean estimated mean abundance and associated standard deviation for cod caught at stratified random longline station from 2012-2018.	54
Figure III-3: Delta mean estimated mean abundance and associated standard deviation for Atlantic halibut caught at stratified random longline station from 2012-2018.	55
Figure III-4: Delta mean estimated mean abundance and associated standard deviation for white hake caught at stratified random longline station from 2012-2018.	56
Figure III-5: Delta mean estimated mean abundance and associated standard deviation for cusk caught at stratified random longline station from 2012-2018.	57
Figure III-6: Relative Abundance of Atlantic cod at all random jig (JJ & JJO & JL) Stations from 2012-2018.	60
Figure III-7: Relative Abundance of Atlantic cod at all Inshore Jig (JJ Stratum 0) Stations from 2012-2018.	61
Figure III-8: Relative Abundance of Atlantic cod at Offshore Jig (JJO) Stations from 2012-2018.	62
Figure III-9: Fitted and predicted nominal, GAM, and BRT standardized CPUEs and associated standard deviation Atlantic cod derived from fishermen’s choice stations from 2012 to 2018.	65
Figure III-10: Fitted and predicted nominal, GAM, and BRT standardized CPUEs and associated standard deviation for Atlantic halibut derived from fishermen’s choice stations from 2012 to 2018.	66

Figure III-11: Fitted and predicted nominal, GAM, and BRT standardized CPUEs and associated standard deviation for White Hake derived from fishermen’s choice stations from 2012 to 2018.67

Figure III-12: Fitted and predicted nominal, GAM, and BRT standardized CPUEs and associated standard deviation for cusk derived from fishermen’s choice stations from 2012 to 2018.68

Figure III-13: Longline model-derived relationships between catch abundance and bait for Atlantic cod, Atlantic halibut, white hake, and cusk in which the blue line represents the mean and the shadow represents the uncertainty.73

Figure III-14: Longline model-derived relationships between catch abundance and depth for Atlantic cod, Atlantic halibut, white hake, and cusk in which the blue line represents the mean and the shadow represents the uncertainty.74

Figure III-15: Longline model-derived relationships between catch abundance and observed sediment class for Atlantic halibut and white hake in which the blue line represents the mean and the shadow represents the uncertainty.....75

Figure III-16: Longline model-derived relationships between catch abundance and sea surface temperature for Atlantic cod, Atlantic halibut, white hake, and cusk in which the blue line represents the mean and the shadow represents the uncertainty.76

Figure III-17: Longline model-derived relationships between catch abundance and bottom temperature for Atlantic cod, Atlantic halibut, white hake, and cusk in which the blue line represents the mean and the shadow represents the uncertainty.77

Figure III-18: Longline model-derived relationships between catch abundance and month for Atlantic halibut and white hake in which the blue line represents the mean and the shadow represents the uncertainty.....78

Figure III-19: Jigging Model-derived relationships between cod abundance and sediment type, depth, presence/absence of Mackerel, presence/absence of Pollock, bottom temperature, and sea surface temperature for Atlantic cod in which the blue line represents the mean and the shadow represents the uncertainty.79

Figure III-20: Abundance estimates derived from National Marine Fisheries Service Spring and Fall bottom trawl survey.86

Figure III-21: Results of the cross-validation tests between observed and predicted values. Solid black line represents a Line with slope of 1.90

Figure III-22: Results of the cross-validation tests for jigging models. Solid black line represents a Line with slope of 1.91

Figure III-23: Results of the cross-validation tests for inshore jigging models. Solid black line represents a Line with slope of 1.92

Figure III-24: Results of the cross-validation for offshore jigging models. Solid black line represents a Line with slope of 1.92

Figure IV-1: Top: Map of the Gulf of Maine Atlantic cod (*Gadus morhua*) management assessment area (gray).105

Figure IV-2: Map of proposed Atlantic cod sub-stock areas in the Gulf of Maine (adapted from Pershing 2013) to be used as a template for spatially explicit growth analysis.109

Figure IV-3: Histogram of Age class density observed on the NEFSC bottom trawl survey from 1970-2018.111

Figure IV-4: Mean change in cod weight from ages 1-2 in the eastern GOM, western GOM, and George’s bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.116

Figure IV-5: Mean change in cod length from age 4-5 in eastern GOM from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.117

Figure IV-6: Mean change in cod length from age 2-3 in western GOM from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.118

Figure IV-7: Mean change in cod length from age 3-4 in western GOM from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.119

Figure IV-8: Mean change in cod length from age 1-2 in Great South Channel from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.120

Figure IV-9: Mean change in cod length from age 2-3 in Great South Channel from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.121

Figure IV-10: Mean change in cod length from age 3-4 in Great South Channel from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.122

Figure IV-11: Mean change in cod length from age 1-2 on George’s Bank from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.123

Figure IV-12: Mean change in cod length from age 2-3 on George’s Bank from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.124

Figure IV-13: Mean change in cod length from age 4-5 on George’s Bank from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.125

Figure IV-14: Median change in cod length from age 4-5 in eastern GOM from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.126

Figure IV-15: Median change in cod length from age 3-4 in western GOM from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.....**127**

Figure IV-16: Median change in cod length from age 1-2 in Great South Channel from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.**128**

Figure IV-17: Median change in cod length from age 2-3 in Great South Channel from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.**129**

Figure IV-18: Median change in cod length from age 3-4 in Great South Channel from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.**130**

Figure IV-19: Median change in cod length from age 1-2 on George’s Bank from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.**131**

Figure IV-20: Median change in cod length from age 2-3 on George’s Bank from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.....**132**

Figure IV-21: Median change in cod length from age 4-5 on George’s Bank from 1970-2018 based on fall and spring NEFSC bottom trawl surveys.....**133**

Figure IV-22: Mean change in cod weight from age 4-5 in eastern GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.....**134**

Figure IV-23: Mean change in cod weight from age 2-3 in western GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.....	135
Figure IV-24: Mean change in cod weight from age 4-5 in western GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.....	136
Figure IV-25: Mean change in cod weight from age 1-2 on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.....	137
Figure IV-26: Mean change in cod weight from age 2-3 on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.....	138
Figure IV-27: Mean change in cod weight from age 4-5 cod weight on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.....	139
Figure IV-28: Median change in cod weight from age 4-5 in eastern GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.....	140
Figure IV-29: Median change in cod weight from age 4-5 in western GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.....	141
Figure IV-30: Median change in cod weight from age 1-2 in Great South Channel from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.	142

Figure IV-31: Median change in cod weight from age 3-4 on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.....**143**

Figure IV-32: Age 1 mean cod condition factor in eastern GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.**144**

Figure IV-33: Age 3 mean cod condition factor in eastern GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.**145**

Figure IV-34: Age 4 mean cod condition factor in eastern GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.**146**

Figure IV-35: Age 2 mean cod condition factor in western GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.**147**

Figure IV-36: Age 1 mean cod condition factor on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.**148**

Figure IV-37: Age 2 mean cod condition factor on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.**149**

Figure IV-38: Age 3 mean cod condition factor on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys.**150**

Figure IV-39: Age 5 mean cod condition factor on George’s Bank from 1992-2018
based on fall and spring NEFSC bottom trawl surveys.151

Figure IV-40: Age 5 mean cod condition factor on George’s Bank from 1992-2018
based on fall and spring NEFSC bottom trawl surveys.152

Figure IV-41: Age 3 median cod condition factor in eastern GOM from 1992-2018
based on fall and spring NEFSC bottom trawl surveys.153

Figure IV-42: Age 2 median cod condition factor in western GOM from 1992-2018
based on fall and spring NEFSC bottom trawl surveys.154

Figure IV-43: Age 5 median cod condition factor in western GOM from 1992-2018
based on fall and spring NEFSC bottom trawl surveys.155

Figure IV-44: Age 1 median cod condition factor on George’s Bank from 1992-2018
based on fall and spring NEFSC bottom trawl surveys.156

Figure IV-45: Age 2 median cod condition factor on George’s Bank from 1992-2018
based on fall and spring NEFSC bottom trawl surveys.157

Figure IV-46: Age 3 median cod condition factor on George’s Bank from 1992-2018
based on fall and spring NEFSC bottom trawl surveys.158

Figure IV-47: Age 4 median cod condition factor on George’s Bank from 1992-2018

based on fall and spring NEFSC bottom trawl surveys.159

Figure IV-48: Age 5 median cod condition factor on George’s Bank from 1992-2018

based on fall and spring NEFSC bottom trawl surveys.160

CHAPTER 1

**AN INTRODUCTION TO THE ATLANTIC COD (*GADUS MORHUA*) FISHERY
AND GROUND FISH SURVEY PROGRAMS IN THE
EASTERN GULF OF MAINE**

Over the past several decades, the Atlantic cod (*Gadus morhua*) stock in the Gulf of Maine (GOM) has undergone a steep decline in abundance and changes in spatial distribution (Steneck *et. al.*, 2013). Although the cod fishery in the Eastern Gulf of Maine (EGOM) remains open to fishing, there is a low cod stock density in the region and, consequently, virtually no directed fishing effort (Palmer, 2014; Pershing *et. al.*, 2013; Murawski *et al.* 1998) despite lobstermen having reported catching cod as bycatch in their traps (Boenish and Chen, 2018). Fisheries-independent survey programs, such as bottom trawl surveys, by the Maine DMR and National Marine Fisheries Service (NMFS) have sampling stations within the EGOM, but their spatial and temporal coverage is limited because of restricted gear use in areas with complex bottom topography and high density of fixed gear (e.g., lobster traps; Figure I-1:Top). Thus, trawl survey catchability for groundfish that reside in complex benthic habitats (e.g., cod, cusk, and halibut) tends to be low. Despite the spatial imbalance of fishing effort between the western Gulf of Maine (WGOM) and the EGOM (Palmer, 2014; Murawski *et al.* 1998), the cod stock assessment assumes a single stock that encompasses the entirety of the Gulf of Maine (GOM; Figure I-1:Bottom). As a result, the current cod stock assessment may misrepresent the true status of cod in the GOM. This misrepresentation could lead to scenarios of regional stock overexploitation and inadequate management or it could lead to under-exploitation and an accelerated stock rebuilding process. Although it is difficult to confirm the directionality of the impact that these biases may have on fisheries management in

the future, the overall lack of success rebuilding the cod stock provides some qualitative evidence that regional overexploitation could be more likely.

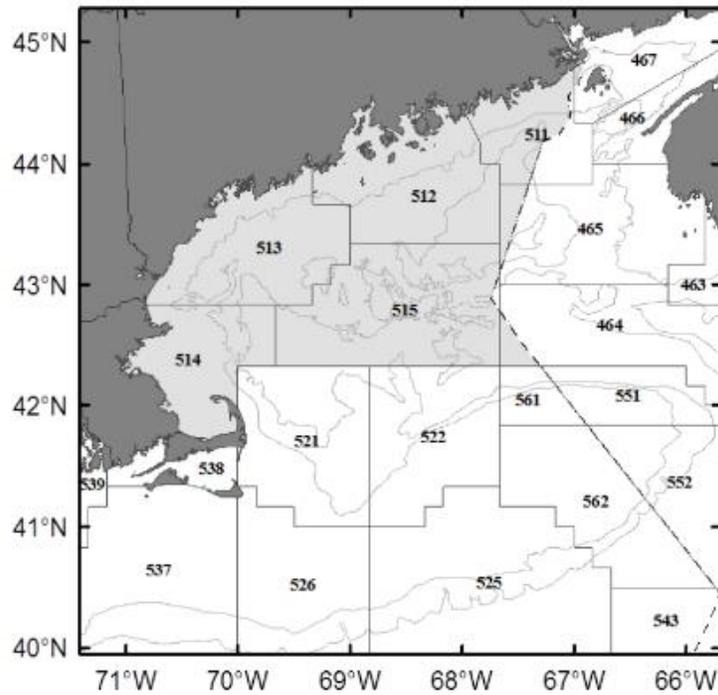
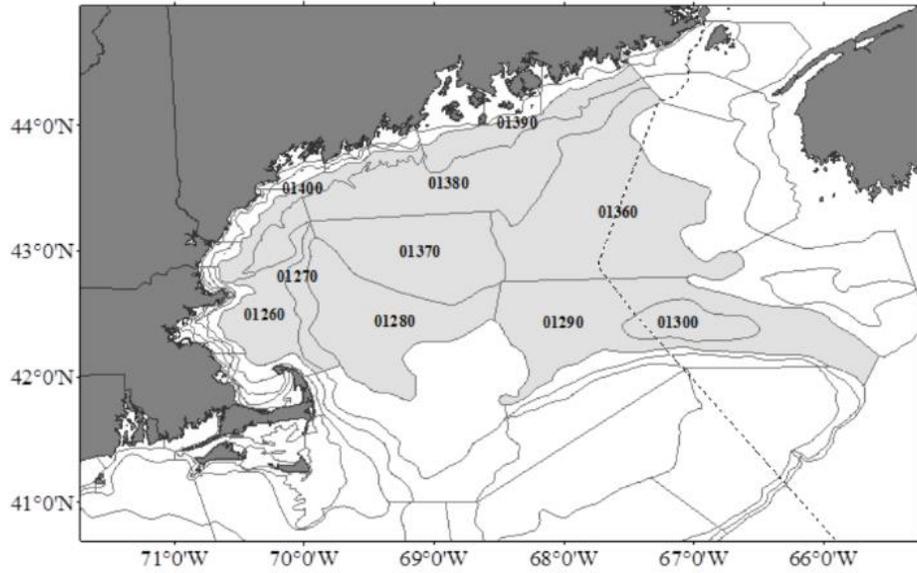


Figure I-1. Top: Map of the Northeast Fisheries Science Center bottom trawl survey data used in the Gulf of Maine Atlantic cod stock assessment as adapted from the NMFS: 2014 Atlantic cod Stock Assessment Update Report. Bottom: Map of the Gulf of Maine Atlantic cod (*Gadus morhua*) management assessment area (gray).

Assessing and managing under a single stock framework has many associated assumptions, one of which is that the variability in phenotypical life history parameters is small enough across the Gulf of Maine such that the failure to account for this variability would not introduce any major bias in the stock assessment or impede rebuilding the cod stock in the GOM. It assumes there is no statistically significant difference in life history parameters such as growth rates or maturation schedules exhibited by cod across the GOM. To satisfy this assumption, there must be significant reproductive mixing between cod aggregates throughout the GOM. Given the evidence for geographically isolated reproduction areas and the variation in habitat, ecosystem structure, and food availability, it is unlikely that making such assumptions in the current management regime will help to rebuild the overall cod stock and reduce overfishing in each potential subpopulation in the GOM (Ames, 2004; Jones, 2002). Minimal success in rebuilding the GOM cod fishery has led research efforts to become more focused on elucidating finer-scale population structure to identify significant factors governing cod distribution and life history characteristics (Pershing *et. al.* 2013; Palmer *personal communication*; Chen *personal communication*).

Spatial gaps in the available data, which have been caused by low stock abundance and little fishing activity, highlight a need for close monitoring of groundfish populations in the EGOM. To fill the aforementioned gaps in spatial coverage by state and federal trawl survey programs, the Eastern Gulf of Maine Sentinel Survey has been implemented from Penobscot Bay to the Canadian border (Figure I-2). This survey utilizes longline and jigging gear to increase sampling efficiency for those groundfish species which tend to have low catchability and prefer labyrinthine habitat. In addition to improving the sampling coverage of an area with minimal fishery data and is also inadequately sampled, the EGOM Sentinel Survey provides a

platform to collect fine-scale data on important groundfish species and gain a better understanding of the spatial dynamics of groundfish stocks within the GOM.

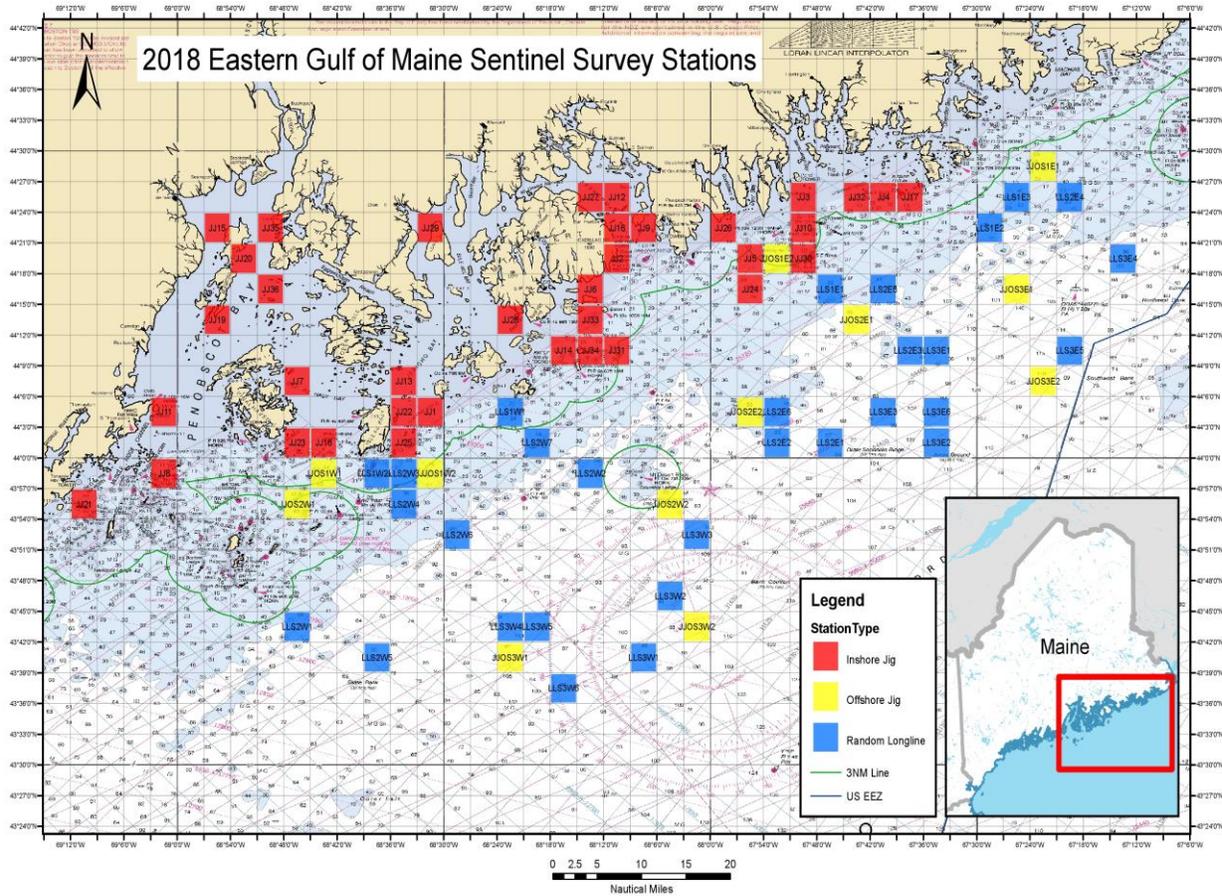


Figure I-2. Map of the 2018 Eastern Gulf of Maine Sentinel Survey area.

Based on the limitations of the current management scheme for cod in the GOM, the need to increase survey effort is supported by the need to develop accurate, fine-scale estimates of fish abundance and a need to understand the spatial variability in life history parameters of cod in the GOM at a scale smaller than what is currently assessed. This study will explore catchability as a potential source of inherent gear bias in scientific surveys and incorporate catchability into the estimates of abundance to develop a more robust and accurate method of calculating species abundance. In addition to developing this modeling framework

for abundance, I will test and compare multiple modelling frameworks (Boosted Regression Trees and Generalized Additive Models) with an observation-based framework to find the most reliable estimate of abundance. Finally, a non-parametric bootstrap approach will be used to explore the spatio-temporal variability in life history parameters (e.g. length at age, weight at age, and condition factor) to make inferences about inter-regional growth rates between the EGOM, WGOM, and George’s Bank (GBK; Figure I-3). This work is intended to further the understanding of inter-regional differences in life history parameters of cod and explore the evidence for a complex metapopulation structure in the GOM (Elsdon *et al.* 2008; Jones, 2002).

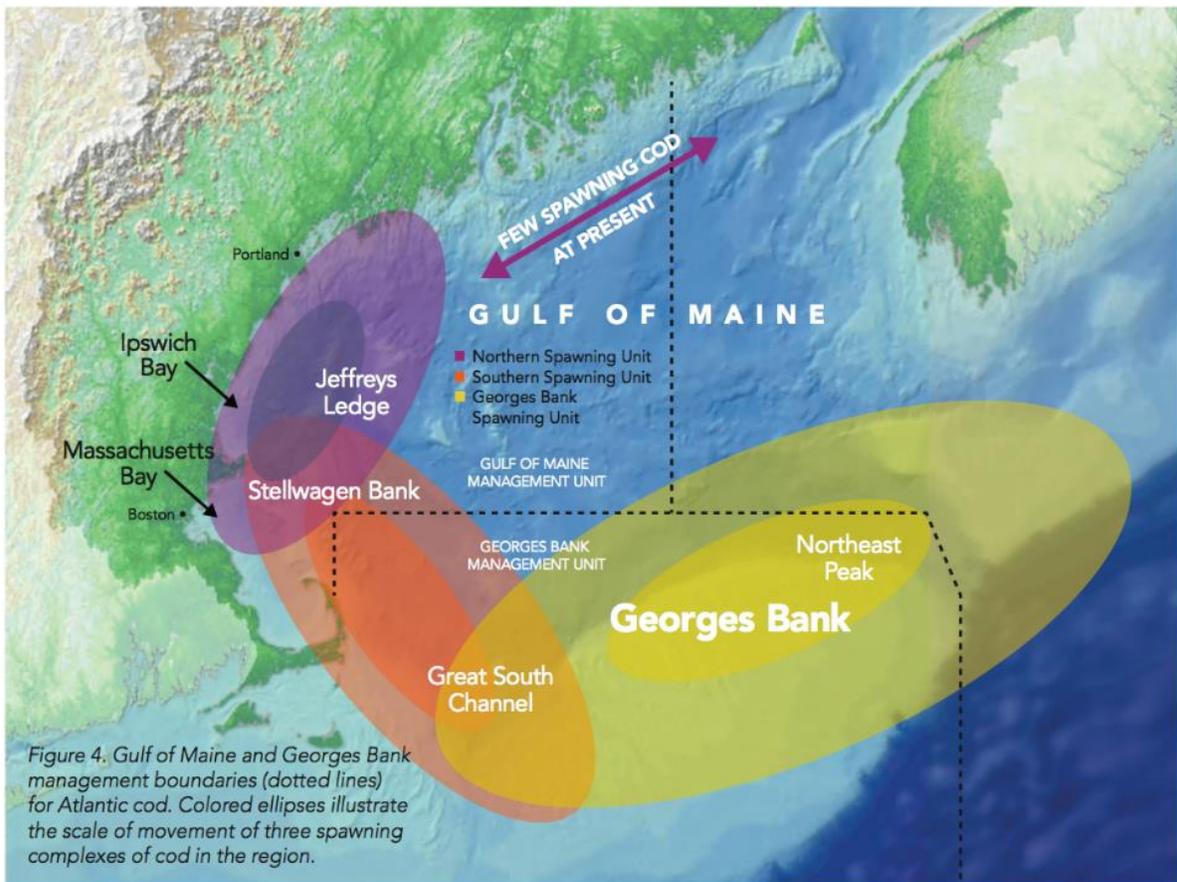


Figure I-3. Map of proposed Atlantic cod sub-stock areas in the Gulf of Maine (adapted from Pershing 2013) to be used as a template for spatially explicit growth analysis.

The overarching purpose of this study is to provide insight into the spatial dynamics of the cod stock within the EGOM, improve the analysis and interpretation of the fine-scale hook-and-line surveys, provide suggestions to improve fishery survey designs, and provide more information to better inform regional science and management efforts in the Gulf of Maine. This research, as well as the sentinel survey, is designed to develop a robust dataset that will improve the understanding of GOM cod stock structure. Although there is an important distinction to be made between statistical significance and biological significance, the presence of statistically significant differences in allometrics may implicate a need for fisheries scientists to develop a more spatially explicit stock assessment that will limit the occurrence of overexploitation in separate cod stocks. The information resulting from this study will give scientists and managers a better understanding of what environmental factors and/or pressures play a significant role in the determining the distribution and behavior of cod in geographically different areas within the GOM. Fisheries science appears to be on the verge of a major shift to more localized management, but the greatest limiting factor is available data (e.g. lacking sufficient data in time and space due to poor spatial resolution, or low sampling density; Palmer, *personal communications*). If significant differences exist in cod population structure and life histories in the EGOM, it may suggest a need for more directed understanding of fine-scale biological differences and, ultimately, perhaps a more localized management of cod and other groundfish species (Murawski *et al.* 1998).

In Chapter two of this thesis, the role and implications of inherent gear catchability limitations will be explored in regard to accurately estimating groundfish abundance on hook and line surveys. The EGOM Sentinel Survey dataset will be used to develop a modeling framework to calculate the probabilities of site occupancy and species detection for Atlantic

cod caught on jigging gear. This work aims to identify potential areas of consistently high abundance which may skew catch rates depending on the proportion of randomly selected stations that lie over these areas of preferred habitat. Additionally, I hope to quantify the impact that gear catchability may have on calculations of abundance using detection probability as a proxy for catchability to better understand non-environmental variables that may be influencing the annual trends in relative cod abundance derived from EGOM Sentinel Survey data.

Chapter three will focus on the development of a robust modeling framework aimed towards reducing the impact of outlying catch instances on relative abundance calculations and, consequently, reducing the coefficient of variation (CV) values around EGOM Sentinel Survey abundance estimates for cod, cusk (*Brosme brosme*), white hake (*Urophycis tenuis*), and halibut (*Hippoglossus hippoglossus*). Additionally, the model-based framework will further develop the underlying understanding of how environmental variables such as depth, bottom temperature, sea surface temperature, and sediment class influence groundfish catch. Multiple model types, such as Boosted Regression Tree models (BRTs) and Generalized Additive Models (GAMs), will be utilized to calculate multiple model-based abundance indices and compare model performance to the design-based abundance estimate. Models will be compared using a cross validation scheme to test model fit and mean squared error (MSE) in order to evaluate which model type is most appropriate to model Sentinel Survey data. Ultimately, this research aims to develop a robust and representative index of relative abundance for each of the four targeted groundfish species on the EGOM Sentinel Survey with the goal of providing these indices of abundance to inform the federal stock assessment process.

In Chapter four, I will evaluate if there has been a temporal shift in cod growth parameters such as length at age, weight at age, and condition factor using 48 years of data collected from the Northeast Fishery Science Center (NEFSC) bottom trawl survey. Furthermore, this research will explore spatially explicit cod growth and compare spatially explicit allometric keys between proposed cod sub-stocks illustrated by Pershing *et. al.* (2013). This research is targeted towards understanding key spatio-temporal differences in cod growth in the Gulf of Maine and will be discussed in terms of management implications (i.e. developing a more localized management strategy for GOM cod that will reduce the opportunity for regional overexploitation that exists under the current blanket management approach).

Finally, Chapter five will consist of conclusions drawn from the research presented in Chapters two through four. This work will cover the necessity of re-evaluating the current management strategy for cod in the GOM as it relates to regional differences in biology, highlight the important role of fine-scale survey efforts for developing better-informed groundfish stock assessments in the GOM to inform management decisions, and, finally, the importance of evaluating survey methodologies for potential sources of bias to ensure the surveys are providing accurate indices of abundance for stock assessments.

CHAPTER 2
EVALUATING SITE-SPECIFIC OCCUPANCY AND DETECTION
PROBABILITY AS A MEASURE OF ASSESSING GEAR
CATCHABILITY IN HOOK AND LINE SURVEYS

INTRODUCTION:

The Eastern Gulf of Maine (EGOM) Sentinel Survey operates with the goal of collecting fine-scale data to improve fisheries management practices in the Gulf of Maine by augmenting the data incorporated into stock assessments and by providing improved estimates of abundance for commercially significant groundfish species. To do this, the Sentinel Survey must operate under the assumption that the relative index of abundance is directly proportional to the density of the targeted species population (Pollock, 2002). To ensure the quality of data, it is important to evaluate survey methodology for potential sources of uncertainty that may have an impact on or even bias estimations of abundance, potentially leading to survey estimates that are dissociated from population trends.

One of the most common, and perhaps the most unrealistic assumption in a species count or occurrence-based survey is that occupancy (the probability that a given site is occupied by the target species at a given time) and detection (the probability that one may catch or detect a target species at a given site) remain constant through time and space (Wenger, 2008; Royle, 2003; Pollock, 2002). Given the known life history of Atlantic cod and range of habitat suitability within the Gulf of Maine, it is likely that these assumptions are violated. Furthermore, any heterogeneity in animal abundance will lead to heterogeneity in the detection probability of a species because it is inherently linked to changes in the size of a population (Royle, 2003;

Bayley and Peterson, 2001; Pollock, 2002). The only instance in which variation in detection and the variation in population size are dissociable from one another is when detection probability remains constant over time and space (Pollock, 2002).

Often, detection and occupancy parameters are relatively easy to measure in a mark-recapture study, when individuals are tagged and the location of survey sites between years remains fixed. However, fisheries surveys designed to estimate relative abundance do not typically tag and recapture individuals, nor do they resample the same sites each year, making occupancy and detection difficult to estimate. The EGOM Sentinel Survey employs a random station selection strategy where individuals are caught and kept for biological samples rather than being tagged and released. However, it is important to design a scientific survey in which the methodology of the survey allows for the testing of the hypothesis that occupancy and detection are constant (Pollock, 2003; MacKenzie, 2002). As is consistent with a stratified random survey design, the proportion of stations that fall over suitable habitat may vary from year to year. Because occupancy and detection often vary with environmental variables and habitat structure, it is important to evaluate how occupancy and detection vary from year to year in a time series. The ability for a certain gear to catch a target species is directly related to the probability that there is a fish occupying the site being sampled, so years with a greater number of stations over suitable habitat may exhibit an increase in abundance from years with fewer stations over suitable habitat. However, that change in abundance may only reflect the fluctuation in the number of stations over suitable habitat rather than a change in the size of the population.

On the EGOM Sentinel Survey, jigging drops terminate upon catch, regardless of whether a target or a non-target species is caught. The goal of the research in this chapter is

multi-faceted: to evaluate if the catch of non-target species inherently biases the ability to catch the target species (cod), to identify potential concentrations of suitable habitat, or ‘hotspots’, within the survey area that may consistently exhibit a high probability of detection, and to evaluate the validity of the assumption that site occupancy and detection are constant over time and space within the survey area. Identifying areas with higher probabilities of occupancy or detection can provide valuable information for an index of cod habitat usage and a habitat suitability index. Additionally, failure to account for disparity in detection can bias estimations of abundance and, thus, should be accounted for in future analyses to ensure that the abundance estimates reflect changes in the population rather than changes in detection probability (MacKenzie, 2002). Ultimately, this research aims to increase the quality of abundance estimates by testing the efficacy of Sentinel Survey methodology. Additionally, the results of this research may provide a metric by which future estimations of abundance can be standardized in the event that the proportion of randomly selected stations over suitable habitat is not consistent between years.

METHODS:

Survey Methods:

The EGOM Sentinel Survey uses jigging gear at inshore and offshore stations. Each station is three nautical miles by three nautical miles in size, selected at random, and boat captains are encouraged to seek fish aggregations or suitable habitat within the boundaries of the station square. At each station, two anglers drop a jig consisting of three different hook sizes and complete five drops with a duration of five minutes. However, jig drops terminate upon catch of

any non-target species (fish, squid, etc.) and the angler cannot re-drop for the remainder of the allotted time. In order to transform the data to be compatible with an unmarked occupancy framework, each drop was treated as a site resample to create a capture history for cod caught on the jigging gear. With two anglers, an encounter history of ten resamples was developed which included 1 for the presence of cod or 0 for the absence of cod. In addition, environmental data including sediment type, bottom temperature, surface temperature, depth were collected in addition to data on the presence and absence of non-target species.

Modeling Methods:

To assess the assumption that detection probability remains constant over time, a single species, single season occupancy model from the package ‘*unmarked*’ in R was applied to each year in the time series. Occupancy and detection were evaluated as a function of being constant, or as a function of a combination of available covariates to create a two-stage sequential model building framework in which occupancy (γ) is represented by the equation

$$\gamma_0 = \log\left(\frac{\psi}{1 - \psi}\right)$$

in which γ_0 represents the probability of occupancy and ψ represents the count of individuals occupying a given site. Detection (β) is represented by

$$\beta_0 = \log\left(\frac{p}{1 - p}\right)$$

in which p is equal to the occupancy. Table II- 1 below shows the models built and the covariates used under the sequential modeling framework to evaluate spatio-temporal changes in occupancy and detection. First, a null model was developed in which detection and occupancy

were treated as constant (.). Then, occupancy was kept constant while detection was a function of the environmental covariates (depth, sediment type, bottom temperature (btemp), sea surface temperature, and the presence/absence of pollock and mackerel). Afterwards, detection remained a function of the environmental covariates and occupancy was modeled as a function of time (year, month, or a combination of the two). The same sequential model building process was applied in order to model detection (Table II-1). After selecting a suite of covariates which may impact site occupancy or species detection, both occupancy and detection were modeled as a function of all possible combinations of the covariates. The top five models were selected from a list containing all models using the *modsel()* function in the package *unmarked* which selects the best performing models based on their Akaike Information Criterion value (AIC).

Table II- 1: Model building process for site-occupancy and site-detection.

Model Building Framework	
Occupancy	Detection
p(.) psi(.)	p(.) psi(.)
p(.) psi(covariate(s))	p(covariate(s)) psi(.)
p(year) psi(covariate(s))	p(covariate(s)) psi(year)
P(year + month) psi(covariate(s))	p(covariate(s)) psi(year + month)

RESULTS:

Results show that the best performing models accounted for a seasonal and temporal trend in occupancy and detection (Tables II-2 and II-3). Additionally, both modeling frameworks identify that the best performing model contains sediment type, presence/absence of pollock, and

depth as environmental covariates. The null model for constant detection and constant occupancy was not selected within the top five performing models in either modeling framework.

Models indicate a statistically significant and positive correlation between the probability of cod detection or occupancy and the presence of pollock. Additionally, both models suggest a statistically significant and negative correlation with mixed sediments. No other variables were observed to have a statistically significant impact on cod occupancy. However, cod detection was significantly and positively correlated with depth (Table II- 4).

Table II- 2. Output of the occupancy modelling framework in which the top five performing models are reported and organized according to AIC value.

Occupancy Model	nPars	AIC	delta	AICwt	cumltvWt
p(year + month) psi(sediment + depth + pollock)	16	824.91	0.00	0.71	0.71
p(year + month) psi(sediment + depth + pollock + mackerel)	17	826.83	1.92	0.27	0.99
p(year + month) psi(sediment + depth + btemp)	16	834.91	10.00	<0.01	0.99
p(year) psi(sediment + depth + pollock)	11	835.15	10.24	<0.01	1
p(year + month) psi(pollock)	13	835.27	10.36	<0.01	1

Table II- 3. Output of the detection modelling framework in which the top five performing models are reported and organized according to AIC value.

Detection Model	nPars	AIC	delta	AICwt	cumltvWt
p(sediment + depth + pollock) psi(year + month)	16	836.27	0.00	0.68	0.68
p(sediment + depth + pollock + mackerel) psi(year + month)	17	838.14	1.88	0.27	0.95
p(sediment + depth + pollock) psi(year)	11	843.00	6.74	0.02	0.97
p(sediment) p(.)	4	843.96	7.70	0.02	0.99
p(sediment + depth + mackerel) psi(year + month)	16	844.29	8.02	0.01	1

Table II- 4. Model Output to evaluate the significance of the relationship between cod detection, cod occupancy, and each of the environmental covariates. Asterisks (*) are used to denote levels of statistical significance for p-values less than 0.05 in which (***) is the most statistically significant and (*) is the least statistically significant.

Model Output				
Covariate	Detection		Occupancy	
	Estimate	P- Value	Estimate	P- Value
Intercept	-3.77	***	-1.26	0.17
Mixed Sediment	-2.89	**	-2.56	*
Soft Sediment	-15.60	0.97	-13.37	0.95
Depth	0.07	**	0.04	0.33
Pollock	0.75	**	2.12	***

Figures II-1:6 illustrate an increase in the probability of site occupancy from June to September. There are relatively few data points in October and November for all years, but these months appear to exhibit similar values to those calculated for September. Figures II-7:12 do not indicate any noticeable temporal trend in occupancy between years. All occupancy Figures seem to indicate a band of higher probability of site occupancy over inner Schoodic Ridge.

No noticeable seasonal or temporal changes were observed for values of detection probability (Figures II-13:24). However, contrary to the output of the occupancy model, detection values show very little variation both spatially and temporally indicating a relatively constant and relatively low probability of detection. It should be noted that the log-based scale on all detection Figures II-13: 24 has been reduced to a range of 0.00 to 0.50 in order to increase the visual contrast in the detection values.

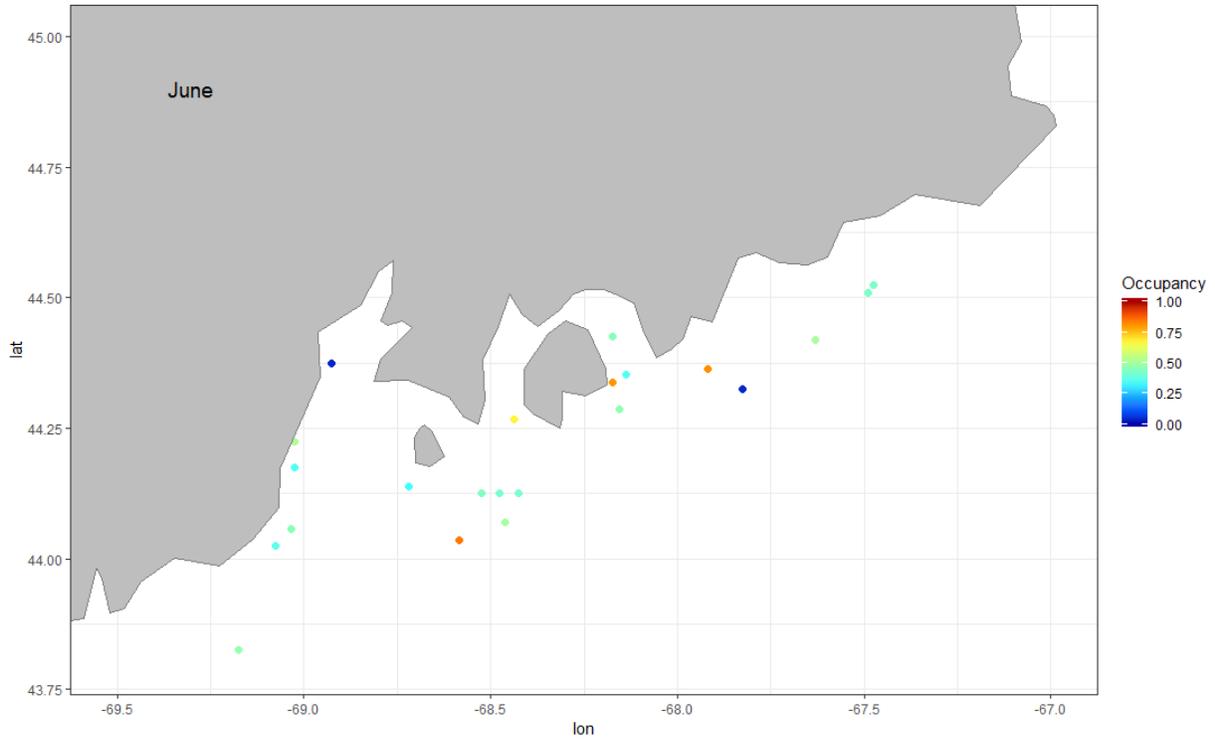


Figure II-1. Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in the month of June from 2012-2017.

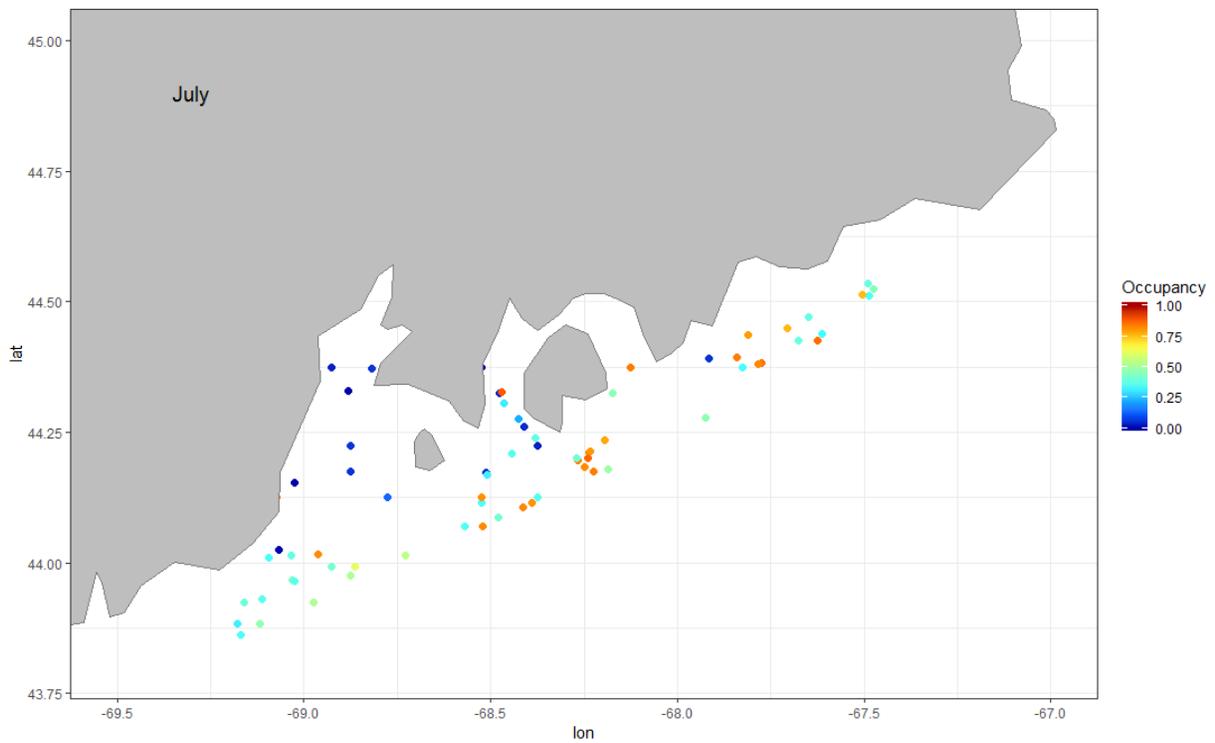


Figure II-2. Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in the month of July from 2012-2017.

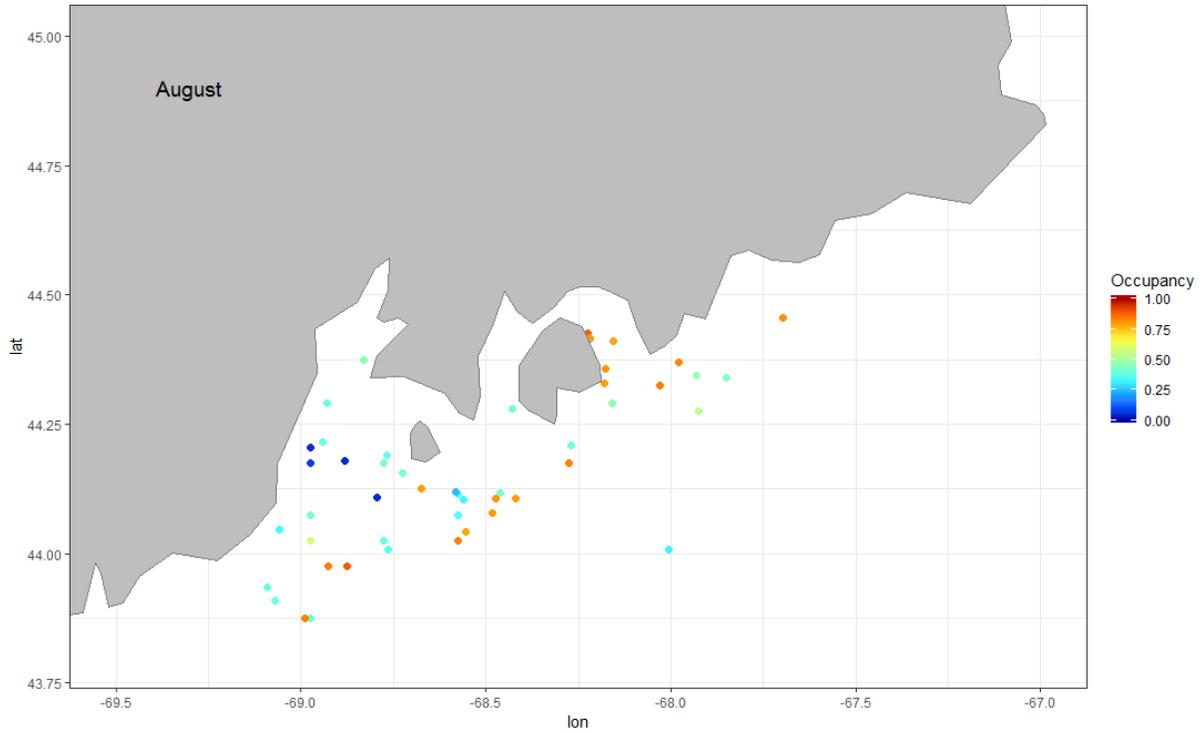


Figure II-3. Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in the month of August from 2012-2017.

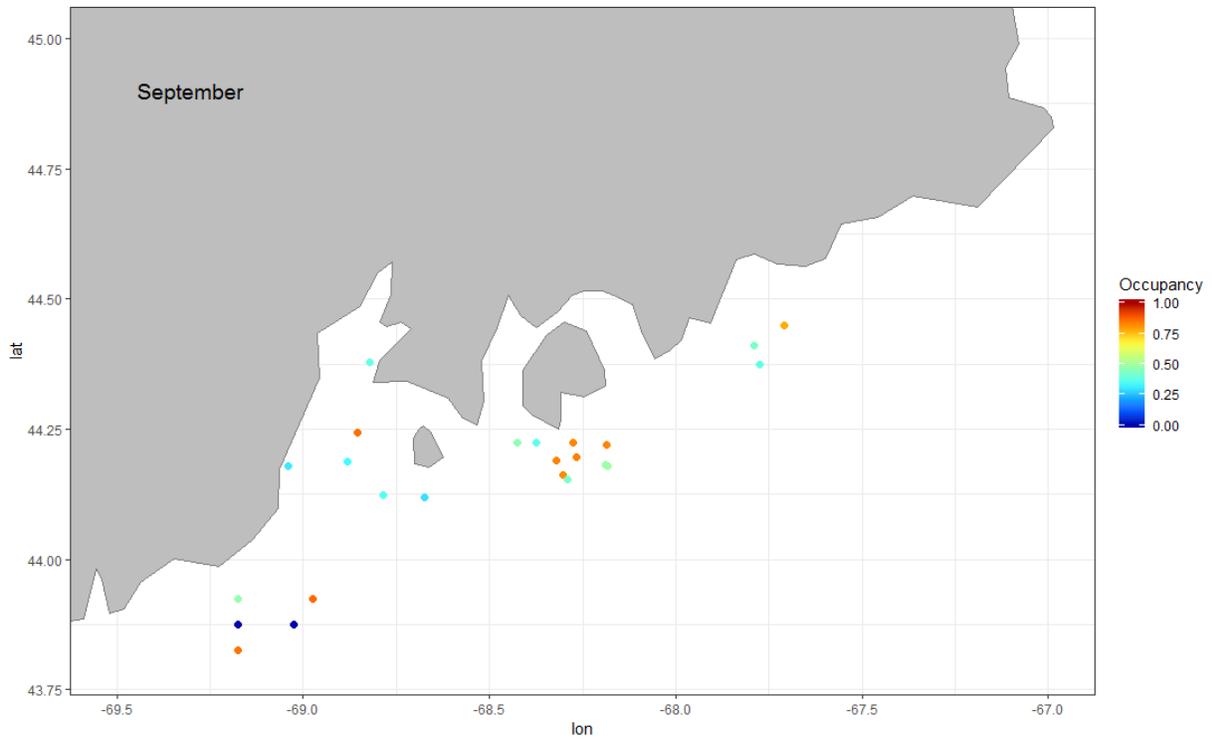


Figure II-4. Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in the month of September from 2012-2017.

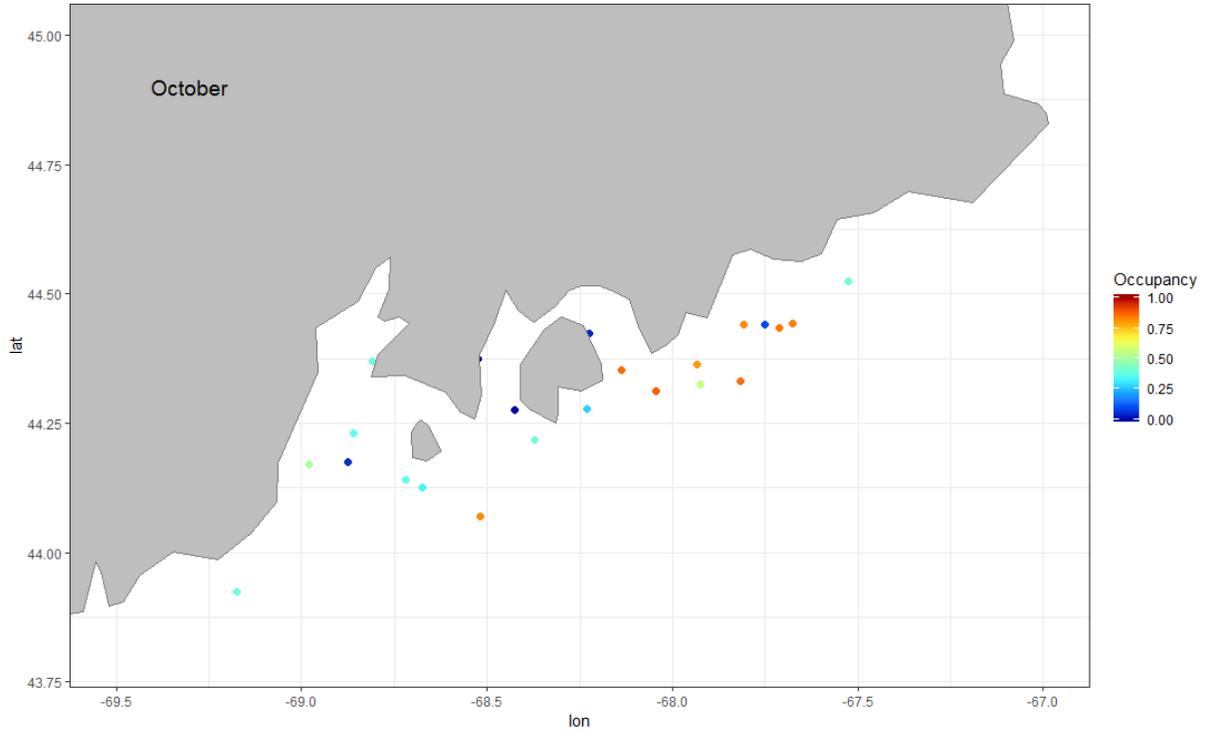


Figure II-5. Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in the month of October from 2012-2017.

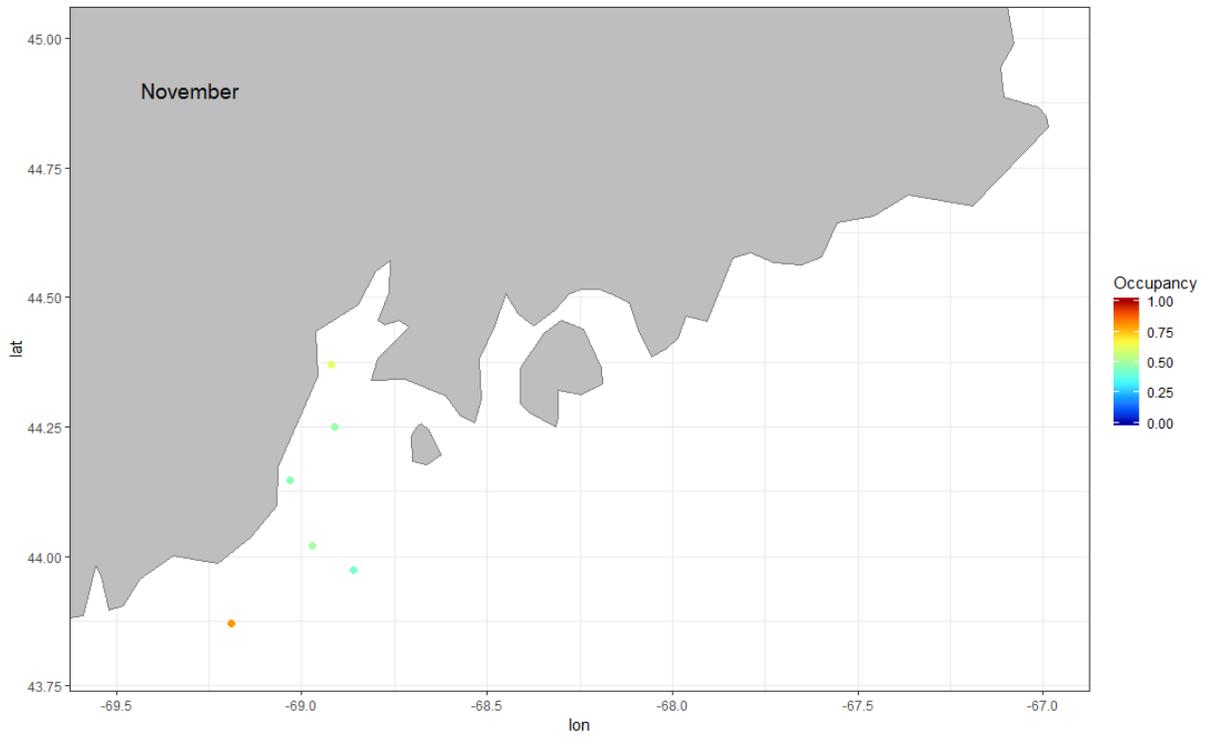


Figure II-6. Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in the month of November from 2012-2017.

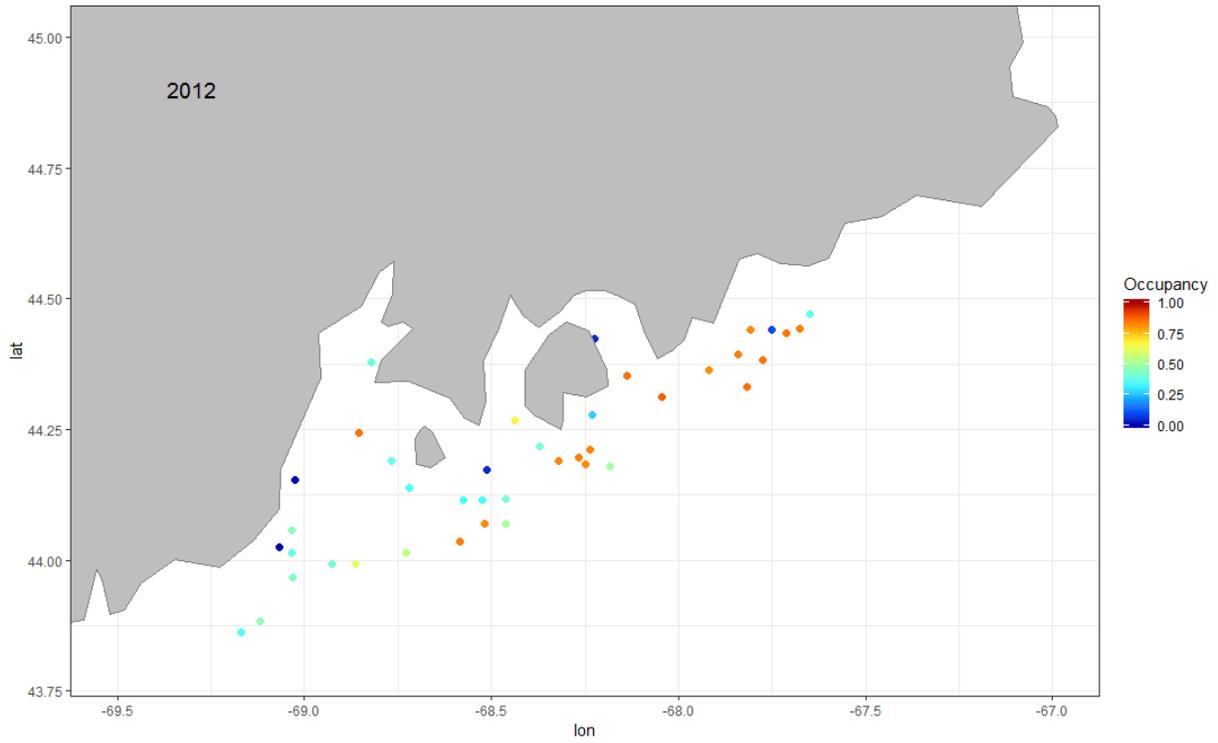


Figure II-7. Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in 2012.

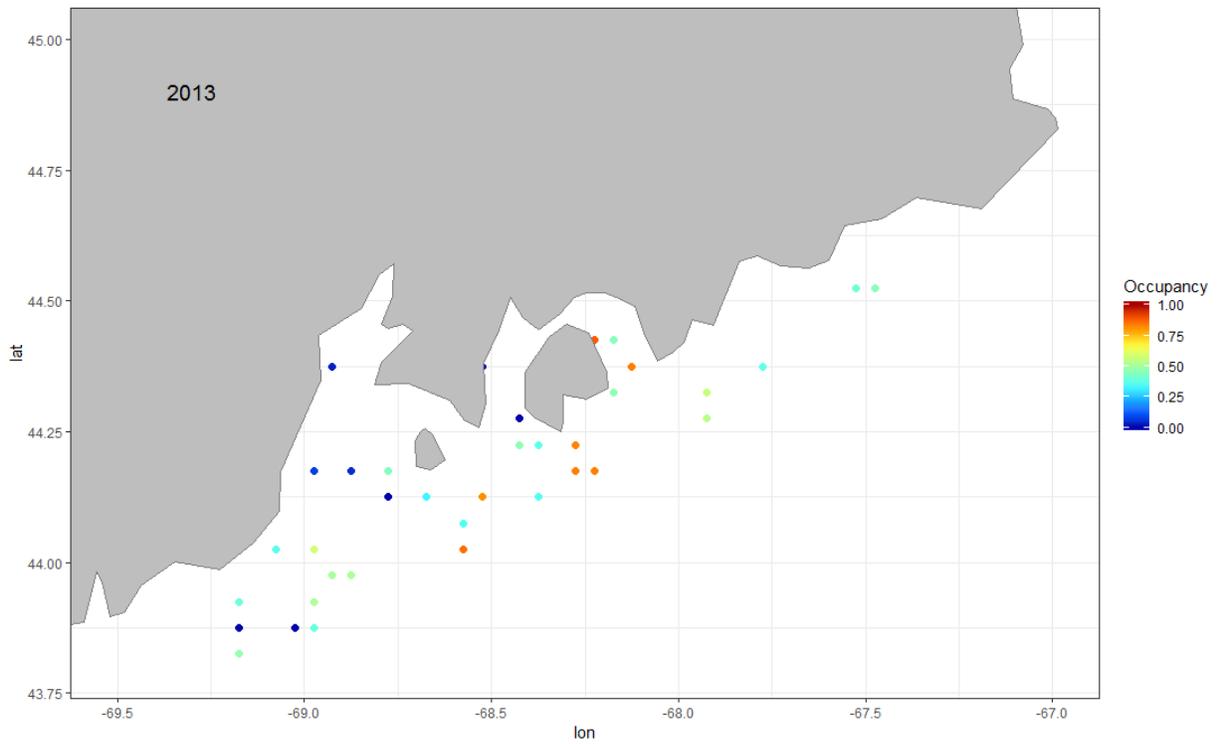


Figure II-8. Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in 2013.

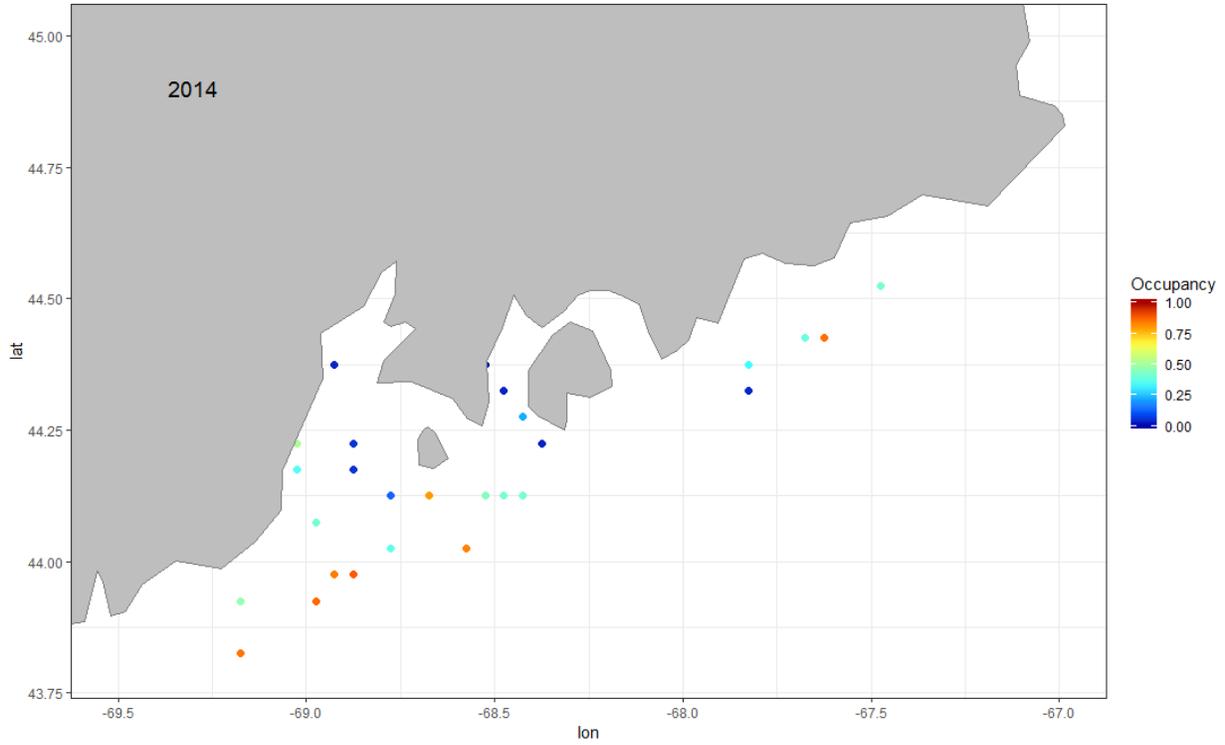


Figure II-9. Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in 2014.

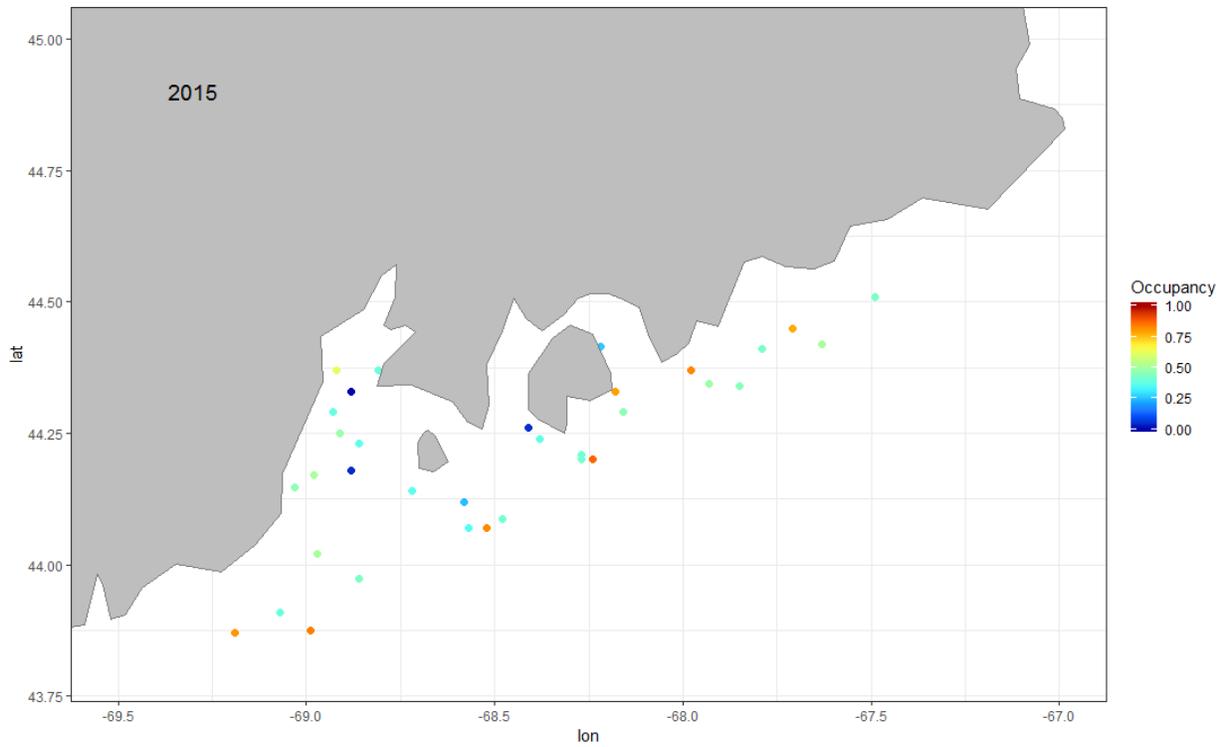


Figure II-10. Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in 2015.

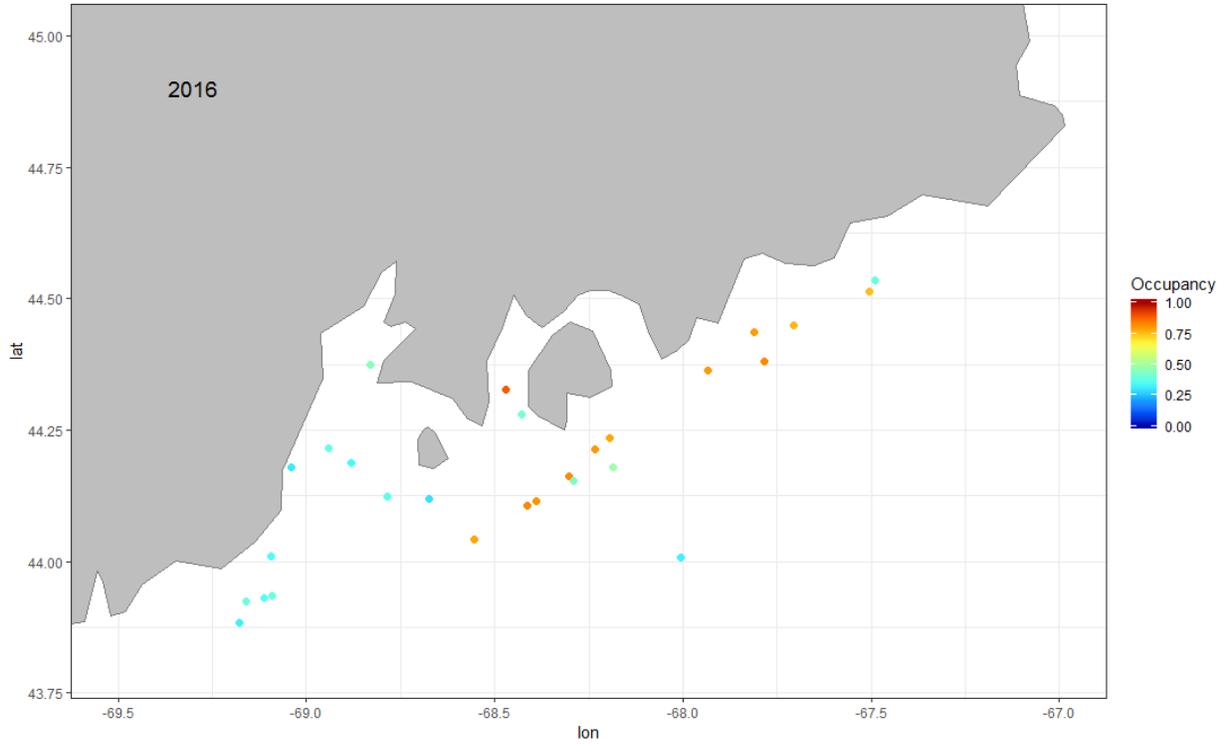


Figure II-11. Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in 2016.

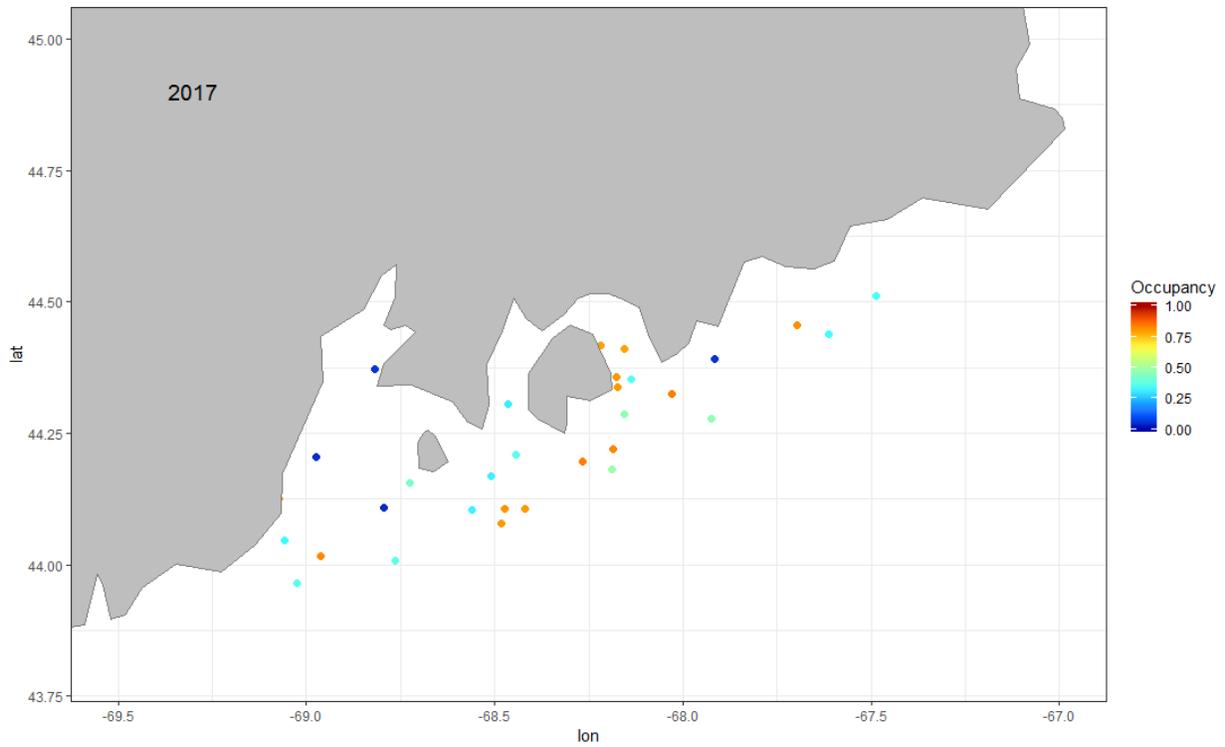


Figure II-12. Map of EGOM Sentinel Survey sampling area displaying probability of site occupancy in 2017.

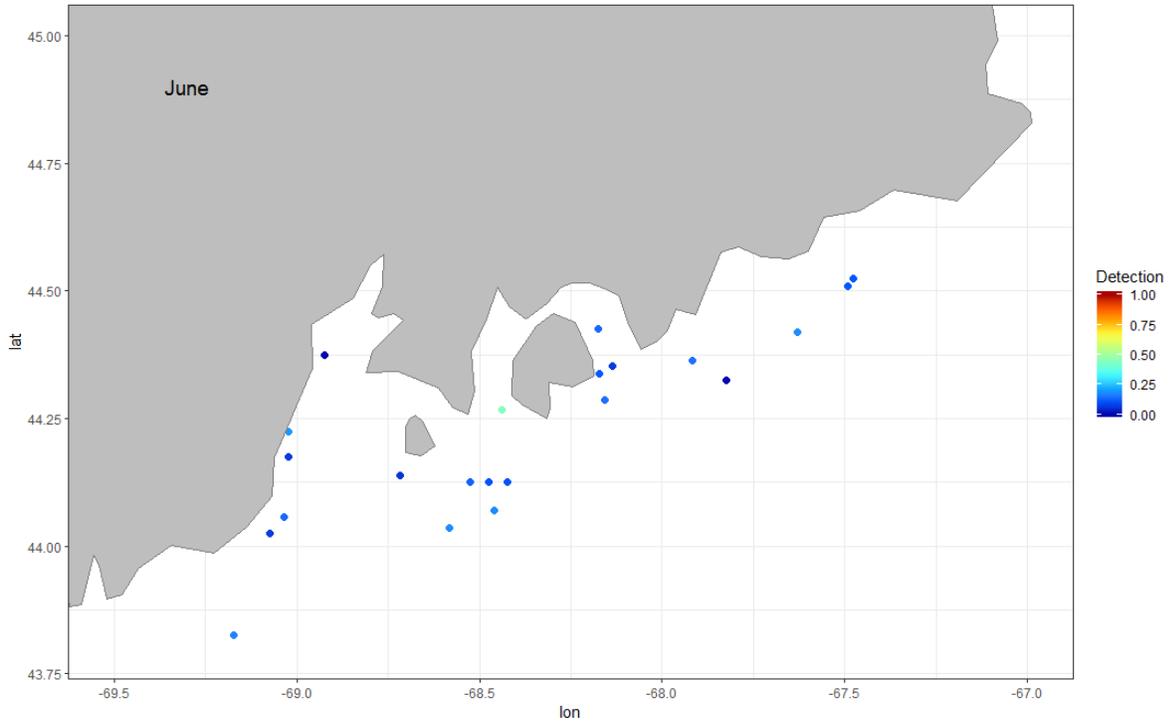


Figure II-13. Map of EGOM Sentinel Survey sampling area displaying probability of detection in the month of June from 2012-2017. Note that the scale has been reduced to a range of 0.00 to 0.50 in order to increase the visual contrast in the detection values.

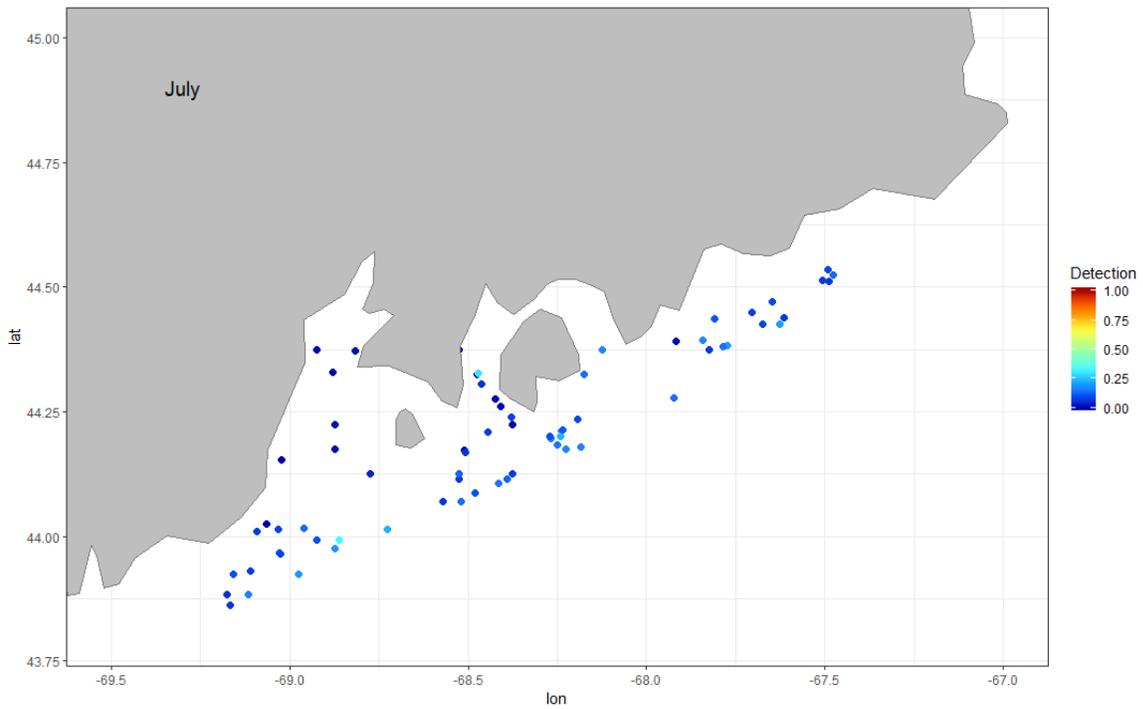


Figure II-14. Map of EGOM Sentinel Survey sampling area displaying probability of detection in the month of July from 2012-2017. Note that the scale has been reduced to a range of 0.00 to 0.50 in order to increase the visual contrast in the detection values.

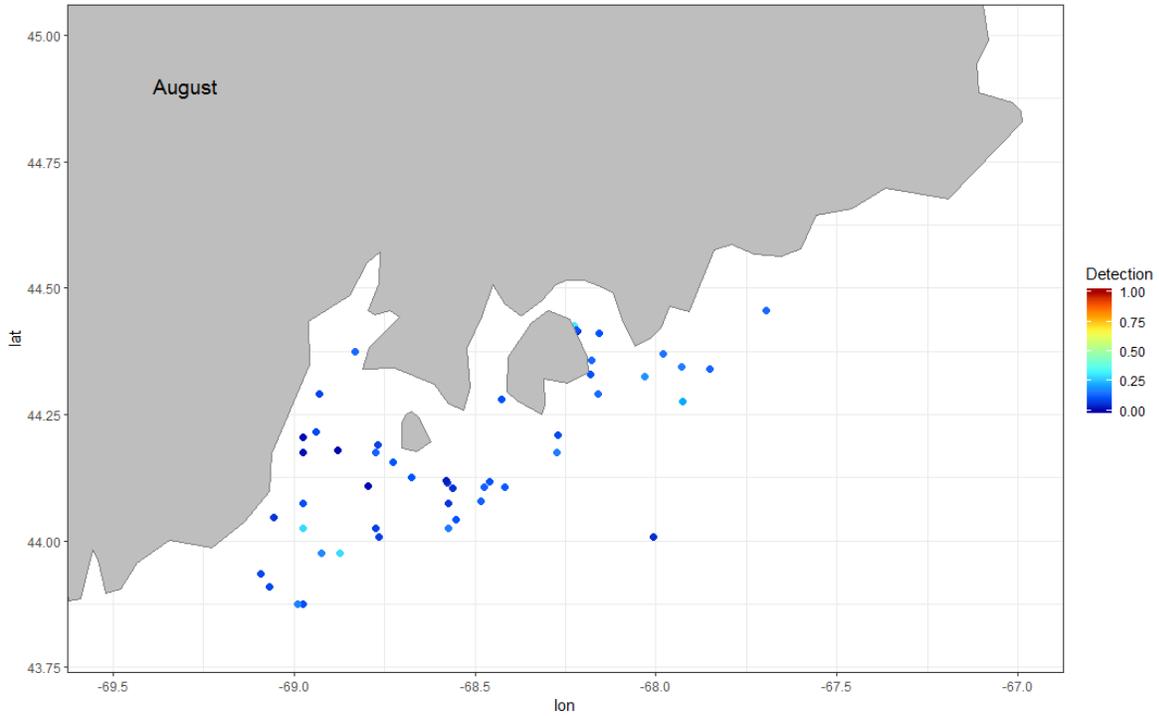


Figure II-15. Map of EGOM Sentinel Survey sampling area displaying probability of detection in the month of August from 2012-2017. Note that the scale has been reduced to a range of 0.00 to 0.50 in order to increase the visual contrast in the detection values.

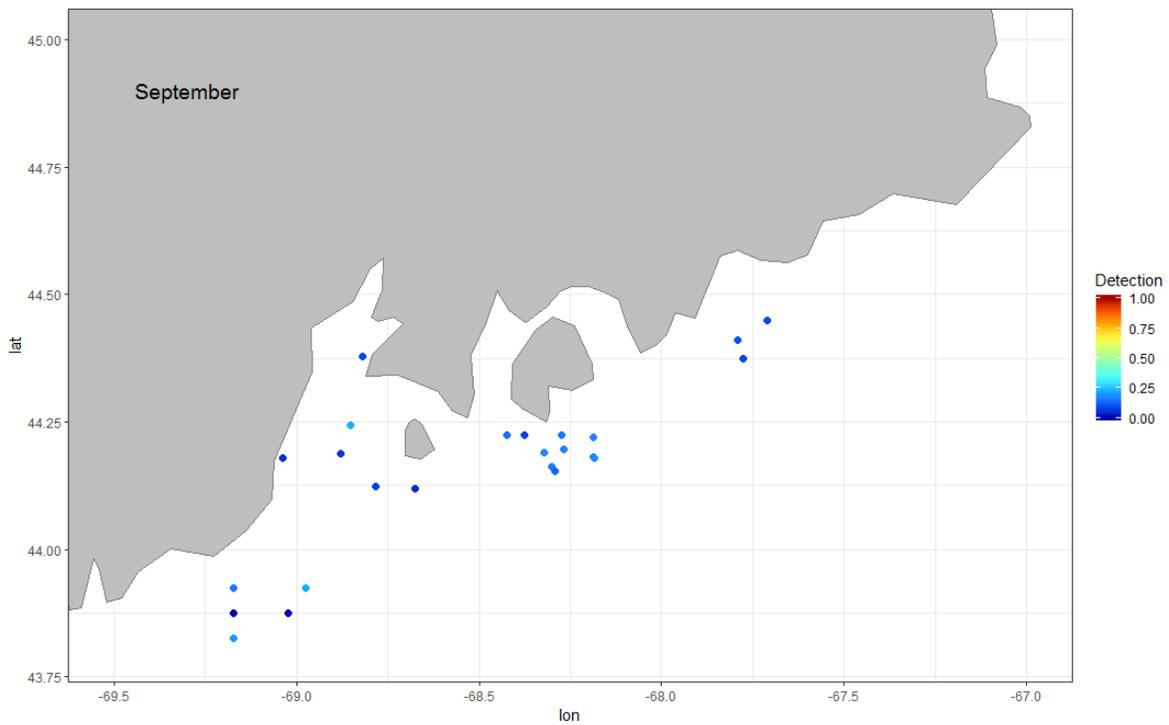


Figure II-16. Map of EGOM Sentinel Survey sampling area displaying probability of detection in the month of September from 2012-2017. Note that the scale has been reduced to a range of 0.00 to 0.50 in order to increase the visual contrast in the detection values.

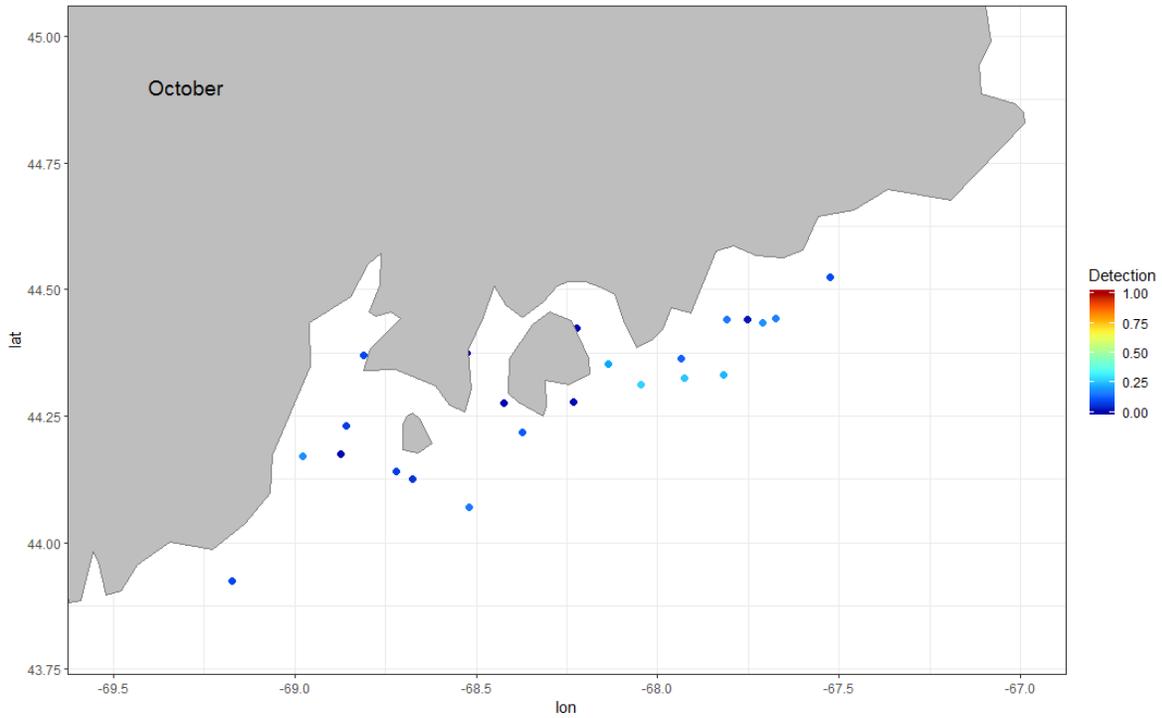


Figure II-17. Map of EGOM Sentinel Survey sampling area displaying probability of detection in the month of October from 2012-2017. Note that the scale has been reduced to a range of 0.00 to 0.50 in order to increase the visual contrast in the detection values.

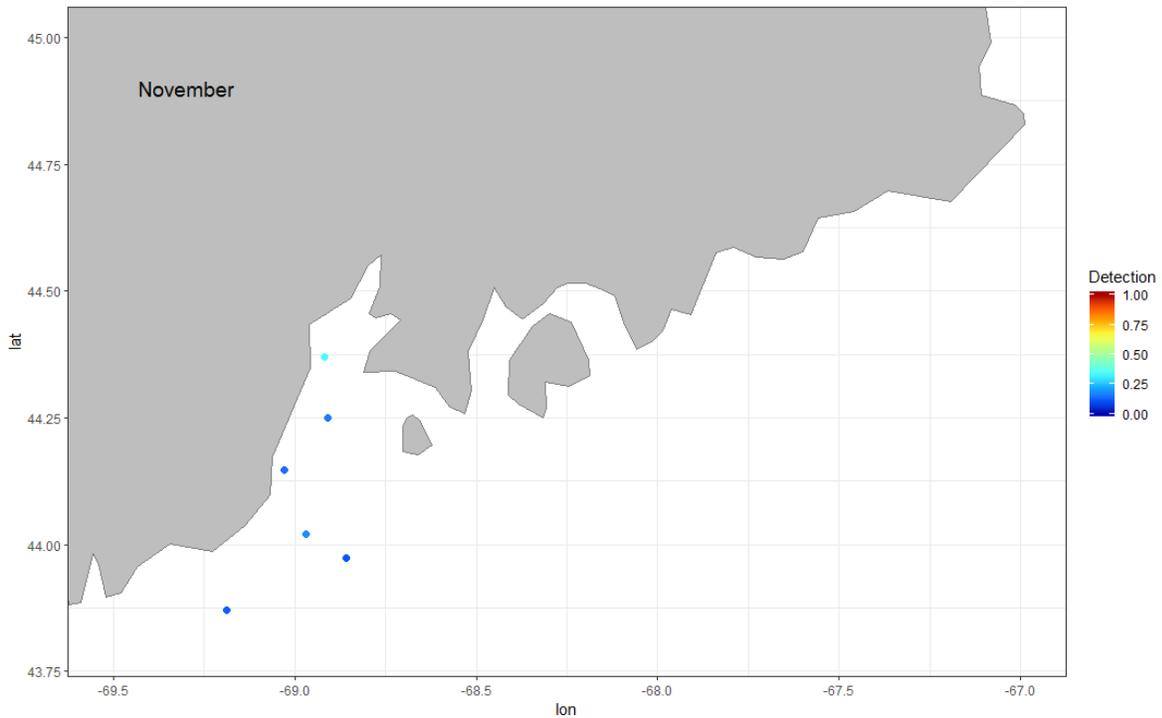


Figure II-18. Map of EGOM Sentinel Survey sampling area displaying probability of detection in the month of November from 2012-2017. Note that the scale has been reduced to a range of 0.00 to 0.50 in order to increase the visual contrast in the detection values.

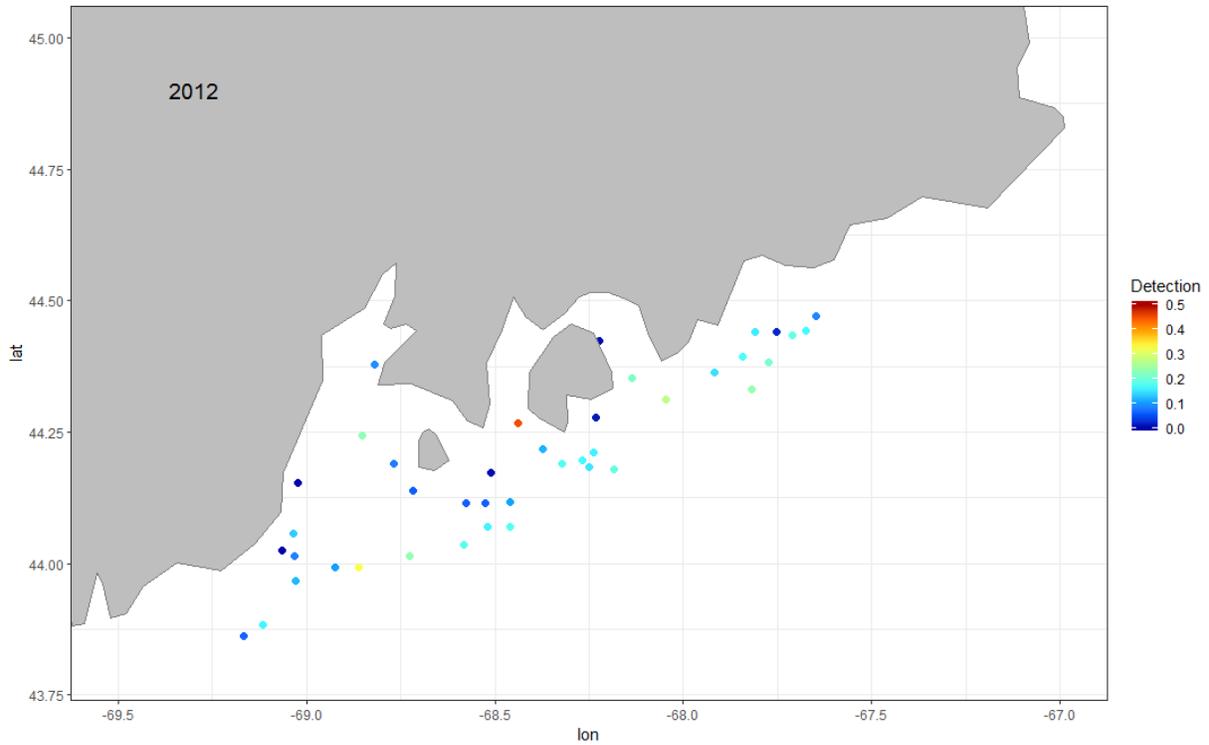


Figure II-19. Map of EGOM Sentinel Survey sampling area displaying probability of detection in 2012. Note that the scale has been reduced to a range of 0.00 to 0.50 in order to increase the visual contrast in the detection values.

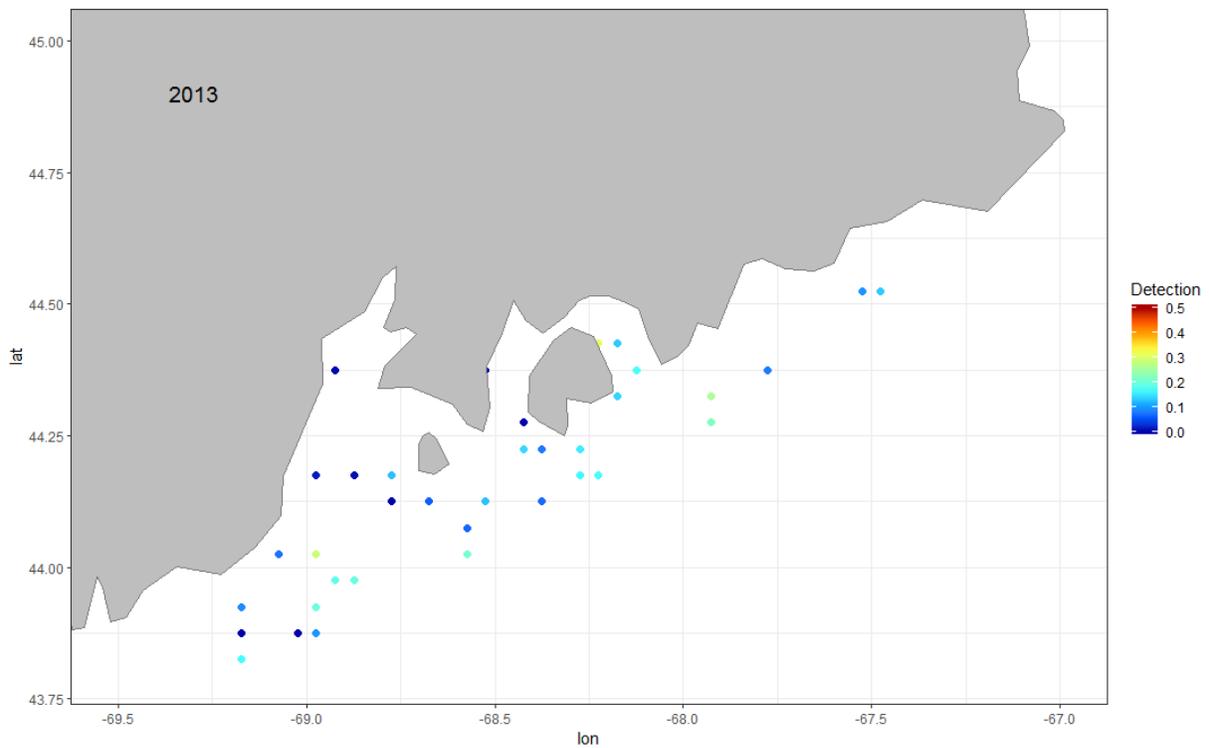


Figure II-20. Map of EGOM Sentinel Survey sampling area displaying probability of detection 2013. Note that the scale has been reduced to a range of 0.00 to 0.50 in order to increase the visual contrast in the detection values.

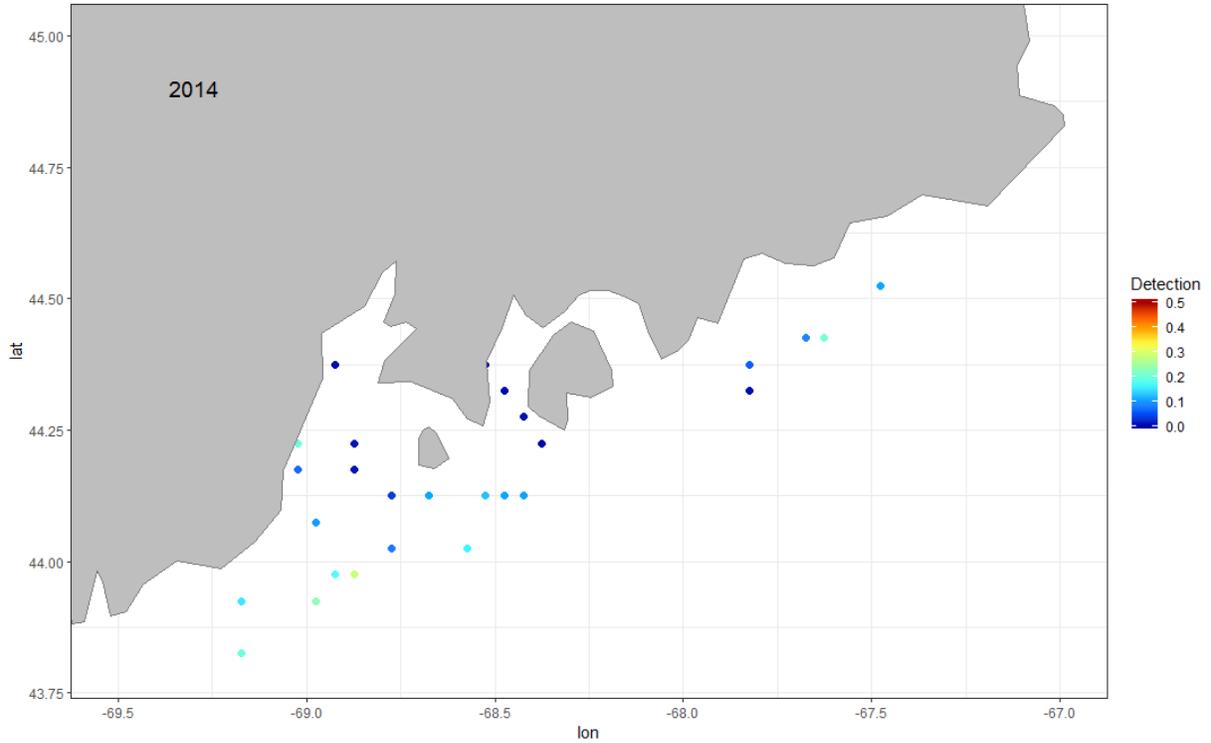


Figure II-21. Map of EGOM Sentinel Survey sampling area displaying probability of detection in 2014. Note that the scale has been reduced to a range of 0.00 to 0.50 in order to increase the visual contrast in the detection values.

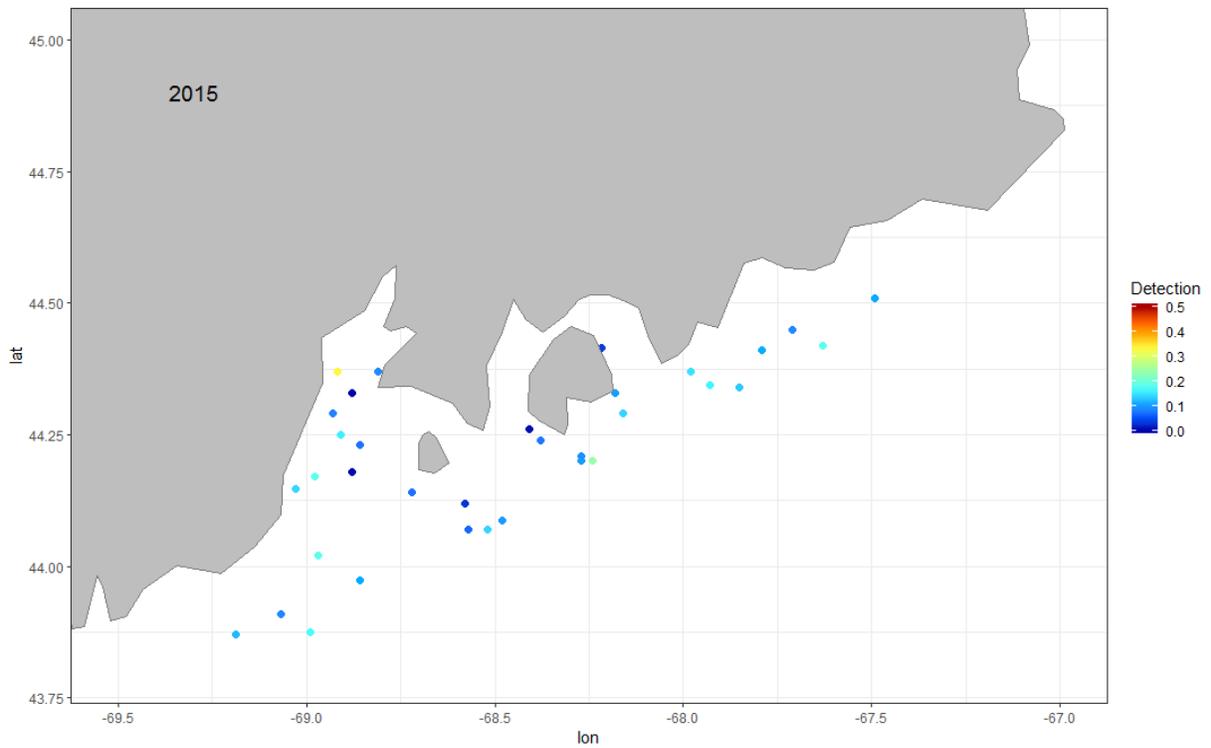


Figure II-22. Map of EGOM Sentinel Survey sampling area displaying probability of detection in 2015. Note that the scale has been reduced to a range of 0.00 to 0.50 in order to increase the visual contrast in the detection values.

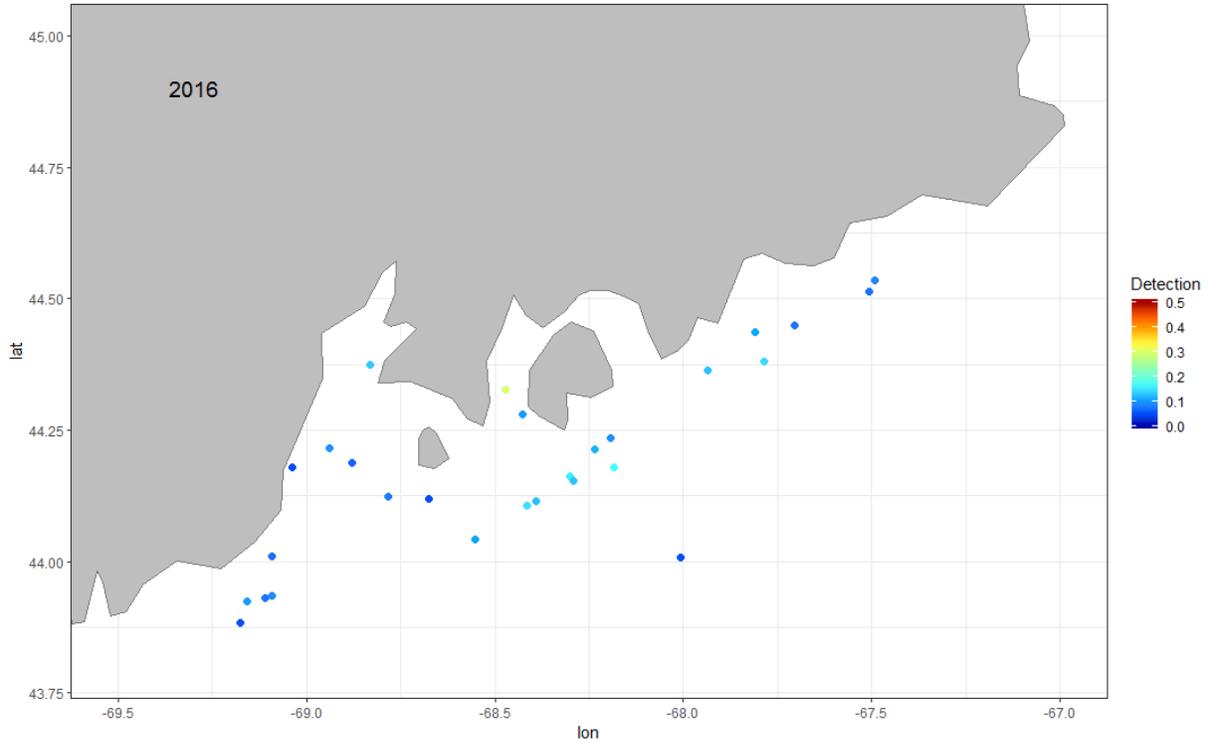


Figure II-23. Map of EGOM Sentinel Survey sampling area displaying probability of detection in 2016. Note that the scale has been reduced to a range of 0.00 to 0.50 in order to increase the visual contrast in the detection values.

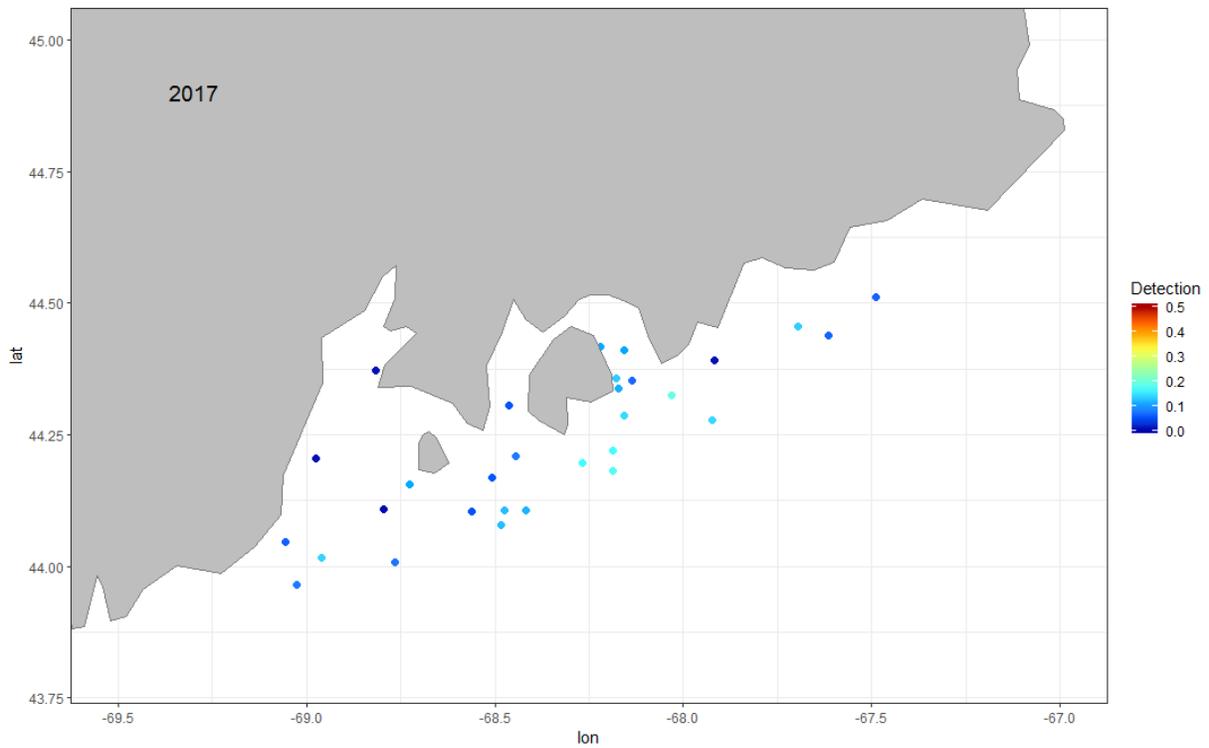


Figure II-24. Map of EGOM Sentinel Survey sampling area displaying probability of detection in 2017. Note that the scale has been reduced to a range of 0.00 to 0.50 in order to increase the visual contrast in the detection values.

DISCUSSION:

Based on the results of the modeling framework, results indicate that the catch of non-target species (bycatch) does not inhibit the ability to catch target species (cod) in the jigging portion of the EGOM Sentinel Survey. Although models indicated a negative correlation between cod detection and the presence of mackerel, this relationship was not statistically significant. Additionally, cod detection was positively and significantly correlated with the presence of pollock, indicating that pollock and cod are likely to be caught together. This is concurrent with what is known about juvenile cod and pollock: both are aggregating species and are known to cohabitate as they exhibit similar life history strategies, habitat preferences, and food sources (Bigelow and Schroeder, 2002). Consequently, these results justify the continued use of the current methodology in which jigging drops terminate upon catch of a given fish without biasing estimates calculated from this data. It should be noted that juvenile fish are explicitly identified because the Sentinel Survey catches mostly premature cod and pollock on the jig. A preliminary analysis of cod otoliths show that most cod caught on the sentinel survey are between 1 and 3 years old, with the majority of fish falling below the age of sexual maturity (Pentilla, 2017; Bigelow and Schroeder, 2002). Despite the limited catch of adult cod, these models were still able to provide valuable information in regard to what is observed and what Sentinel Survey methodology might be missing.

In addition to finding cod detection uninhibited by the catch of non-target species, results indicate a rejection of the null models, which were built to test the assumption that occupancy and detection do not vary over space and time. Model outputs suggest a strong temporal and spatial trend in occupancy which is corroborated by Figures II-1:24, illustrating a clear band of higher occupancy just offshore. This is consistent with what is known and described in the

literature in regard to Atlantic cod migration habits. Although Atlantic cod do not exhibit behaviors of a highly migratory species, however, they do exhibit annual migrations back to their natal spawning grounds that are governed by bathymetric contours (Armstrong *et. al.*, 2013; Dean *et. al.*, 2012; Ames, 2004; Robichaud and Rose, 2001). Additionally, there are at least two temporally explicit spawning stocks of cod in the Western Gulf of Maine: a fall/winter and spring spawning stock (Runge *et. al.*, 2010). The seasonal increase in occupancy from June to September appears to coincide with cod beginning to aggregate over the inshore spawning areas identified by Ames (2004).

Interestingly, even though the null model assuming constant detection was rejected, there appears to be a relatively constant value for detection (between 0.0 and 0.2) over time and space. Although it is widely accepted that consistent values of detection can be ignored (Pollock, 2002; MacKenzie, 2002), Royle (2003) describes an issue in which observed detection can be the function of two types of zeroes: false zeroes (non-detection at a site that is occupied by the target species) and true zeroes (non-detection at a site which is truly unoccupied by the target species). Royle (2003) goes on to conclude that a model which can simultaneously estimate occupancy and detection can distinguish between these two types of zeroes. Although the modeling framework developed for this analysis did, in fact, simultaneously estimate detection and occupancy, the consistency in the results hovers very closely to a detection probability of zero. This has led to questions about the balance of true and false zero occurrence, or perhaps moreso questions regarding the saturation of false zeroes in the data. Heterogeneity in animal abundance should inherently lead to heterogeneity in detection probability (Wenger 2008; Royle, 2003; Pollock, 2002; MacKenzie, 2002). However, heterogeneity was not observed and model

adjustments were not made to make detection constant (as suggested by MacKenzie, 2002) because the purpose of this study was to evaluate detection and occupancy for heterogeneity.

Although information such as hook placement is not explicitly collected on the Sentinel Survey, and should consequently be treated as equivocal observations, on board observers frequently report that cod are often foul-hooked (i.e., snagged through some portion of the body other than the mouth) rather than truly caught. As a method of testing the hypothesis that the consistency in detection is the result of poor gear catchability, Sentinel Survey observers deployed camera gear while sampling at fisherman's choice station. Although one cod was caught (foul-hooked) during the jigging period, video footage and images retrieved from the camera revealed several small cod ($\leq 36\text{cm}$) and pollock in the area swimming under a large school of mackerel. These observations provide some insight as to size-selectivity and raise important questions regarding the catchability of the gear types utilized on the EGOM Sentinel Survey.

Despite the questions surrounding the consistency in detection, the null models for constant detection and occupancy were rejected. As a result, the assumption that either of these parameters is constant over time and space should be treated as invalid and measures should be taken to account for the heterogeneity of these parameters to avoid sources of bias in calculations of cod abundance. Aside from incorporating detection probability into abundance estimates as a method of accounting for gear catchability, it is important to continue to explore the saturation of false zeros in Sentinel Survey data. The results of this study have implications in fisheries survey methodology as any survey which relies on immediate target presence may be suffering from issues with detectability; issues which may mask the true trend in the population size.

It should be noted that there is very little information on the incorporation of detection into abundance estimates (Royle 2003; MacKenzie, 2002). Furthermore, much of the literature surrounding the evaluation of detection probability and occupancy on scientific surveys is in regard to mark-recapture surveys and distance sampling. Although detection and occupancy are easiest to estimate in these types of surveys, they are not applicable to the Sentinel Survey, which follows a robust stratified random design like many fisheries surveys, including the federal trawl survey. Unfortunately, Sentinel Survey methods cannot be altered without disregarding previous data collected and consequently removing the value from a time series. However, surveys can, and should, explore methods of validating gear types that will allow for an estimation of detection and occupancy which can provide a metric by which estimates can be adjusted accordingly to account for variation in detection, or catchability.

The EGOM Sentinel Survey targets cod in an area that is known to have a low cod abundance which inherently makes the detection of cod more difficult than in areas where cod are more densely aggregated. Additionally, the Sentinel Survey has only succeeded in catching immature, schooling sized cod that are on the cusp of reaching sexual maturity. Therefore, the results of this study may be unique to this dataset and the targeted species. Other survey programs relying on hook-and-line gear that operate in different areas for different target species are encouraged to explore the role of detection or gear catchability as it may impact or relate to target species abundance. However, failure to evaluate or account for the effects of this statistical problem, where the available data permits it, would mean an *a priori* acceptance of the constant detection assumption, which makes it impossible to determine whether trends in abundance reflect changes in the population size, or simply reflect changes in detection probability (MacKenzie, 2002). Finally, the use of exclusively design-based relative abundance indices is ill-

advised as (Wenger, 2008; Pollock, 2003; MacKenzie 2002; Skalski, 1983) as observations are circumstantial and subject to outliers. Efforts of estimating abundance should be rooted in trying to provide the most accurate and well-informed estimate of abundance (Wenger, 2008; Pollock, 2003; MacKenzie, 2002).

CONCLUSIONS:

Aboard the EGOM Sentinel Survey, there are two gear types that are deployed to catch groundfish: jigging gear and a baited longline. Although it will be described in greater detail in Chapter 3, one of the major drawbacks to hook and line surveys is accounting for detection and evaluating detection as it relates to gear catchability, or the probability that the gear being deployed can actually catch the species being targeted. Non-baited gear types, like jigging gear, rely heavily on the target species being present at the site being sampled (occupancy). As a result, estimates resulting from this type of survey data are susceptible to being influenced by the probability of detection.

Although observe areas or pockets in the survey area with higher occupancy or detection were not observed, low catchability did not fluctuate with occupancy, which could skew estimates of abundance. Ideally, the probability of detection should increase with an increase in occupancy: the more likely a cod is to be present, the more likely it becomes to catch one. Detection probabilities appear to be independent of occupancy, as it remains fixed close to zero regardless of whether the probability of occupancy is closer to one (100% probability) or closer to zero (0% probability). Because the ability to detect cod can be treated as a measure of gear catchability, it seems likely that the consistency in estimates of detection is the result of low gear

catchability, which may have tremendous implications on the abundance estimates derived from Sentinel Survey data.

The EGOM Sentinel Survey is designed to fill gaps in current survey coverage in order to better inform regional stock assessments and fisheries management. To provide this information, Sentinel Survey abundance estimates should reflect the trend in the population. Typically, a coefficient of variation (CV) less than or equal to 0.2 is considered to be highly precise (Chen, *personal communication*). If Sentinel survey derived abundance estimates fall below a CV of 0.2, it would allow for greater confidence in the accuracy of abundance estimates. However, it should be noted that estimations of relative abundance are not designed to estimate the number of individuals in a population, but rather to illustrate the overall trend in population size from year to year. This research illustrates that the jigging methodologies adopted by the Sentinel Survey have led to catch rates that are not only low but may be representative of catchability rather than be representative of the population trend. As a result, the Sentinel Survey, along with all other hook-and-line survey programs, should assess the impact of gear catchability on estimations of relative abundance to avoid biased estimates.

CHAPTER 3

DEVELOPING A ROBUST MODELING FRAMEWORK TO ESTIMATE GROUNDFISH ABUNDANCE FROM HOOK AND LINE SURVEYS

I. INTRODUCTION:

Despite spawning stocks having been almost completely extirpated, the Eastern Gulf of Maine (EGOM), although not closed to groundfish fishing, has been perceived to have a low groundfish stock density relative to historic landings in the region (Ames, 2004) and other areas in the GOM (Armstrong *et. al*, 2013). As explained in Chapter 1, there is virtually no directed fishing effort for groundfish species in this region, but it is known that cod still occupy this area. Active state and federal fisheries-independent bottom trawl survey programs in the GOM have sampling stations within the EGOM, but their spatial and temporal coverage is limited because of restricted gear use in areas with complex bathymetry and a high density of fixed gear (i.e. lobster traps). Consequently, trawl survey monitoring effort for groundfish that reside in complex benthic habitats tends to be low and estimations of abundance derived from that survey data may be misrepresentative of the local population. As discussed, groundfish stock assessments typically assume a single stock that encompasses the entirety of the Gulf of Maine (GOM) despite the spatial heterogeneity of fishing effort, catch and likely heterogeneity in life history traits between the western Gulf of Maine (WGOM) and the EGOM (Mike Palmer, NOAA, *personal communications*). Because of the recent failures to rebuild the cod stock, it seems unlikely that the directionality of bias in the stock assessment is leading to under-exploitation, as this would inherently accelerate the rebuilding process. Subsequently, it seems more likely that these biases may be leading to scenarios of further stock overexploitation and inadequate

management (Pershing *et. al.* 2013).

In order to understand the fine-scale spatial variability in fish populations, which may skew estimations of fish abundance, fine-scale surveys such as the EGOM Sentinel Survey are essential for providing spatially explicit data that uses a different methodology in an area that is not well covered by existing monitoring programs. Additionally, fine-scale surveys can provide the necessary data for stock assessments to account for this spatial variability in abundance. The EGOM Sentinel Survey provides a platform to test some of the implicit assumptions in a scientific survey. In addition, it can provide data for a sparsely sampled area to augment survey coverage and, consequently, the stock assessment that is derived from these survey datasets. However, because fine-scale surveys are subject to the finite list of environmental conditions and habitat structures that occur within their spatially restricted survey area, but they can suffer from a high level of spatial variability in comparison with coast-wide surveys, which sample a more representative suite of habitats and environmental conditions, given that they are not limited by sampling density or gear restrictions resulting from complex habitat. Consequently, and depending on the bounds of the survey area, fine-scale surveys can be more susceptible to abundance estimates associated with high uncertainty, making it challenging to incorporate the data into the stock assessment process.

This Chapter focusses on the analysis of catch data from seven seasons of the EGOM Sentinel Survey to develop a modeling framework for estimating groundfish abundance. Statistical models were used to evaluate which environmental variables might influence groundfish abundance indices and to understand habitat preferences of cod, cusk, white hake, and halibut for the stratified random stations. Fisherman's choice stations (locations based on prior fishing knowledge of where target species were historically abundant) were also tested with

these models to ensure that depth, which is used to stratify the survey, remained the most significant variable impacting catch of these species. High frequencies of zero catch observations for species such as cod and cusk, in combination with possible patchy distributions of fish populations, makes modeling catch data difficult. As data collection continues, it is likely that future models will provide a better fit with a more robust dataset. Thus, the methods described in this study can be used in future Sentinel Survey data analysis.

II. METHODS:

II-1. Sentinel Survey Sampling Methods:

II-1.A. Pilot Seasons (2010, 2011):

2010 and 2011 are considered the pilot seasons for the Sentinel Survey. In 2010, one boat sampled 30 stations and in 2011, two boats sampled 60 stations (30 per boat). All stations in 2010 and 2011 are considered fishermen's choice stations because fishing locations were determined by the boat captains based on focus group meetings with other fishermen and sentinel fishery participants that identified historical fishing grounds. Stations were fished using a 2 nautical mile demersal longline with 2,000 hooks baited with a combination of squid and herring. In 2011, survey areas were divided into two regions: (1) between Vinalhaven and Swans Island, and (2) between Swans Island and Schoodic Ridges; to ensure even spatial coverage. National Oceanic and Atmospheric Administration (NOAA) fisheries observers or trained research assistants observed all trips.

II-1-B. 2012 Addition of Random Inshore Jigging Component:

2012 was the first year that incorporated a stratified random survey design. Longline gear was unchanged from the previous two years (2 nautical mile longline with 2,000 hooks, baited with squid and/or herring). Target soak time was two hours although actual soak time varied depending upon tide strength and logistical constraints. Trained research assistants observed all sampling trips. Most of the longline effort was allocated to stratified random stations. The survey was stratified into three depth strata:

Strata 1: 50-80m

Strata 2: 80-150m

Strata 3: 150m or greater

Strata were determined based upon analysis of catch data from the Maine DMR inshore bottom trawl survey and the previous two years of the Sentinel Survey. Stations were randomly selected from these strata in proportion to the total area of the strata. The remaining 18 stations (37.5% of the effort) were allocated as fishermen's choice stations. Fishermen were instructed to select stations where cod would most likely be caught based on historic fishing areas or habitat structure. All stations were sampled between July and October.

Due to fixed gear conflicts (congestion of lobster traps) that prohibit longline sampling in depths under 50 m, NEFSC suggested that an inshore jigging component was added to the survey in 2012. The jigging aspect of the survey was modeled after a hook and line survey used in a west coast stock assessment of Bocaccio rockfish (Harms et al., 2010). To remain consistent with the stratified random design of the fishery independent portion of the Sentinel Survey, all inshore jig stations were classified under one depth strata:

Strata 0 for inshore Jig Only: 0-50m

48 randomly selected stations were surveyed from June through October. Drop sites were selected within the confines of the allotted station area based on assumed cod habitat or on reports from lobster fishermen who had recently caught cod as bycatch in traps. Five drops lasting a maximum of five minutes were completed at each station. Drop time started at the time the jig hit bottom and terminated with the catch of any fish or with the end of the allotted five minutes. Once a fish is caught and reeled in, anglers do not have the opportunity to re-drop jigs for whatever duration remains of the five-minute drop window. There were two anglers per boat: each fishing a rod and reel rigged with three hooks for a total of 6 hooks and up to 10 minutes fishing time per drop. Survey design was evaluated; examining the choice of depth stratification and the effect of soak time on catch rates. Based on the evaluation, it was concluded that the choice of depth in the stratified random survey design was appropriate. From 2013-2015, a stratified random survey design was followed for the majority of sampling effort. Longline gear remained unchanged from the previous five years (2 nautical mile longline with 2,000 hooks, baited with squid and/or herring) as did the two-hour target soak time.

II-1-C. 2013 Jigging Incorporated at Longline and Fisherman's Choice Stations:

In 2013, a jigging component designed to target Atlantic cod was added to all station types to increase overall sampling effort. The decision to incorporate a jig component at all stations was made based on the comparative analysis between longline and jigging gear, which showed that jigging gear was more effective at catching cod than longline gear. The overall

allocation of sampling effort with the addition of jig gear at all stations remained consistent in 2014 and 2015. Because of logistical constraints (e.g. weather, bait acquisition, and fishermen participation) sampling in 2015 was more limited. In 2015, 29 of 30 selected stratified random longline stations were sampled and 9 of 12 allotted fishermen's choice longline stations were sampled. However, all 47 selected jigging stations (35 inshore jigging stations and 12 offshore jigging stations) were sampled. Consistent with 2013 and 2014, jigging was also applied to the 29 stratified longline stations and all 9 fishermen's choice longline stations that were sampled, adding an additional 38 jigging stations in 2015.

II-1-D. 2016 Jigging-Only Season:

In 2016, the overall allocation of sampling effort consisted of jig-only stations, unlike previous years (2010-2015) in which the survey was conducted using longline gear and jig gear. Sampling in 2016 was limited to jig gear because of financial constraints that supported limited sampling with only one gear type. Consequently, stations were randomly allocated and stratified by depth between strata 0 and 2. Because jig gear was the only gear type used in 2016, other groundfish species (e.g. halibut, white hake, and cusk) with low catchability on jig gear were not targeted. Instead, the gear limitations in the 2016 survey season lead to a primary focus on Atlantic cod, pollock, and mackerel. Despite limited catchability of other species, jig gear can be a more efficient gear type in areas with high densities of fixed gear complex bathymetry. As a result, the jigging survey design remained comparable to the jig methods followed from 2012-2015. 2016 data is incorporated in the jigging portion of this analysis, but there is no available longline data for 2016.

II-1-E. 2017 Shortened Longline:

Due to an increasing level of gear congestion and the logistical difficulties for sampling in the survey area, an analysis was conducted to evaluate the effects of fishing with a shortened, 200-hook longline. The results of the analysis showed that there was minimal temporal variation between sizes of longline sets and there was no statistical significance between abundance trends calculated for the 2000-hook set versus the 200-hook set. As a result, it was feasible to use a shortened set to alleviate logistical issues without adversely affecting the design-based abundance index that is derived from the stratified random stations. The full justification for the shortened set can be found in the section XI-1 of the appendix.

As a result of the shortened longline, the target soak time was also reduced from two hours to one hour. Consistent with previous years, soak time was reevaluated with the statistical models and confirmed to have no statistically significant impact on catch at longline stations. 2017 was the first year in which 200 hook longlines were used and allowed to soak for shorter duration. Ultimately, the use of fewer hooks led to fewer total fish being caught. However, this did not indicate changes in calculated abundance. In the models used to calculate abundance indices, historical Sentinel Survey data were standardized to find average catch for 200 hook sets. Additionally, soak time of historic Sentinel data were re-evaluated to assure that it does not have a statistically significant impact on catch. This standardization scheme allows all years to be compared on the same scale, while still reflecting similar abundance trends to those calculated in previous years. Jigging methods remained consistent from 2012 and through 2018.

II-2. Modeling:

II-2-A. Modeling Approaches:

In prior versions of this report, three model types were used to model data and alleviate the effect of the high frequency of zeros in Sentinel Survey catch data: generalized linear models (GLMs), zero-inflated models, and generalized additive models (GAMs). GLMs were initially developed as a baseline model for understanding relationships between variables and the response but were not fit to model Sentinel Survey catch data. Packages (*'pscl'* and *'mgcv'*) in R software were used to generate zero-inflated models and generalized additive models, which are designed to allow for the use of standard distributions on over-dispersed catch data without violating statistical assumptions (Jackman. 2015; Martin et al., 2005). However, in comparison to GAMs, zero-inflated models provided poor fits to the data. Results in the 2017 Sentinel Survey report (Carlucci and Chen, 2018) showed that GLMs and zero-inflated models performed poorly and were not nearly as flexible as the Tweedie distributed GAM. Therefore, zero-inflated models and GLMs were not considered here.

Generalized additive models allow for flexible parameterization of error distribution. A Poisson distribution is applied because the standard deviation distribution is consistent with standard deviation distribution expected in count or catch data. As a result, it is commonly used to model fisheries data with high frequencies of zero catch. Since it is impossible to have negative catch data, a Poisson distribution is designed to only account for catch from zero to infinity (Zurr et. al. 2009). Similar to the zero-inflated model, a Tweedie distribution is a more complicated distribution used in generalized additive models that considers Poisson distributions. However, in addition to the Poisson distribution, the Tweedie distribution considers gamma

distributions as well as Poisson-gamma distributions that are continuous to assess variance by covariate as it relates to the mean error (Zurr, 2009).

Despite the flexibility of the Tweedie GAM, it remains subject to statistical assumptions that can limit model performance. In 2018, boosted regression trees (BRT) were incorporated as an additional and robust model to ensure the use of models most appropriate for the Sentinel Survey dataset. Boosted regression tree models utilize a machine learning process that is not subject to the same statistical assumptions as the Tweedie GAM. Unlike a GAM in which insignificant variables must be removed to better explain relationships between explanatory variables and the response, BRT's perform best as a fully-informed model containing all explanatory variables regardless of their significance in the model. As a result, the BRT can utilize more data to better explain the relationships between explanatory variables and the response variable (Elith and Leathwick, 2016).

Due to the growing interest in using Tweedie GAM's to model fisheries such as the lobster industry in the Gulf of Maine (Tanaka and Chen, 2016) and using boosted regression trees for ecological modeling, an analysis of model types was conducted to determine which model type is most appropriate for the Sentinel Survey dataset. Simple generalized linear models (GLMs), zero-inflated models, and generalized additive models (GAM's) with a Tweedie distribution were built from the 'mgcv' package in R for each target species. The *gbm.step()* function with a Poisson distribution from the 'gbm' package was used to create boosted regression trees for all target species. Each model contained the number of individuals caught as the response variable in order to develop a method of modeling catch of each species based on all explanatory variables that may influence fish distribution and abundance (depth, sea surface temperature (SST), bottom temperature, sediment type, month, bait type used, and presence

absence of non-target species such as pollock or mackerel). These models were used to estimate habitat preference and estimate the standardized catch per unit of effort (CPUE) for each species. All models were produced in the statistical program R (R Core Team 2012).

II-2-B. Incorporating Catchability (Probability of Detection) into Model-Based

Estimates:

Based on results from the study conducted in (Chapter 2), jig models in 2018 modeled cod catch as a function of environmental covariates in addition to detection probability (a measure of gear catchability) and the presence or absence of non-target species most commonly caught on the jigs: pollock (*Pollachius virens*) and mackerel (*Scomber scombrus*). The overall goal was to evaluate whether the catchability of jigging gear was impacting catch results in a significant way, and to evaluate whether (due to the nature of the jig methods) the catch of non-target species inhibited the ability to detect or catch target species. Utilizing an unmarked occupancy framework in the R package ‘*unmarked*’, a two-tier modeling process in which occupancy and detection were modeled simultaneously to estimate site-specific occupancy and detection. Using only inshore jigging data, the probability of site-occupancy was modeled as a function of time and the environment while detection was modeled as a function of occupancy, time, the environment, and catch of non-target species in order to quantify jigging gear catchability.

II-2-C. Cross Validation and Model Selection:

Prior to developing any models, all potential explanatory variables are run through a variance inflation test to remove covariates that are colinear with one another. A VIF value of 3.0 was selected as the maximum VIF value for variables to be included in the modelling framework. Initial models were generated for random longline and jigging data that included all the explanatory variables that may influence distribution and abundance of target groundfish: year (included as a random effect), depth, sea surface temperature, bottom temperature, sediment class (soft, medium, or hard as classified by Poppe, 2005), bait type, and month. Limited spatiotemporal coverage of the Sentinel Survey resulted in limited contrast in the data. As a result, some explanatory variables were not be suitable for inclusion in the models. As is consistent with developing GAMs, terms that were not statistically significant ($p > 0.05$) were dropped sequentially beginning with the highest p -value and then compared to the full model containing all variables using Akaike Information Criterion (AIC) (Burnham and Anderson, 2004). A combination of AIC and the cross-validation scheme described by Tanaka and Chen (2016) were used to compare similar models. Based on AIC values, the model with the lowest AIC score was selected as the better model. However, AIC values tend to penalize models that contain more covariates. In this analysis, AIC values selected the simplest models with the fewest number of covariates, even though simpler models explain less of the deviance in the data. In every instance, the full model outperformed the reduced model across all three model-types. As a result, the cross-validation scheme described by Tanaka and Chen (2016) was used to select the best models.

Although the *gbm.step* function has a built-in cross validation scheme when building the model, GAMs do not. Cross validation methods adopted from Tanaka and Chen (2016) were used in which a random subset of 80% of the original dataset is used as a “training” data set while the remaining 20% of the data is used as a “test” dataset. In this method, the predicted values based on the training dataset are compared to the observed values within the test set. A linear regression is used to evaluate the performance of the model being tested and repeated 2000 times, generating 2000 individual regression lines based on random subsets of the data. A mean regression was calculated for each set of regressions run on each model type for each of the four species. Theoretically, the model with an intercept closest to 0, slope closest to 1, and R^2 closest to 1 is the best model. All three models tended to perform well, so as an additional criterion for choosing the best model, root mean squared error (RMSE) was calculated for each model. A combination of RMSE, R^2 , slope, and intercept were considered when choosing the model with the best fit for each species. The equation for RMSE can be found below:

$$RMSE = \sqrt{\frac{\sum_{k=1}^{1000} (predicted - observed)^2}{n_{samples} * n_{simulations}}}$$

Although zero-inflated models are a popular choice for modeling abundance in longline fisheries data (Walsh et al., 2013; Minami et al., 2007; Ichinokawa et al., 2012), the BRT had a lower MSE for all species. The GAM models had the lowest MSE of all model types. Due to updates in the ‘*pycl*’ package, the predict function in R has not been updated to predict for a zero-inflated distribution. Since the BRTs and GAMs performed best, they were chosen for

habitat and bait preference because it could be predicted appropriately in R. MSE, intercept, slope, R^2 , and repetitive simulations can be found in Tables III-11 and 12 as well as Figure III-20 in section V-2 of the discussion.

II-3. Calculation of Abundance Indices:

II-3-A. Design-Based Abundance Index:

Sophisticated model-based approaches can be useful in standardizing abundance indices, however, there are many assumptions that must be satisfied in order to benefit from their use (ICES, 2004). Comparisons of model-based approaches often show limited improvement over simpler methods of abundance estimates (ICES, 2004). For the longline catch, all models demonstrate quantitatively that depth was a statistically significant factor that influenced catch at fisherman's choice stations. Random stations are stratified by depth so that the influence of depth is accounted for. Since the influence of depth is accounted for in the survey design, a stratified mean abundance and variance can be used for an abundance index that still includes depth as a variable. Because of the large number of zeroes in the dataset, the delta mean method described in Pennington (1983) was adopted to estimate abundance at stratified random stations. By this method, the stratified mean abundance and standard deviation for each species of interest is calculated using weighted area data, then summed per strata such that:

$$\bar{x} = \sum_{s=1}^3 \bar{x}_s * w$$

and:

$$\sigma_{\bar{x}} = \sqrt{\sum_{s=1}^3 w^2 * \left(1 - \frac{n_{sampled}}{area}\right) * s^2}$$

where the stratified mean (\bar{x}) is equal to the sum of the mean number of fish within each of three strata (\bar{x}_s) multiplied by the weight (w). Stratified standard deviation is equal to the square root of the summation of one minus the number of stations sampled in each of three strata ($n_{sampled}$) divided by the number of possible stations in a given strata multiplied by the weight squared and the variance squared (s^2). Mean abundance and variance were calculated for both the longline and jig data with the delta mean approach (Pennington, 1983) using the ‘*fishmethods*’ package (Nelson, 2013) in R. Estimates of abundance were calculated separately for fish caught at stratified random longline (LL) stations, inshore random jigging (JJ) stations, offshore jigging (JJO & JL) stations, and a combination of all jigging data (JJ & JJO & JL) for each year. Abundance indices were calculated for cod, halibut, cusk, and white hake inside the survey region.

II-3-B. Model-based Abundance Index:

GAMs and BRTs were used to model abundance based on all variables (identified in section II-2-A) that could have an influence on catch. Based on the models run for each species, fitted values were used in the delta mean method in the same way observed count numbers were used in the design-based abundance calculations. Although zero-inflated models performed marginally better for cusk and cod, there were too many N/A values in the model output to conduct a meaningful model-based abundance estimate. Consequently, GAMs with Tweedie

distributions and BRTs with Poisson distributions were used for the model-based abundance estimates of cod and cusk.

II-4. Standardizing Catch Per Unit of Effort:

Catch data from 2012-2018 fishermen's choice stations are considered fisheries dependent data because fishing locations were chosen by fishermen. Fisheries catch per unit of effort (CPUE) data can be used in the stock assessment process to supplement fisheries independent survey abundance indices. However, fisheries CPUE data violates the assumption that catch rates are related to stock abundance because fisherman are targeting known aggregations of fish (Hilborn and Walters, 1992). The violation of this assumption stems from the idea that catch rates are often influenced by other variables, such as fishermen's experience, knowledge, and fishing location; variables that are not related to stock abundance. In order to use fisheries CPUE data as an index of abundance, CPUE must be standardized to remove the effect of other variables so that only stock abundance is considered (Maunder and Punt, 2004). Based on cross-validation results, the GAM's and BRTs consistently had a lower mean squared error for each species. Since the variables in the CPUE models are the same as the variables included in the habitat model, a decision was made to proceed with the generalized additive model with a Tweedie distribution and the BRT with a Poisson distribution to calculate the standardized CPUE for all four species of interest. Models were generated for each species using data from all fishermen's choice stations. Year was initially included as a categorical random effect the model to evaluate annual variation, even though year is consistently statistically insignificant ($p > 0.05$). However, models including year as a random effect performed more poorly than models that did not contain year as a covariate. Consequently, year was not included in any of the final models.

II-5. Allocation of Fishing Effort:

Table III- 1. Annual allocation of fishing effort on the Sentinel Survey from 2012-2018. Longline is abbreviated as LL.

Year Station Type	2012		2013		2014		2015		2016		2017		2018	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Random LL	29	31	30	22	30	22	29	24			30	23	24	33.8
Strata 1	5	17	5	3.7	9	6.5	5	17			5	17	4	12.5
Strata 2	11	38	12	8.8	10	7.2	13	45			13	43	12	37.5
Strata 3	13	45	13	9.6	11	7.9	11	38			12	40	8	25
Fisherman's LL	16	17	14	10	16	12	9	7			12	9	8	11.3
Jigging Only	48	52	48	35	47	34	47	38	62	87.3	47	36	39	55
Strata 0	48	100%	36	26.5	36	26	35	74	36	50.7	36	77	27	69.2
Strata 1			4	2.9	4	2.9	5	11	9	12.7	4	8	4	10.2
Strata 2			4	2.9	4	2.9	3	6	17	23.9	3	6	4	10.2
Strata 3			4	2.9	3	2.2	4	9			4	8	4	10.2
Jig at LL (JL)			30	22	30	22	29	24			30	23	23	32.4
Jig at FL (JF)			14	10	16	12	9	7	9	12.7	12	9	8	11.3

II-6. 2018 Sentinel Survey Stations:

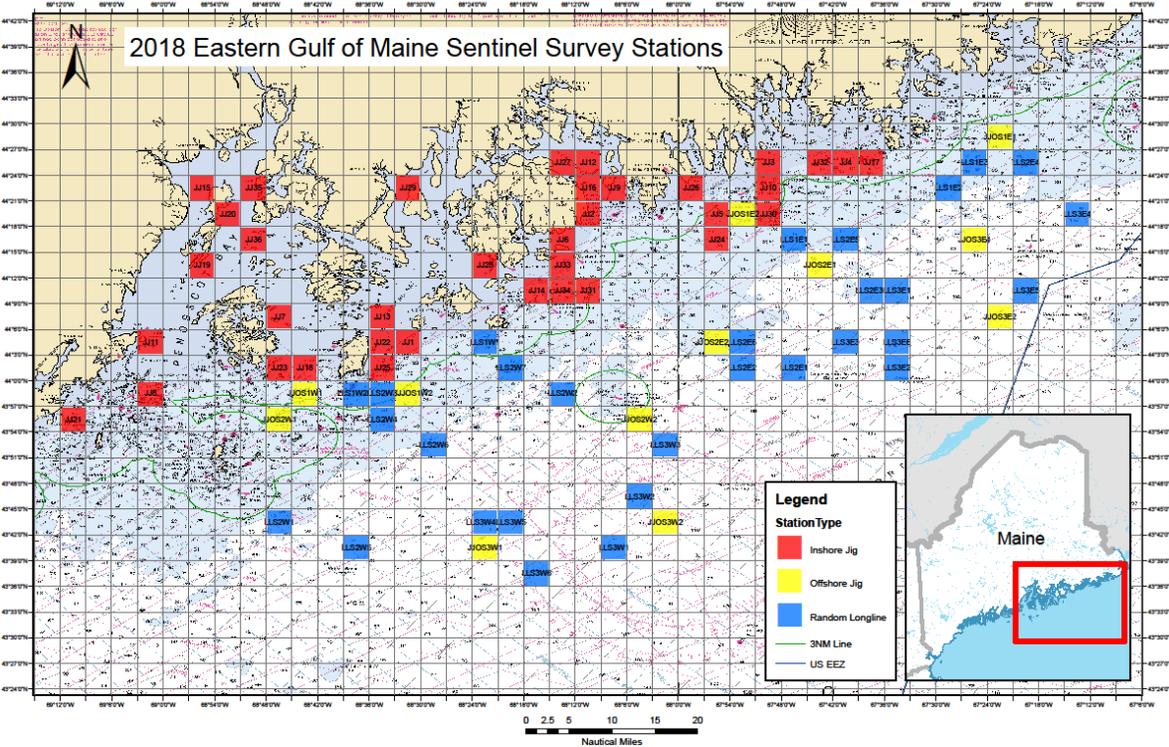


Figure III-1. 2018 Eastern Gulf of Maine Sentinel Survey Stations.

III. RESULTS:

III-1. Estimated Abundance Indices:

III-1-A. Design-based Abundance – Stratified Random Longline Stations:

Results showed cod exhibited the greatest amount of variation in abundance since 2012 while halibut, white hake, and cusk show relatively little change in abundance throughout the time series (Figures III-2, 3, 4, and 5). Halibut, white hake, and cusk show instances of high abundance, which may be attributed to outlying catch values in the outlying year as variance was also greater in years with unusually high catch values.

Based on Figure III-2, there is no clear trend in Atlantic cod abundance. The design-based abundance trend appears to be sinusoidal, illustrating an increase from 2012 to 2013 then a decrease from 2013 to 2015. However, Atlantic cod abundance appears to be increasing since 2015. Halibut abundance experienced a decrease in abundance from 2012 to 2013 (Figure III-3). From 2013 to 2018, halibut abundance showed little inter-annual variation, but abundance seems to continue to decline, although to a much lesser extent. There was little variation in white hake abundance over the time series (Figure III-4). White hake abundance increased from 2012 to 2013 to an unusually high level before declining in 2014. Based on the results and the large margin of error around the 2013 estimate for white hake, 2013 appears to be an outlying year for white hake catch. After 2013, white hake abundance returned to a similar level observed in 2012 and remained relatively unchanged from 2014 through 2018. Cusk experienced a decline in abundance from 2012 to 2014 but have been experiencing an increase in abundance from 2014 through 2018 (Figure III-5).

It is important to note that the magnitude of the changes in abundance for each species is different. Cod caught at random longline stations have a maximum estimated abundance of 0.06 in 2018 and a minimum estimated abundance of 0.01 in 2012 and 2015 (Table III-2). Table III-2 also shows that white hake reached a maximum estimated abundance of 4.04 in 2013 and a minimum estimated abundance of 0.86 in 2015. Estimated abundance of Atlantic halibut reached a maximum value of 0.48 in 2012 and a minimum value of 0.10 in 2018. Cusk were the only species to exhibit values similar to cod, maintaining a minimum around 0.01 in 2013 and 2014 before rising to a maximum abundance of 0.13 in 2018. All design-based abundance estimates, standard deviations, and coefficients of variation for all four target species caught at random longline stations are included in Table III-2.

III-1-B. Model-based Abundance – Stratified Random Longline Stations:

Despite developing robust models with acceptably low margins of error, only cusk and halibut showed model-derived estimates of abundance that followed the design-based abundance trends for the species. Unfortunately, there were no instances in which both model-types produced the same trend as the design-based abundance. Although the BRT-based values for Atlantic halibut abundance are closer to the design-based estimates compared to the estimates from the Tweedie GAM, the BRT estimated an increase in abundance from 2017 to 2018 when the design-based abundance showed a decrease in abundance (Figure III-3). Although the GAM estimated values were consistently higher than what was observed, these estimates matched the abundance trend exhibited by Atlantic halibut. On the contrary, the GAM estimates of white hake abundance did not follow the trend of the design-based abundance for white hake (Figure III-4). The BRT proved to be the better estimate of white hake abundance as the BRT estimates

were close to the design-based estimates and the overall trend in design-based abundance was replicated by the BRT. For Atlantic cod, estimates from the BRT and design-based abundance index show similar trajectories in abundance, but the trend differs from the design-based estimates from 2015 to 2017 and the BRT model estimated values that were quite different from what was observed. The GAM-based estimates of cod abundance do not show a similar trend or have similar values. Interestingly, the GAM was the better model for estimating cusk abundance even though cod and cusk exhibit similar abundance and catch values on the survey. The GAM was able to produce the same trend as the design-based abundance estimates for cusk, but the BRT was not able to produce similar values or a similar trend to what was observed for cusk. Model-based abundance estimates, standard deviations, and CV values for all four target species can be found in Table III-3 (GAM) and Table III-4 (BRT).

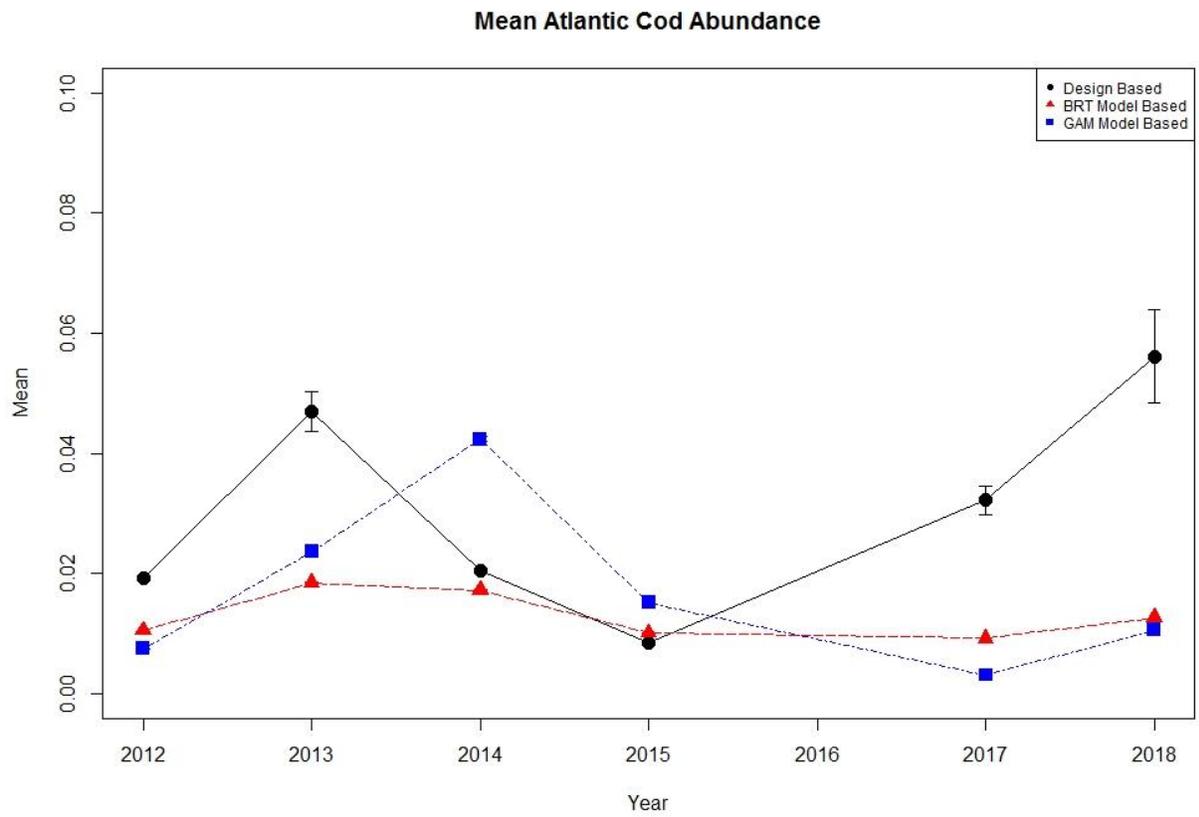


Figure III-2. Delta mean estimated mean abundance and associated standard deviation for cod caught at stratified random longline station from 2012-2018.

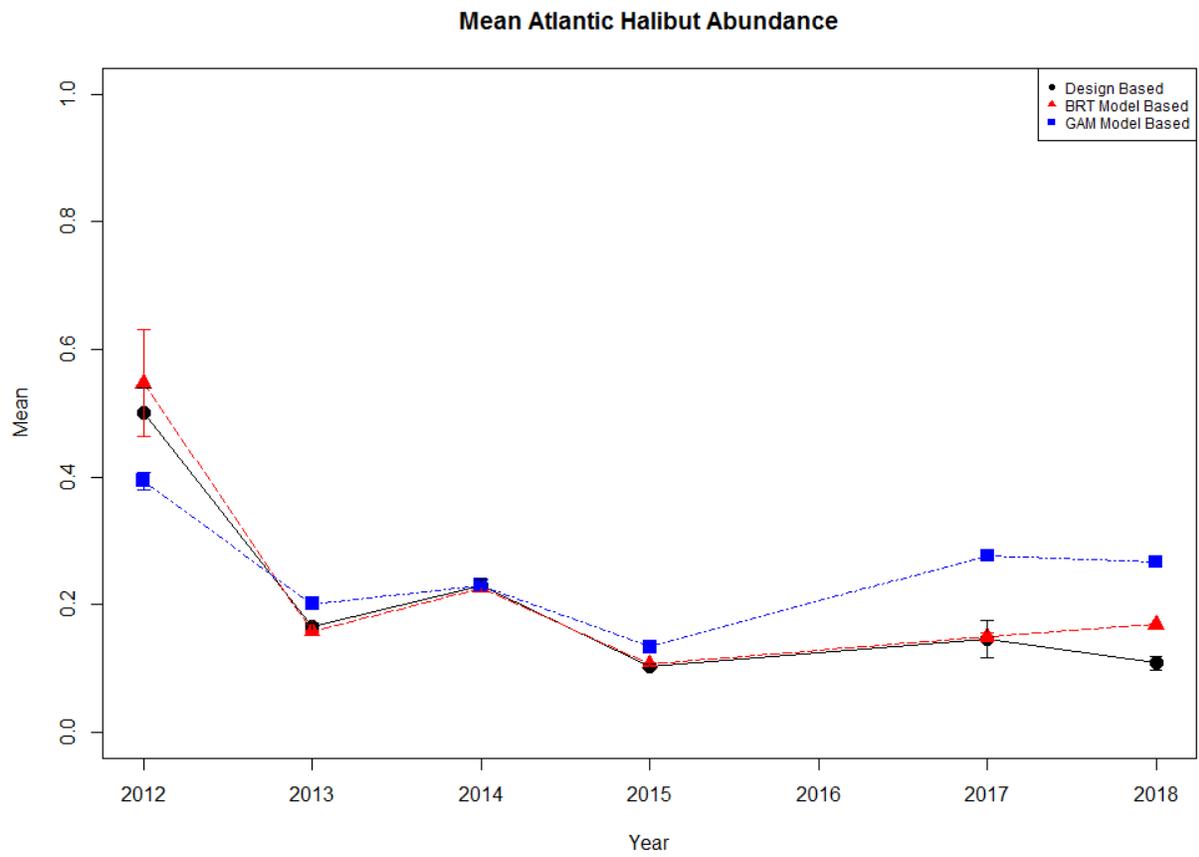


Figure III-3. Delta mean estimated mean abundance and associated standard deviation for Atlantic halibut caught at stratified random longline station from 2012-2018.

Mean White Hake Abundance

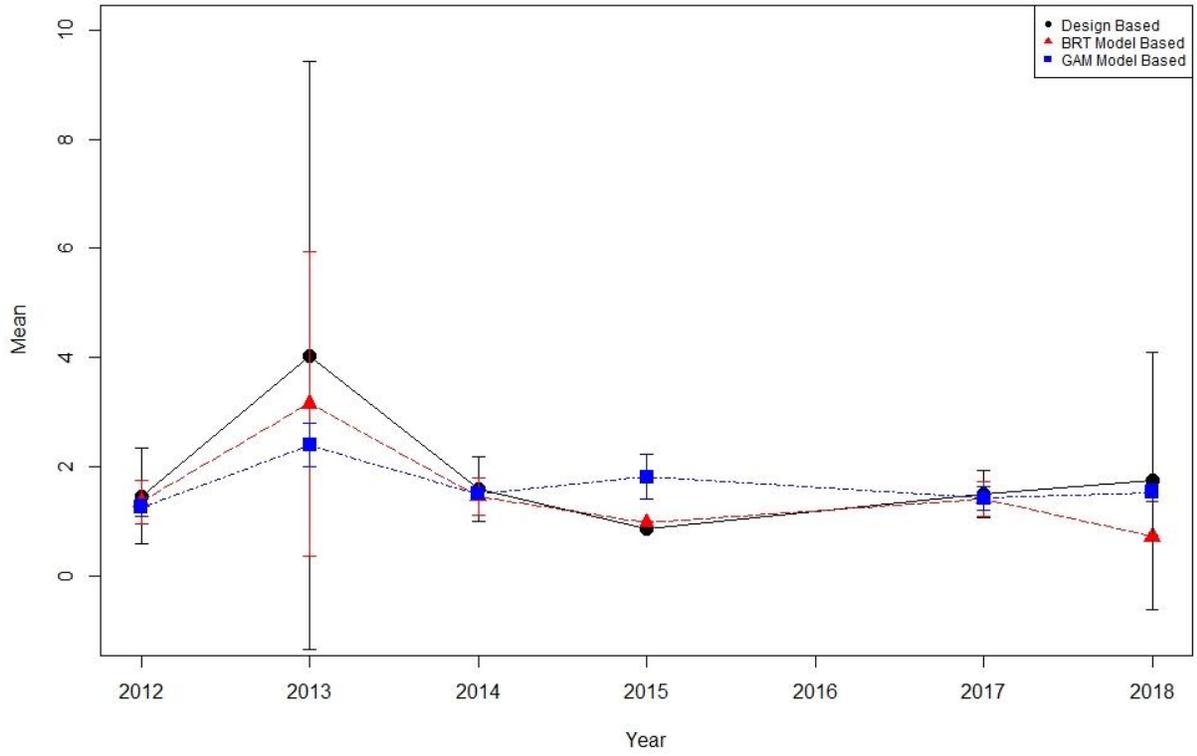


Figure III-4. Delta mean estimated mean abundance and associated standard deviation for white hake caught at stratified random longline station from 2012-2018.

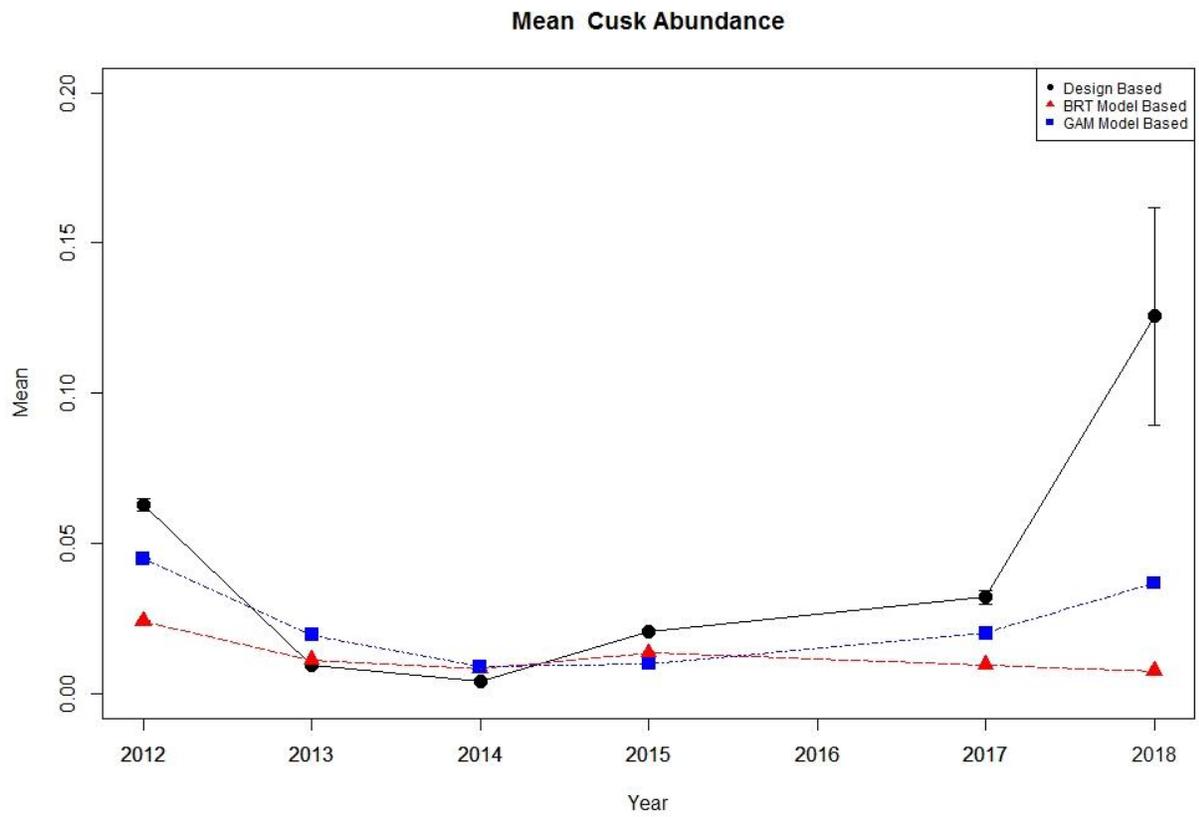


Figure III-5. Delta mean estimated mean abundance and associated standard deviation for cusk caught at stratified random longline station from 2012-2018.

Table III- 2. Design-based delta mean estimated abundance, standard deviation ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for cod calculated based on stratified random longline data from 2012-2018.

Species	Cod			Halibut			White Hake			Cusk			
	Year	Abundance	$\sigma_{\bar{x}}$	CV	Abundance	$\sigma_{\bar{x}}$	CV	Abundance	$\sigma_{\bar{x}}$	CV	Abundance	$\sigma_{\bar{x}}$	CV
2012		0.01	<0.01	0.02	0.48	0.04	0.08	1.47	0.89	0.60	0.06	<0.01	0.03
2013		0.05	<0.01	0.07	0.16	0.01	0.04	4.04	5.38	1.33	0.01	<0.01	0.01
2014		0.02	<0.01	0.01	0.23	0.01	0.05	1.60	0.60	0.37	<0.01	<0.01	0.01
2015		0.01	<0.01	0.01	0.12	<0.01	0.03	0.86	0.03	0.03	0.02	<0.01	0.02
2017		0.03	<0.01	0.08	0.14	0.03	0.21	1.51	0.44	0.29	0.03	<0.01	0.07
2018		0.06	0.01	0.14	0.10	0.01	0.09	1.75	2.35	1.35	0.13	0.04	0.29

Table III- 3. Generalized Additive Model-based delta mean estimated abundance, standard deviation ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for cod calculated based on stratified random longline data from 2012-2018.

Species	Cod			Halibut			White Hake			Cusk			
	Year	Abundance	$\sigma_{\bar{x}}$	CV	Abundance	$\sigma_{\bar{x}}$	CV	Abundance	$\sigma_{\bar{x}}$	CV	Abundance	$\sigma_{\bar{x}}$	CV
2012		0.01	<0.01	<0.01	0.40	0.01	0.04	1.26	0.16	0.12	0.05	<0.01	<0.01
2013		0.02	<0.01	<0.01	0.20	<0.01	0.01	2.40	0.40	0.17	0.02	<0.01	<0.01
2014		0.04	<0.01	0.01	0.23	<0.01	0.01	1.51	0.10	0.07	0.01	<0.01	<0.01
2015		0.02	<0.01	<0.01	0.13	<0.01	0.01	1.82	0.41	0.23	0.01	<0.01	<0.01
2017		<0.01	<0.01	<0.01	0.28	<0.01	0.01	1.43	0.21	0.15	0.02	<0.01	<0.01
2018		0.01	<0.01	<0.01	0.27	<0.01	0.01	1.53	0.15	0.10	0.04	<0.01	<0.01

Table III- 4. Boosted Regression Tree model-based delta mean estimated abundance, standard deviation ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for cod calculated based on stratified random longline data from 2012-2018.

Species	Cod			Halibut			White Hake			Cusk			
	Year	Abundance	$\sigma_{\bar{x}}$	CV	Abundance	$\sigma_{\bar{x}}$	CV	Abundance	$\sigma_{\bar{x}}$	CV	Abundance	$\sigma_{\bar{x}}$	CV
2012		0.01	<0.01	<0.01	0.53	0.07	0.14	1.36	0.41	0.30	0.02	<0.01	<0.01
2013		0.02	<0.01	<0.01	0.15	<0.01	0.01	3.16	2.80	0.89	0.01	<0.01	<0.01
2014		0.02	<0.01	<0.01	0.22	0.01	0.02	1.46	0.35	0.24	0.01	<0.01	<0.01
2015		0.01	<0.01	<0.01	0.11	<0.01	0.01	0.97	0.03	0.03	0.01	<0.01	<0.01
2017		0.01	<0.01	<0.01	0.13	<0.01	0.01	1.41	0.32	0.23	0.01	<0.01	<0.01
2018		0.01	<0.01	<0.01	0.18	<0.01	<0.01	0.72	0.03	0.04	0.01	<0.01	<0.01

III-1-C. Design-based Abundance – Stratified Random Jigging Stations:

Results from the delta mean estimation of abundance show that estimates of abundance for cod at all random jigging stations (JJ, JJO, and JL) decline from 2012 to 2013 before increasing steadily from 2013 to 2016, and then declining again from 2016 to 2018 (Figure III-6). Combined jig data appears to highlight an overall decline in cod abundance for this component of the survey.

Estimates of abundance from the inshore stations only (strata 0: 0-50m) decreased from 2012 to 2013 before increasing to a maximum in 2014. Cod abundance declined from 2014 to 2016, increased in 2017, and finally declined in 2018 (Figure III-7). Overall, this trend appears to be sinusoidal with a large amount of variation. It is not clear whether there is an overall increase or decrease in cod abundance from the inshore jigging component of the survey.

Data from 2012 are not available from offshore jigging stations because this component was not added until 2013, as mentioned in section II-1-C of the methods. As a result, all offshore abundance estimates are from 2013 to 2018. As with the combined jig data, abundance estimates from random offshore stations (strata 1, strata 2, and strata 3; JJO and JL stations) show an increase from 2013 to 2016 then declining from 2016 to 2017. However, offshore abundance increases from 2017 to 2018 (Figure III- 8), which is different from what was seen inshore jigging and in the combined jig abundance indices. All abundance estimates, standard deviations, and coefficients of variation for cod abundance estimations are included in Table III-5.

III-1-D. Model-based Abundance – Stratified Random Jigging Stations:

In all years, the model-based cod abundance estimates from the inshore jigging data followed the same trends as the design-based abundance estimates (Figure III-7). Although the

model-based estimates show a very similar trend to the design-based estimates for the combined jig data, both models predicted a decrease in cod abundance from 2014 to 2015 when there was a slight increase in abundance observed in the design-based estimations. Similarly, offshore jig data showed only one year in which the model predicted a different trend in abundance from the design-based estimate (2017 to 2018, Figure III- 8). Despite the benefits of using BRTs over GAMs, BRTs were not fitted to offshore jigging data because there is not enough data for a BRT to converge. All model-based estimates of abundance, standard deviations, and coefficients of variation for cod caught at random jigging stations are included in Tables III-5, 6 (GAM), and 7 (BRT).

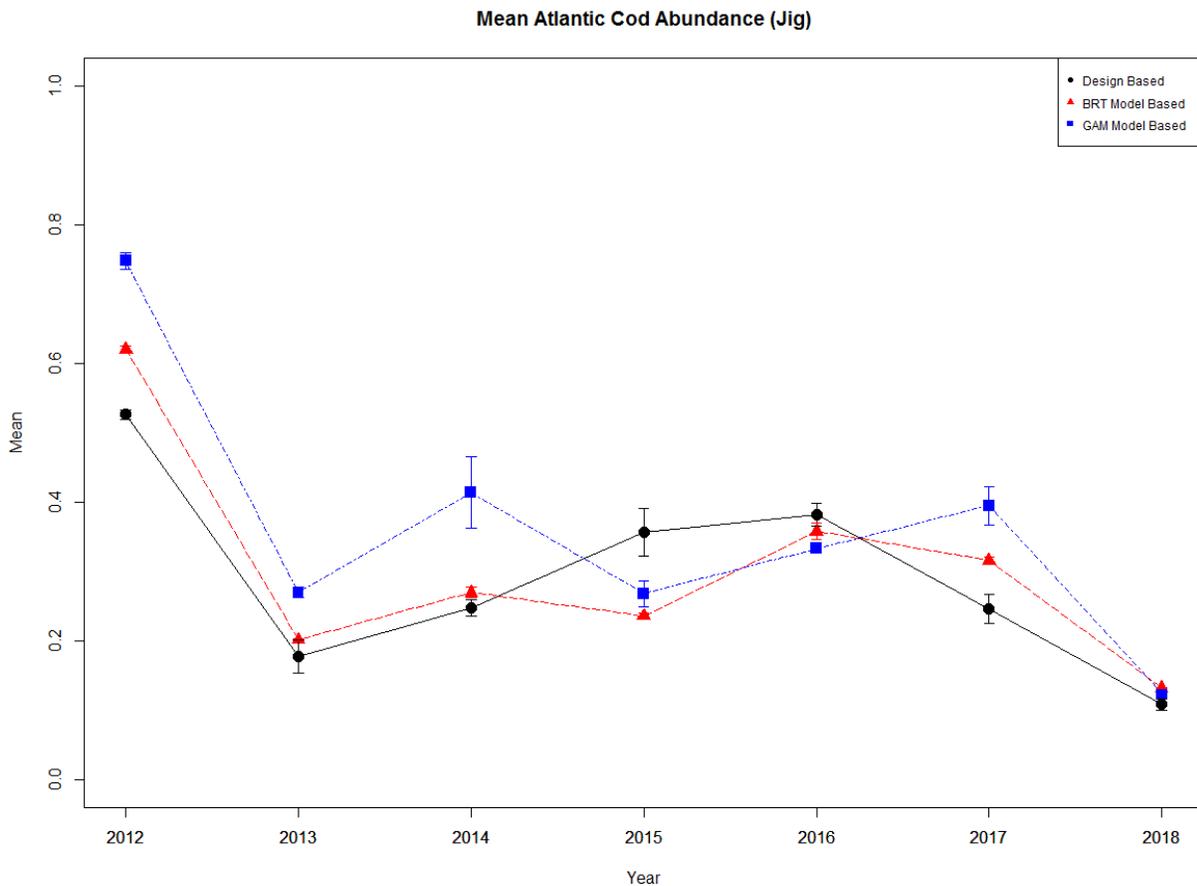


Figure III- 6: Relative Abundance of Atlantic cod at all random jig (JJ & JJO & JL) Stations from 2012-2018.

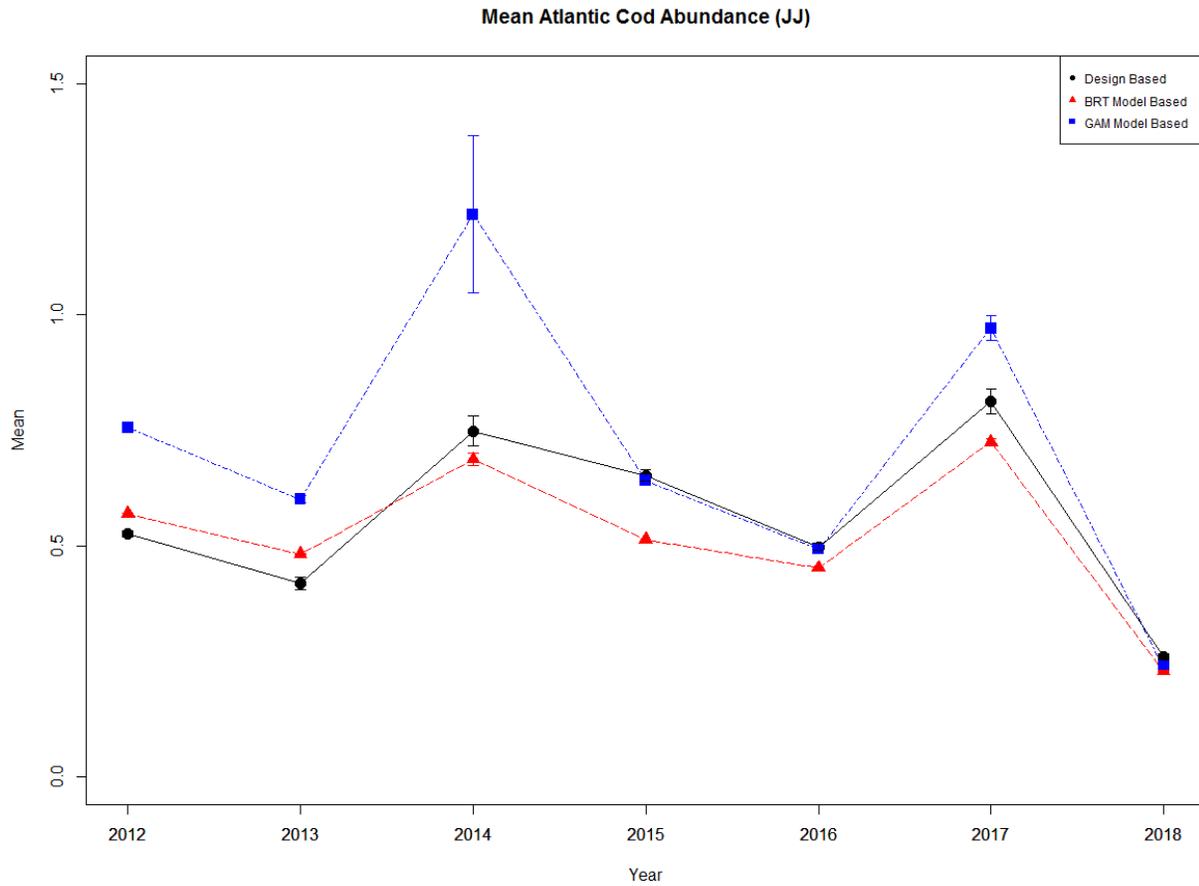


Figure III- 7: Relative Abundance of Atlantic cod at all Inshore Jig (JJ Stratum 0) Stations from 2012-2018.

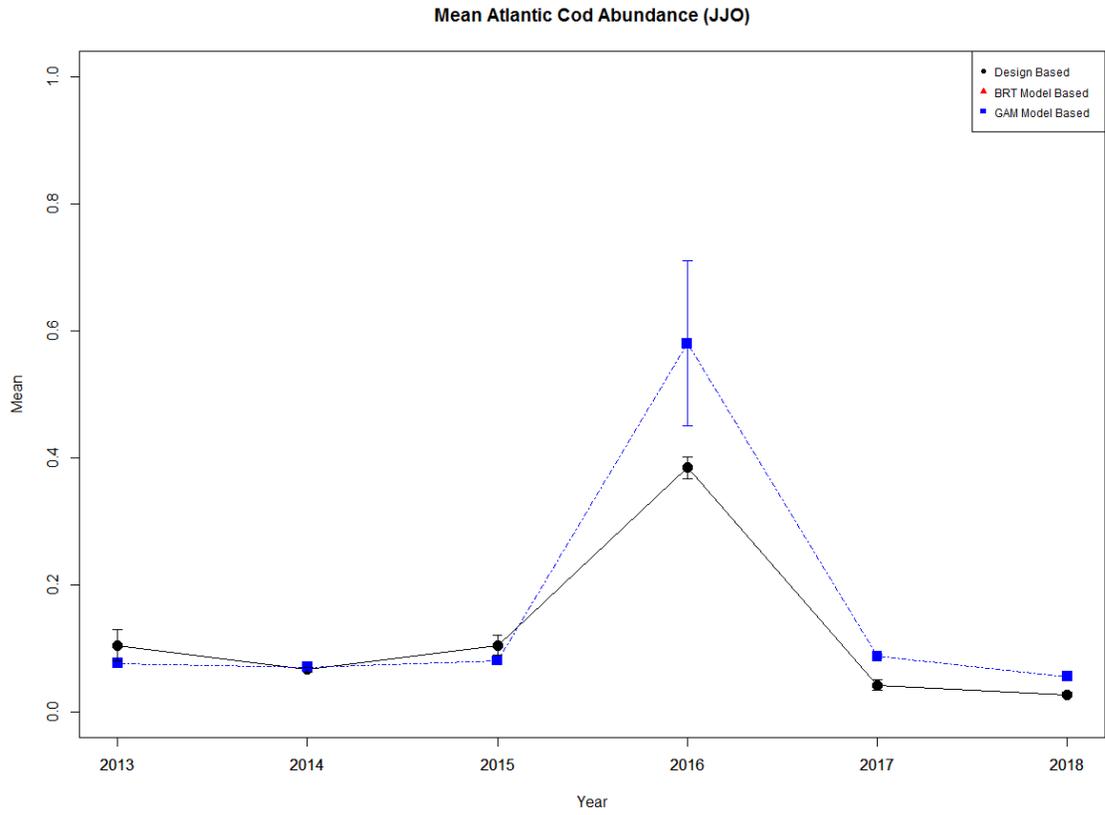


Figure III- 8: Relative Abundance of Atlantic cod at Offshore Jig (JJO) Stations from 2012-2018.

Table III- 5. Design-based delta mean estimated abundance, standard deviation ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for cod calculated based on jigging data from 2012-2018. JJ denotes inshore jigging stations, JJO denotes offshore jigging stations, and JL denotes jig at longline stations.

Species				Cod					
Station Type	All Jigging			Inshore Jigging			Jig Offshore		
	(JJ, JJO, & JL)			(JJ)			(JJO & JL)		
Year	Abundance	$\sigma_{\bar{x}}$	CV	Abundance	$\sigma_{\bar{x}}$	CV	Abundance	$\sigma_{\bar{x}}$	CV
2012	0.53	0.01	0.01	0.53	0.01	0.01			n/a
2013	0.18	0.02	0.13	0.42	0.01	0.03	0.10	0.02	0.24
2014	0.25	0.01	0.05	0.75	0.03	0.04	0.07	0.00	0.05
2015	0.36	0.03	0.10	0.65	0.01	0.02	0.10	0.02	0.15
2016	0.38	0.02	0.04	0.50	0.01	0.02	0.38	0.02	0.05
2017	0.25	0.02	0.08	0.81	0.03	0.03	0.04	0.01	0.20
2018	0.11	0.01	0.08	0.25	0.01	0.03	0.03	0.00	0.13

Table III- 6. GAM-based delta-mean estimated abundance, standard deviation ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for cod calculated based on jigging data from 2012-2018. JJ denotes inshore jigging stations, JJO denotes offshore jigging stations, and JL denotes jig at longline stations.

Species				Cod					
Station Type	All Jigging			Inshore Jigging			Jig Offshore		
	(JJ, JJO, & JL)			(JJ)			(JJO & JL)		
Year	Abundance	$\sigma_{\bar{x}}$	CV	Abundance	$\sigma_{\bar{x}}$	CV	Abundance	$\sigma_{\bar{x}}$	CV
2012	0.75	0.01	0.02	0.76	0.01	0.01			n/a
2013	0.27	0.01	0.03	0.60	0.01	0.01	0.08	<0.01	0.01
2014	0.41	0.05	0.12	1.22	0.17	0.14	0.07	<0.01	0.04
2015	0.27	0.02	0.07	0.64	0.01	0.02	0.08	0.01	0.06
2016	0.33	0.01	0.02	0.49	0.00	0.01	0.58	0.13	0.22
2017	0.39	0.03	0.07	0.97	0.03	0.03	0.09	<0.01	0.03
2018	0.12	0.00	0.02	0.24	<0.01	0.02	0.06	<0.01	0.01

Table III- 7. BRT-based delta-mean estimated abundance, standard deviation ($\sigma_{\bar{x}}$), and coefficient of variation (CV) for cod calculated based on jigging data from 2012-2018. JJ denotes inshore jigging stations, JJO denotes offshore jigging stations, and JL denotes jig at longline stations.

Species				Cod						
Station Type	All Jigging (JJ, JJO, & JL)			Inshore Jigging (JJ)			Jig Offshore (JJO & JL)			
	Year	Abundance	$\sigma_{\bar{x}}$	CV	Abundance	$\sigma_{\bar{x}}$	CV	Abundance	$\sigma_{\bar{x}}$	CV
2012	0.62	0.01	0.01	0.57	<0.01	<0.01				n/a
2013	0.20	<0.01	0.01	0.48	<0.01	<0.01	n/a	n/a	n/a	n/a
2014	0.27	0.01	0.03	0.69	0.01	0.02	n/a	n/a	n/a	n/a
2015	0.24	<0.01	0.02	0.51	<0.01	<0.01	n/a	n/a	n/a	n/a
2016	0.36	0.01	0.03	0.45	<0.01	<0.01	n/a	n/a	n/a	n/a
2017	0.32	0.01	0.02	0.72	0.01	0.01	n/a	n/a	n/a	n/a
2018	0.13	<0.01	0.01	0.23	<0.01	<0.01	n/a	n/a	n/a	n/a

III-2. Standardized CPUE:

Nominal, model-predicted, and model-fitted standardized CPUE estimates for cod show a decrease from 2012 to 2013, an increase in 2014, a decrease in 2015, increase to their highest level in 2017, and then decline in 2018 (Figure III-9). All standardized CPUE values for halibut showed a similar decrease from 2012 to 2013, but then varied between 1 and 4 from 2014 to 2017 before decreasing in 2018 (Figure III-10). Standardized CPUE estimates for white hake show an increase in CPUE from 2012 to 2013, but a decrease from 2014 through 2018 (Figure III-11). CPUE estimates for cusk show an increase from 2012 to 2014, a decrease from 2014 to 2015, an increase from 2015 to 2017, and a decrease from 2017 to 2018 (Figure III-12). Again, there are no estimates from 2016 because of the financial constraints explained in section II-1-D of the methods. All nominal and model-based standardized CPUE estimates, standard deviation

and coefficients of variation values associated with the presented estimates are included in Table III-8.

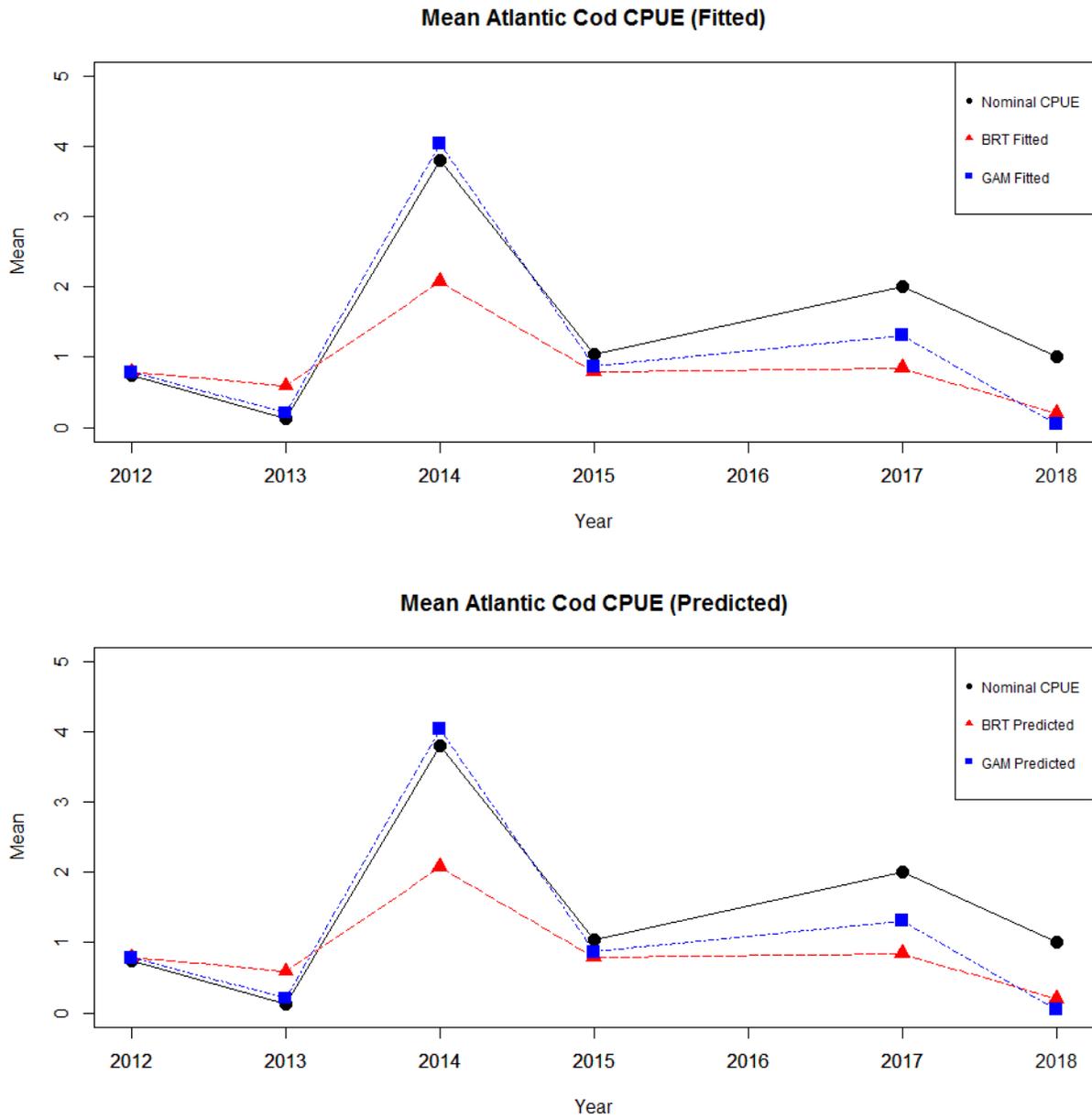


Figure III-9. Fitted and predicted nominal, GAM, and BRT standardized CPUEs for and associated standard deviation Atlantic cod derived from fishermen’s choice stations from 2012 to 2018.

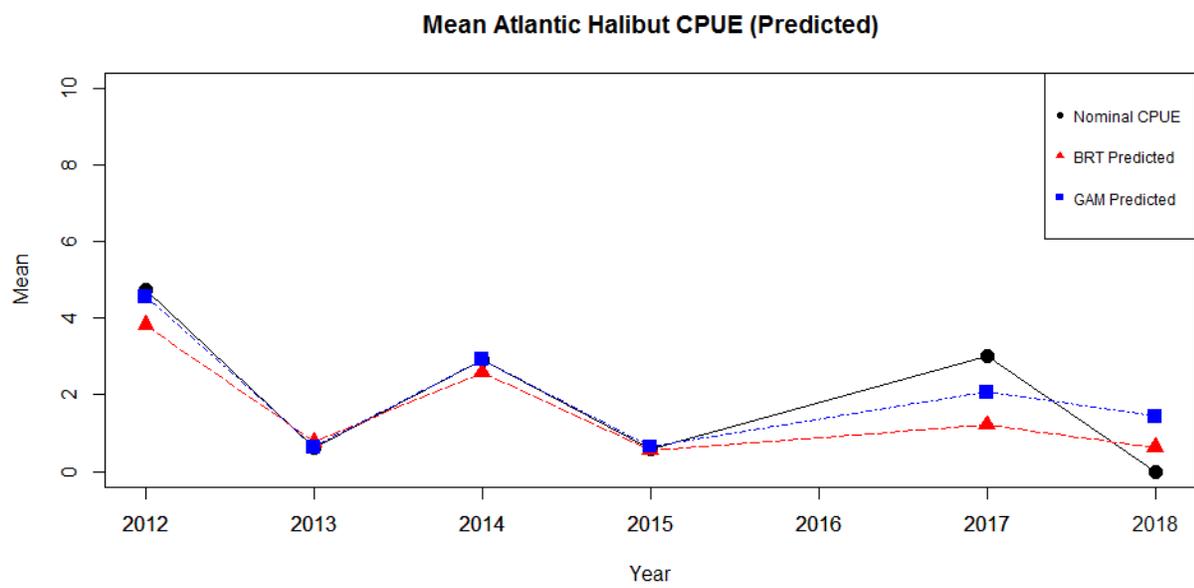
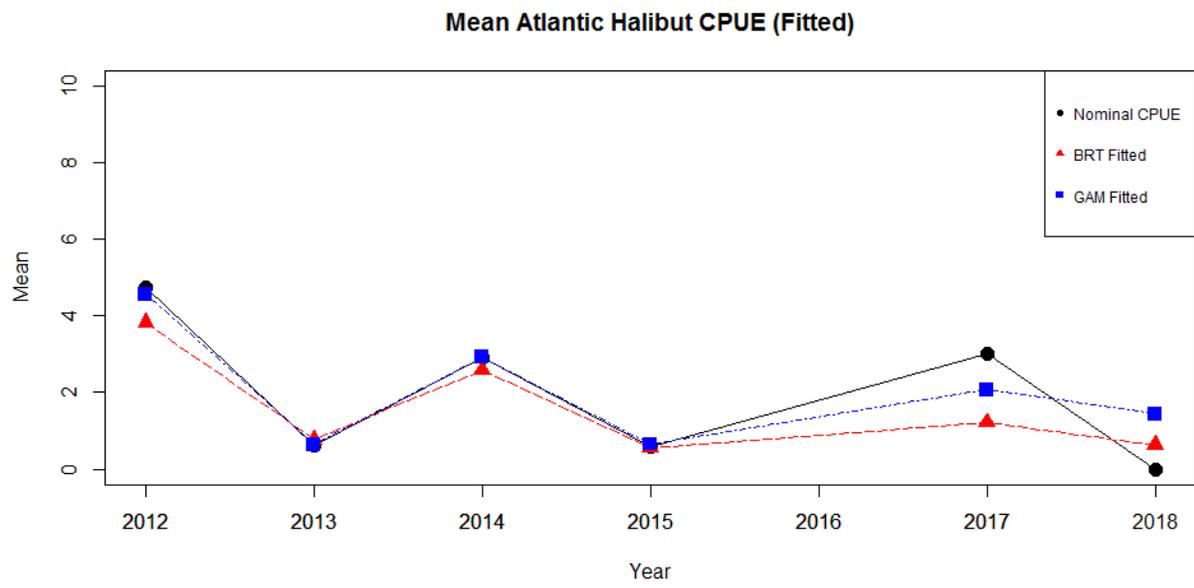


Figure III-10. Fitted and predicted nominal, GAM, and BRT standardized CPUEs and associated standard deviation for Atlantic halibut derived from fishermen’s choice stations from 2012 to 2018.

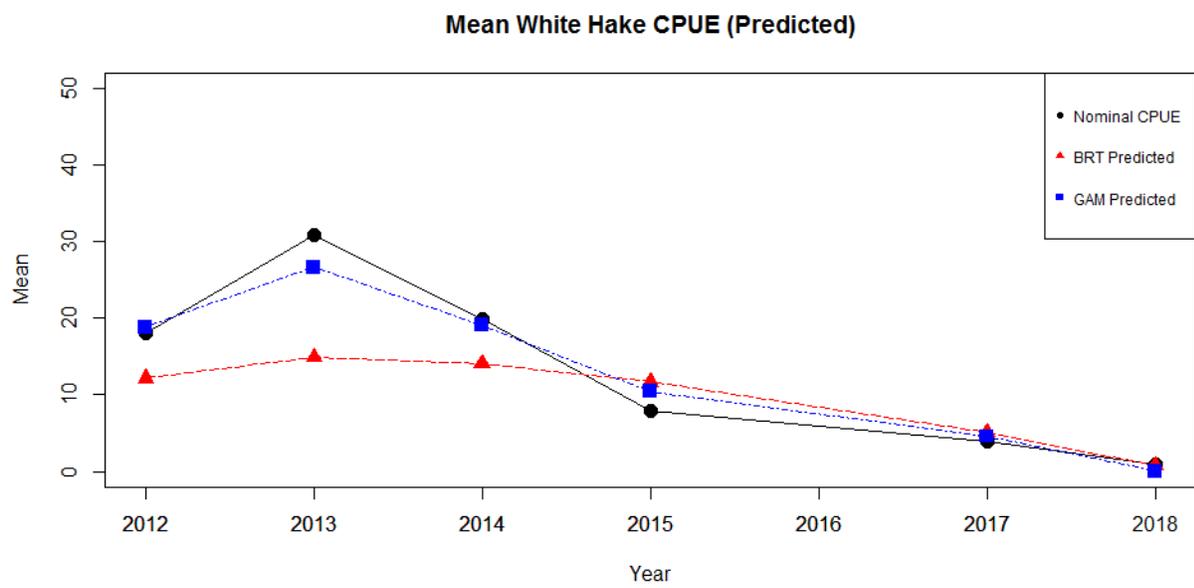
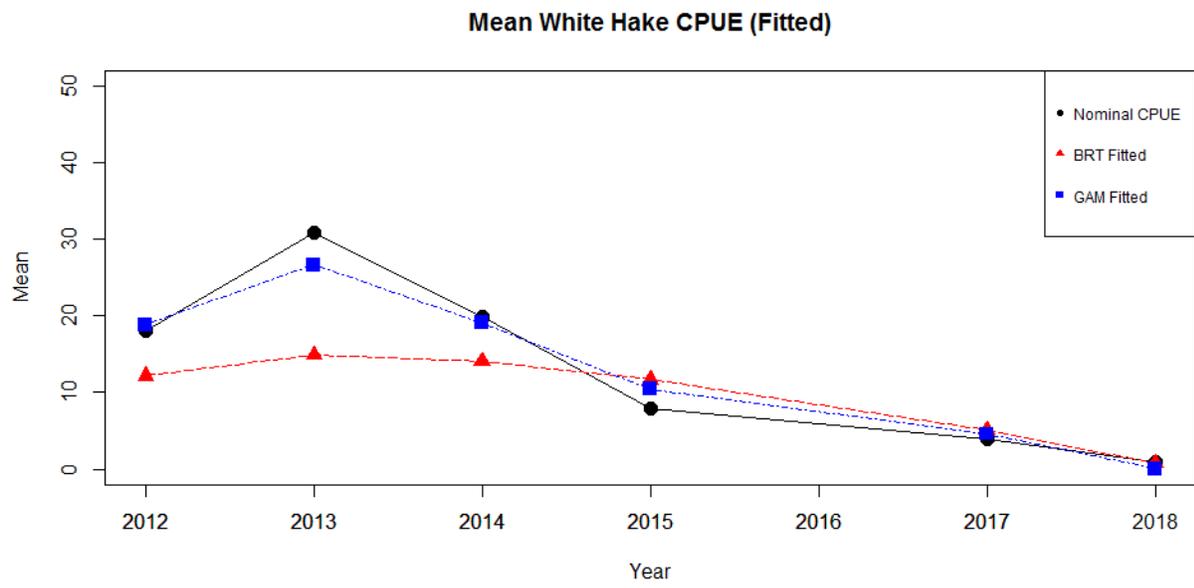


Figure III-11. Fitted and predicted nominal, GAM, and BRT standardized CPUEs and associated standard deviation for White Hake derived from fishermen’s choice stations from 2012 to 2018.

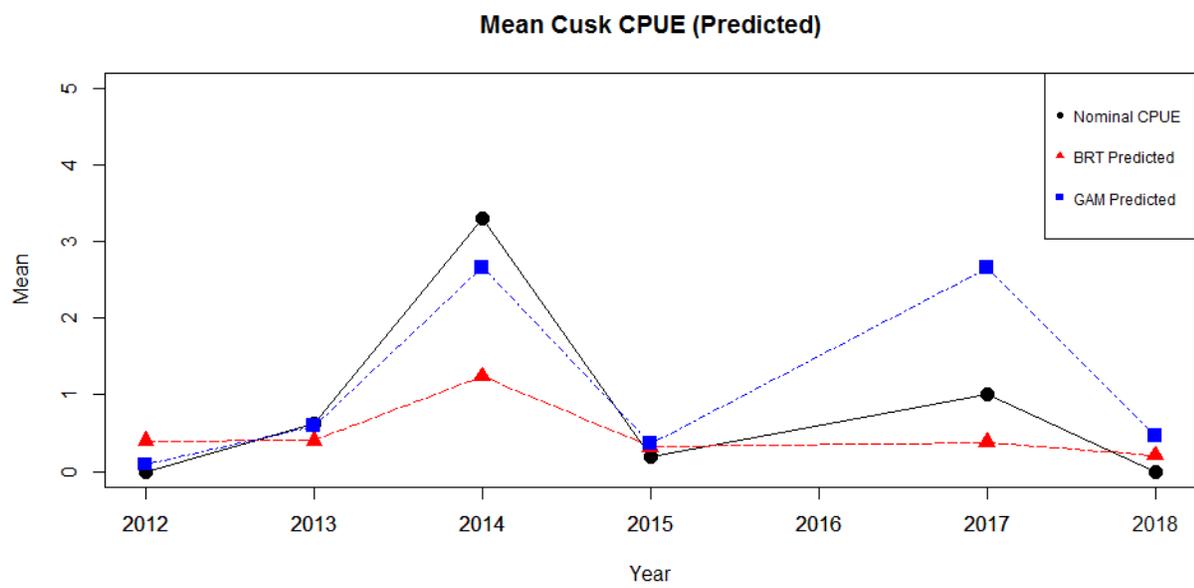
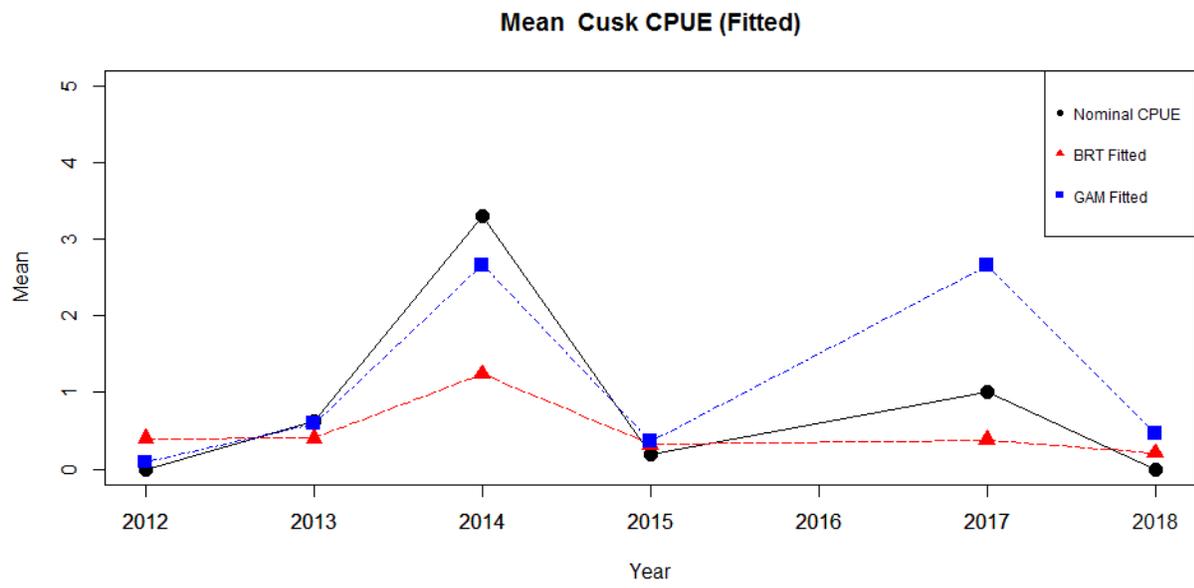


Figure III-12. Fitted and predicted nominal, GAM, and BRT standardized CPUEs and associated standard deviation for cusk derived from fishermen’s choice stations from 2012 to 2018.

Table III-8. Standardized nominal CPUE, GAM estimated CPUE, and BRT estimated CPUE for survey abundance index based on fisherman’s choice data for targeted groundfish species.

Species Year	Cod			Halibut			White Hake			Cusk		
	Nominal CPUE	GAM	BRT	Nominal CPUE	GAM	BRT	Nominal CPUE	GAM	BRT	Nominal CPUE	GAM	BRT
2012	0.75	0.78	0.55	4.75	4.57	3.83	18.00	18.83	17.13	<0.01	0.09	0.23
2013	0.13	0.21	0.24	0.63	0.65	0.77	30.88	26.69	30.48	0.63	0.60	0.31
2014	3.80	4.04	3.22	2.90	2.92	2.58	19.90	19.10	19.44	3.30	2.67	2.24
2015	1.03	0.87	0.80	0.60	0.65	0.56	7.84	10.47	8.21	0.20	0.37	0.23
2017	2.00	1.31	1.06	3.00	2.07	1.22	4.00	4.60	3.44	1.00	2.66	0.29
2018	1.00	0.05	0.09	<0.01	1.44	0.63	1.00	0.06	0.12	<0.01	0.46	0.14

III-3. Bait Type and Habitat Preference:

Results of the Tweedie GAM indicate a statistically significant relationship between bait type and catch of cod, halibut, and white hake from longline data (Figure III-13). Cod and white hake appear to prefer hooks baited with squid over hooks baited with herring while Atlantic halibut prefer herring over squid. The Tweedie GAM showed no statistically significant relationship between catch of cusk and bait type used on the longline. BRT models showed bait to be only marginally influential for all target species (Table III-9). However, in comparing all four target species, the BRTs suggest that bait type had the most influence over cod and halibut catch.

Results of the GAM show that depth was determined to be a statistically significant variable for halibut and white hake (Figure III-14) with halibut being caught more often in shallower water (~50 - 100m) while white hake were more likely to be caught in deeper waters (~ 250m or greater). The GAM showed no statistically significant relationship between depth and the catch of cod or cusk. On the contrary, BRTs suggest that depth is the second most influential variable in predicting cusk catch. However, results of the BRT agree with results of the GAM regarding the influence of depth on halibut and white hake while exhibiting little influence on cod catch (Tables III-9 and 10). Additionally, depth was found to be significant, and a highly influential variable in the combination of all jig data to model cod catch.

Observed sediment type was only included in the GAMs for Atlantic halibut and white hake because there is not enough cod or cusk catch across all substrate types for a GAM to produce meaningful results. As a result, there are no GAM results for how sediment may impact catch of cod and cusk. However, the BRTs were able to incorporate sediment type. This will be discussed further in the discussion. GAM results indicate that sediment type is only statistically

significant for white hake, which appear to prefer mixed and soft sediments to hard sediments. The GAM showed no statistically significant relationship between sediment type and halibut catch (Figure III-15). This is corroborated by the results of the BRT, which suggest that sediment has relatively low influence on halibut catch. However, the BRT also suggests that sediment has little influence on cod and white hake as well. Among all four target species, BRT results show that cusk is the most influenced by sediment type (Table III-10). The GAM suggests that sediment type was highly significant for all jig data, but not inshore. However, the BRT calculated sediment type to be insignificant for both all jig and inshore jig data. Offshore jigging models are excluded here because they are poorly fit in comparison to the combination of jig data and the inshore data.

Based on both model types, sea surface temperature was a statistically significant and highly influential factor when it came to catch of cod, halibut, and white hake (Figure III-16). Cod and halibut were caught more often at lower sea surface temperature (~ 8° C) while white hake were caught most frequently with warmer sea surface temperature (~ 12-18° C). The GAM and the BRT for cusk showed sea surface temperature to be insignificant with little influence on cusk catch. Both GAMs for the jigging data also suggest that sea surface temperature is insignificant. However, both BRTs consider sea surface temperature to be moderately influential relative to the other covariates in the model (Table III-10).

Similar to the results for surface temperature, results of the Tweedie GAM indicate a statistically significant relationship between bottom temperature and catch of halibut and white hake, but no significant relationship for cod and cusk. However, the BRT suggests that bottom temperature is the most influential explanatory variable for longline cod, halibut, and cusk. Bottom temperature is the second most influential variable in the BRT for white hake catch. Cod

and halibut were caught most frequently when bottom temperature was greater than 10° C while hake and cusk were most abundant when bottom temperature was around 8° C (Figure III-17). Comparatively, jigging GAMs do not suggest that bottom temp has a significant influence on cod in shore or in a combination of jig data. This is corroborated by the BRT models on the jig data, which also suggest that bottom temperature is one of the least influential variables in the model.

To evaluate the presence or absence of seasonal trends in catch, this analysis included month as a categorical variable in all GAM and BRT models where possible. Similar to sediment type, there is not enough resolution and contrast in cod and cusk catch data for a GAM to produce meaningful results. As a result, the GAMs for cod and cusk do not contain month as an explanatory variable. Based on GAM output for halibut and white hake, there appears to be a statistically significant relationship between month and catch. Halibut appear to be most abundant in the earliest month of the sampling season with abundance declining as the sampling season approaches the end of the sampling season in October. White hake abundance peaks in July, decreases in June increasing into September. BRTs suggest that month is moderately influential (relative to the other covariates) and might indicate the presence of a seasonal trend in the catch of all target species but to varying degrees. Additionally, both jig models suggest some significant influence of month in the jigging data. Both GAMs indicate that cod catch is positively correlated with September, indicating a seasonal trend in cod catch, which increases in the month of September. All values and levels of significance for bait and habitat variables are included in Table III-9 (GAM) and Table III-10 (BRT).

Because site-specific detection was only estimated for inshore jigging data (the portion of the survey with the most allocation sampling effort), offshore jigging data could not be modeled with detection probability. Despite this, the GAM for inshore jigging data concluded that cod catch is not significantly influenced by catchability, but there is a significant, positive correlation between cod catch and the presence of pollock for both GAM models. On the contrary, detection probability was the most influential variable for the inshore jigging data, indicating heavy influence of gear catchability. Both BRTs also suggest that the presence of pollock is moderately influential relative to other covariates in the model.

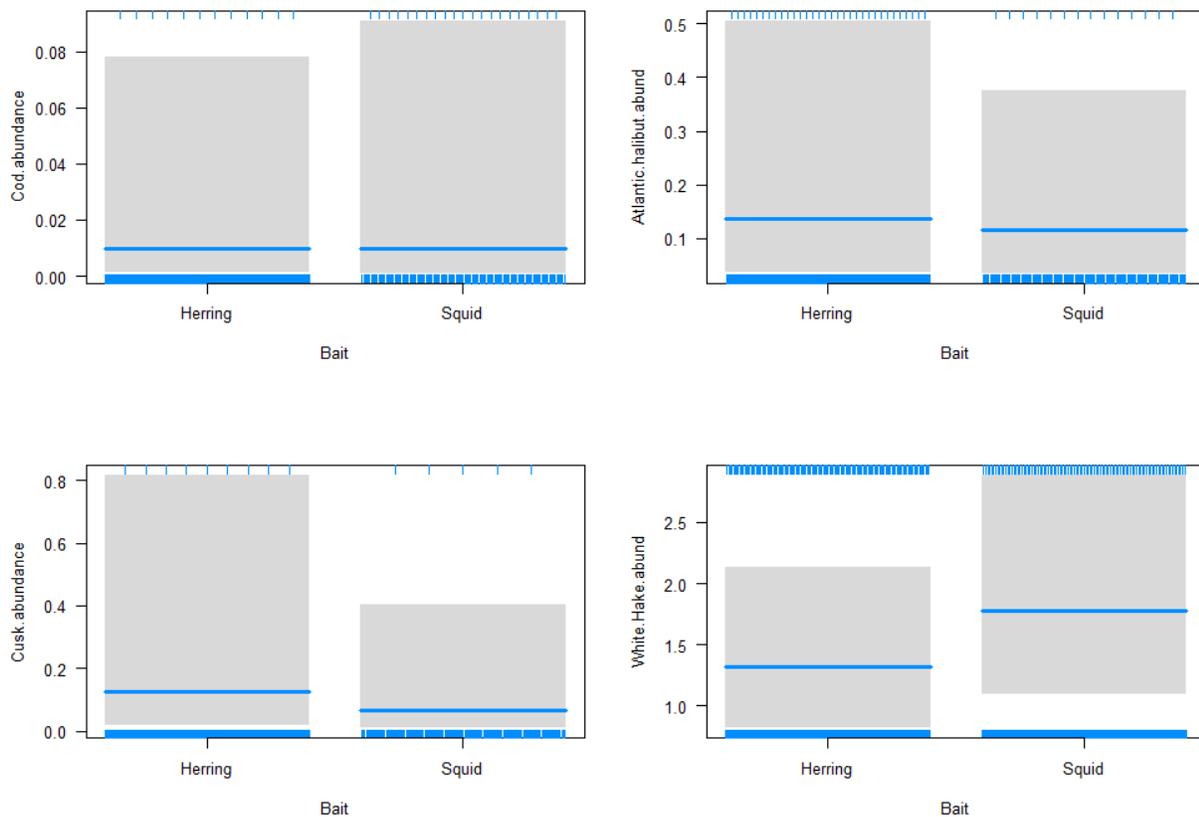


Figure III-13: Longline model-derived relationships between catch abundance and bait for Atlantic cod, Atlantic halibut, white hake, and cusk in which the blue line represents the mean and the shadow represents the uncertainty. Needle lines at top represent individual observations of species catch. Needle lines on bottom represent observations of the covariate displayed.

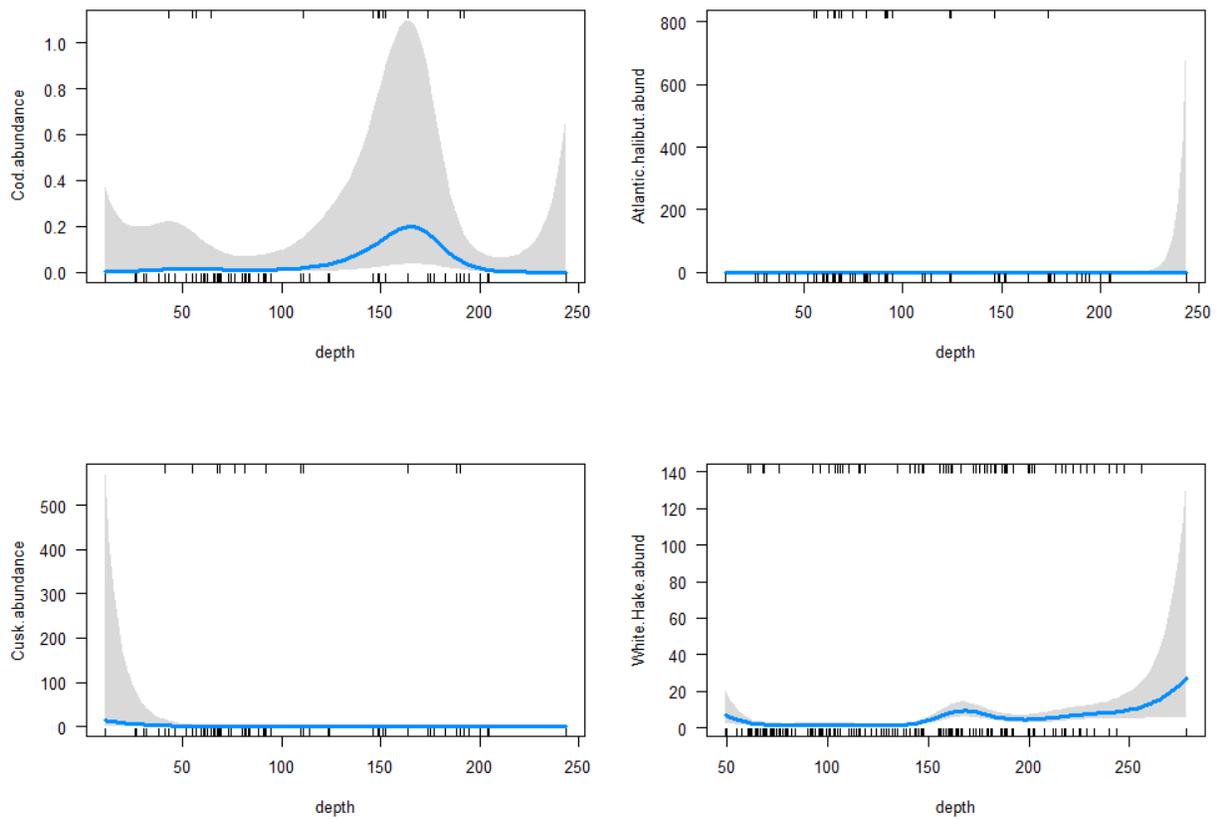


Figure III-14: Longline model-derived relationships between catch abundance and depth for Atlantic cod, Atlantic halibut, white hake, and cusk in which the blue line represents the mean and the shadow represents the uncertainty. Needle lines at top represent individual observations of species catch. Needle lines on bottom represent observations of the covariate displayed.

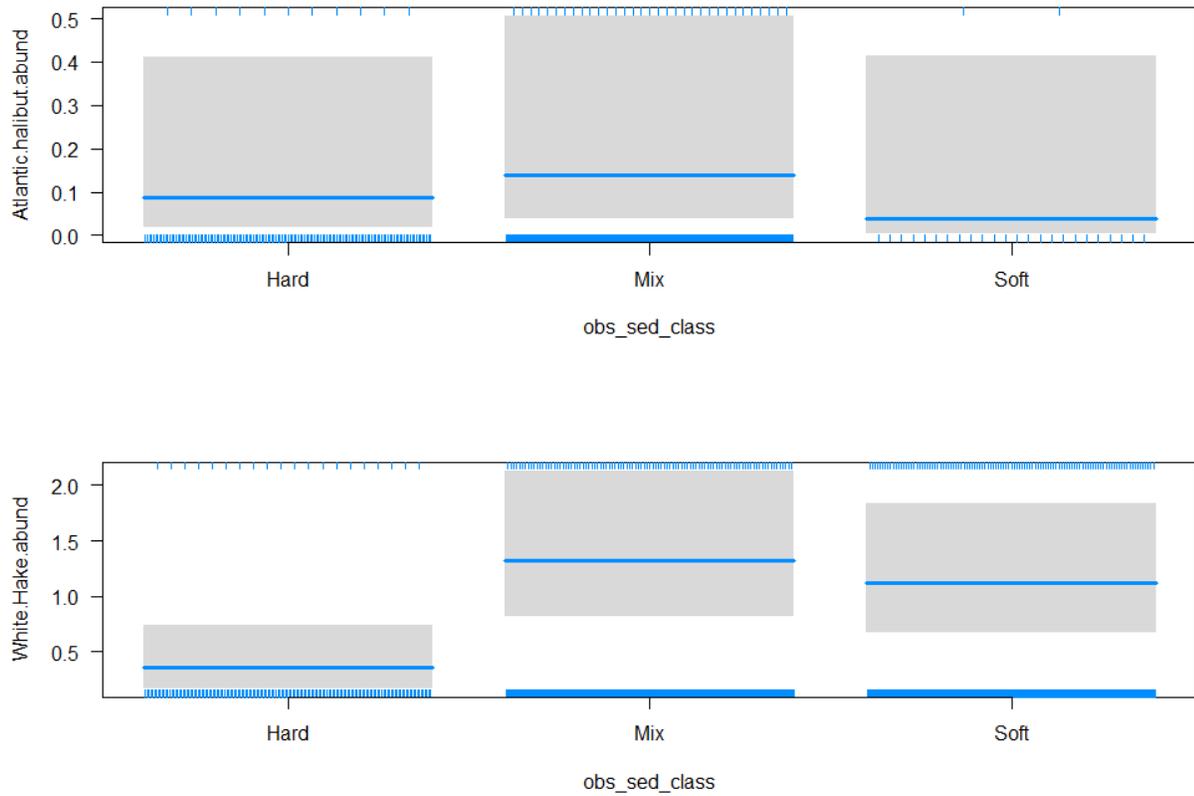


Figure III-15: Longline model-derived relationships between catch abundance and observed sediment class for Atlantic halibut and white hake in which the blue line represents the mean and the shadow represents the uncertainty. Cod and cusk were excluded from the figure because models of these species could not be fit with this variable. Needle lines at top represent individual observations of species catch. Needle lines on bottom represent observations of the covariate displayed.

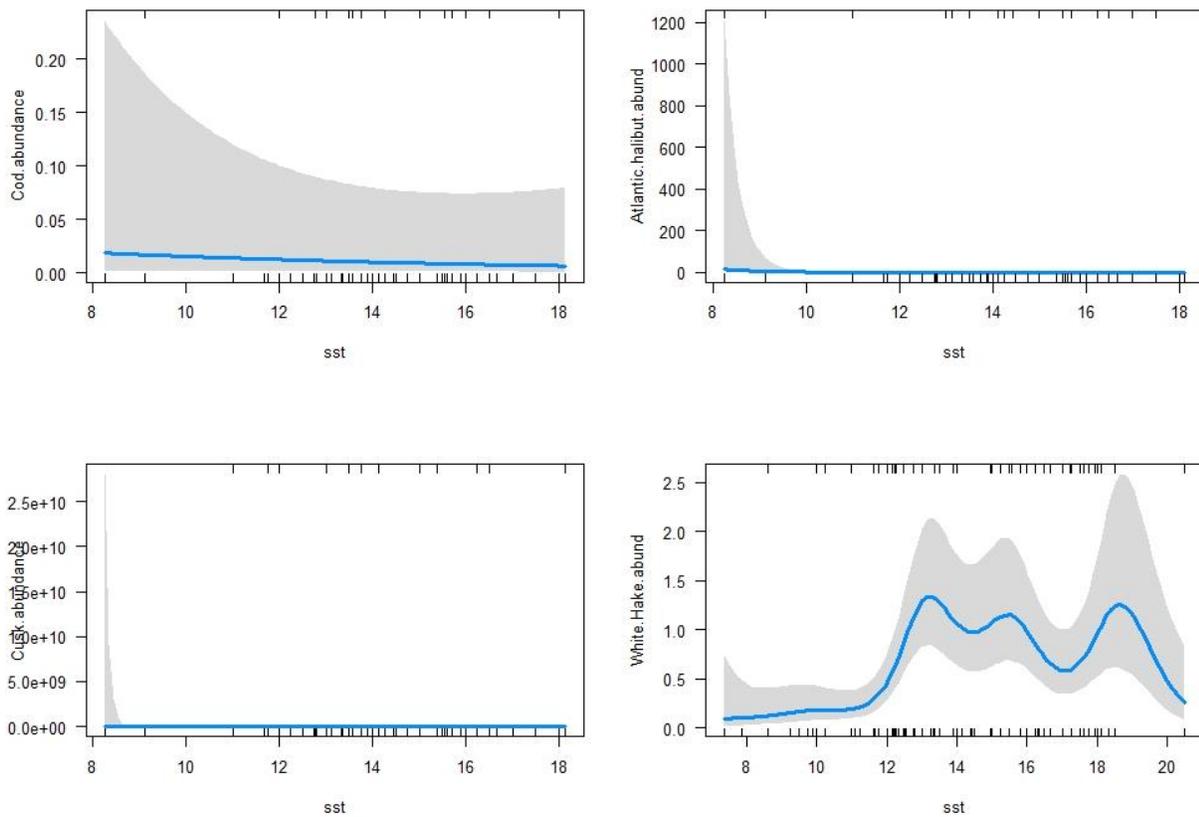


Figure III-16: Longline model-derived relationships between catch abundance and sea surface temperature for Atlantic cod, Atlantic halibut, white hake, and cusk in which the blue line represents the mean and the shadow represents the uncertainty. Needle lines at top represent individual observations of species catch. Needle lines on bottom represent observations of the covariate displayed.

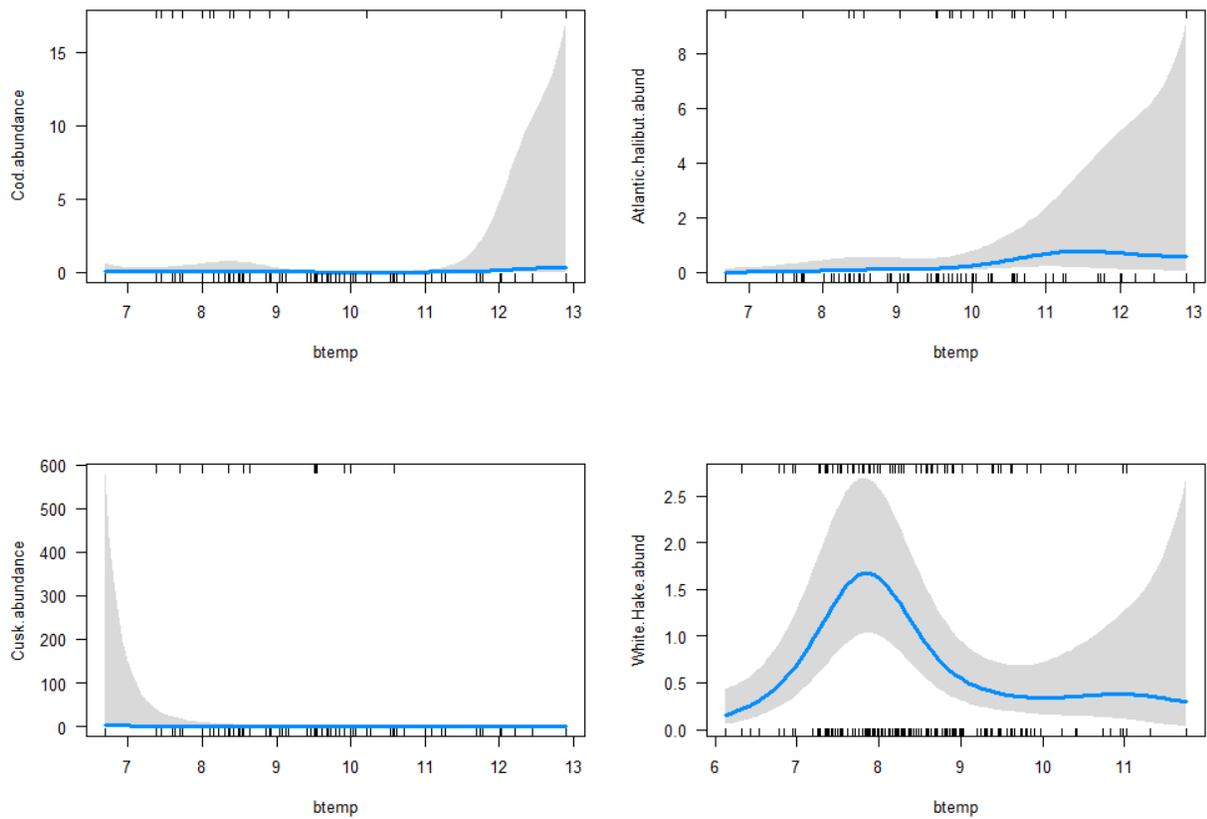


Figure III-17: Longline model-derived relationships between catch abundance and bottom temperature for Atlantic cod, Atlantic halibut, white hake, and cusk in which the blue line represents the mean and the shadow represents the uncertainty. Needle lines at top represent individual observations of species catch. Needle lines on bottom represent observations of the covariate displayed.

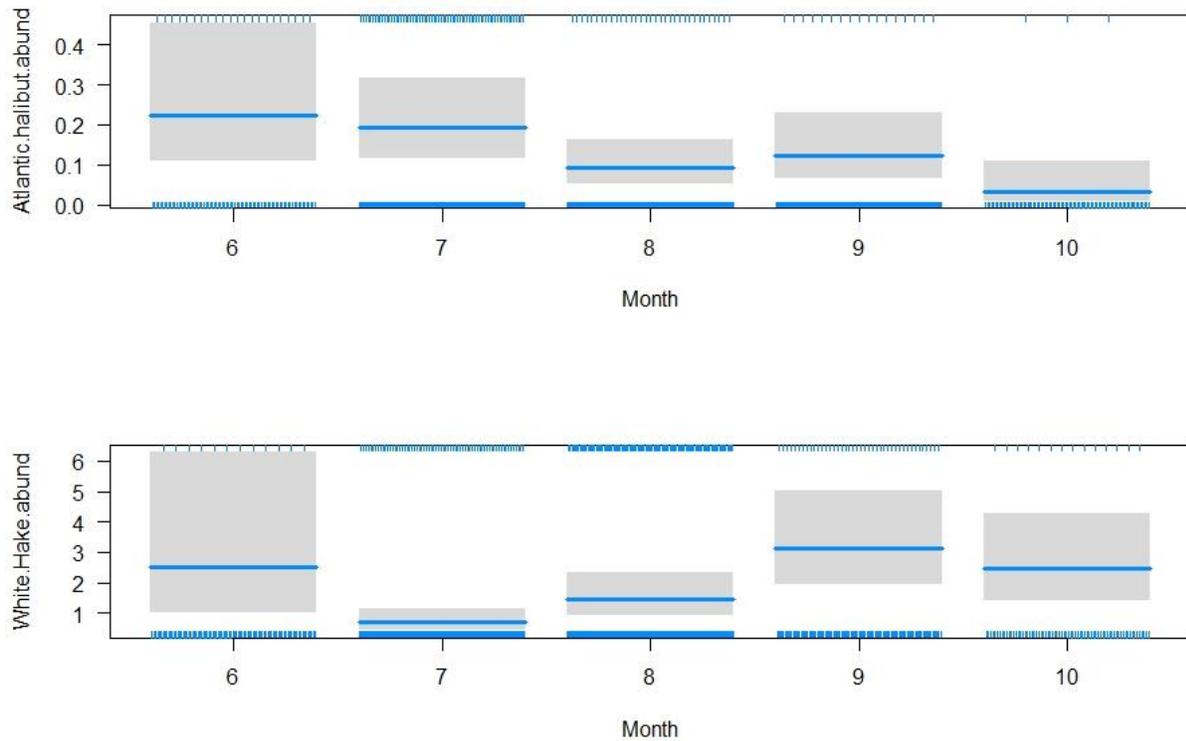


Figure III-18: Longline model-derived relationships between catch abundance and month for Atlantic halibut and white hake in which the blue line represents the mean and the shadow represents the uncertainty. Cod and cusk were excluded from the figure because models of these species could not be fit with this variable. Needle lines at top represent individual observations of species catch. Needle lines on bottom represent observations of the covariate displayed.

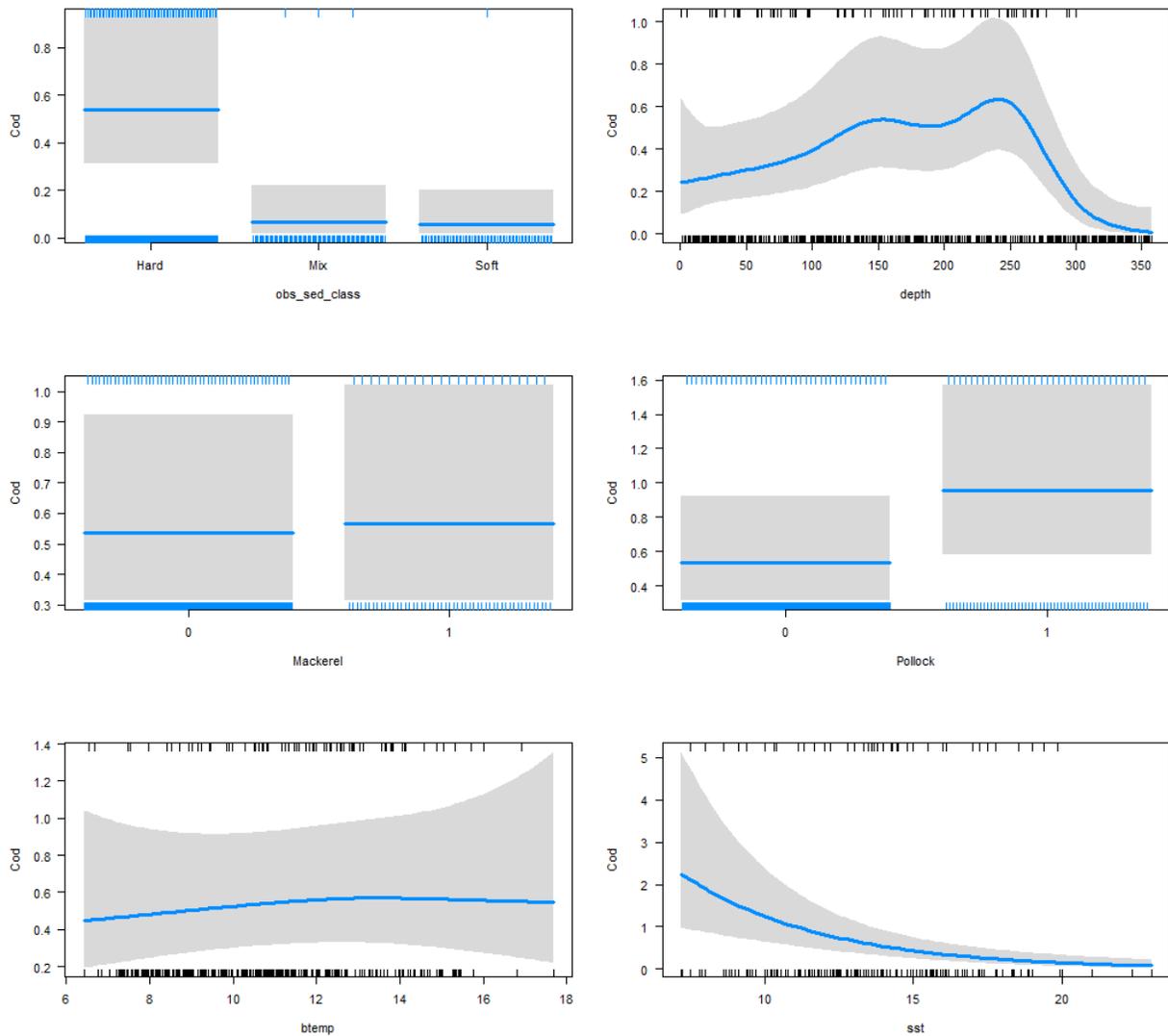


Figure III-19: Jigging Model-derived relationships between cod abundance and sediment type, depth, presence/absence of Mackerel, presence/absence of Pollock, bottom temperature, and sea surface temperature for Atlantic cod in which the blue line represents the mean and the shadow represents the uncertainty. Needle lines at top represent individual observations of species catch. Needle lines on bottom represent observations of the covariate displayed.

Table III-9. Results of the Tweedie GAM for each target species in the longline data. Asterisks (*) denote levels of significance for each variable (no asterisk means the variable is not statistically significant ($p>0.05$), (***) represents most significant variable(s) ($P<0.05$).

Random Longline Data								
Species	Halibut		Cod		White Hake		Cusk	
	Estimate	P-Value	Estimate	P-Value	Estimate	P-Value	Estimate	P-Value
Intercept	-1.60	***	-4.48	**	-0.90	*	-4.72	***
Mix Sediment	0.28	0.15	NA	NA	1.32	***	NA	NA
Soft Sediment	0.33	0.12	NA	NA	1.10	***	NA	NA
July	-0.14	0.58	-1.52	0.34	-1.29	**	NA	NA
August	-0.87	**	-1.69	0.31	-0.55	0.21	NA	NA
September	-0.60	0.12	-0.22	0.89	0.21	0.64	NA	NA
October	-1.94	**	-86.03	0.99	-0.03	0.94	NA	NA
Squid	-0.91	***	1.39	*	0.30	*	-0.72	0.28
SST	1.81	*	1.95	*	7.19	***	3.42	0.26
BT	6.69	***	2.38	0.15	5.36	***	1.53	0.15
Depth	3.23	***	2.28	0.23	7.67	***	2.81	0.12
Deviance Explained		28.8%		35.5%		44.2%		21.4%

Table III-10. Results of the Tweedie GAM for cod in the jig data. Asterisks (*) denote levels of significance for each variable (no asterisk means the variable is not statistically significant ($p>0.05$), (***) represents most significant variable(s) ($P<0.05$).

All Jigging Data								
Species	Cod							
Model	All Jigging		All Jigging (Det)		Inshore Jigging		Inshore Jigging (Det)	
	Estimate	P-Value	Estimate	P-Value	Estimate	P-Value	Estimate	P-Value
Intercept	-1.71	***	-2.48	*	-1.53	***	-1.93	***
Mix Sediment	-2.11	***	0.09	0.97	-2.27	*	-0.15	0.95
Soft Sediment	-2.20	***	0.04	0.99	-74.71	1.00	-73.30	1.00
Pollock	0.58	**	0.66	***	0.38	0.06	0.51	*
Mackerel	0.05	0.78	0.00	0.98	0.01	0.96	-0.05	0.82
July	0.55	0.13	0.40	0.27	0.73	0.08	0.70	0.08
August	0.53	0.19	0.31	0.44	1.02	*	0.87	0.06
September	0.95	*	0.63	0.13	1.30	**	1.14	*
October	-0.14	0.76	-0.27	0.56	0.27	0.60	0.26	0.61
November	-79.47	1.00	-94.40	1.00	-75.39	1.00	-76.65	1.00
Year	0.00	0.43	0.00	0.39	0.00	0.58	0.00	0.68
Depth	5.01	**	3.24	*	2.36	0.15	2.24	0.46
BT	1.32	0.74	1.44	0.47	1.00	0.12	1.00	0.31
SST	1.00	***	1.00	***	2.42	***	1.65	***
Predicted Detection	NA	NA	3.80	*	NA	NA	3.56	0.14
Deviance Explained		40.5%		42.7%		32.8%		36.6%

Table III- 11. Results from the BRT models for each species illustrating the average relative influence of each explanatory variable in predicting species abundance.

Random Longline Data				
Species	Cod	Halibut	White Hake	Cusk
	Relative Influence	Relative Influence	Relative Influence	Relative Influence
Depth	2.8	25.45	35.97	22.98
Sediment	0.13	4.75	0.95	9.87
SST	24.49	17.59	22.17	9.96
BT	55.4	35.64	27.15	41.46
Month	14.57	13.33	12.92	15.7
Bait	2.62	3.24	0.83	0.02

Table III- 12. Results from the BRT models for jigging models illustrating the average relative influence of each explanatory variable in predicting cod abundance.

Random Jigging Data					
Species Area	All Jigging		Inshore Jigging		Cod
	Relative Influence	Relative Influence	Relative Influence	Relative Influence	
Year	5.48	4.10	13.27		13.30
Depth	15.33	16.94	5.40		5.38
Sediment	0.07	0.02	0.00		0.01
BT	9.18	8.56	8.30		8.37
Month	8.09	8.18	10.46		10.81
Pollock	10.79	12.19	6.93		6.67
Mackerel	0.26	0.14	0.03		0.03
SST	9.46	8.92	18.31		18.29
Predicted Detection	NA	40.94	NA		37.15

IV. DISCUSSION:

IV-1. Abundance Indices:

Although the proportion of stations selected from each of the three strata is fixed, the selection of stations within each stratum remains random. As a result, there will be variability in the number of stations occurring at locations with suitable habitat for some target species. Since sediment type was a significant factor for two target species and other species have too little data to make definitive conclusions about sediment type, the number of stations over suitable habitat in a given year could have a substantial effect on catch and, consequently, a substantial effect on abundance estimates on a year-to-year basis. This highlights the need to evaluate the annual variability in stations occurring at locations with suitable habitat in order to assess potential bias in the dataset.

IV-1-A. Abundance Indices – Stratified Random Longline and Stratified Random

Jigging:

Mean abundance and variance were calculated for stratified random longline data and stratified random jig data using the delta mean approach. The stratified random survey was conducted between 2012 and 2018. However, 2016 is excluded from stratified random longline abundance estimates due to the financial constraints explained in section II-1-D of the methods. Therefore, trends in longline abundance estimates should not be assumed to be continuous from 2015 to 2017 because stratified random longline data are unavailable.

Despite some minor variability, all abundance trends calculated using the model-based fitted values and the delta mean method produced similar trends to those calculated from the design-based method (Figures III-2:8, Tables III-2:7). In every instance, there was at least one

model which matched the trend of a given species while the other model calculated a different trajectory for only one or two years. The similarities in catch trends between the model-based estimates and the design-based estimates indicate that the stratified random survey design is appropriate for the data collected in order to calculate unbiased abundance estimates for the EGOM. Because predicted abundance values are relatively consistent with the observations seen in the field, the continued use of a stratification-by-depth approach is justified as the survey design is accounting for expected sources of bias in catch data. In all years, total catch values of cod and cusk from the sampled stratified longline stations is very low. Despite low catch for cod and cusk, the predictive models performed similarly to the design-based calculations of abundance. In spite of the confidence in the robustness of the survey design, model-based estimates should always be checked against the design-based estimates to evaluate similarity between results of each approach. Any mismatch between model-based abundance trends and design-based abundance trends should be evaluated and, if possible, attributed to an explicit source of variability (outliers in the data, model parameters used, limitations of the model type being used, etc.) Matching trends between model and design-based abundance can be an indication of the robustness of the survey design, given that the results of both indices are unbiased. It should be noted that discrepancies are not explicitly indicative of a poor survey design, as survey designs can be robust, but results can remain limited by small sample sizes.

In regard to the trajectory of changes in relative abundance, all of the cod abundance trends calculated from different gear types and combinations of data within the survey area are dissimilar from one another. However, this may be the result of the scale at which abundance is being evaluated. Additionally, the trends in observed and modeled inshore cod abundance and cod CPUE are similar to the trend in abundance estimates derived from the Massachusetts

Department of Marine Fisheries (MADMF) spring bottom trawl survey. Interestingly, this inshore jigging model is the only model to incorporate a measure of gear catchability. This provides some evidence that trends in inshore cod abundance are not exclusively the results of the survey area, given the similarity with other survey efforts. Additionally, the BRT model-based abundance estimates from a combination of all jigging stations matches the trend in abundance derived from the NEFSC fall bottom trawl survey in the Gulf of Maine (Figure III-20). This makes sense seeing as most cod catch on the jigs tends to occur in September each year. Given the similarities in abundance trends between the most data rich estimates and the federal/state estimates of abundance, this data suggests cod in the EGOM may exhibit similar temporal trends to other areas within the GOM. This also provides support for selecting the BRT as the most well-informed and accurate estimate of abundance for cod.

Despite the similarities discussed, it remains inherently difficult to provide a quantitative comparison of relative abundance numbers calculated from the Sentinel Survey and NMFS or MADMF bottom trawl because the surveys encompass different areas within the Gulf of Maine with MADMF having higher inshore sampling effort and the NEFSC survey having a substantial amount of offshore sampling effort. In addition to a difference in the timing of each of these surveys, there also a difference in gear type, leading to an inherent difference in gear selectivity. However, comparing trend shapes can be useful to visualize whether trends are unique to the survey area, or consistent across various surveys and survey areas. Regardless of the similarities identified between abundance trends, it is crucial to note that this study does not evaluate the dynamics of localized stock structure, not does it quantify estimates of key population reference points such as spawning stock biomass. Subsequently, similarities in abundance indices should not be interpreted as complete similarity between localized populations.

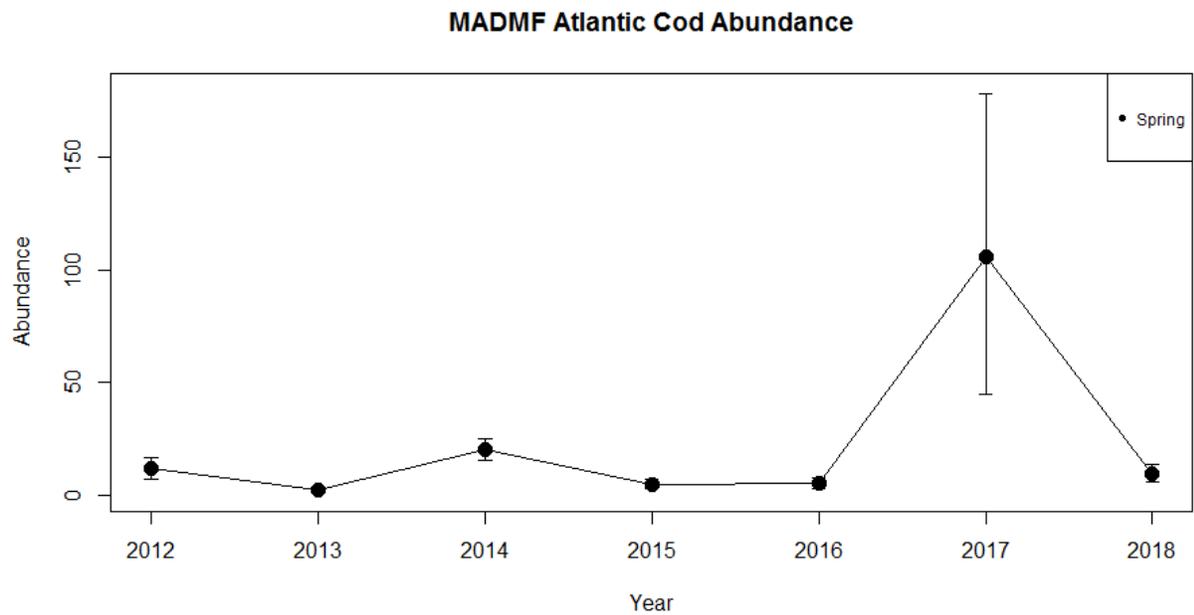
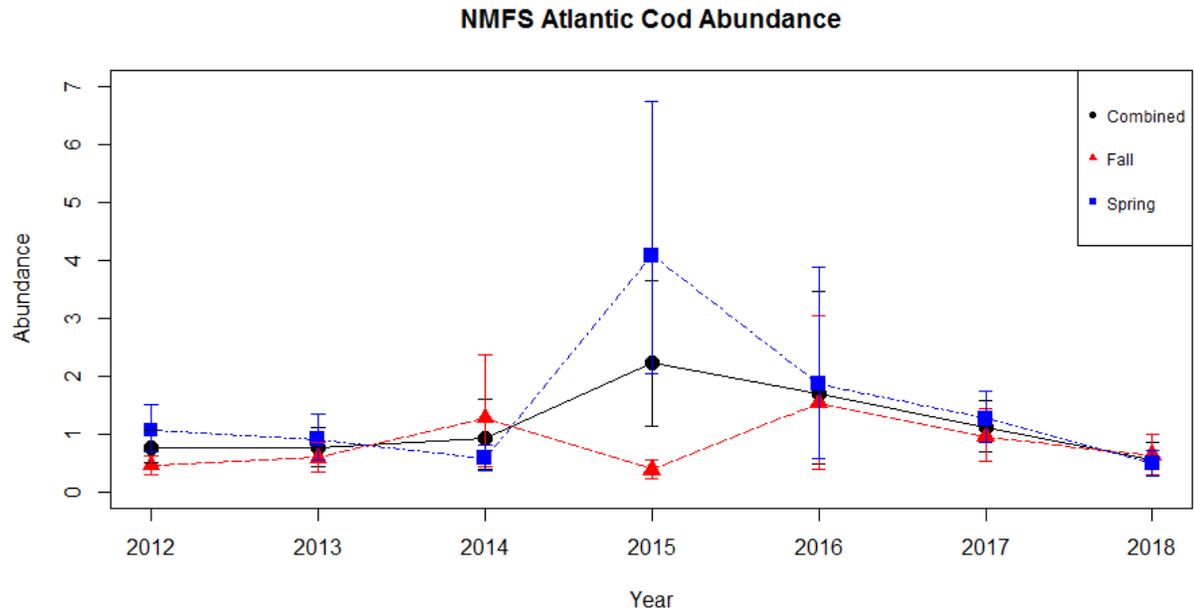


Figure III-20. Abundance estimates derived from National Marine Fisheries Service Spring and Fall bottom trawl survey.

Coefficients of variation (CV) values that are calculated from abundance estimates are used as an indicator of estimate precision. The lower the CV value, the greater the precision of

the associated abundance estimates. Based on the CV values calculated from the design and model-based estimates of longline abundance, CV values are highly precise with the exception of a few outlying years with high catch numbers that are also linked to high margins of error (Tables III-2, 3, and 4). The lack of precision behind the longline abundance estimates is indicative of either a sampling error, an issue with the small sample size for a species, or a consequence of patchy distribution. Since sample sizes are small for cusk, it makes sense that precision is low in 2018 because of the drastic increase in observed abundance resulting from high catch at one station. Although there is an appreciable sample size of white hake, they have a very patchy distribution as white hake are an aggregating species (Bigelow and Schroeder, 1953). As a result, there is higher variability in white hake catches, leading to higher CV values. Similarly, halibut show a significant seasonal trend in catch in which higher catch rates are observed in the beginning of the survey season and catch declines as the season progresses. As a result, the variation in halibut catch in the early months of the survey season may lead to the higher CV values calculated in 2017. In regard to other species, cusk had similar results to cod where CV is consistently very low ($CV < 0.01$). This may be the result of consistently low catch rates for cod and cusk each year on the longline. Despite the precision of the abundance estimates for cod and cusk, the number of zero observations resulting from gear catchability may lead to a high number of “false zeros”, or instances in which a target species is present but is not caught by the gear deployed. There is a need to validate catchability of the longline gear.

Similar to the estimates calculated for cod from stratified random longline stations, the estimates resulting from the combination of all jigging data indicates that all design and model-based estimates are highly precise in all years ($CV \leq 0.16$). For all years, inshore jigging estimates are associated with a $CV \leq 0.04$ (Tables III-5, 6, and 7). CV values become less precise

for estimates calculated exclusively from offshore jigging stations. The imprecision of offshore jigging abundance estimates may be due to the increasingly patchy distribution of cod offshore in combination with a very low sample size of cod caught at these offshore stations.

IV-2. Selecting the Most Robust Index of Abundance and Comparing Model Types:

Even though design-based abundance estimates are not subject to the statistical assumptions and bounds implicit when using any type of statistical model, it is important to note that observation-based calculations, especially of a sample mean, are far more susceptible to being skewed by outlying observations and variation in the data. The influence of variation and outlying values becomes increasingly problematic with a smaller sample size. In addition, observation-based estimates of abundance are not dependent on any relationships between the response and explanatory values. Although the design-based values of abundance tend to be precise in most cases, this method of calculating abundance proves to have some difficulty when estimating the abundance of white hake and cusk; both species that suffer the presence of outliers and high variation in catch values. However, having considered the assumptions and bounds mentioned above, statistically robust models that are well fit to describe the dataset do not often predict outlying values of the response because they do depend on explanatory variables to calculate a sensible estimate. Consequently, the abundance estimates derived from model-based values are less susceptible to be skewed by an outlying prediction.

It was determined that the most representative index for abundance is derived from methods least susceptible to bias. As a result, and because model-derived estimates are based on statistically informed relationships between the response and explanatory variables, the model-based abundance indices are the most likely to be representative of what might be true trends in

the population. Despite this conclusion, it is clear in Figures III-21:24 that the two model types utilized in this analysis did not perform equally for all species. In all instances, the BRT produced the lowest mean squared error (MSE), which were two orders of magnitude lower than the MSE from the Tweedie GAMs (Tables III-13 and 14). Tables III-15 and 16 contain the values which assess how each model is fit to the data. In addition to a lower MSE, the BRT results had much higher R^2 values than the results of the Tweedie GAM for all four species. This suggests that the BRT models had a better overall fit to the data, despite some of the imbalance between predicted and observed values seen in Figures III-21:24. Although the intercept (beta) values for the BRTs were consistently higher than those of the GAM, both models estimated predicted values that were below the observed values for cod, halibut, and cusk. White hake were the only species in which both models predicted estimates higher than what was observed.

Consistency in which the models under or over-predict abundance estimates may be the result of overdispersion in the data. However, it is important to note that although BRTs appear to be the best choice for modelling the abundance of cod, halibut, white hake, and cusk within the dataset, the BRT models for data-poor species (cod and cusk) do not fit the data well. Because BRTs utilize a machine learning process, they will become better as more data is collected and the time series continues to grow.

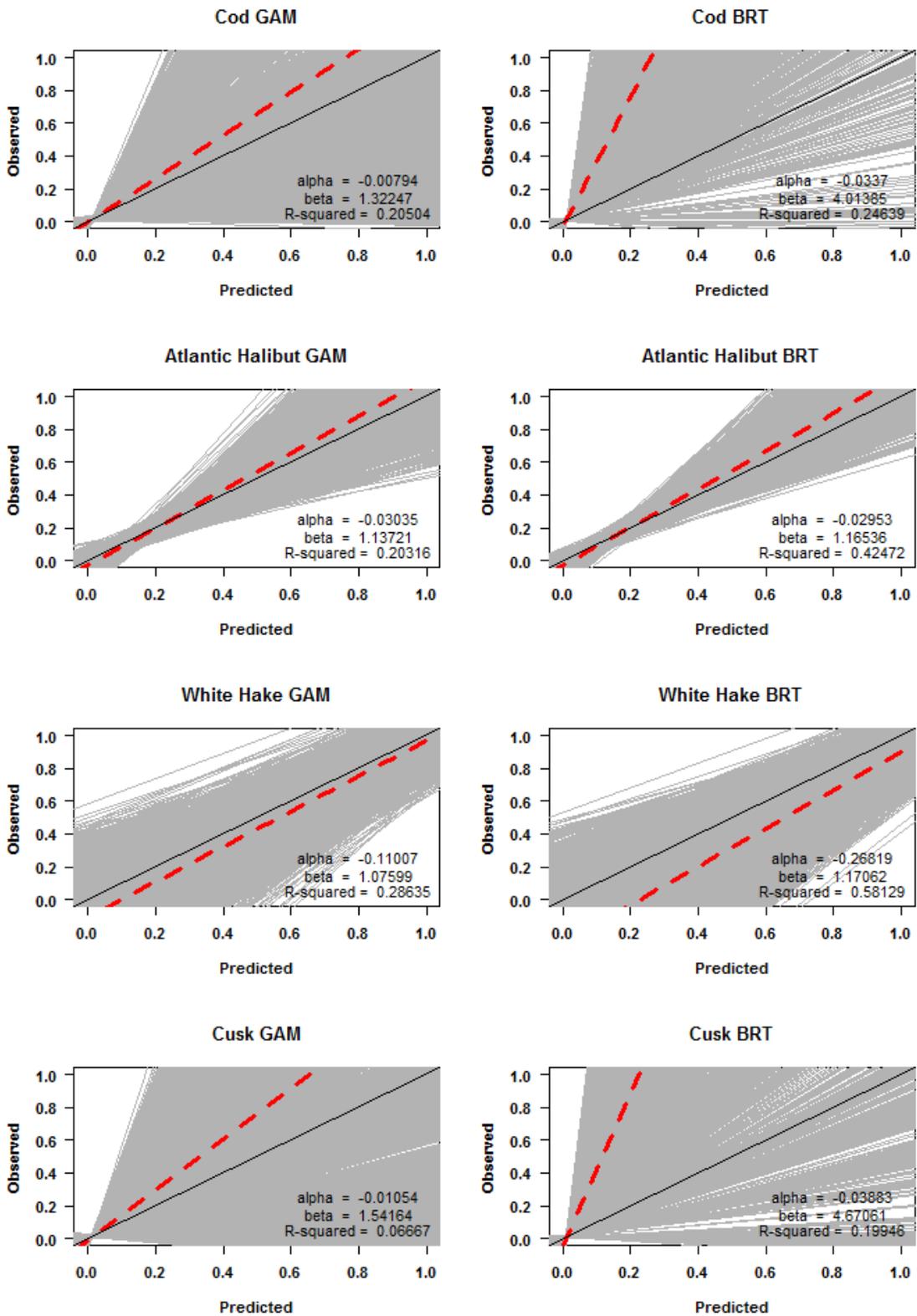


Figure III-21. Results of the cross-validation tests between observed and predicted values. Solid black line represents a Line with slope of 1. The dashed line represents the mean of the 2000 simulations. Alpha represents the intercept, beta represents the slope, and R² represents the line fit. Grey lines represent individual simulations.

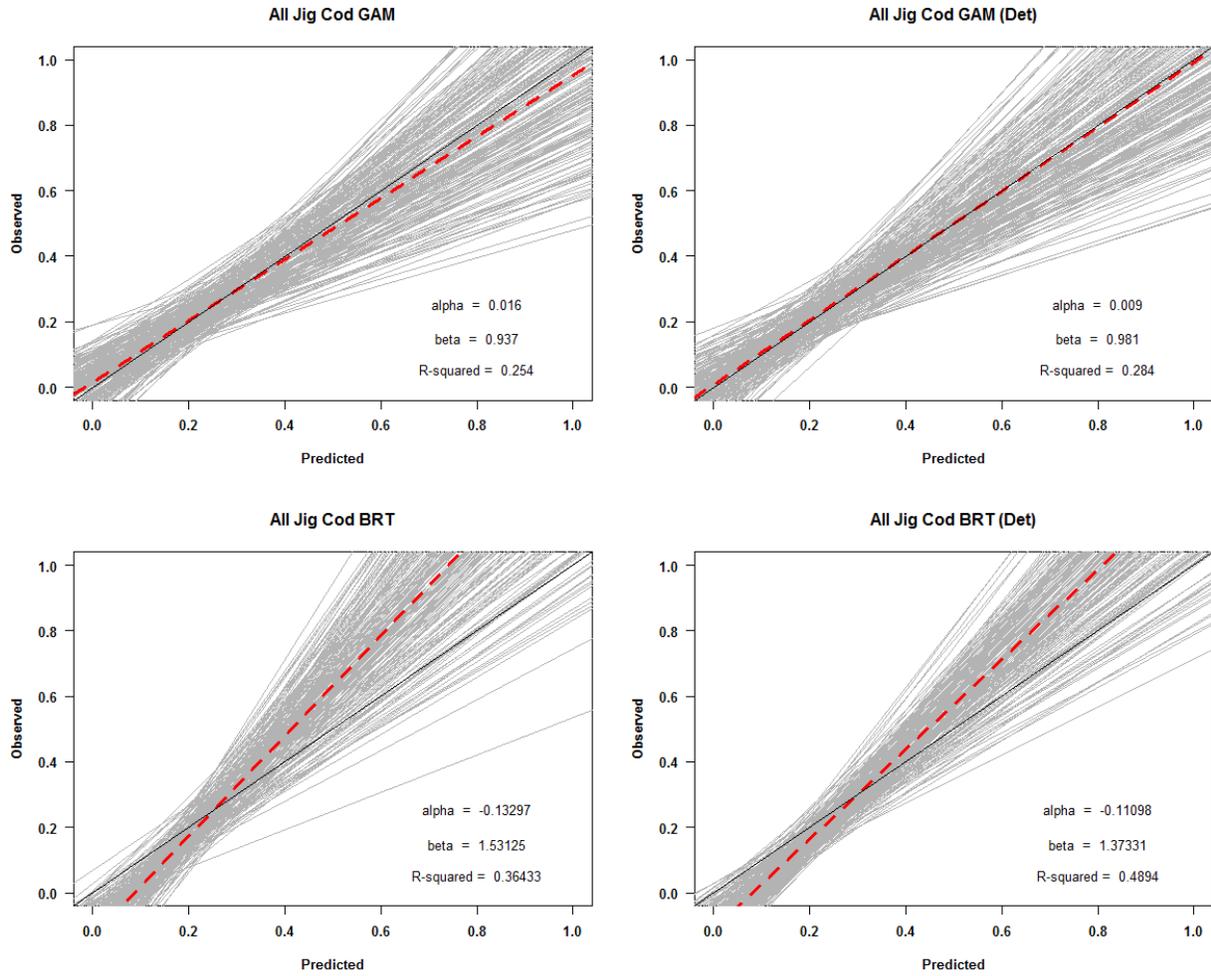


Figure III-22. Results of the cross-validation tests for jigging models. Solid black line represents a Line with slope of 1. The dashed line represents the mean of the 2000 simulations. Alpha represents the intercept, beta represents the slope, and R² represents the line fit. Grey lines represent individual simulations.

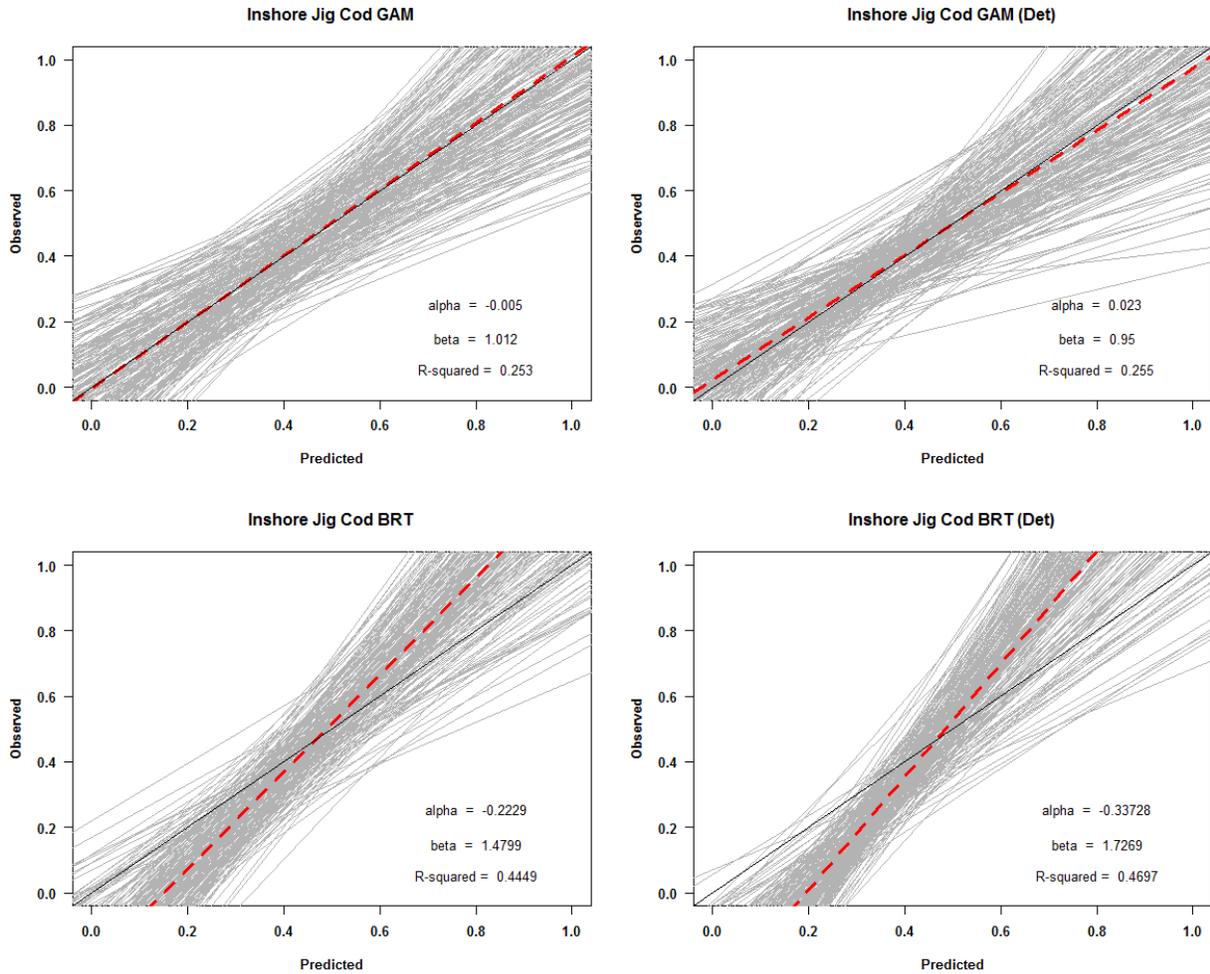


Figure III-23. Results of the cross-validation tests for inshore jigging models. Solid black line represents a Line with slope of 1. The dashed line represents the mean of the 2000 simulations. Alpha represents the intercept, beta represents the slope, and R^2 represents the line fit. Grey lines represent individual simulations.

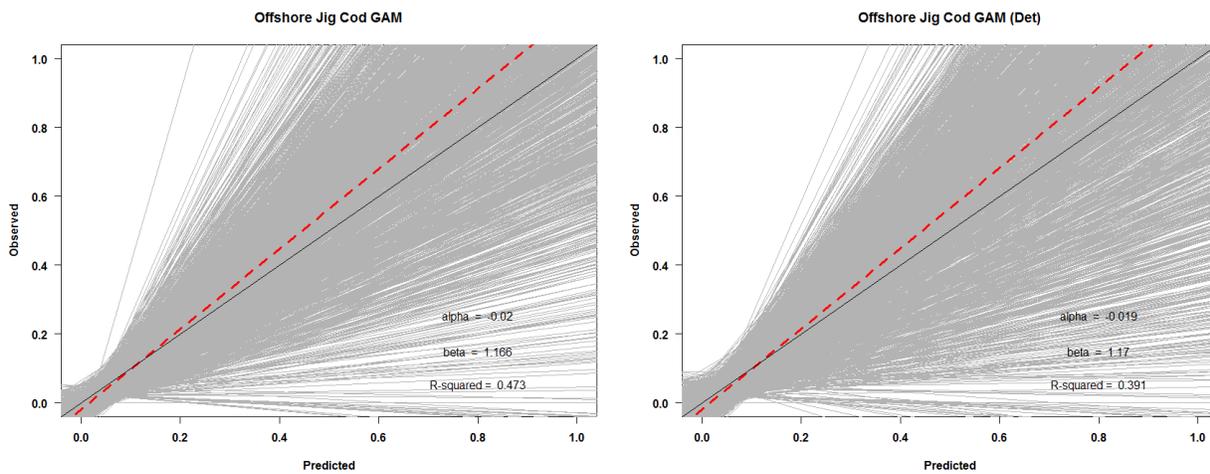


Figure III-24. Results of the cross-validation for offshore jigging models. Solid black line represents a Line with slope of 1. The dashed line represents the mean of the 2000 simulations. Alpha represents the intercept, beta represents the slope, and R^2 represents the line fit. Grey lines represent individual simulations.

Table III- 13. Mean squared error of each longline model for each species.

Species Model	Cod MSE	Halibut MSE	White Hake MSE	Cusk MSE
GAM	<0.001	<0.001	0.001	<0.001
BRT	<0.001	0.002	0.010	<0.001

Table III- 14. Mean squared error of each jigging model.

Species Model	All Jig MSE	Inshore Jig MSE	Cod Offshore Jig MSE
GAM	0.13	0.20	0.02
GAM (Det)	0.12	0.20	0.02
BRT	0.002	0.002	NA
BRT (Det)	0.001	0.002	NA

Table III- 15. Intercept, Slope, and R² resulting from the cross validation of different model types for each target species caught on the longline.

Species Model	Cod			Halibut			White Hake			Cusk		
	Intcpt	Slope	R²	Intcpt	Slope	R²	Intcpt	Slope	R²	Intcpt	Slope	R²
GAM	-0.01	1.32	0.21	-0.03	1.14	0.20	-0.11	1.08	0.29	-0.01	1.54	0.06
BRT	-0.03	4.0	0.25	-0.03	1.17	0.43	-0.27	1.17	0.58	-0.03	4.67	0.20

Table III- 16. Intercept, Slope, and R² resulting from the cross validation of different model types for cod caught in the jigging portion of the survey.

Species Model	All Jigging			Inshore Jigging			Offshore Jigging		
	Intcpt	Slope	R²	Intcpt	Slope	R²	Intcpt	Slope	R²
GAM	0.01	0.97	0.26	0.01	0.98	0.24	-0.02	1.18	0.48
GAM (Det)	<0.01	0.99	0.29	<0.01	0.98	0.27	-0.02	1.18	0.39
BRT	-0.01	1.45	0.35	-0.23	1.48	0.47	NA	NA	NA
BRT (Det)	-0.11	1.37	0.48	-0.34	1.74	0.47	NA	NA	NA

IV-3. Standardization of CPUE:

Standardized CPUE from fisherman's choice stations are another method used to assess the survey design. Ideally, a properly standardized CPUE for fishery dependent data should reflect underlying trends in species abundance. The presence of a pattern in standardized CPUE can also indicate an issue with sampling, but it may also be the result of high variance. As mentioned before, this survey suffers from large variance resulting from small sample sizes and patchy fish distribution. Trends in CPUE were used as method for comparing the trends seen in fishery-dependent data and fishery-independent data. Not all CPUE trends observed in the random survey match the trends seen in the fishery data (Figures III-9:12). The trend in halibut CPUE matches the trend in relative abundance, which provides more confidence in the accuracy of halibut estimates. The trend in hake CPUE is very similar to the trend in hake abundance, apart from minor differences. However, the trends in cod and cusk CPUE are dissimilar from the trends in cod and cusk abundance. This is likely the result of small sample sizes and overdispersal issues noted above. Additionally, catchability limitations may be inhibiting the ability to calculate accurate estimates of CPUE because funding constraints limit the Sentinel Survey to sampling only 12 fisherman's choice stations each year. For example, the design-based abundance for cusk in 2018 appears to be twice the maximum value over the last five sampling seasons. However, the reason for this is because three cusk (an unusually high catch) were caught at a single station in 2018. In each of the previous years, three cusk were not caught from all random stations combined. Consequently, small sample sizes resulting from little fishery-dependent sampling effort may make CPUE estimates more heavily biased by instances of false zeros. Although standardized CPUE trends can be a valuable tool in assessing the quality of

abundance indices, inadequate sample sizes of fisheries-dependent stations make it difficult to identify any definitive trends in catch.

IV-4. Bait Type, Habitat Preference, and Seasonal Trends:

IV-4-A. Bait Preference:

Model results indicate bait preference by Atlantic cod, white hake, and Atlantic halibut (Figure III-13). Both cod and white hake appeared to prefer squid, while halibut preferred herring. A relationship between bait type and catch could highlight a source of bias in the survey methods and the survey may need to be standardized to account for the preference by these target species. It is of note that white hake and cod are closely related within the family *Gadidae* (Ryan, 1979) and display the same bait preference, but the observed bait preference is contrary to what is commonly found in the literature regarding the feeding habits of these species.

In several diet analyses conducted on cod and white hake, it was common for larger fish to contain herring and other small pelagic fishes while juvenile specimens most often contained species of *Mysidacea* (Shrimps; Davis, 2004; Garrison, 2000; and Powles, 1958). In the 1958 study conducted by Powles, there were only nine instances of Cephalopoda observed from all 412 cod stomachs that were studied. Seven of nine instances of cephalopod observations were in July and two instances were observed in August. Powles (1958) also identified mysids as the primary species found in cod stomachs in June and steadily decreased throughout the summer with an increase in herring occurrence. This appears to be indicative of a seasonal trend in feeding habits of cod potentially determined by the life strategies of their prey. In six years of Sentinel Survey data, there were only 24 instances of cod catch on the baited longline, which brings to question the validity of such a significant relationship between bait and catch of cod.

Atlantic halibut and cusk are known to eat a variety of fishes, crustaceans, and cephalopods. Although both species eat primarily fishes as adults, cephalopods have constituted nearly 20% of the biomass in halibut stomach samples. It is surprising that halibut showed preference for herring over squid, as they exhibit a wide range of food sources including scraps of fish discarded from fishing vessels and, in some cases, pieces of anthropogenic material (Bigelow and Schroeder, 2002). The presence of both cephalopods and herring, along with many other species, has been documented in the stomachs of halibut at the same time. This implies that the feeding habits of halibut follow a more opportunistic strategy and depend on what is available in the immediate area. In terms of the Sentinel Survey, it is interesting that the model showed a significant relationship between bait and catch of Atlantic halibut, cod, and white hake because it could potentially bias catch results. However, the sample size for white hake, cod, halibut, and cusk is not large enough to conclude that bait type could bias catch to the extent that it would alter the trends in abundance estimates. More data needs to be collected to more accurately examine the strength of the relationship between bait and catch of each target species. If there continues to be a statistically significant relationship between bait type and catch abundance, there may be a need to standardize survey data for bait to reduce bias in catch data.

IV-4-B. Depth and Sediment Class:

The results of the models indicate that depth and sediment type were significant factors in determining the abundance of Atlantic halibut and white hake (Figures III-14 and 15). The significance of depth is reevaluated annually and has remained a significant factor in determining catch for species with higher catch rates, which is why the Sentinel Survey stations are stratified

by depth (Rodrigue and Chen, 2015). White hake were observed predominantly in waters greater than 200 meters depth, with some occurrence in waters less than 40 and between 150 to 200 meters depth over mixed and soft sediments. The model shows a lower average abundance of white hake in waters 40 to 100 meters deep, consistent with findings by Davis *et. al.* 2004. Contrary to the summation of white hake habits in Bigelow and Schroeder's *Fishes of the Gulf of Maine* (2002), the model shows that white hake do exhibit a statistically significant relationship with depth, reaching maximum average abundance around 175 meters depth. Cusk were more evenly distributed across benthic gradients, caught infrequently, but throughout the depth range of the survey (50 - 250 meters; Figure III-14). These observations are corroborated by the literature, which states that cusk are generally found in deeper water and on hard bottom (Bigelow and Schroeder, 2002). On the contrary, the models show halibut are found in shallow waters 50 to 100 meters depth over mixed and hard sediments (Figures III-14 and 15). It has been documented that halibut have been found over mixed sediments in waters up to 750 to 900 meters depth, which exceeds the limits of the Sentinel Survey study area, but halibut have been documented in waters ranging from 25 to 1000 meters depth (Bigelow and Schroeder, 2002).

In addition to the findings here, the implications of gear selectivity must be considered. Catch trends reflect the abundance of fish with a gape (mouth size) large enough to take the size hooks used on the gear. This excludes fish that the gear is incapable of catching. It is documented that white hake, like cod, inhabit inshore, shallow waters as juveniles and move offshore as they mature. As a result, the abundance estimates calculated for species caught on the longline may be indicative of fish of a certain size class that would correspond with their gape. A robust analysis of gear selectivity would be beneficial to incorporate into future analyses and reports.

IV-4-C. Sea Surface and Bottom Temperature:

Results regarding sea surface temperature were largely inconclusive. It would be sensible to deduce that halibut found in shallow water show a preference to warmer surface temperature and cusk or white hake found in deeper water have a preference to colder surface water because temperature and depth are directly related. However, the amount of error associated with the sea surface temperature for cod does not allow for any conclusions to be drawn relating cod catch to sea surface temperature. Similarly, species caught at 175 meters would not be affected by sea surface temperature. Considering that the only species to show a significant relationship between catch and sea surface temperature are also the only species to show a significant seasonal trend in catch, it would appear as though sea surface temperature is more indicative of a seasonal trend in catch of each species rather than a true relationship with surface temperature. Despite the clear relationship between month and sea surface temperature, both variables passed a variance inflation test prior to being incorporated into any model. It is possible that the variance inflation test did not find month and sea surface temperature to be colinear because month is defined as a factor rather than a numerical variable. However, removing month or sea surface temperature from any model resulted in a model with a poorer performance and a lower deviance explained.

Because of the inconclusiveness of sea surface temperature in the 2017 report, bottom temperature was incorporated into the models in 2018. Data collected from bottom temperature sensors in addition to Finite Volume Community Ocean Model (FVCOM) buoy data was used to model bottom temperature for years in which bottom temperature was not collected. Similar to depth and sea surface temperature, only species with high catch frequencies showed a statistically significant relationship between bottom temperature and catch. However, both models indicate that bottom temperature has a far more significant relationship with catch than

sea surface temperature. Additionally, both model types allow for the incorporation of colinear covariates, which brings to question whether seasonality or temperature are more important drivers of catch numbers. A further analysis of the seasonal trends in surface and bottom temperature and incorporating these covariates into the models in different ways is recommended before making any conclusions about the impact of temperature on catch.

IV-4-D. Evaluating Seasonal Trends in Catch (Month)

Results indicate that there was no seasonal trend in cod catch. This is in agreement with the literature, which suggests that summer months can be described by cod dispersion with minimal aggregating activity (Bigelow and Schroeder, 2002). However, this may be the result of the timing of the Sentinel Survey sampling season, which falls directly between the aggregation timing of the spring and fall spawning complexes identified by Ames (2004). Additionally, there are seasonal trends in feeding habits suggested by Powles (1958; discussed above) and regular seasonal migrations of Atlantic cod to areas that may be more suitable within the Gulf of Maine depending on the time of year (Ames, 2004; Lear and Green, 1984). With all the available information suggesting interregional movements of cod throughout the year, I believe the lack of significance between cod and cusk may be the result of such a small survey area and survey timing.

Halibut are described as “boreal fish” in which catch is most abundant when water temperature is the coolest (Bigelow and Schroeder, 2002). Results here agree with the literature regarding halibut habits because highest catch frequencies are observed in the earliest part of the survey season, June, which is when waters are coolest over the course of the sampling season.

Contrary to the habits of white hake described in Bigelow and Schroeder's *Fishes of the Gulf of Maine* (2002), which suggest that there are no spawning white hake in the Gulf of Maine, several mature male and female white hake have been observed with running milt and vascularized roe in recent years aboard the Sentinel Survey. Like halibut, the catch of these mature, ripe hake is most abundant in earlier part of the survey season, despite the literature suggesting that they spawn at random throughout the year. As a result, white hake spawning behaviors and timing may have implications on Sentinel Survey catch trends for the species, but the data to support this hypothesis is currently unavailable. The increase in white hake abundance during the autumn months may be the result of food availability or increased sampling of stations over suitable habitat, but there are no clear conclusions as to why white hake catch increases in the fall. A more thorough analysis of white hake catch trends is required before any conclusions are made about trends in white hake catch.

IV-4-E. Catchability and Non-Target Species

As discussed in Chapter 2, one of the biggest limitations with the Sentinel Survey jigging methodology is that all jig drops terminate upon catch. Anglers do not re-drop for the remainder of the drop time, whether they catch a target species or not. To reiterate the message from Chapter 2, the goal of the catchability study was to elicit the impact that catching non-target species may have on catch numbers and abundance estimates. Even though this study shows that catching non-target species does not inhibit the ability to catch cod, results of the study showed that the gear used in the jigging methodology had a very low and relatively fixed catchability for cod. Evidence to support these results was provided in the 2018 sampling season by qualitative

video and image data collected by an on-board observer which showed a high density of cod present, but only one cod was foul-hooked on the jigging gear during sampling. Additionally, no cod were observed on a nearby longline. This evidence is subject to being circumstantial as video gear was only deployed at a single fishermen's choice station. It is possible that this one stations could have been a nursery ground for juvenile cod. Nonetheless, implications of the video footage confirm a need to quantify and account for gear catchability in order to limit bias in abundance estimates which is introduced by the gear type.

It can be seen in Tables 10 and 12 in addition to Figures III-21:23 that both model types indicate some level of significance and influence of detection probability. Additionally, BRTs and Tweedie GAMs containing detection probability as a covariate explain a higher percentage of the variance in the data than models without detection probability. Figures III-21:23 show that models containing detection probability outperformed their counterparts in all instances, indicating that the inclusion of detection probability makes for a better fitting model with higher explanatory power.

As a result of the significant influence of catchability on the jigging gear highlighted in this analysis, the Sentinel Survey team is in the process of developing a gear-validation study that aims to use gillnets to quantify the effect of longline catchability so that catchability and selectivity may be incorporated into future calculations and modeling schemes to develop more accurate abundance estimates.

IV-6. Data Gaps and Limitations

Due to the changes in design and the personnel responsible for collecting field data, data collection has varied over the duration of the survey time series. During the pilot years (2010-

2011) observed sediment type was not collected. For these years, USGS data (Poppe et al., 2005) were used to determine sediment type. However, the distance between the sample sites of this data is much greater than that of the Sentinel Survey. In a comparison between the USGS data and observed data in the survey, the USGS sediment data are not reliable on the scale relevant to this survey program. Thus, it was decided in 2012 to use sediment data observed on board during the survey. Bottom temperature was not recorded or only partially recorded for 2010-2013. Additionally, the number of stations sampled varies each year, although the number of stations per station type (inshore jig, offshore jig only, random longline, or fisherman's choice) remained proportional across years. These limitations will be minimized in the future as the survey design and protocols are now standardized.

Modeling data with a high proportion of zero catch observations is complex because there are more zeros in the response variable than is assumed under a Poisson or negative binomial distribution. To prevent zeros from biasing the results, any model would have to consider the number and proportion of zeros and alleviate the effect they would have on the whole data set. It is important to include zeros in count or catch data because it provides resolution to the data set and reduces the chance to create bias in parameter estimates and standard deviations. Therefore, the model must also be able to distinguish between true and false zeros. "True" zeros occur when the survey observes zero fish in an area in which fish abundance is truly zero, while "false" zeros occur when zero fish are observed in an area that does contain fish. False zeroes misrepresent the spatial distribution and abundance of the local fish population. Consequently, there is a constant need for continuous testing of statistical models used by the survey to evaluate their fit to the dataset and ensure that the model appropriately explains the findings in this study.

V. CONCLUSIONS

Without additional biological data, a quantitative explanation of changes in abundance estimates cannot be calculated. Qualitatively, abundance estimates may fluctuate as a result of the number of random stations that fall on top of suitable habitat or as a function of any of the significant explanatory covariates discussed above. Despite this lack of information, current abundance estimates for cod, halibut, and cusk are highly precise in most years of the time series. Additionally, BRT modeled trends in abundance and standardized CPUE estimates for cod are similar to trends observed from NMFS and MADMF trawl survey data, which are the major fisheries independent data sources for the cod stock assessment. As a result, BRT results are considered to be the most robust estimate of abundance as they are supported by similar findings from other survey programs. White hake values are often associated with larger CV values, which is most likely the result of large variance in the data either due to relatively small sample size or patchy fish distributions. Since small sample sizes are observed for two target species and patchy distribution for the other two target species, it seems reasonable that sampling error is unlikely to be the cause of inconsistent standardized CPUE or high CV values. The EGOM Sentinel Survey should continue to collect data without changing the survey design. However, catchability should be evaluated for its impact on catch and abundance estimates and be incorporated in future estimations of abundance. There remains a tremendous need to continue sampling in such a data-poor region. Additional data will provide the opportunity to conduct more reliable analyses on groundfish in the EGOM.

CHAPTER 4
UNDERSTANDING THE SPATIAL VARIABILITY IN LIFE HISTORY
PARAMETERS OF ATLANTIC COD (*GADUS MORHUA*) IN
THE EASTERN GULF OF MAINE

INTRODUCTION:

As discussed in Chapter 1, the Gulf of Maine (GOM) cod stock has endured the confounding effects of declining abundance coupled with shifts in spatial distribution (Steneck *et. al.*, 2013). The cod fishery in the Eastern Gulf of Maine (EGOM) remains open to groundfish fishing, but low stock densities in the EGOM have led to an overall loss of fishing effort in the region GOM (Palmer, 2014; Pershing *et. al.*, 2013; Murawski *et al.* 1998). In addition to the spatial shifts in fishing effort, fisheries independent trawl surveys conducted by the Northeast Fishery Science Center (NEFSC) and the Maine Department of Marine Resources (DMR) are spatially restricted in the EGOM due to high densities of fixed gear (e.g. lobster traps) and complex bathymetry (Figure IV-1).

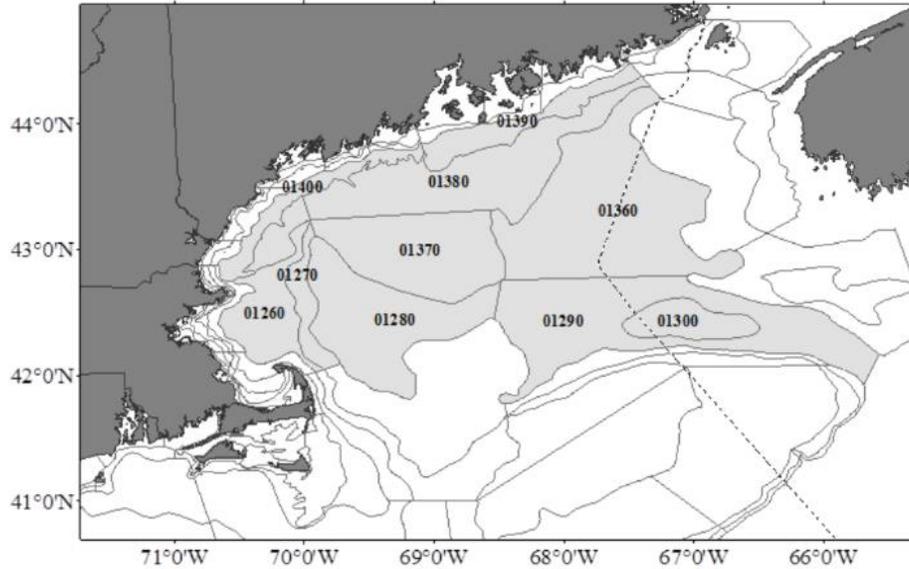
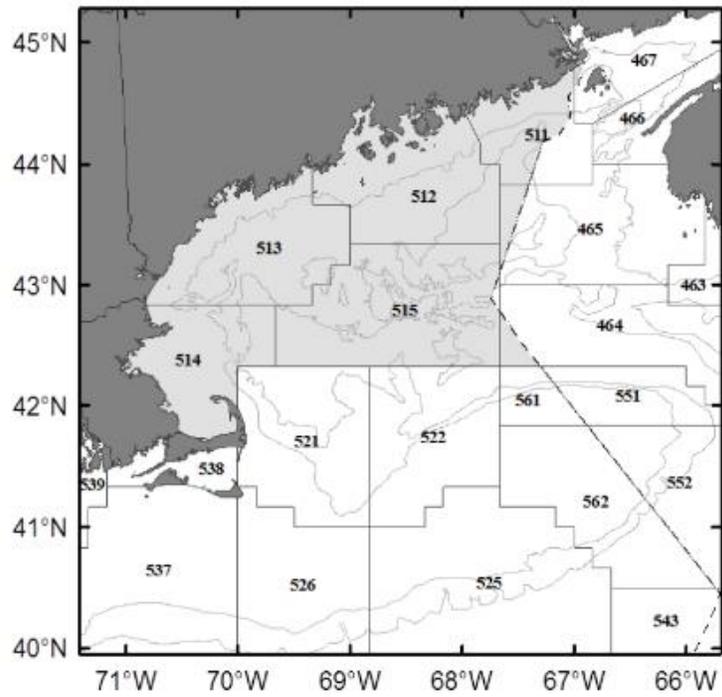


Figure IV-1: Top: Map of the Gulf of Maine Atlantic cod (*Gadus morhua*) management assessment area (gray). Bottom: Map of the Northeast Fisheries Science Center Bottom Trawl Survey data used in the Gulf of Maine Atlantic cod stock assessment as adapted from the NMFS: 2014 Atlantic cod Stock Assessment Update Report.

Despite the spatial habitat restrictions imposed on trawl surveys in the EGOM and the disproportionate fishing effort (Palmer, 2014; Murawski *et al.* 1998), the GOM cod stock is assessed as a single unit stock in which the scale of the assessment may fail to recognize the fine scale dynamics in the system, such as localized extirpations (Ames, 2004). However, the GOM cod population is structurally complex and comprised of several distinguishable sub-stocks (Kovach, 2010; Runge *et al.*, 2010; Ames, 2004). Discrepancies between, or oversimplifications of, management boundaries and realized population boundaries can lead to stock assessments which are misrepresentative of the population status and falsely inform management strategies which are then ineffective in practice (Cao *et al.*, 2014; Zemeckis *et al.*, 2014). Unfortunately, the most limiting factor that is currently preventing these complexities from consideration in the stock assessment is the available data, which does not provide substantiated grounds on which sub-stock boundaries can be clearly defined. Additionally, each additional level of complexity in the stock assessment model comes at an operational cost in which the margin of error increases with increasing model complexity (Collie *et al.* 2014).

The simpler unified stock assessment which informs the management strategy governing the GOM cod fishery operates under many assumptions. One of these assumptions is that degree of difference in phenotypical life history parameters exhibited by cod across the GOM is insignificant and would not impede the success of the management plan, nor would it have any substantial implications in terms of altering catch advice. In other words, the modelling approach assumes that spatial differences in growth, maturation, and natural mortality are sufficiently consistent across the stock area such that any violations of consistency assumptions do not substantially impact the estimates of stock status and catch advice coming

from the assessment model. It is well documented that variables such as population density, ecosystem structure, and food availability can influence life history over time and space (Becker and Chen, 2016; Jones, 2002; Chen and Mello, 1999). The simplicity of the current management regime and its assumptions may be failing to prevent regional overfishing and the overall rebuilding the GOM cod stock. Minimal success rebuilding the GOM cod stock in recent decades has directed some research effort towards elucidating finer-scale population structure to identify significant factors governing cod distribution and life history characteristics (Palmer *personal communication*; Chen *personal communication*).

As fish populations are overfished, fish density decreases and reductions in fish density can lead to temporal shifts (e.g. truncation) in key allometric parameters such as length at age and weight at age. These life history parameters can, consequently, cause shifts in maturation rates because energy that is typically allocated for somatic growth is redirected towards earlier maturation in response to population stress (Becker and Chen, 2016; Chen and Mello 1999; Chen and Harvey 1995). As a result, phenotypical life history traits such as length-at-age, weight-at-age, and condition factor can be used as proxies of population health in which the lack of a negative temporal change in allometric parameters would be indicative of a healthy population. However, failure to account for spatial variation in somatic growth can bias biological reference points used in fisheries stock assessment models (Stawitz *et. al.*, 2019; Ying and Chen, 2011). Consequently, it is possible that the non-consideration of spatially explicit growth variability in GOM cod stock assessments has led to the biased representation of the complex GOM cod population, potentially leading to instances of regional stock overexploitation (Ying and Chen, 2011).

In this chapter, spatially explicit cod growth in the North Atlantic will be evaluated for

inter-regional differences and temporal trends in length-at-age, weight-at-age, and age-specific condition factor. Using 48 years of NEFSC Bottom Trawl Survey data, growth parameters between major areas of the GOM (eastern GOM and western GOM) will be evaluated in an effort to explicate some of the fine-scale, sub-stock level differences in growth parameters. Additionally, a comparison between GOM cod with GBK cod will be conducted in order to test the accepted assessment that GOM cod and GBK cod do not exhibit statistically significant differences in growth parameters. Furthermore, a more spatially restricted template will be used to analyze cod growth in and between proposed sub-stock areas suggested by multiple research studies but illustrated below by Pershing *et. al.* (2013; Figure IV-2).

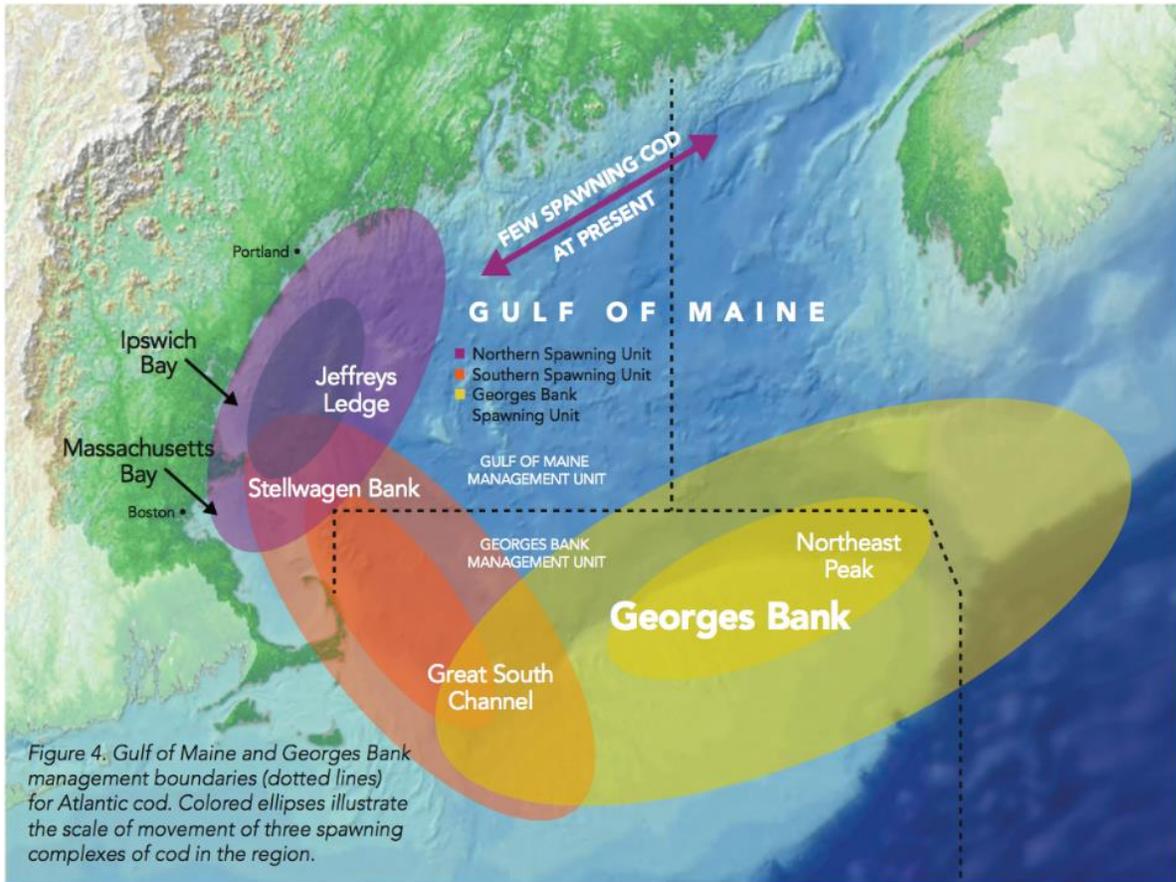


Figure IV-2: Map of proposed Atlantic cod sub-stock areas in the Gulf of Maine (adapted from Pershing 2013) to be used as a template for the spatially explicit growth analysis.

METHODS:

Identifying Spatially Explicit Areas in the Gulf of Maine

To complete this analysis, NEFSC bottom trawl survey age-length data from 1970-2018 was used because age data did not come available until 1970. To remain consistent with the accepted regional boundaries in the Gulf of Maine, (GOM) ArcGIS was used to generate polygons distinguishing the eastern Gulf of Maine (EGOM) and the western Gulf of Maine (WGOM) along the 70°W longitudinal boundary (as recommended by Michael Palmer, NOAA), which also coincides with the genetic grouping presented in Breton (2008) and Kovach *et. al.* (2010). The shapefile in ArcGIS was then overlaid on the federal trawl survey data points in

order to give trawl data locations a general regional label of east versus west. As suggested in Bigelow and Schroeder (2002), GOM cod have historically exhibited different life history parameters, although not significantly different, from cod found on George's Bank (GBK) and have been managed separately due to biological similarities between GBK cod and those found in southern New England and the mid-Atlantic (Serchuk and Wigley, 1992). To test whether GOM and George's Bank cod exhibit no statistically significant growth differences, data from George's Bank were included in this analysis. Furthermore, trawl data was assigned to more spatially limited sub-stock regions using the same methodology in ArcGIS to evaluate inter-regional growth differences among the proposed sub-stock structure presented by Pershing *et. al.* (2013; Figure IV-3).

Assessing Inter-Regional Growth Rates

In order to generate Von Bertalanffy growth curves for length at age and weight at age, all age groups must be sampled sufficiently. However, NEFSC trawl data does not sample all age classes sufficiently. Data obtained from the NEFSC trawl survey shows a heavy saturation of cod age five or less (Figure IV-2). As a result, attempts to fit federal trawl data to a Von Bertalanffy growth equation were unsuccessful as models would terminate upon a calculation of infinity: the result of attempting to fit a curve to a linear line.

Age Class Distribution from NEFSC Bottom Trawl Survey (1970-2018)

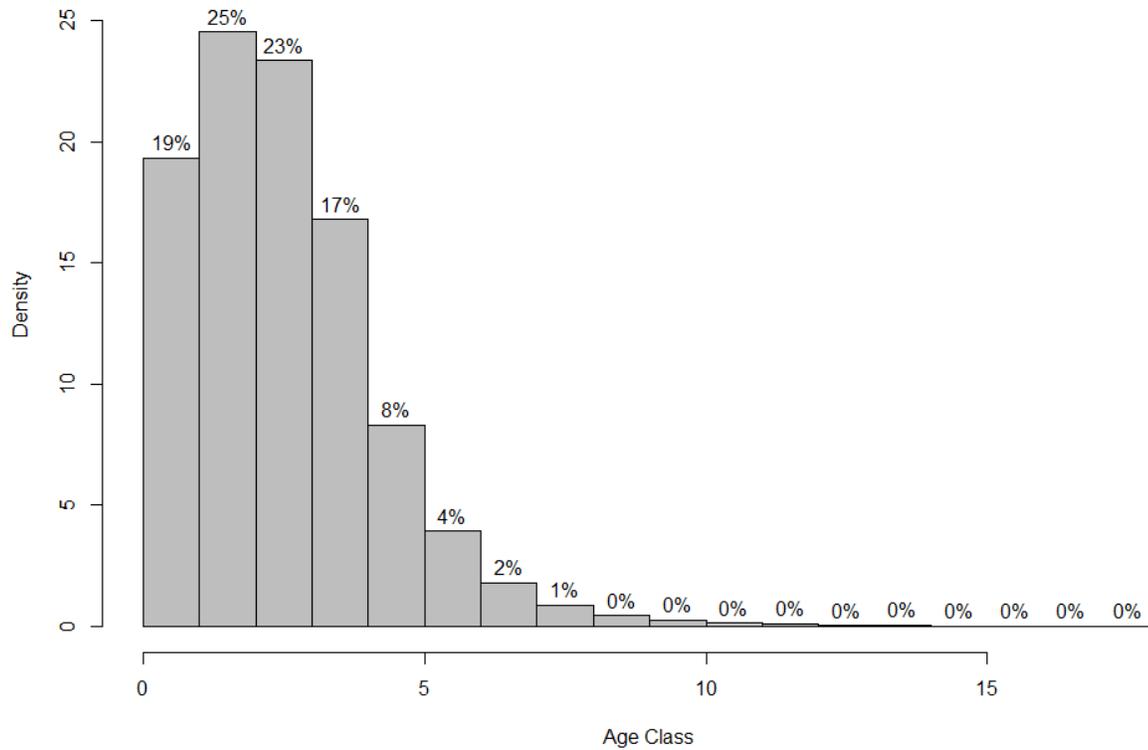


Figure IV-3: Histogram of Age class density observed on the NEFSC bottom trawl survey from 1970-2018.

Because of the failed attempts at utilizing the Von Bertalanffy growth equations, a non-parametric bootstrap approach was used for a maximum likelihood estimate of the mean absolute growth between age classes such that:

$$\bar{x}_{n:n+1} = \frac{\sum_1^{N_{sim}} x_{n+1} - x_n}{N_{sim}}$$

in which the average measurement of the growth parameter (\bar{x}) from age n to $n + 1$ is equal to the sum, from 1 to the number of bootstrap simulations, of growth at a given age (x_n) minus the growth at the antecedent age (x_{n-1}) divided by the number of bootstrap simulations.

Due to the limited sampling of cod greater than age five, a bootstrap analysis on the absolute growth could only be calculated between age classes from age zero to five in the combined season and fall season analysis and from ages one to six for the spring analysis (due to the lack of age zero cod caught on the spring survey). Additionally, limited resolution in cod ages in each individual year prevented the possibility of evaluating an annual temporal trend in cod growth from 1970 to 2018. As a result, a five-year moving window approach was employed to evaluate average growth in which

$$\bar{x}_{n:n+1} = \frac{\sum_{Year_j}^{Year_{j+5}} x_{n+1} - x_n}{n_{samples}}$$

such that the value of the average for a given growth parameter to be used in the bootstrap analysis is an average over a moving five-year window from $Year_j$ to $Year_{j+5}$. This method will allow for greater resolution in the evaluation of a temporal trend in growth parameters rather than five-year groupings, which lack overlap between groups.

Although length and weight are explicit datapoints within the NEFSC federal bottom trawl dataset, condition factor is not calculated. To evaluate inter-regional differences and temporal changes in condition factor, Fulton's K was calculated as a measure of condition factor in which

$$K = \frac{w}{l^3} * 100$$

such that condition factor (K) is equal to the weight of the fish (w) divided by the cubed length of the fish (l). This value is then multiplied by 100.

Evaluating Temporal Trends in Growth Parameters

The aforementioned non-parametric bootstrap methods were applied to compare absolute change in length, weight, and condition factor for explicit age classes between seasons (Spring and Fall), over time (1970/1992 – 2018), between major areas in the GOM (EGOM, WGOM, and George’s Bank), and between proposed sub-stock areas (EGOM, WGOM, Great South Channel, and George’s Bank). Temporal trends were evaluated by plotting the results of the bootstrap analysis, using the *lsfit()* function in the base R program to fit a trendline to the results, and then evaluating determining if the slope of the trendline differed significantly (p -value < 0.05) from a slope of zero such that

$$z = \left(\frac{m - 0}{\sigma / \sqrt{n}} \right)$$

and

$$p = 2 * pnorm(z)$$

in which m is equal to the slope of the fitted trendline, σ represents the standard deviation, and n is equal to the sample size. The p -value is then calculated using the R base function *pnorm()* on the z -value. A slope of zero represents the null hypothesis that there is no significant temporal change in growth over time.

Similarly, the difference between the trendlines of fall and spring time series was evaluated in order to determine if spring and fall time series slopes were significantly different from one another such that

$$z = \left(\frac{m_a - m_b}{\sqrt{s_a^2 + s_b^2}} \right)$$

in which m_a represents the slope of trendline a , m_b represents the slope of trendline b , and s represents the standard error of each trendline. P -values were calculated using the same equation as above.

Evaluating the Statistical Significance of Inter-Regional Growth Differences

To evaluate whether inter-regional growth exhibited statistically significant differences from one another, a 95% confidence interval was calculated around the bootstrap means using the *quantile()* function in R. Once all estimates had an associated confidence interval, R code was written to assign a value of “*True*” when confidence intervals for two means overlapped, or “*False*” for when confidence intervals did not overlap. These values were used to test the amount of time within the time series of data that means were significantly different from one another in which “*True*” represents the null hypothesis that inter-regional growth rates are not significantly different and “*False*” represents instances in which estimates between areas are significantly different from one another.

Limitations

It should be noted that weight and condition factor analyses are only conducted from 1992 to 2018 while the length analysis encompasses the entire time series of the NEFSC trawl survey (1970-2018). This is a result of a change in field methods in which individual weights

were not measured until 1992. Consequently, Fulton's K cannot be calculated for years prior to 1992.

RESULTS:

Seasonal and Temporal Trends in Age-Specific Length, Weight, and Condition Factor

Based on the results of the bootstrap analysis, age 1 – 2 cod on George's Bank were the only subset of cod to exhibit a statistically significant temporal trend over the time series (1992-2018). There is a statistically significant decline in the absolute weight between age 1 and 2 for cod on George's Bank (Figure IV-3). There were no statistically significant temporal trends observed in length or condition factor, and no other age class or areas have experienced a temporal trend in weight since 1992.

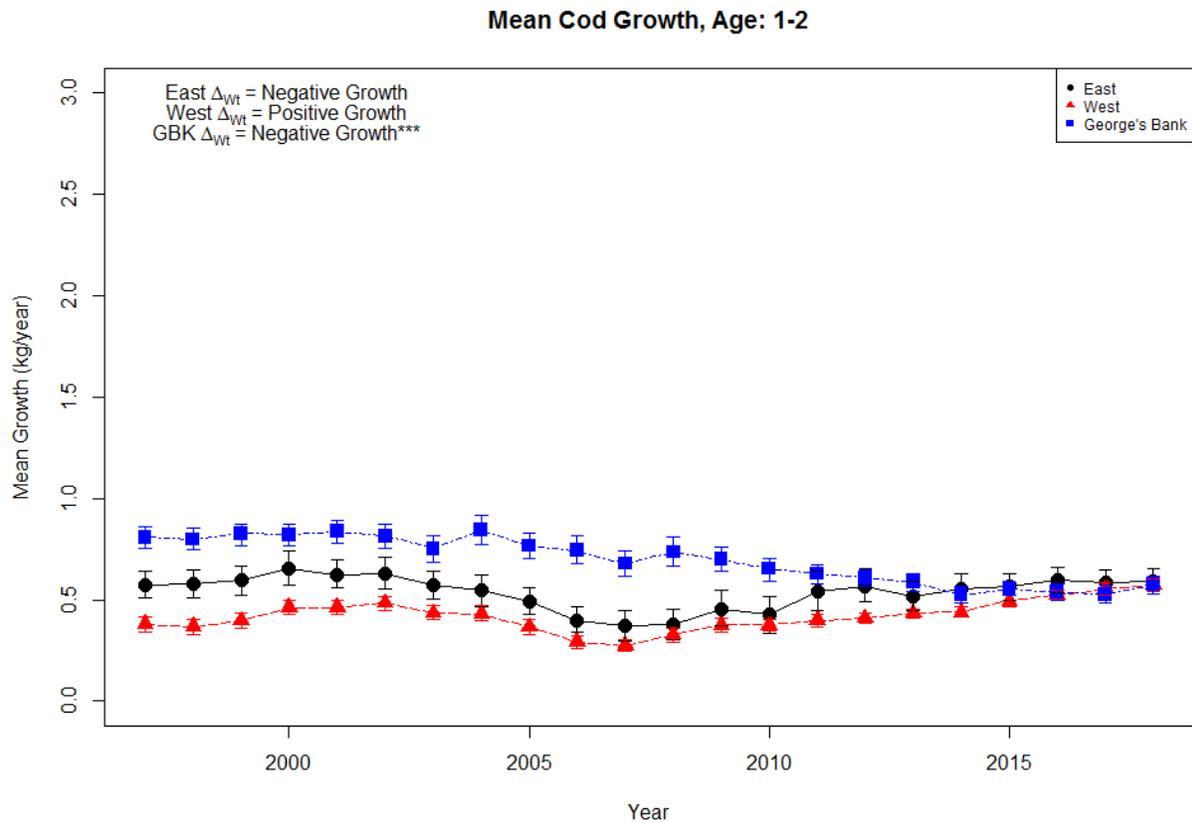


Figure IV-4: Mean change in cod weight ages 1-2 in the eastern GOM, western GOM, and George’s bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Slopes that are statistically significantly different from 0 are represented by asterisks (***)

Although significant temporal trends in length-at-age were not observed, Figures IV-5:21 illustrate substantial differences in the temporal trends between the spring and fall bottom trawl surveys. A statistically significant temporal trend between fall and spring surveys was observed in the Eastern sub-stock for mean and median length from age 4 to 5 (Figures IV-5 and 14). In the Western sub-stock, a significant difference between spring and fall was observed for mean length from age 2 to 3 in addition to mean and median length from age 3 to 4 (Figures IV-6, 7, and 15). Great South Channel exhibits a significant seasonal difference in mean and median length for ages 1 to 2, 2 to 3, and 3 to 4 (Figures IV-8, 9, 10, 16, 17 and 18). George’s Bank cod

show significant seasonal differences in mean and median length at ages 1 to 2, 2 to 3, and 4 to 5 (Figures IV-11, 12, 13, 19, 20, and 21). These results represent a time series of 1970 to 2018.

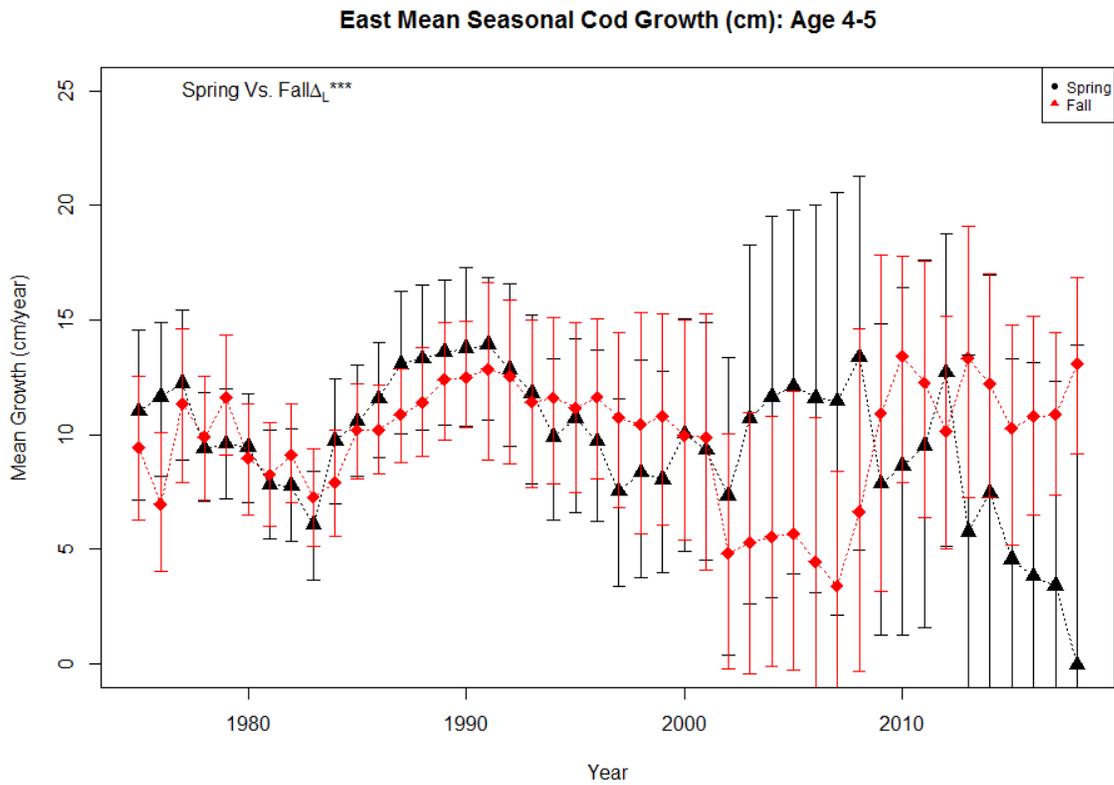


Figure IV-5: Mean change in cod length age 4-5 in eastern GOM from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

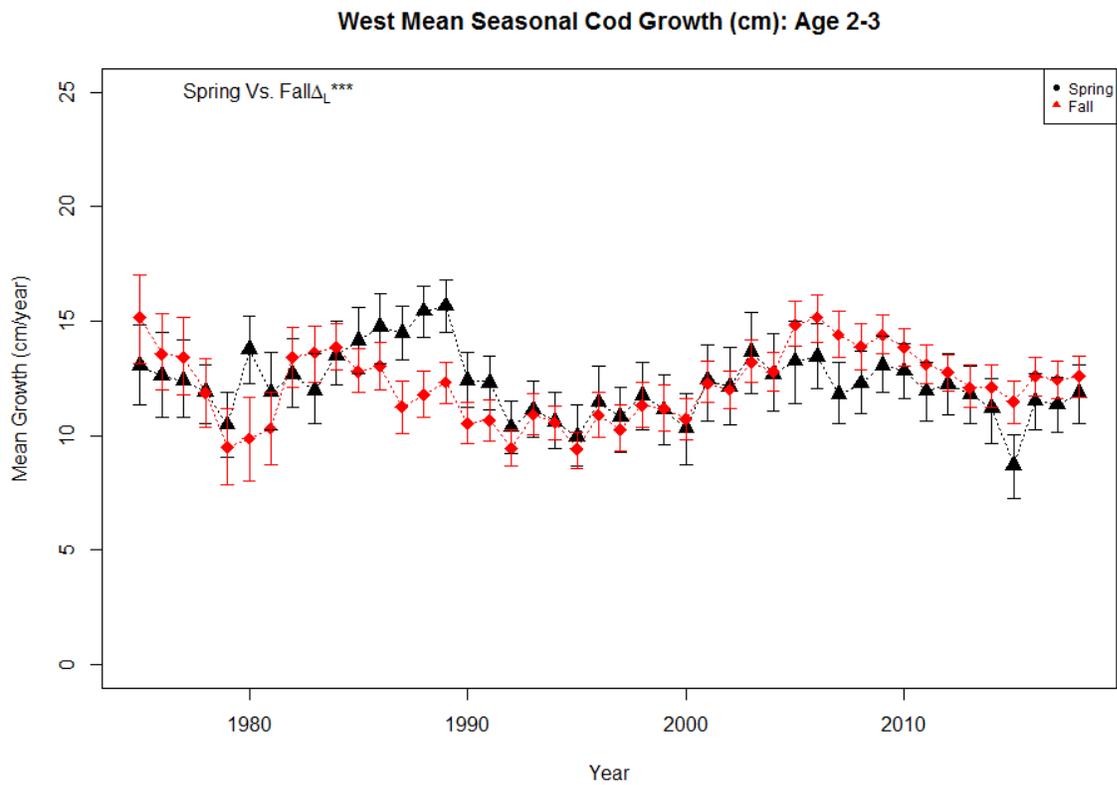


Figure IV-6: Mean change in cod length age 2-3 in western GOM from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

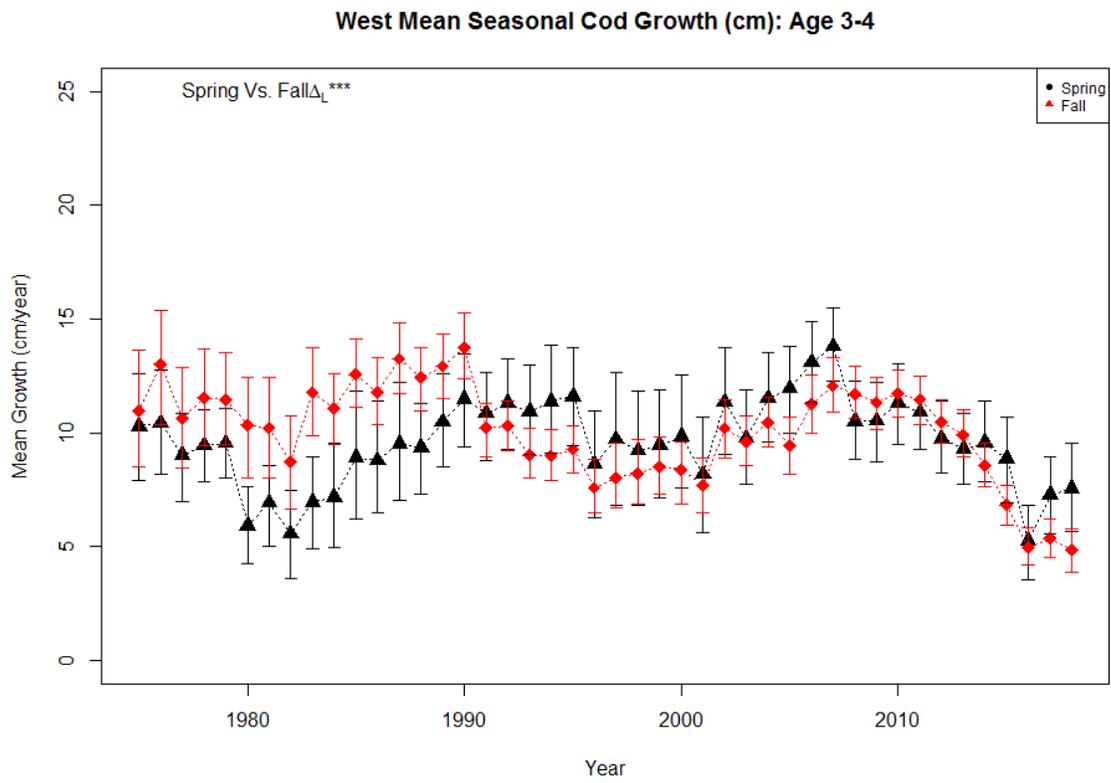


Figure IV-7: Mean change in cod length age 3-4 in western GOM from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

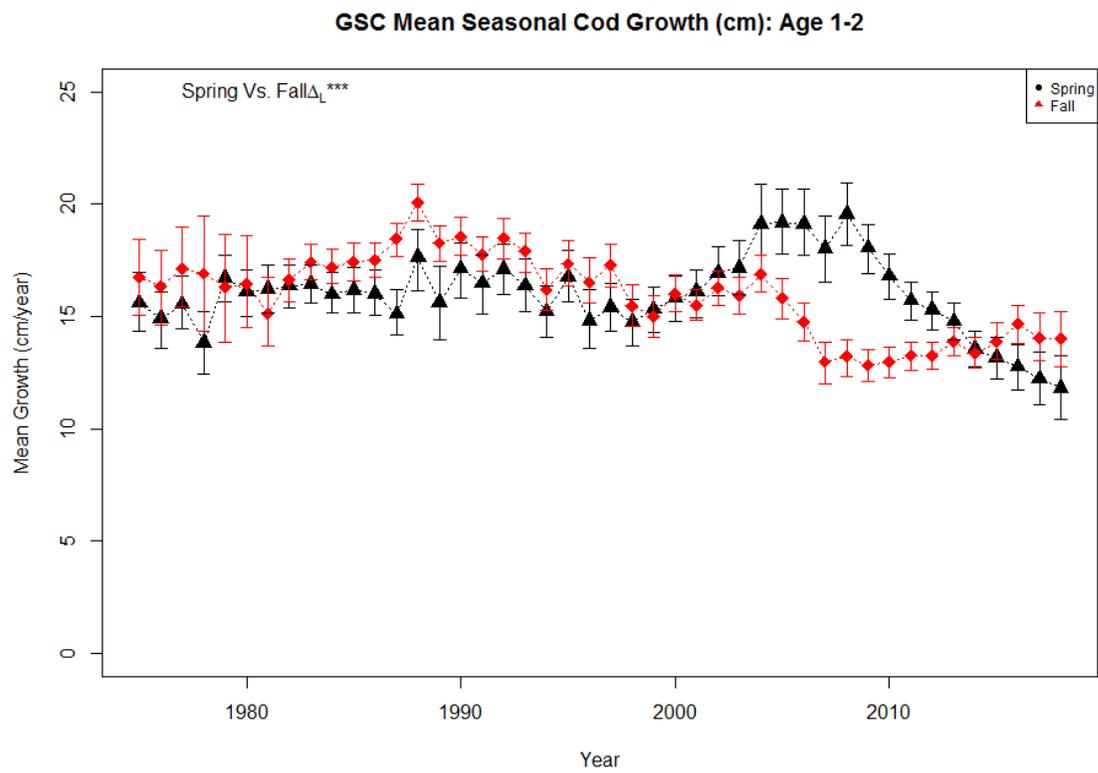


Figure IV-8: Mean change in cod length age 1-2 in Great South Channel from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

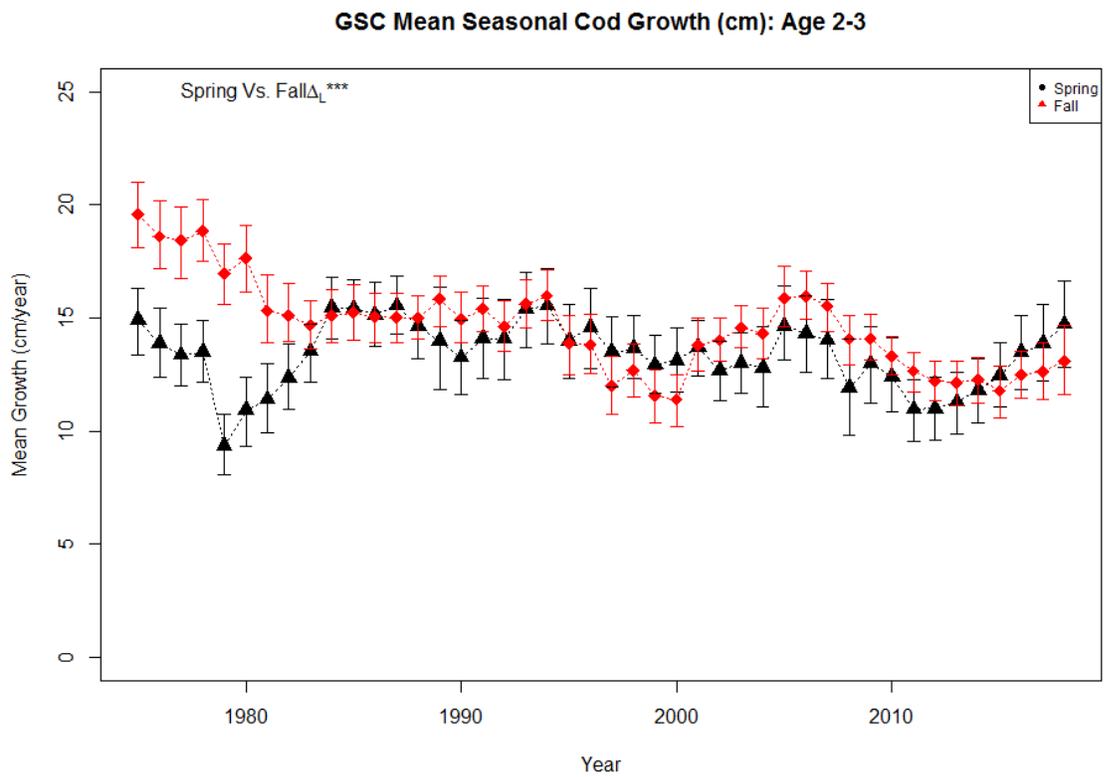


Figure IV-9: Mean change in cod length age 2-3 in Great South Channel from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

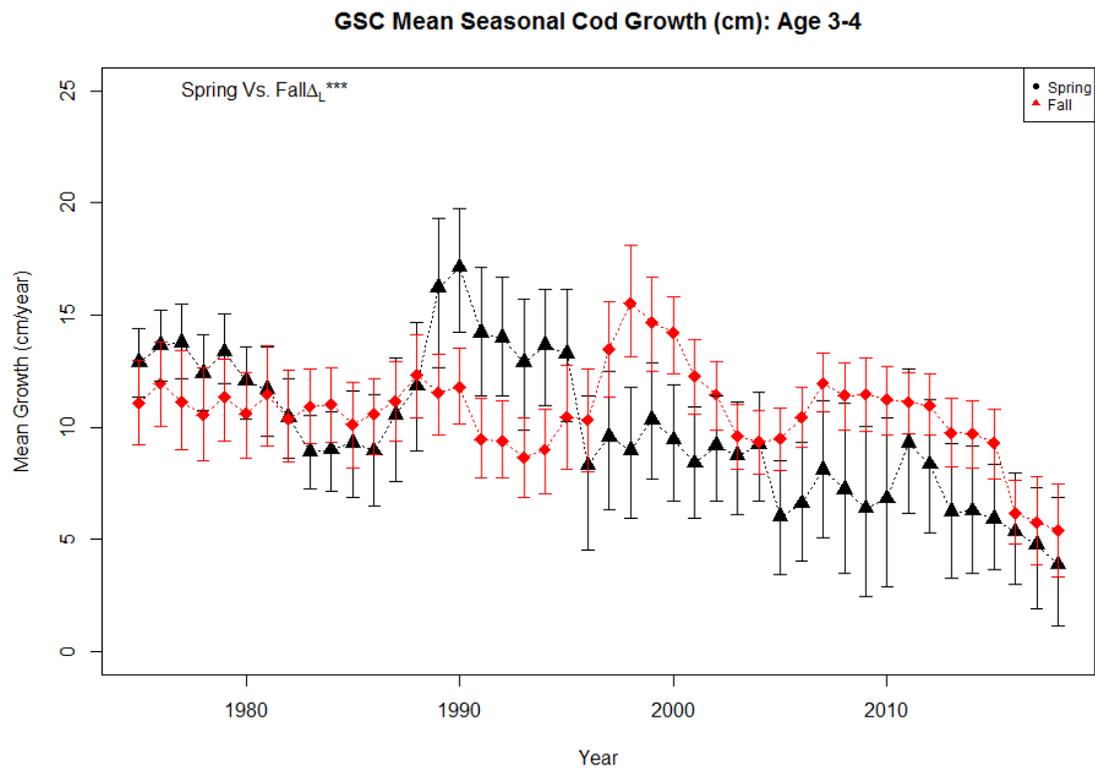


Figure IV-10: Mean change in cod length age 3-4 in Great South Channel from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

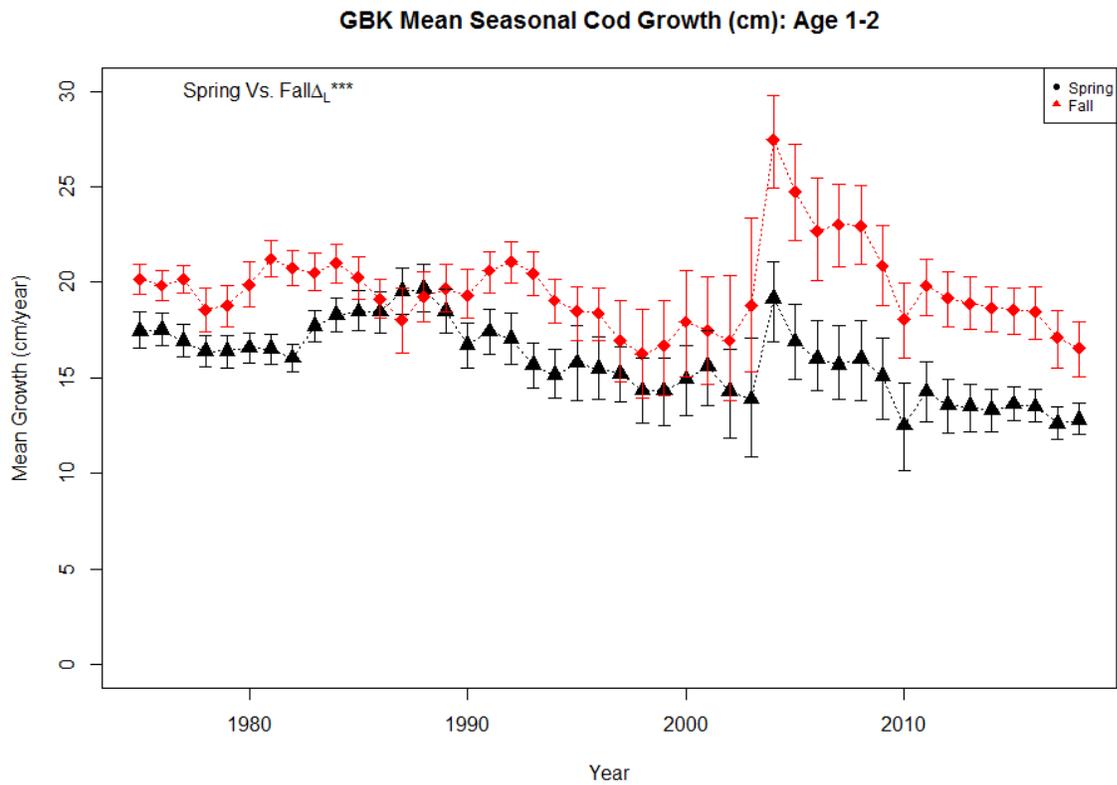


Figure IV-11: Mean change in cod length age 1-2 on George’s Bank from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

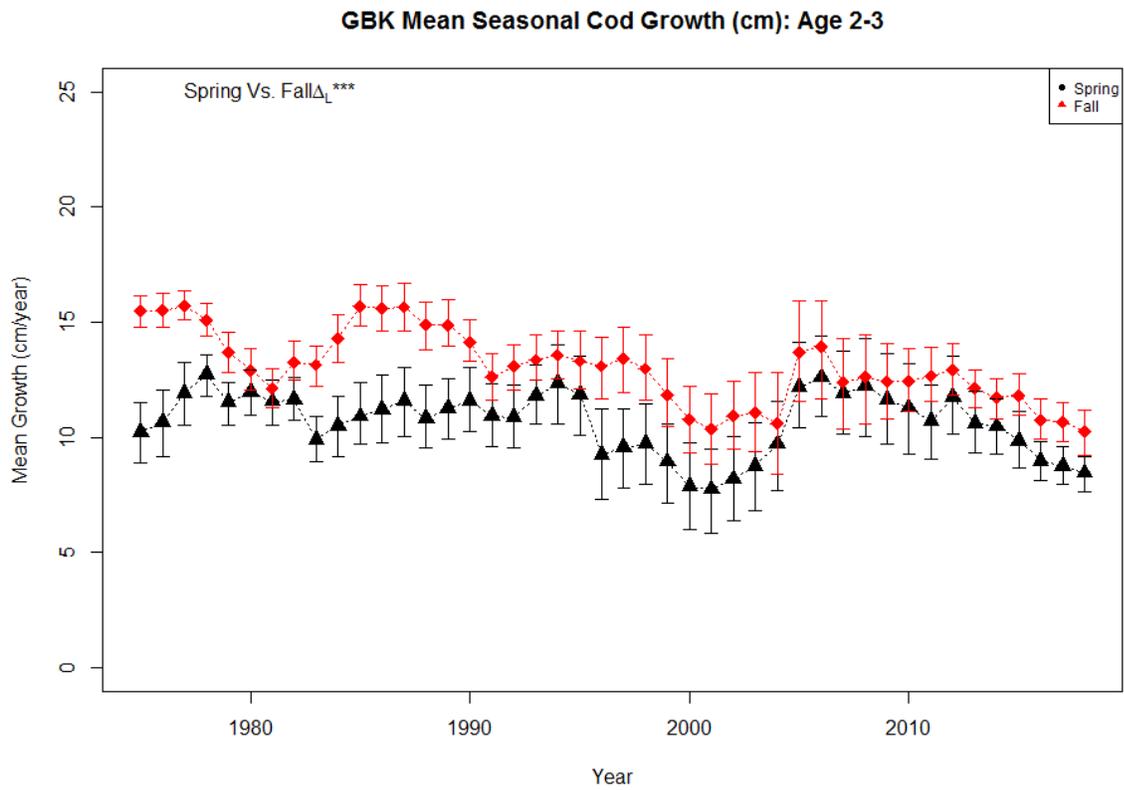


Figure IV-12: Mean change in cod length age 2-3 on George’s Bank from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

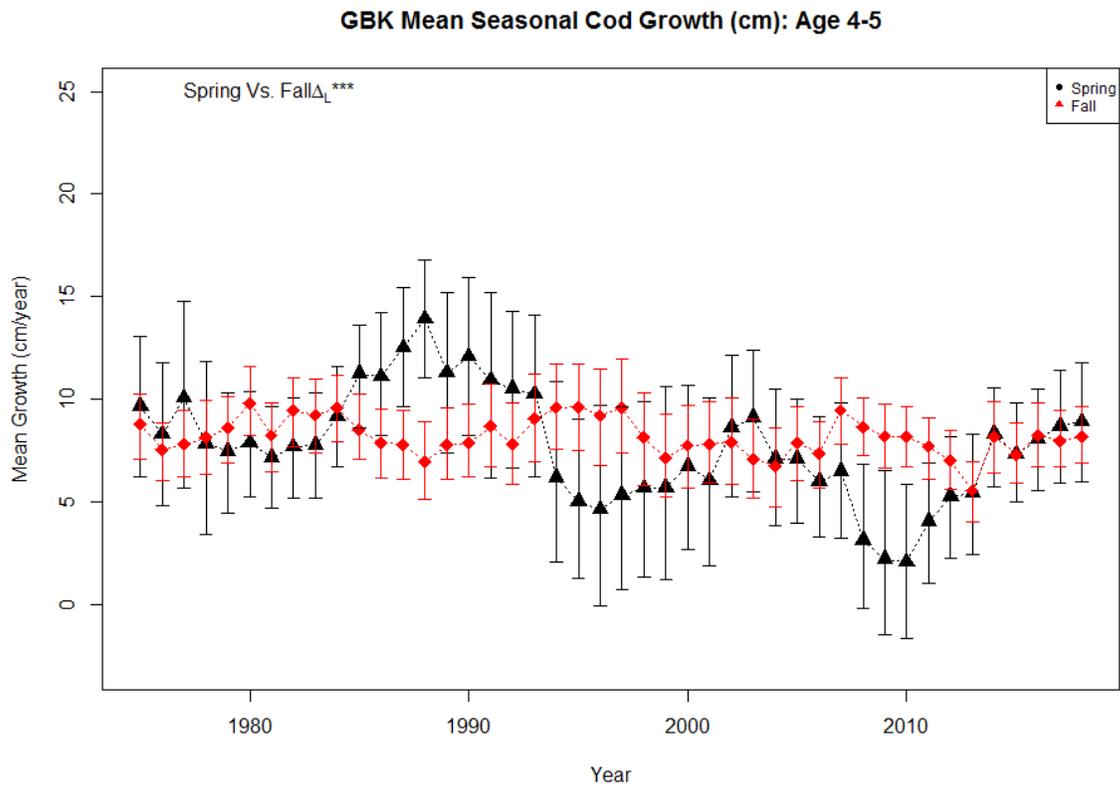


Figure IV-13: Mean change in cod length age 4-5 on George’s Bank from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

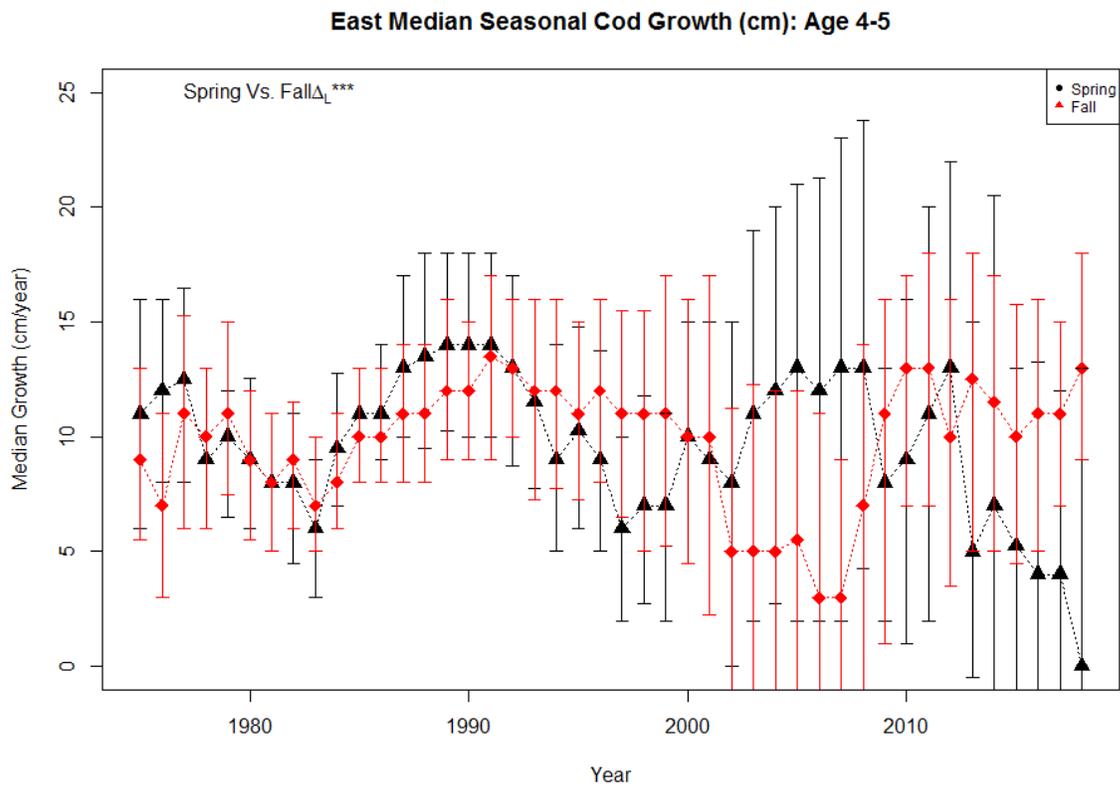


Figure IV-14: Median change in cod length age 4-5 in eastern GOM from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

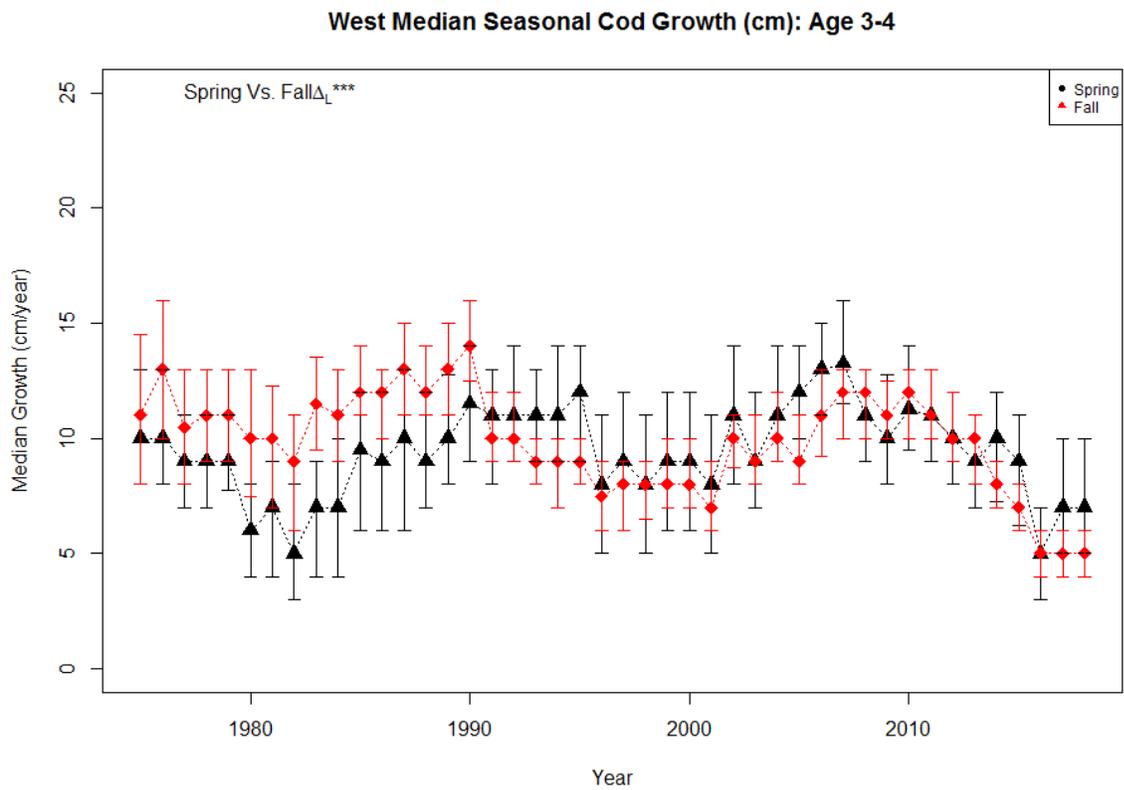


Figure IV-15: Median change in cod length age 3-4 in western GOM from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

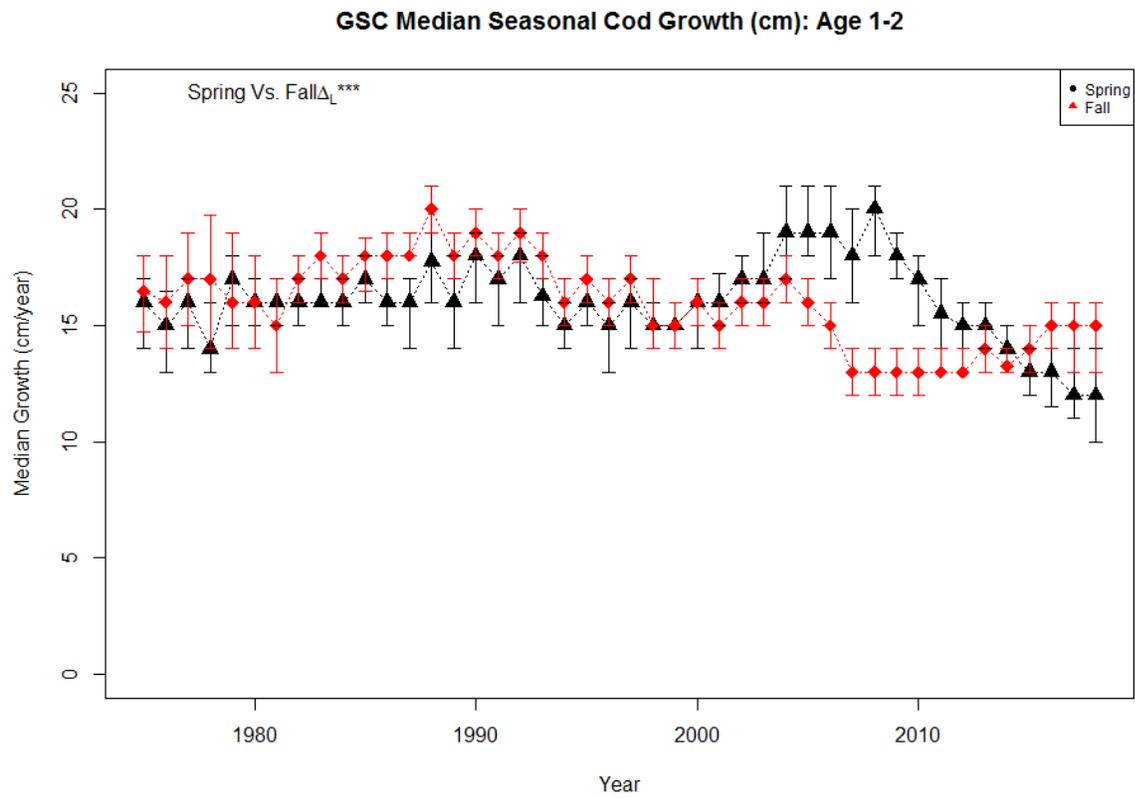


Figure IV-16: Median change in cod length age 1-2 in Great South Channel from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

GSC Median Seasonal Cod Growth (cm): Age 2-3

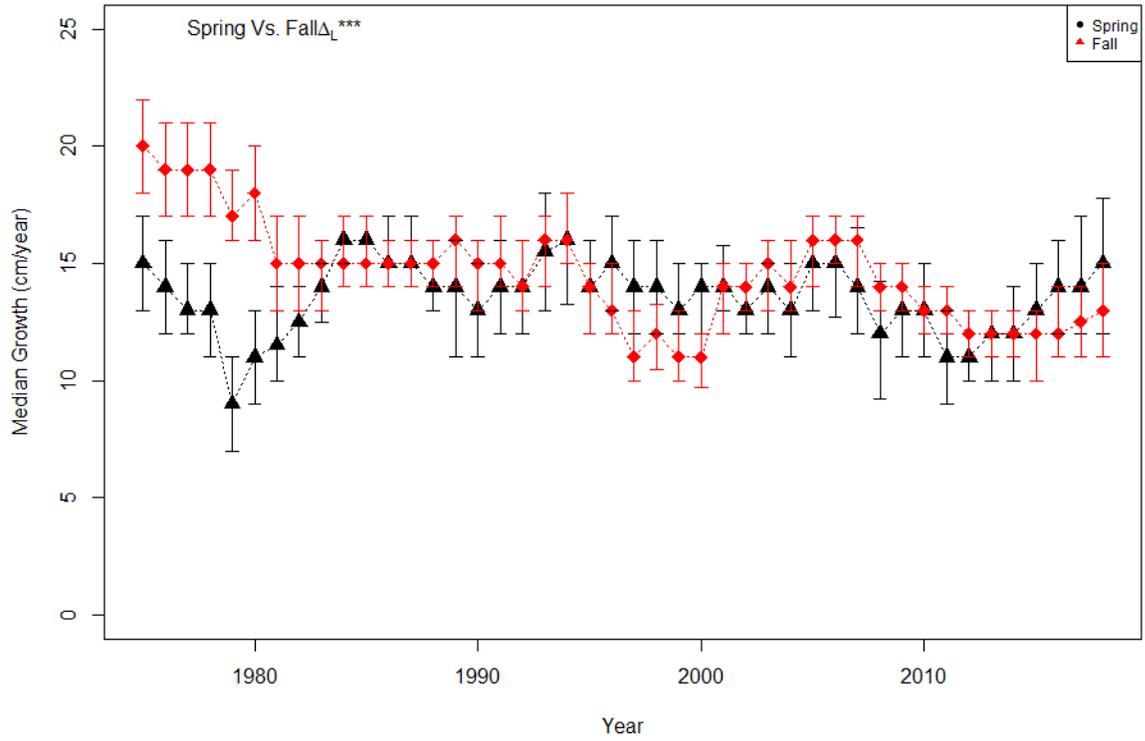


Figure IV-17: Median change in cod length age 2-3 in Great South Channel from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

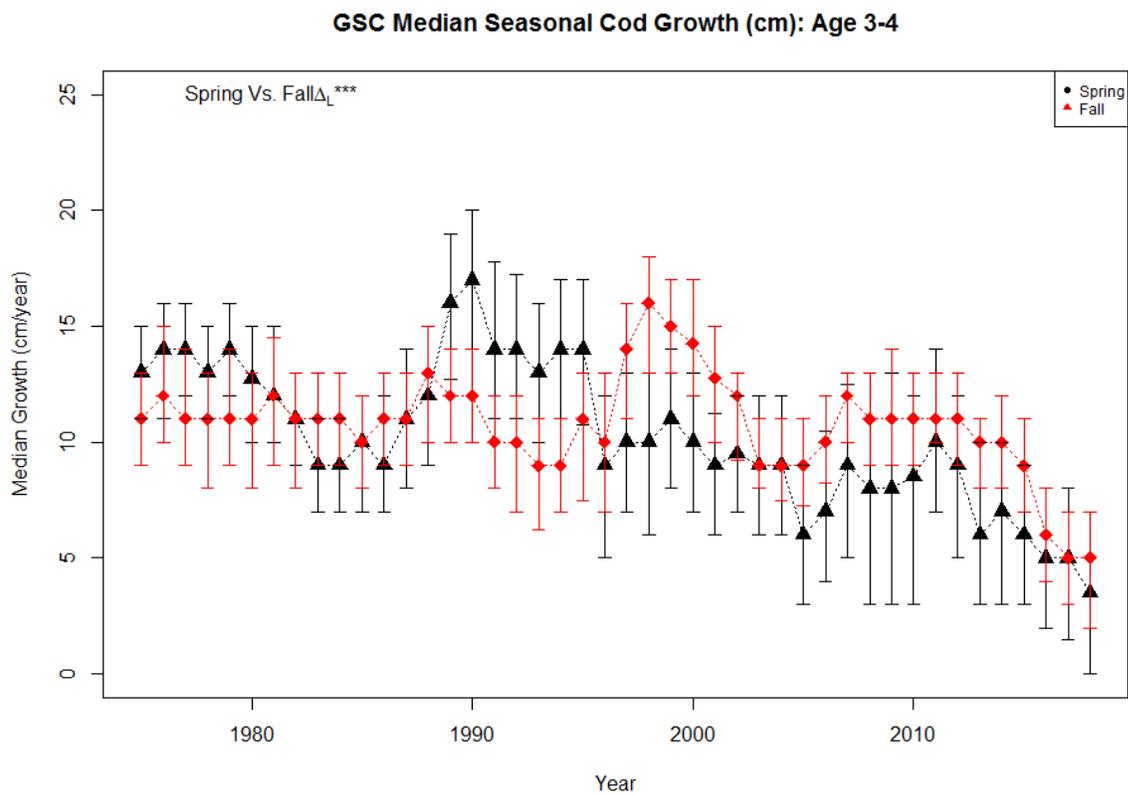


Figure IV-18: Median change in cod length age 3-4 in Great South Channel from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

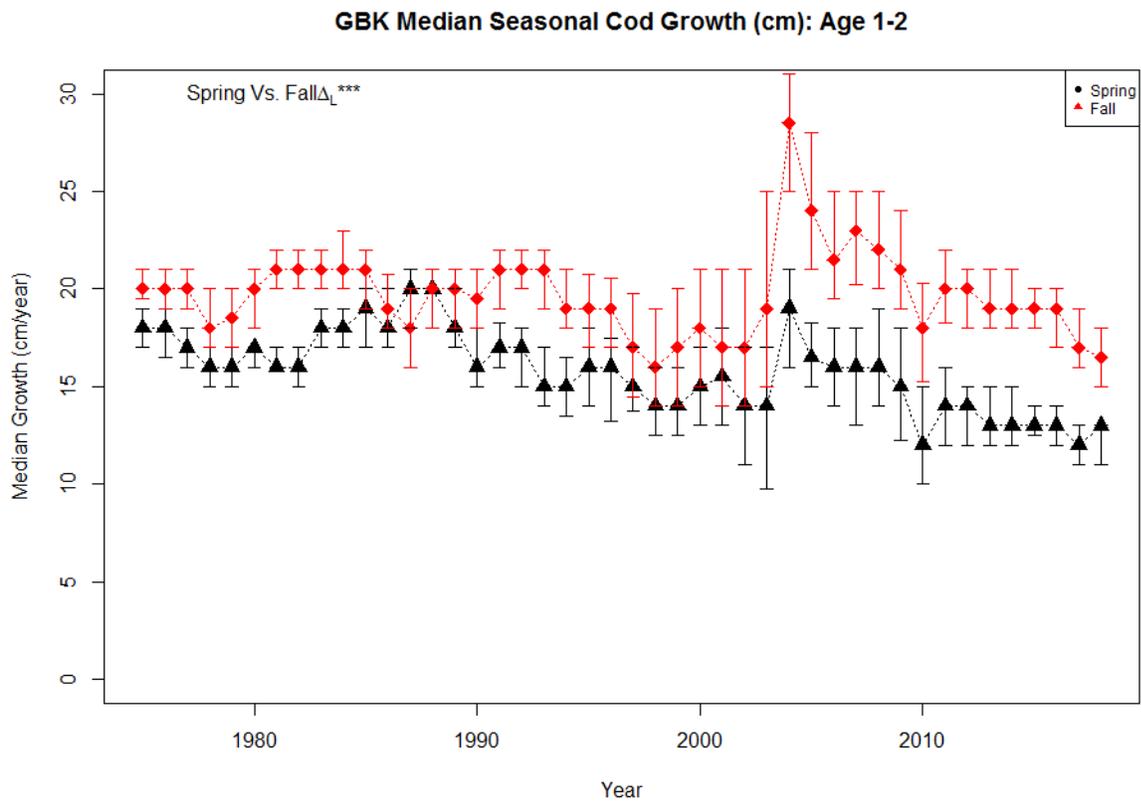


Figure IV-19: Median change in cod length age 1-2 on George’s Bank from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

GBK Median Seasonal Cod Growth (cm): Age 2-3

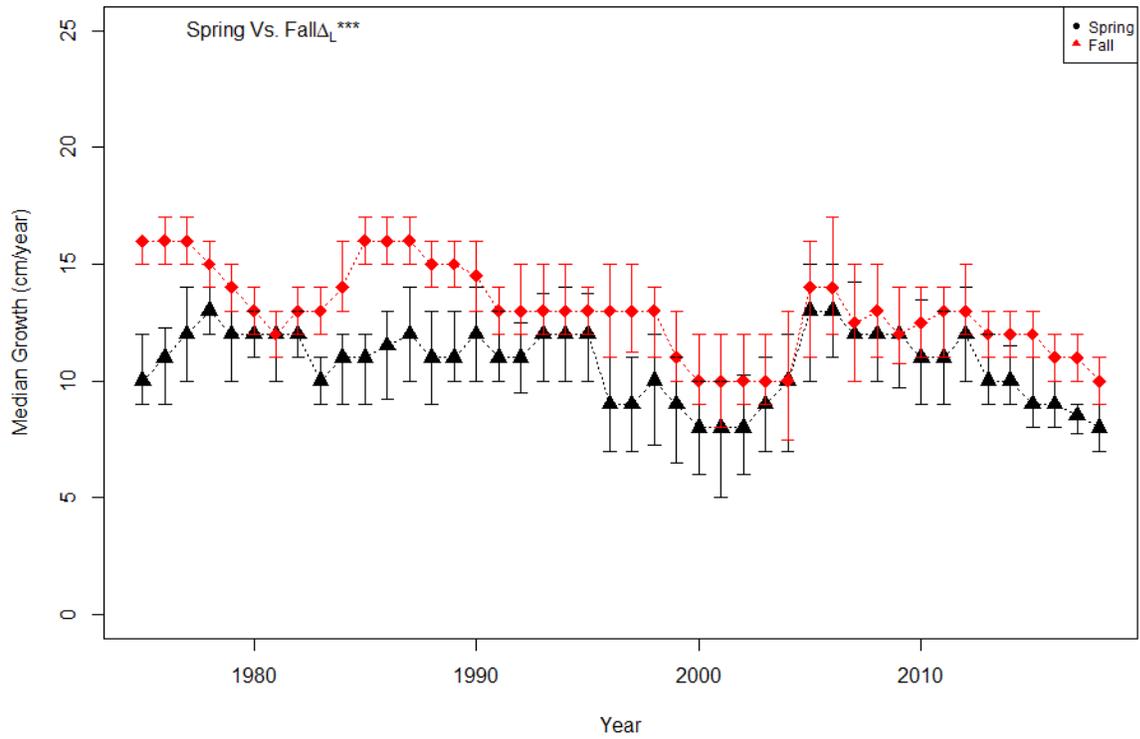


Figure IV-20: Median change in cod length age 2-3 on George's Bank from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

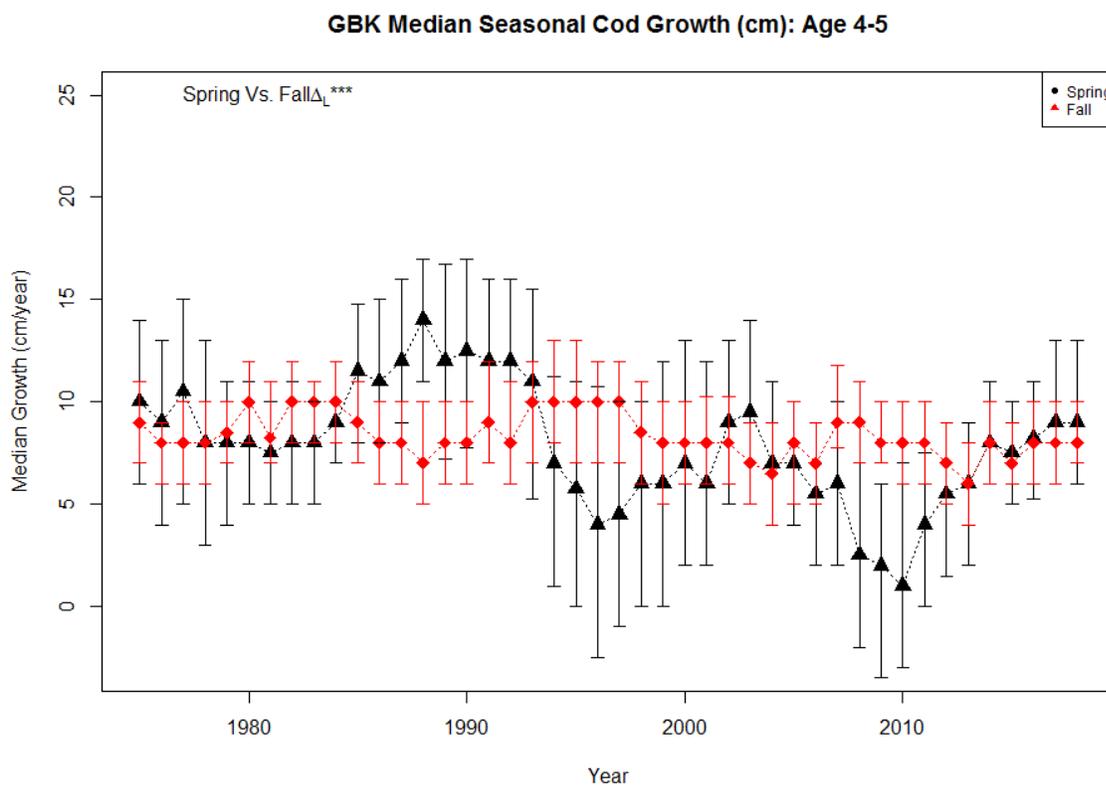


Figure IV-21: Median change in cod length age 4-5 on George’s Bank from 1970-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

Results of the weight analysis show a significant seasonal difference in weight. Similar to the length analysis, the Eastern sub-stock showed seasonal differences in mean and median weight at age 4 to 5 (Figures IV-22 and 28). Significant differences were observed between spring and fall in the Western sub-stock for mean weight at age 2 to 3 as well as mean and median weight at age 4 to 5 (Figures IV-23, 24, and 29). The only significant seasonality difference for cod in Great South Channel is for median weight at age 1 to 2 (Figure IV-30). Unlike the other sub-stocks, mean and median results did not agree for cod on George’s Bank. For cod on George’s Bank, significant seasonal differences were observed in mean weight at

ages 1 to 2, 2 to 3, and 4 to 5 while the only difference in median weight was for age 3 to 4 (Figures IV-25, 26, 27, and 31). These weight at age results represent a time series of 1992 to 2018.

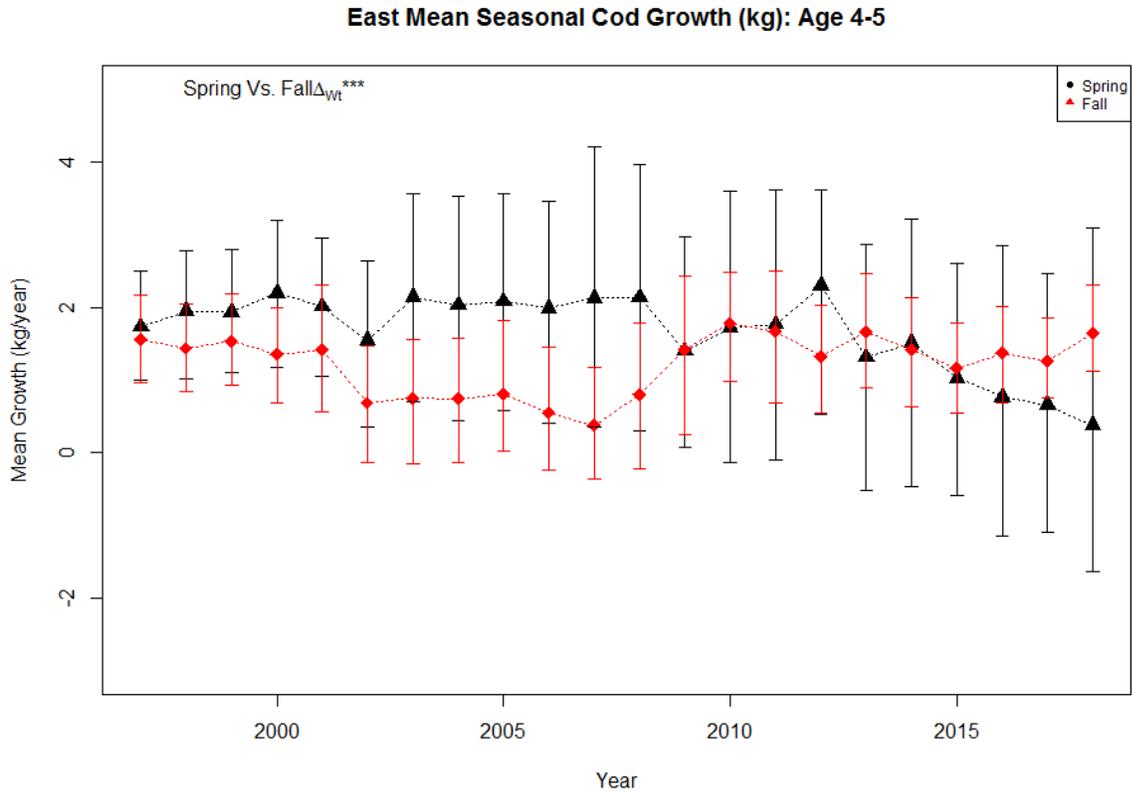


Figure IV-22: Mean change in cod weight age 4-5 in eastern GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

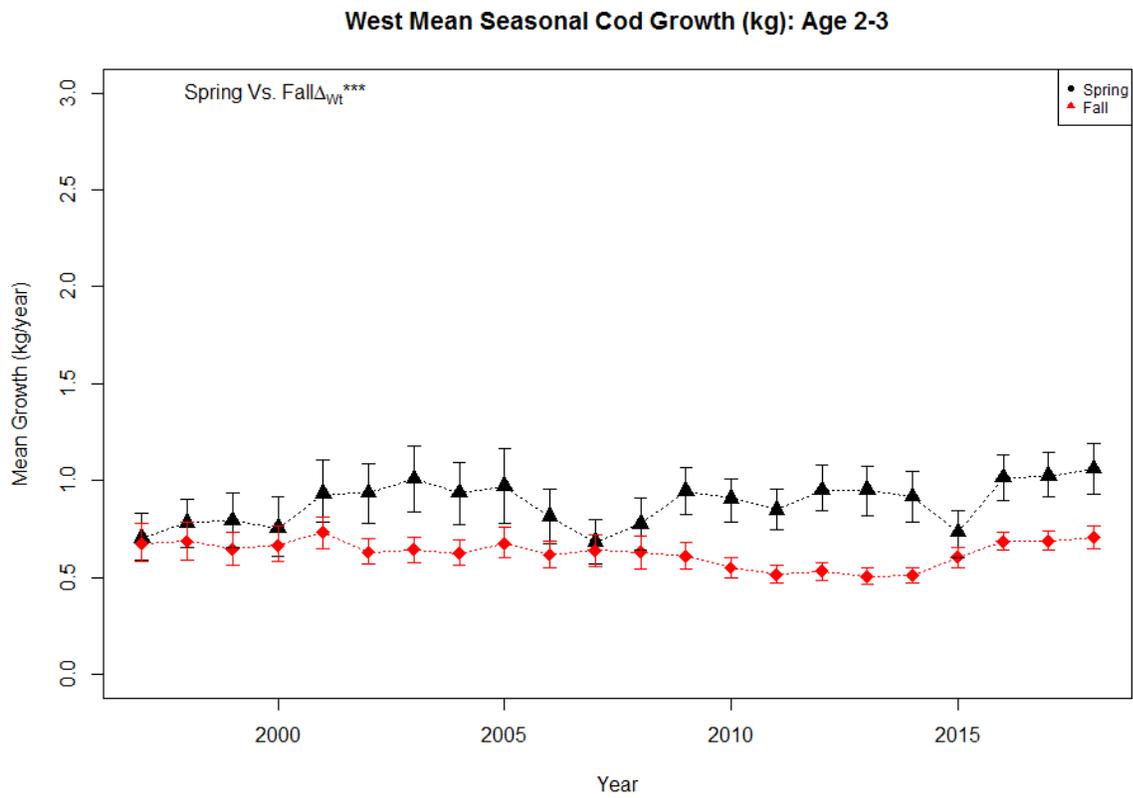


Figure IV-23: Mean change in cod weight age 2-3 in western GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

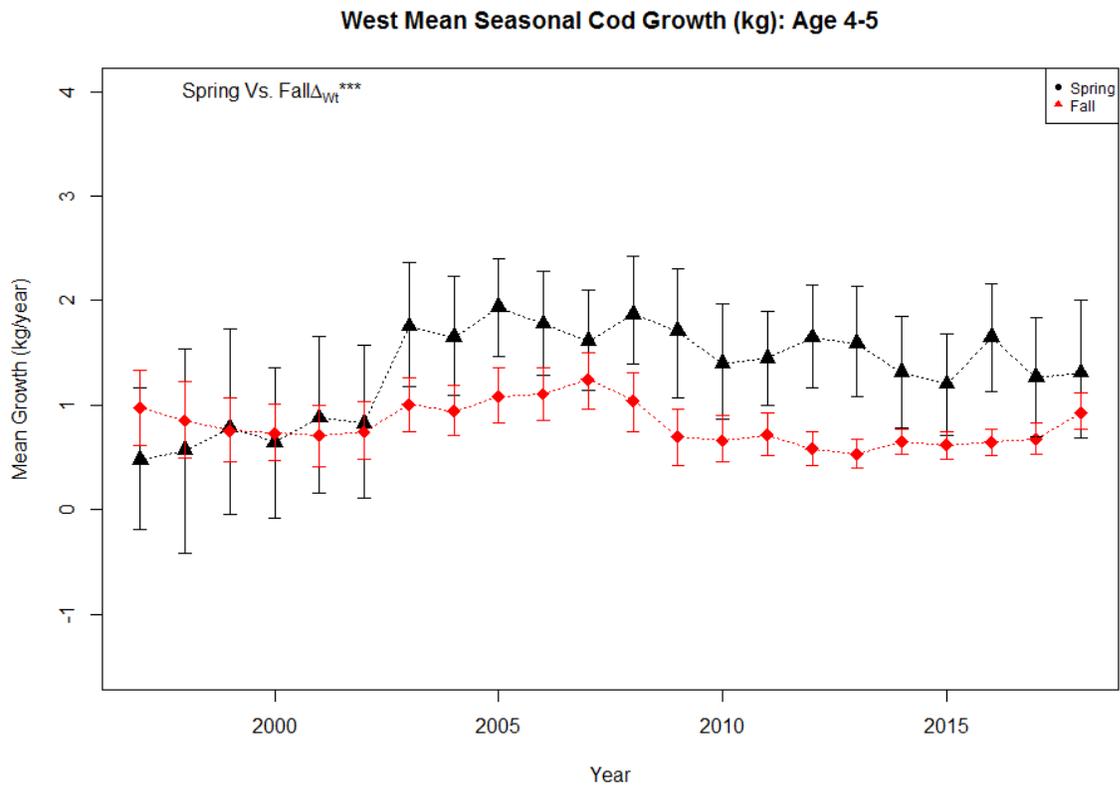


Figure IV-24: Mean change in cod weight age 4-5 in western GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

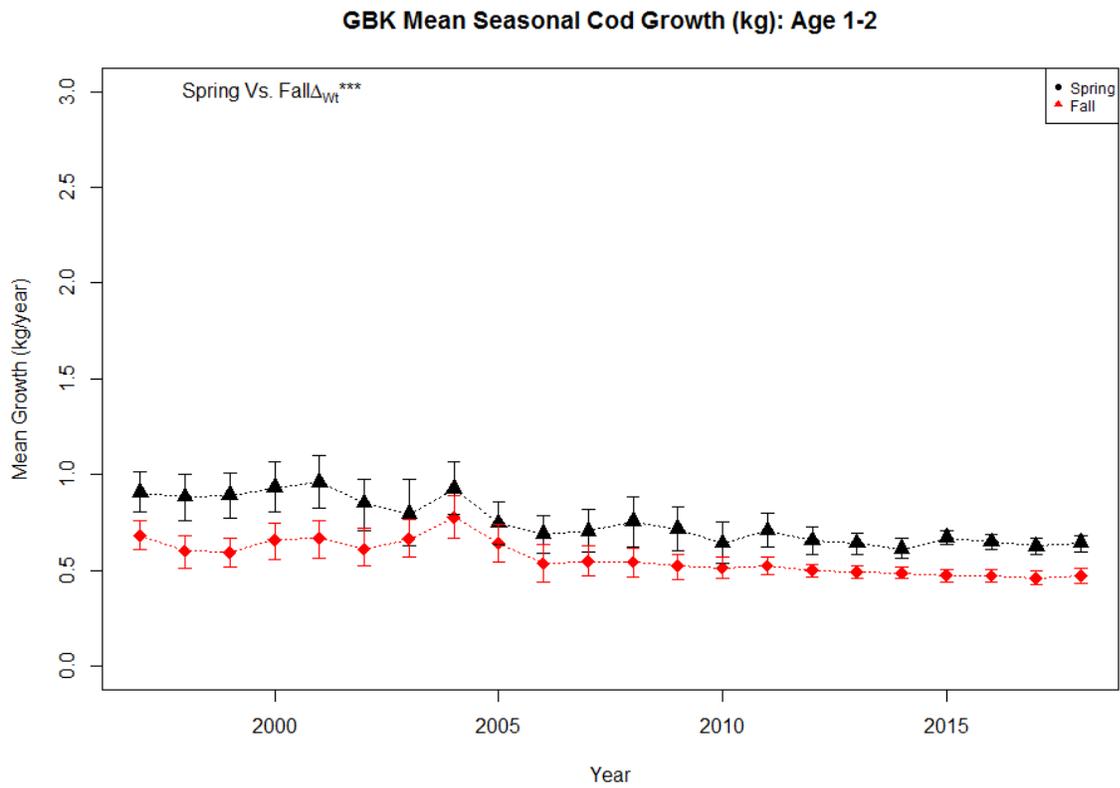


Figure IV-25: Mean change in cod weight age 1-2 on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

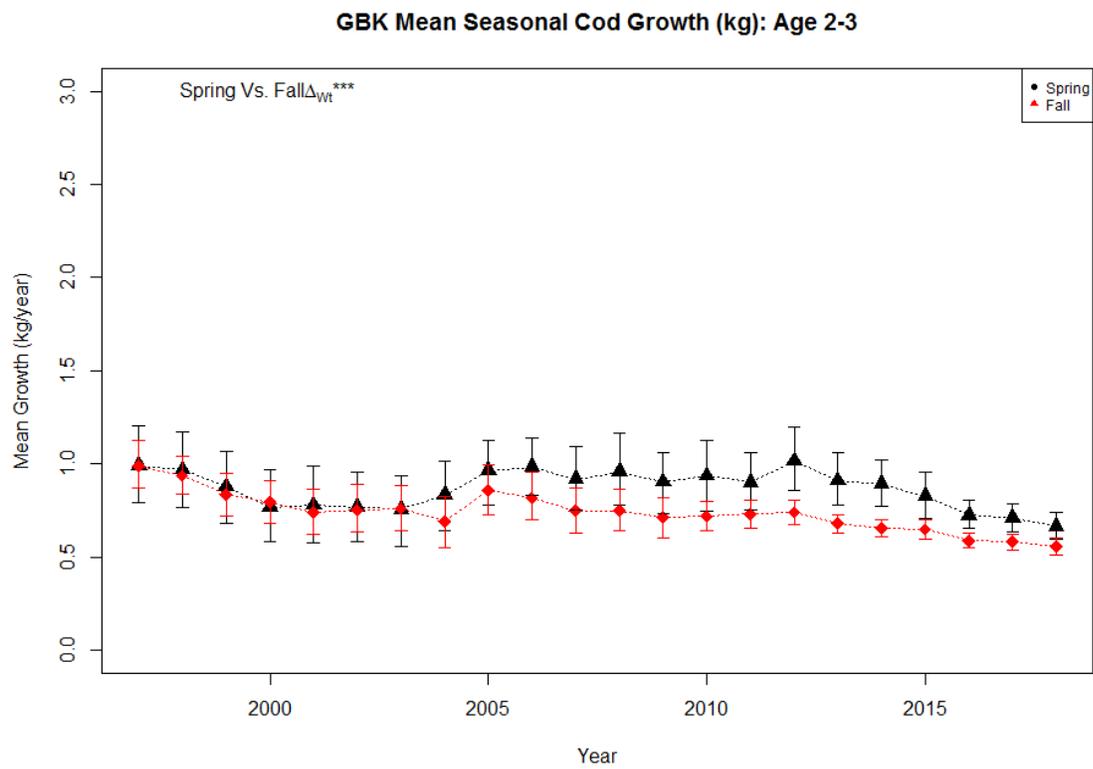


Figure IV-26: Mean change in cod weight age 2-3 on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

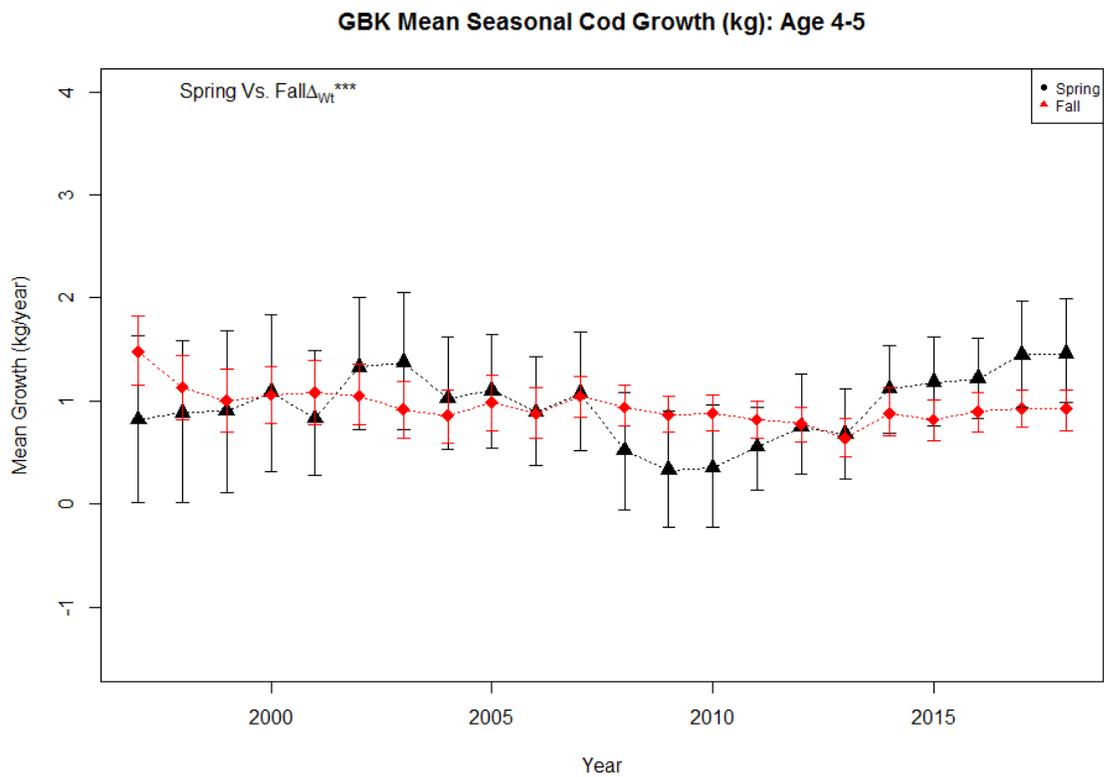


Figure IV-27: Mean change in cod weight age 4-5 cod weight on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

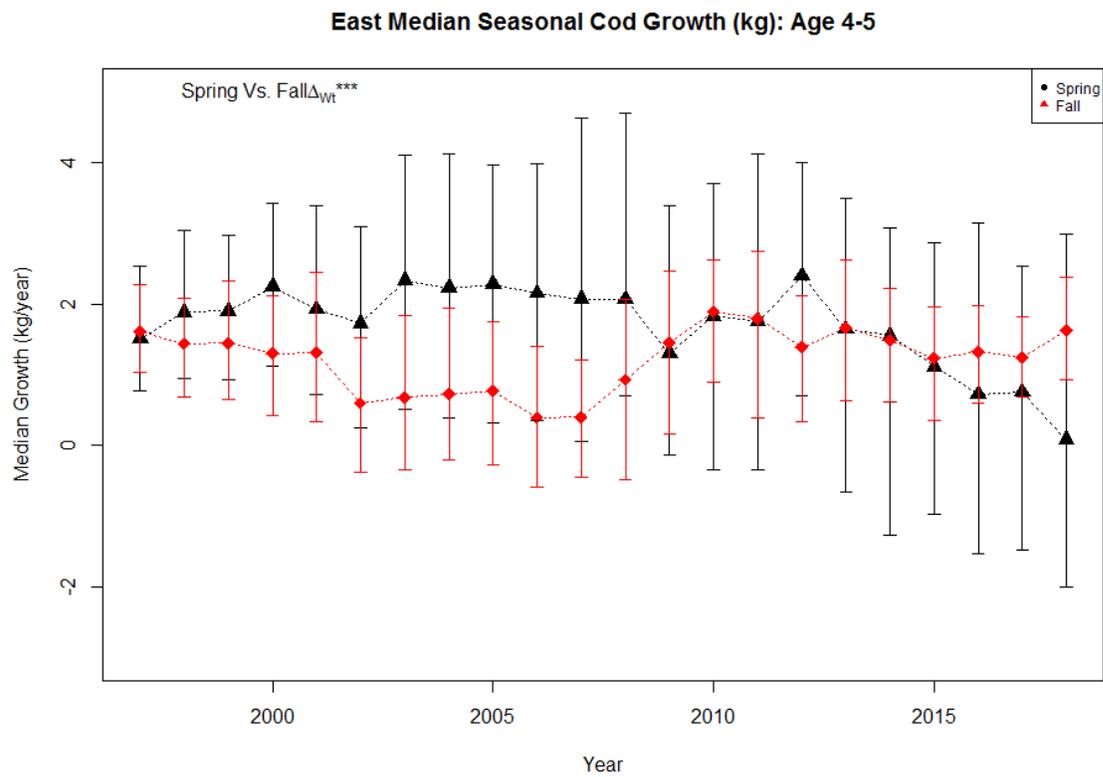


Figure IV-28: Median change in cod weight age 4-5 in eastern GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

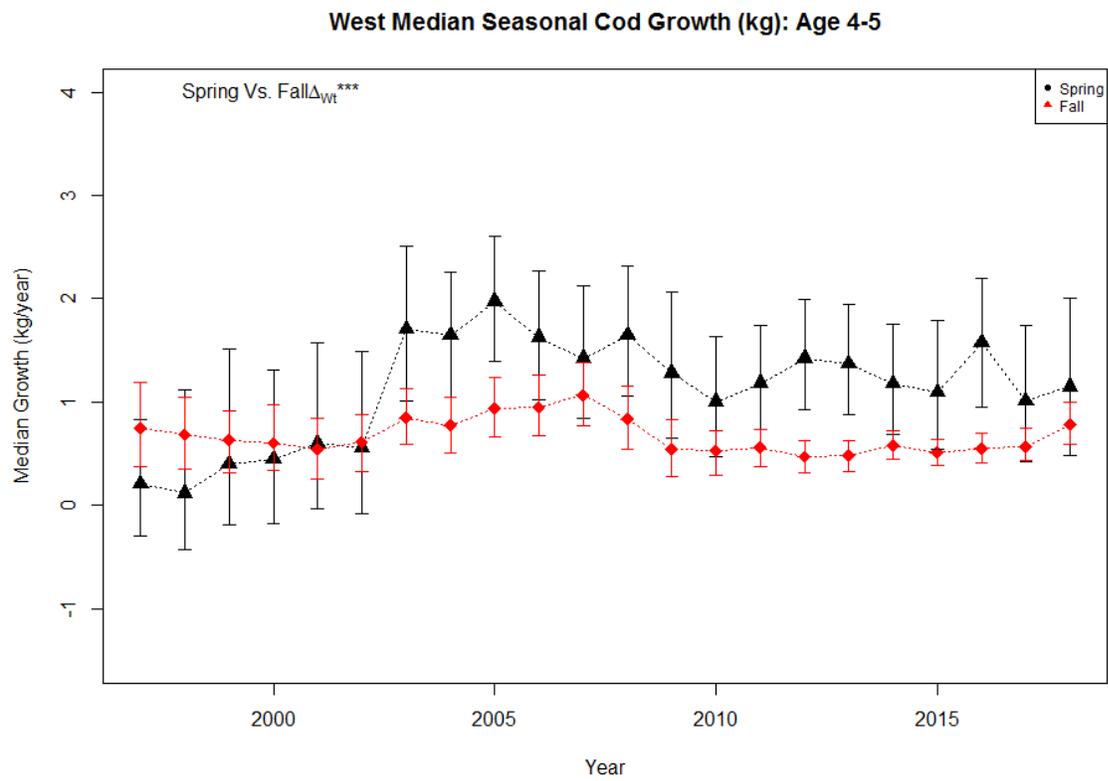


Figure IV-29: Median change in cod weight age 4-5 in western GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

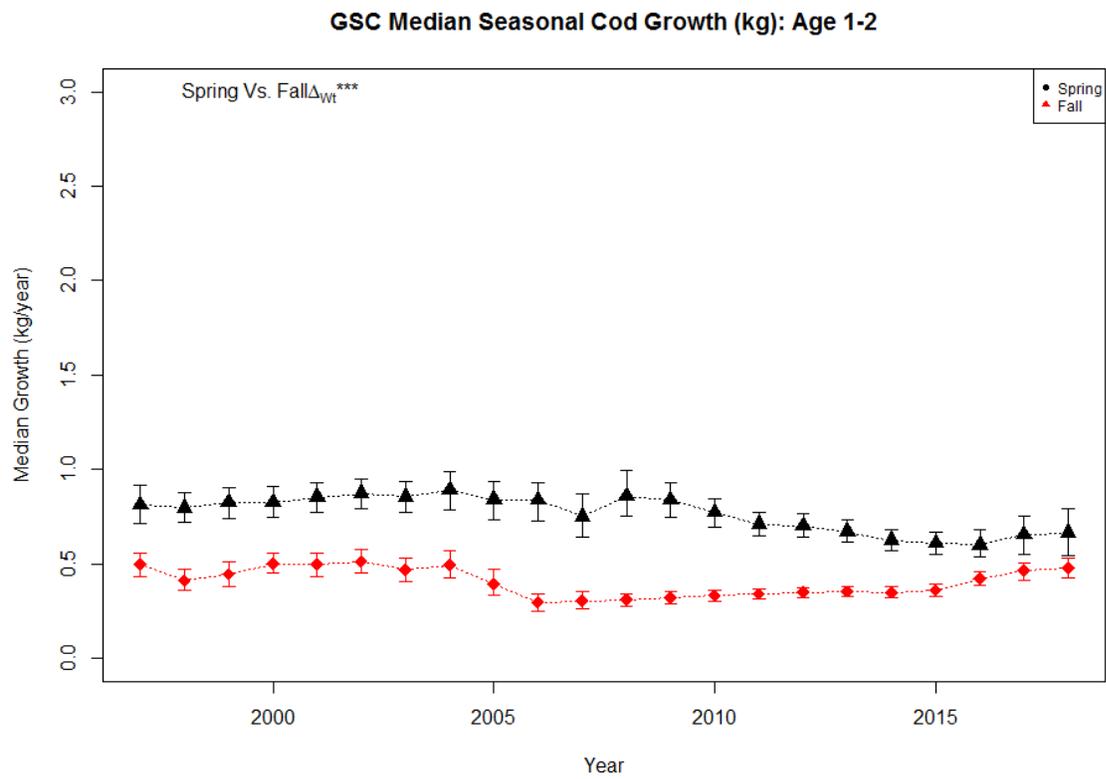


Figure IV-30: Median change in cod weight age 1-2 in Great South Channel from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

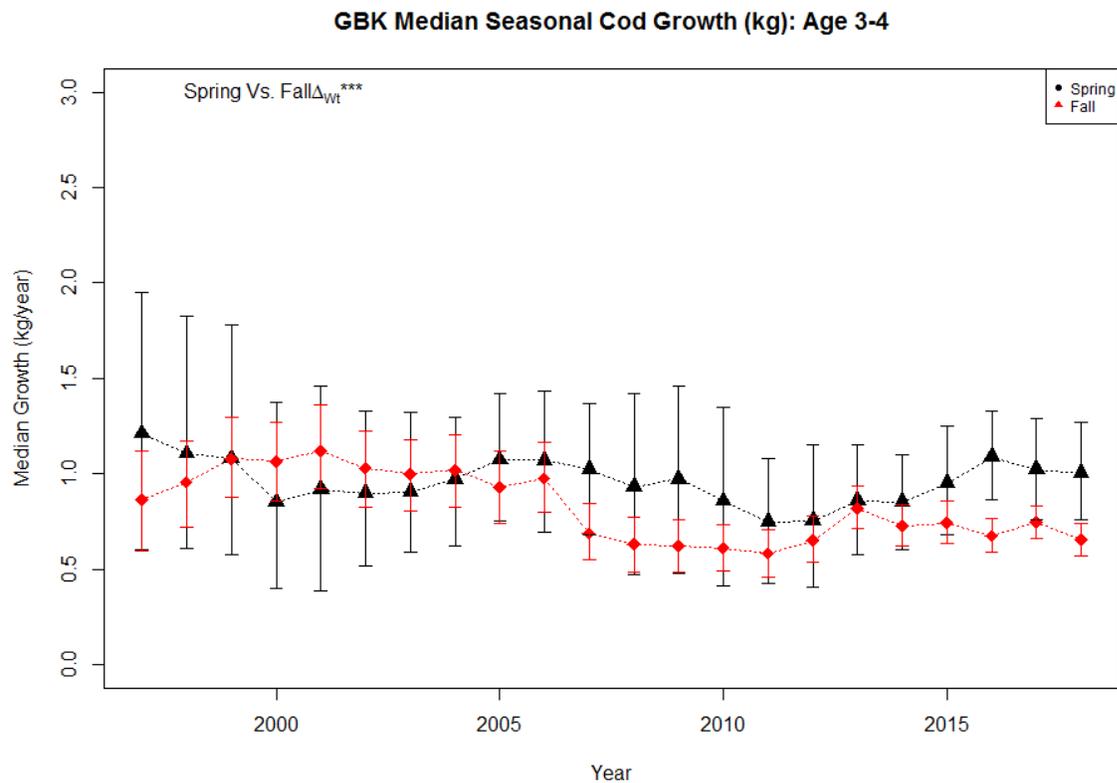


Figure IV-31: Median change in cod weight age 3-4 on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

As was the case with length and weight, the analysis of cod condition factor also shows significant differences between the spring and fall trends. Significant differences were observed in mean condition factor in the Eastern sub-stock for ages 1, 3, and 4 (Figures IV-32, 33, 34, and 41). In the East, spring and fall condition factor were also significantly different at age 3. In the West, statistical significance was observed between spring and fall condition factor of age 2 cod in addition to the median condition factor at age 5 (Figures IV-35, 42, and 43). Great South Channel has observed no statistically significant difference between spring and fall condition factor since 1992. On the contrary, spring and fall cod on George’s bank exhibit significantly different spring and fall trends in condition factor all ages included in the analysis (ages 1 to 5;

Figures IV-36:40 and Figures IV-44:48). These results represent a time series of NEFSC trawl data from 1992 to 2018.

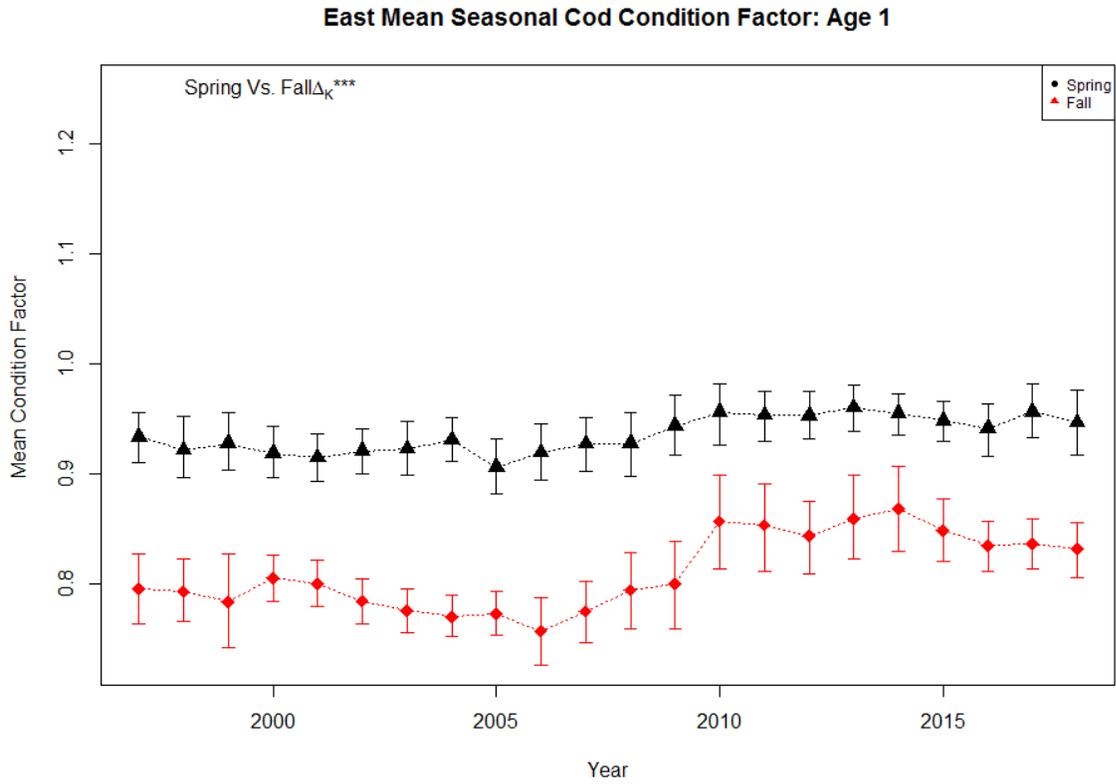


Figure IV-32: Age 1 mean cod condition factor in eastern GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

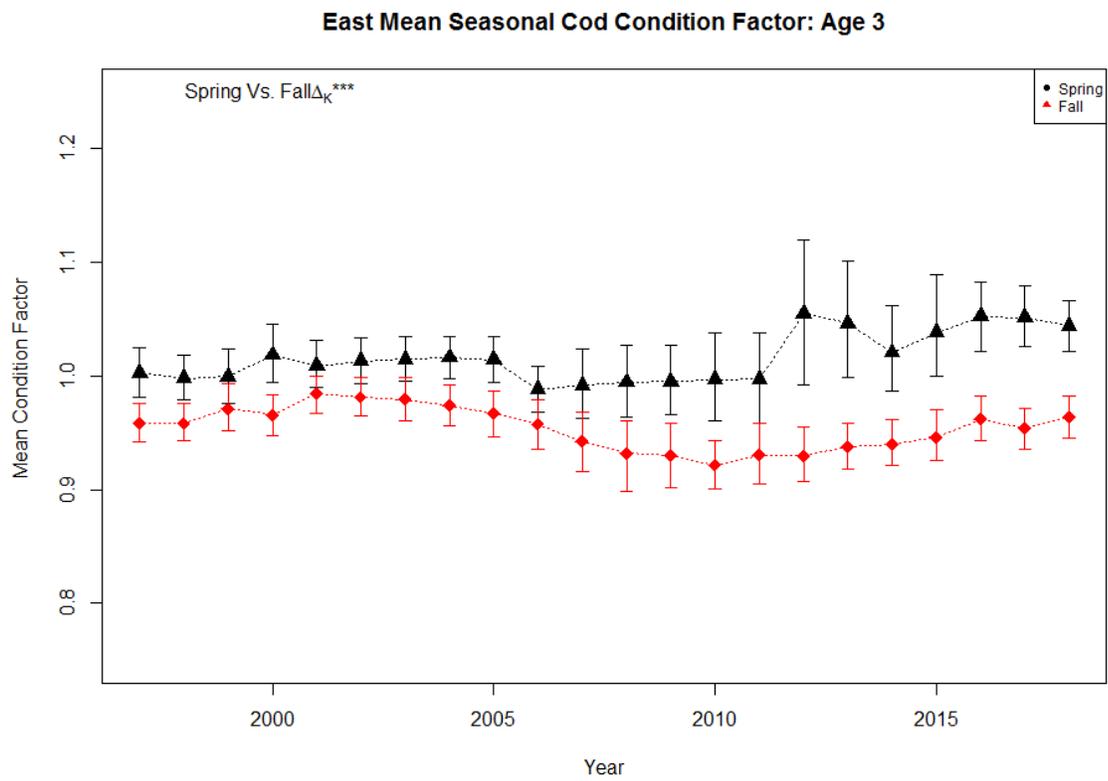


Figure IV-33: Age 3 mean cod condition factor in eastern GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

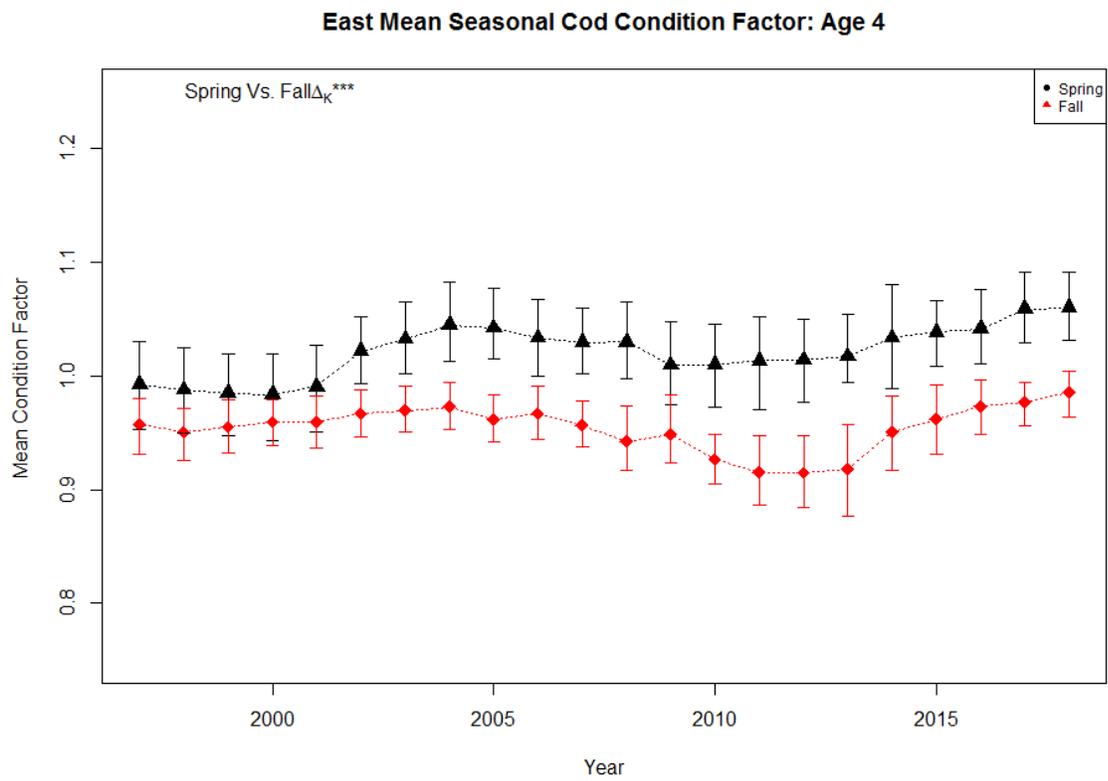


Figure IV-34: Age 4 mean cod condition factor in eastern GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

West Mean Seasonal Cod Condition Factor: Age 2

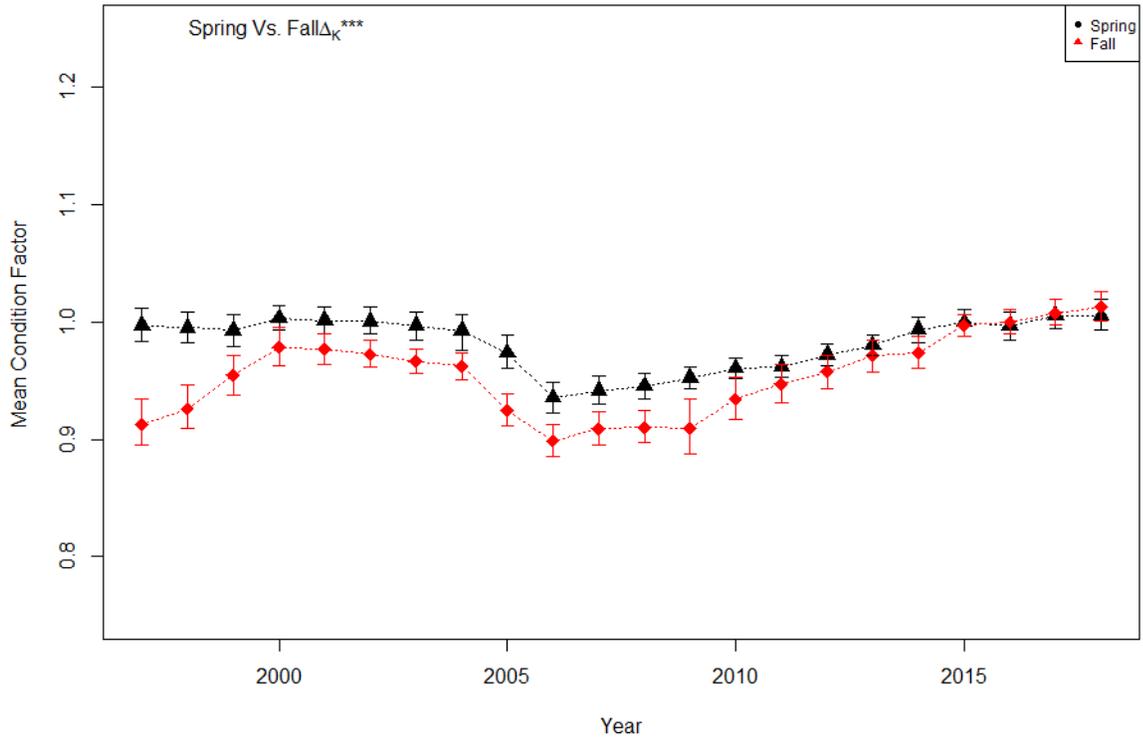


Figure IV-35: Age 2 mean cod condition factor in western GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

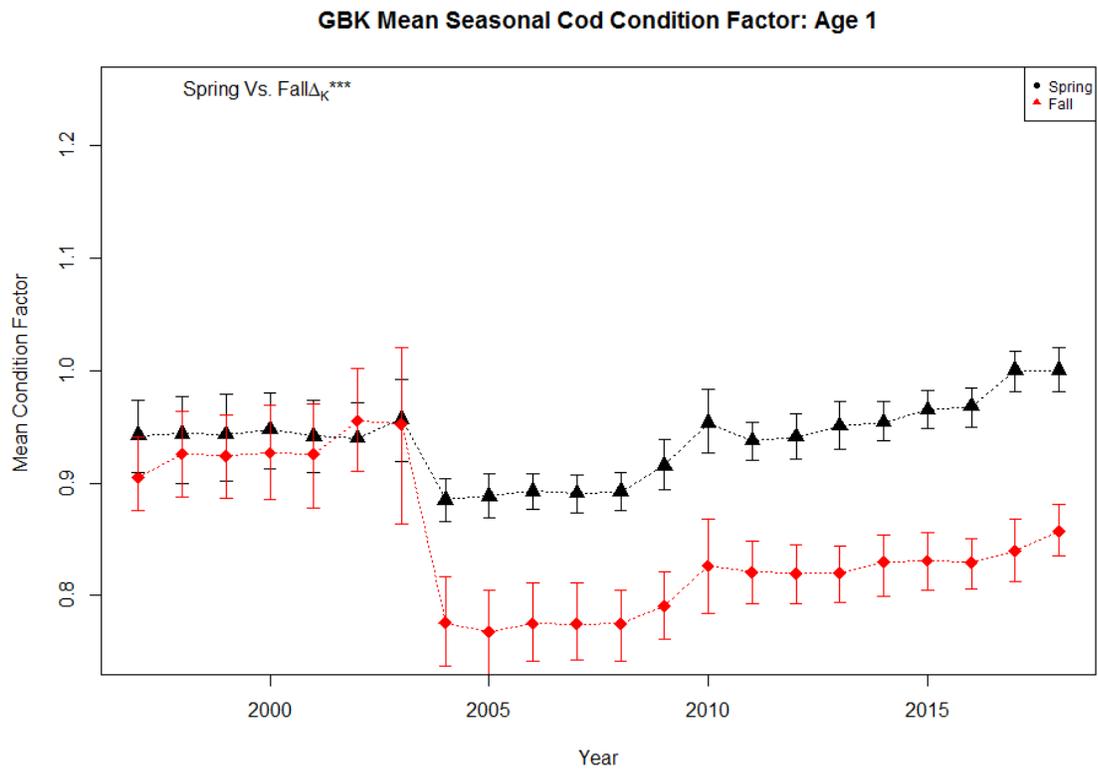


Figure IV-36: Age 1 mean cod condition factor on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

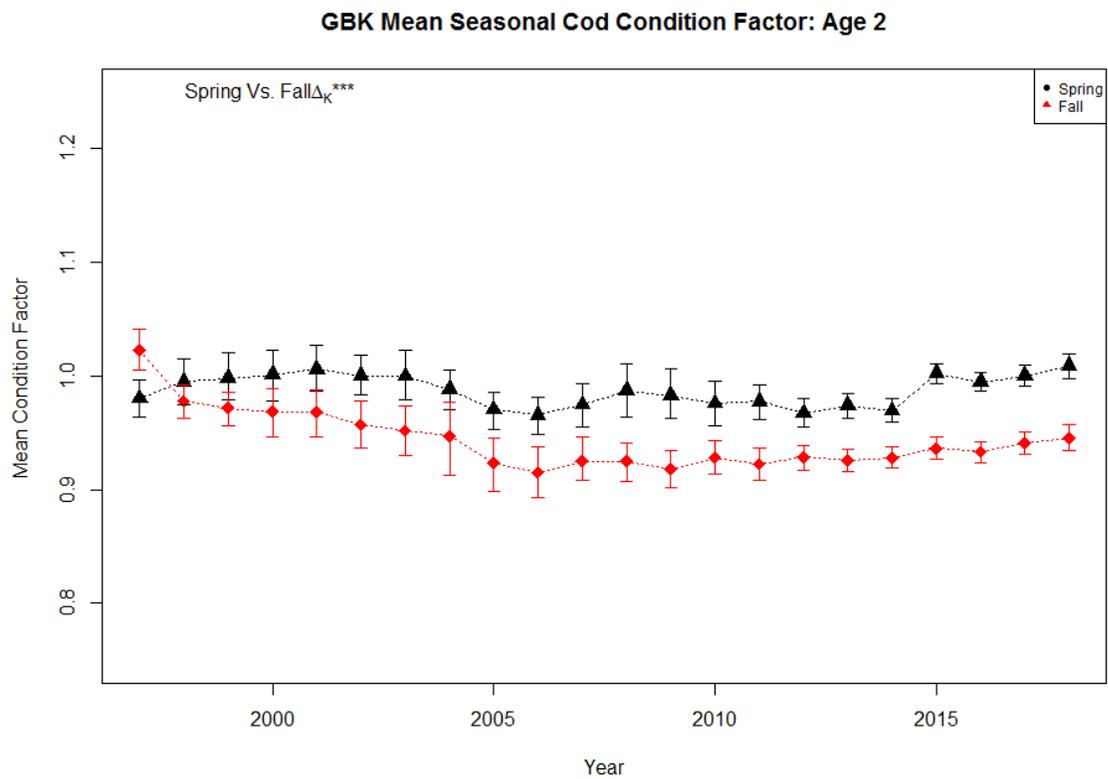


Figure IV-37: Age 2 mean cod condition factor on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

GBK Mean Seasonal Cod Condition Factor: Age 3

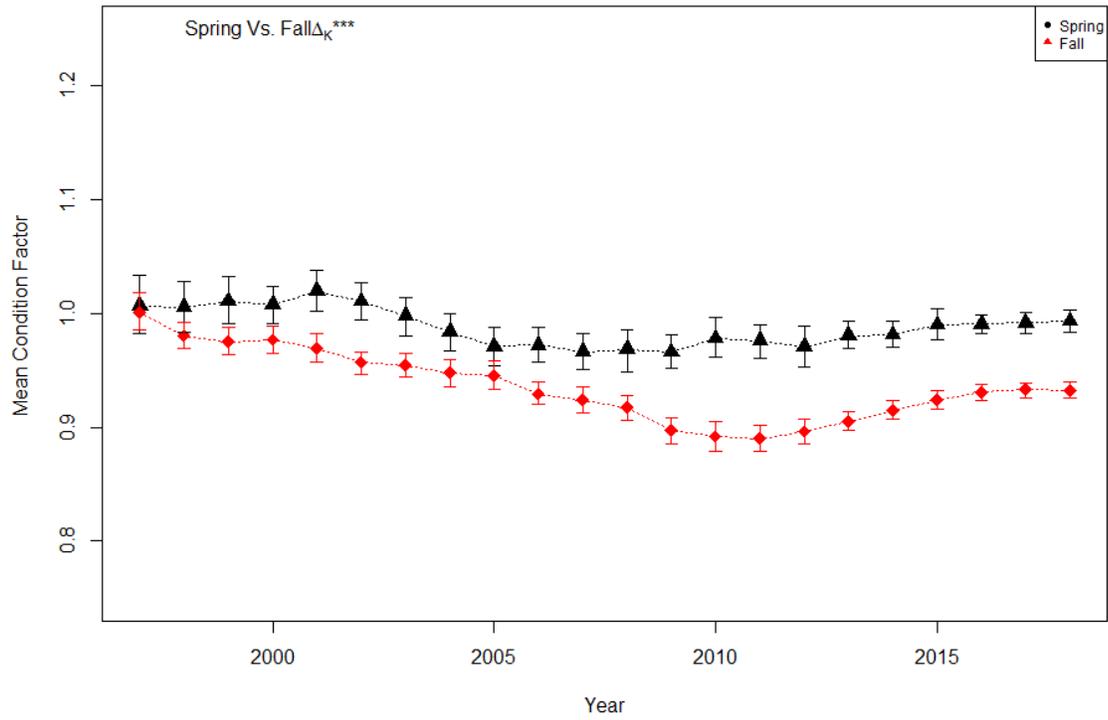


Figure IV-38: Age 3 mean cod condition factor on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

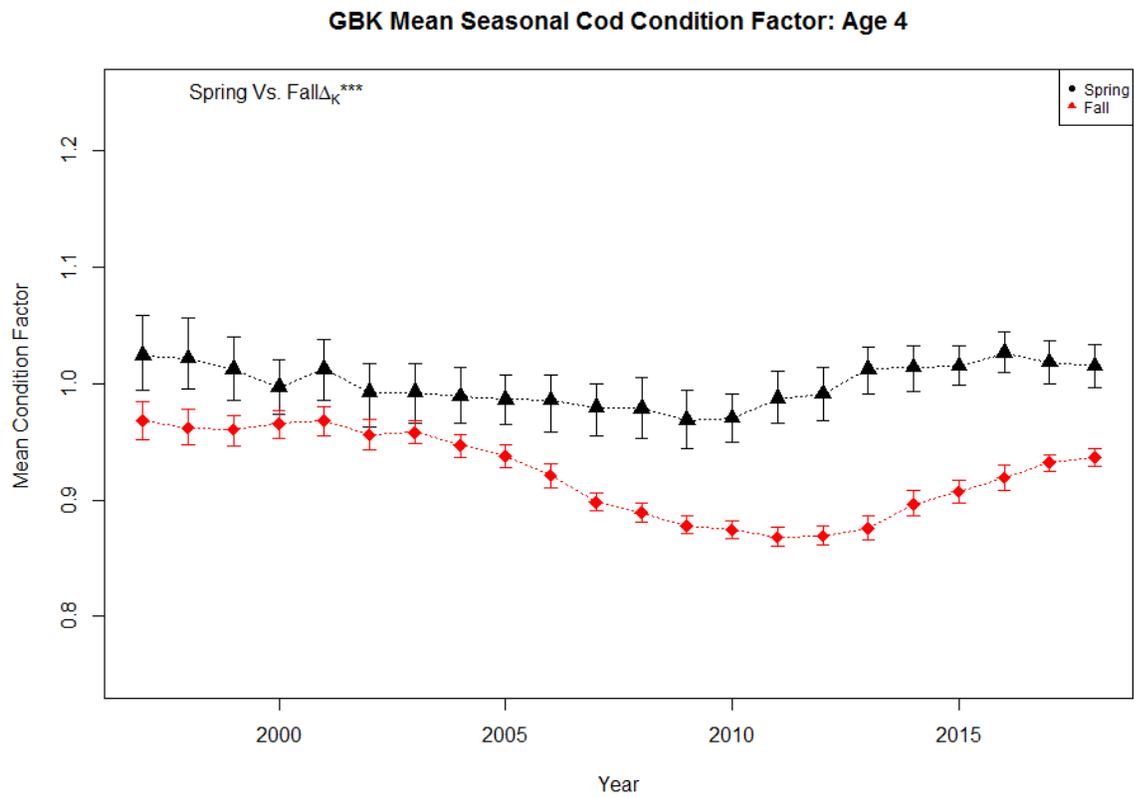


Figure IV-39: Age 5 mean cod condition factor on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

GBK Mean Seasonal Cod Condition Factor: Age 5

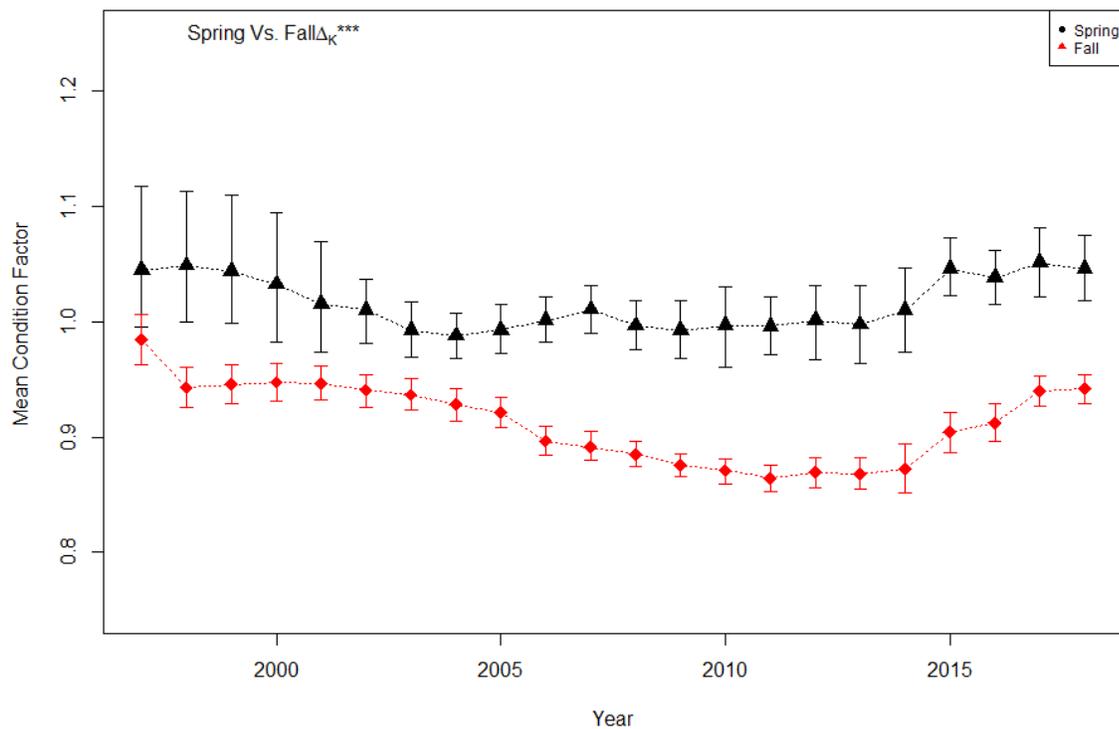


Figure IV-40: Age 5 mean cod condition factor on George's Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

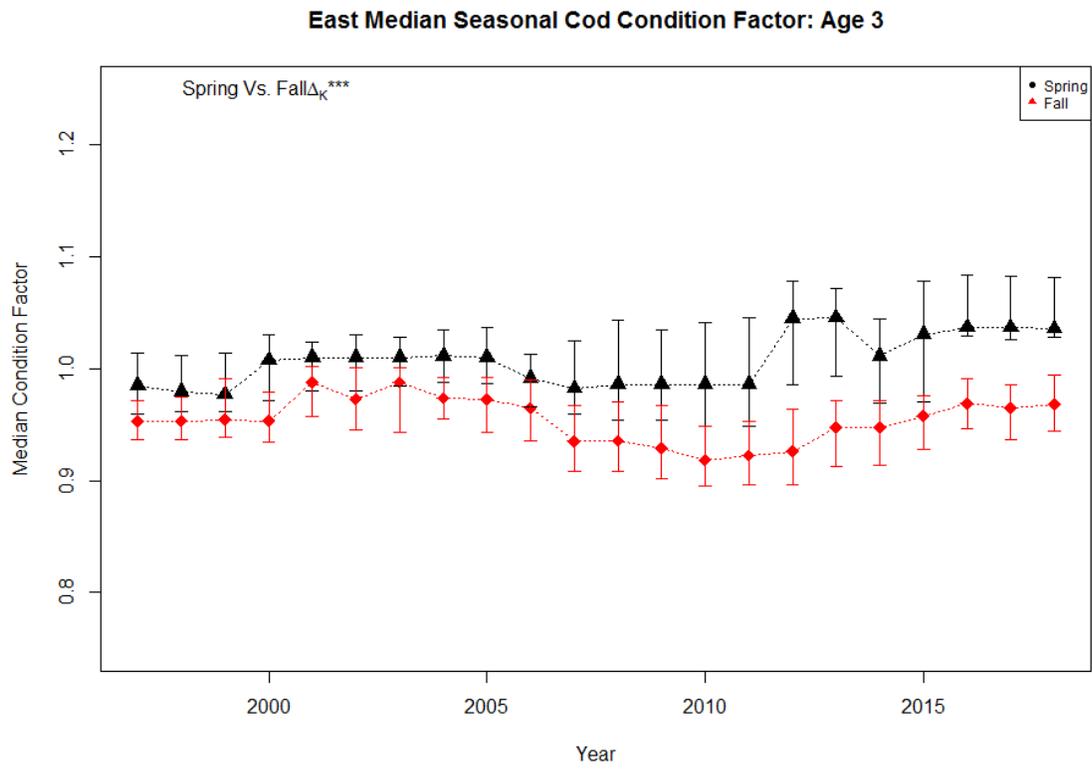


Figure IV-41: Age 3 median cod condition factor in eastern GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

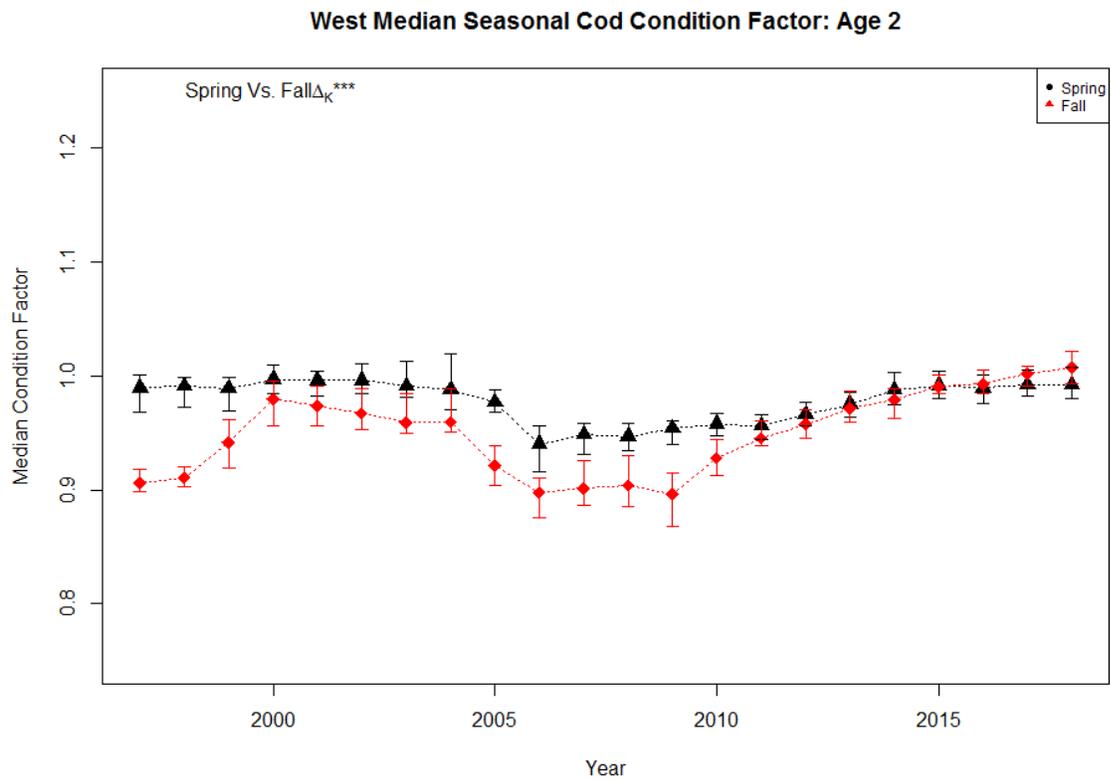


Figure IV-42: Age 2 median cod condition factor in western GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

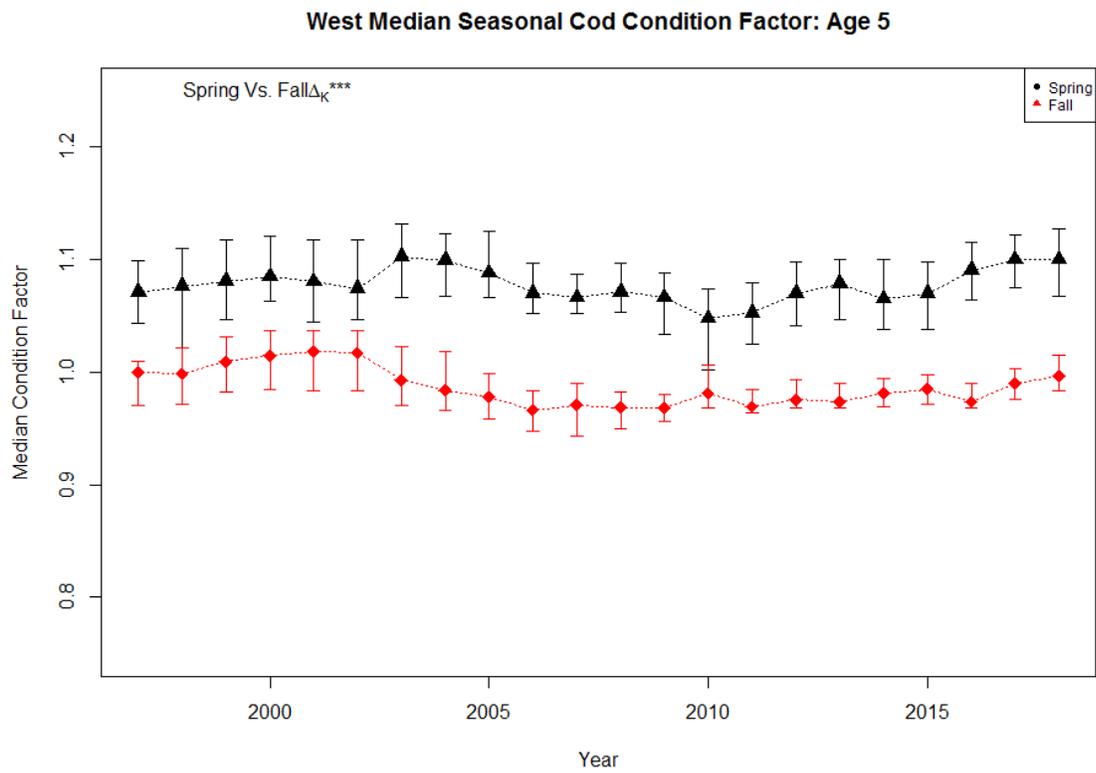


Figure IV-43: Age 5 median cod condition factor in western GOM from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

GBK Median Seasonal Cod Condition Factor: Age 1

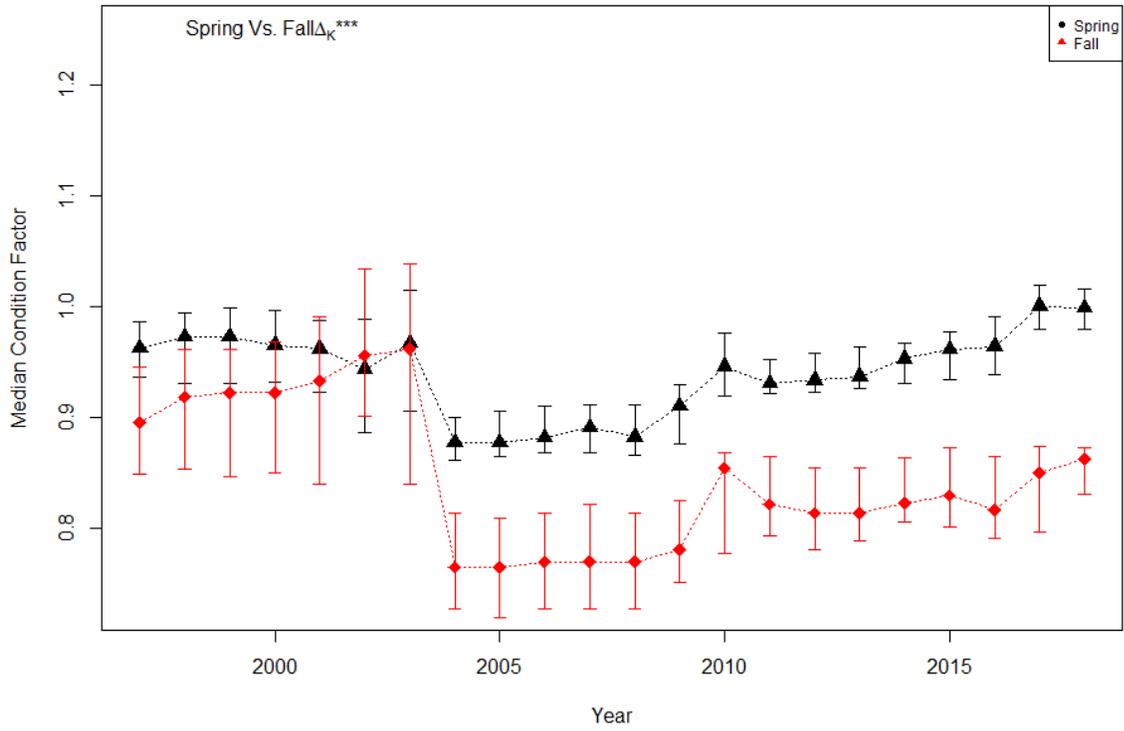


Figure IV-44: Age 1 median cod condition factor on George's Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

GBK Median Seasonal Cod Condition Factor: Age 2

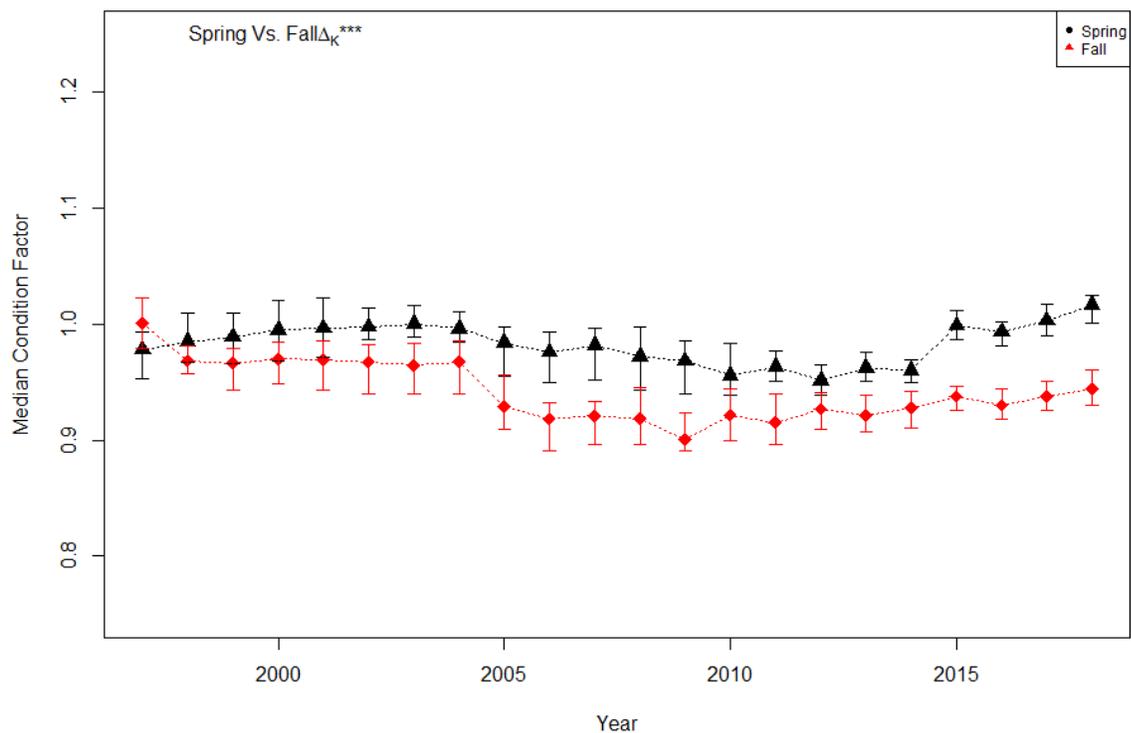


Figure IV-45: Age 2 median cod condition factor on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

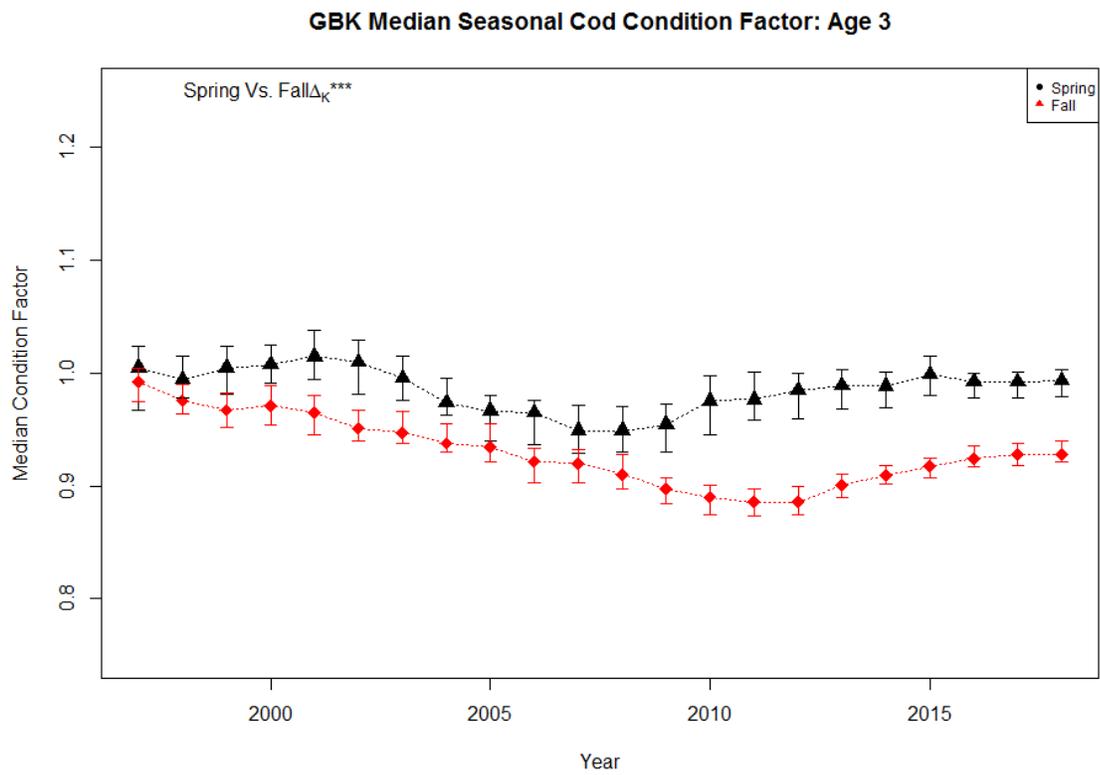


Figure IV-46: Age 3 median cod condition factor on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

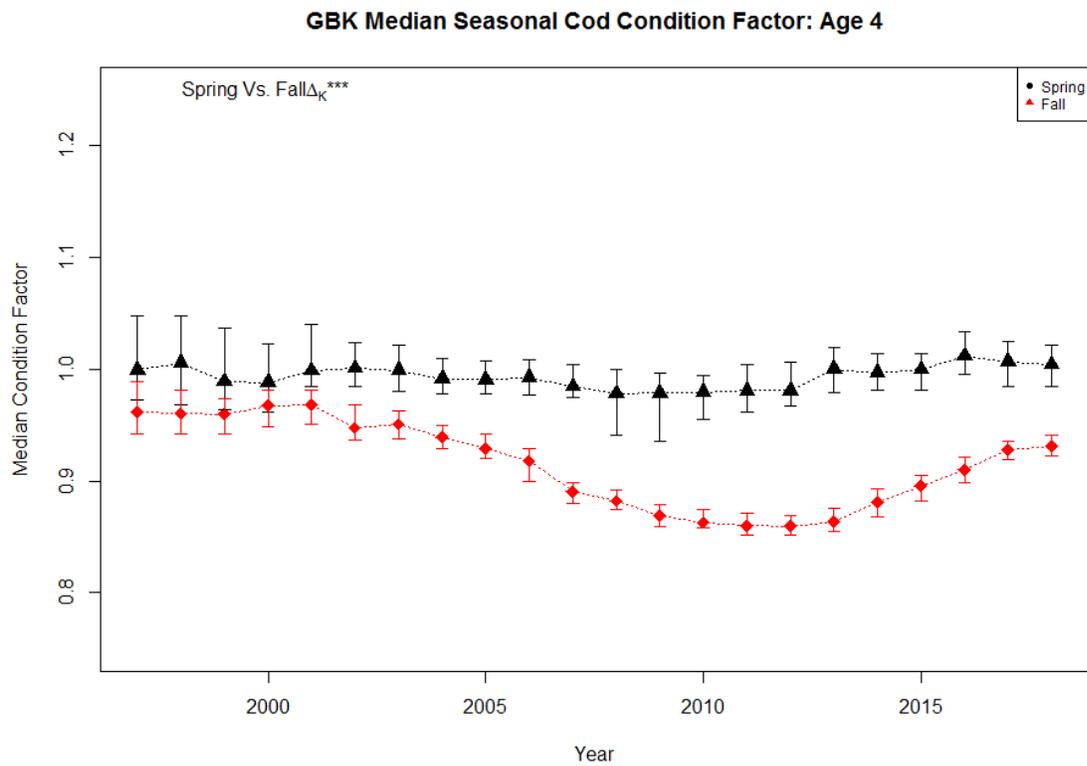


Figure IV-47: Age 4 median cod condition factor on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

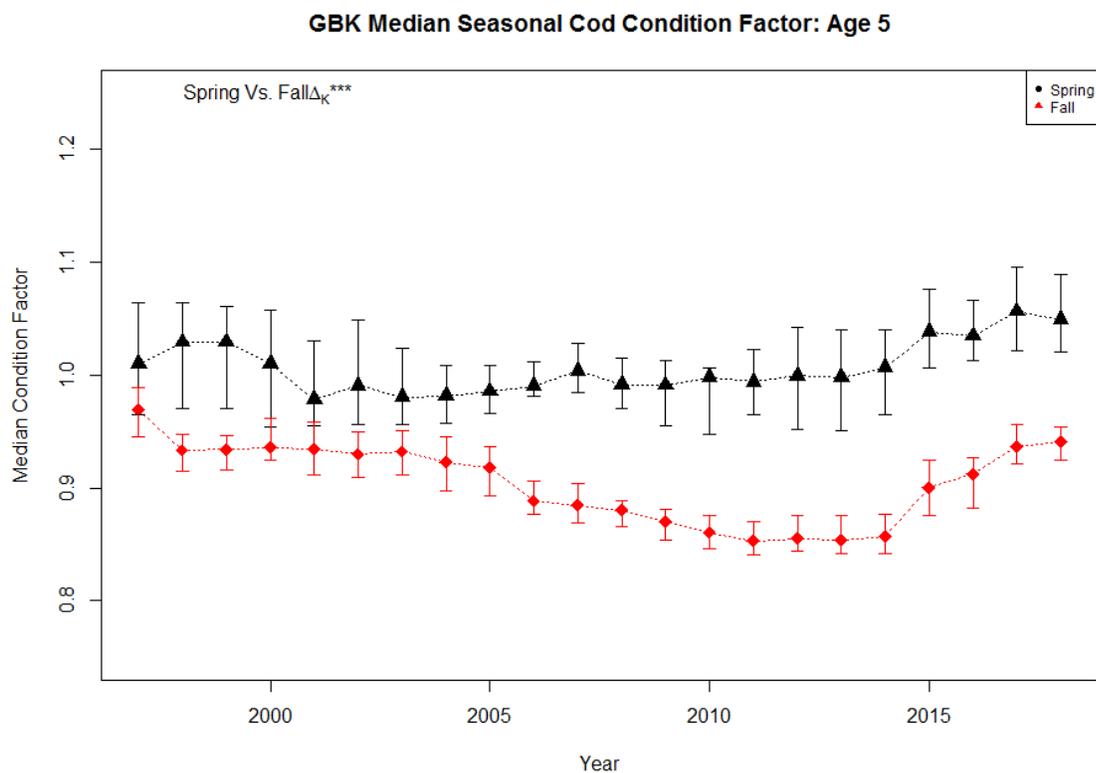


Figure IV-48: Age 5 median cod condition factor on George’s Bank from 1992-2018 based on fall and spring NEFSC bottom trawl surveys. Asterisks (***) denote statistically significant difference between Spring and Fall temporal slopes.

**Frequency of Statistically Significant Differences in Age-Specific Growth Parameters
Between Major Areas and Sub-stocks:**

To evaluate the degree of differences in spatially explicit growth parameters, a percent frequency was calculated which represented the percent of the time series in which growth parameters between two large areas or sub-stock areas were significantly different at a given age transition. Results of the comparisons between major areas in the GOM can be found in Tables 1-3. Results of the comparisons between proposed sub-stock areas can be found in Tables 4-6.

Major Area Comparison (Eastern GOM, Western GOM, and George's Bank):

Results of the comparison between the EGOM and the WGOM indicate that spring data exhibited the greatest amount of significant difference for all three growth parameters evaluated (Table IV-1). From 1970/1992 to 2018, mean and median length, weight and condition factor values from the EGOM and WGOM are statistically significant from one another most frequently between ages 1-3, reaching maximum frequencies of significance for 63% (mean spring length), 90% (mean spring weight), and 91% (mean spring condition factor). Although mean and median values do not typically share the same values, mean and median values follow the same trend through age classes in which frequency of significant difference peaks between ages 1-3 before declining for cod age 3-5. Frequency of significance values calculated from median bootstrap results reach maximums of 52% (length), 91% (weight), and 73% (condition factor) of the time series.

Fall data comparisons showed the smallest frequency of significant difference for length, weight, and condition factor (Table IV-2). As was the case in the spring analysis, mean and median values for growth parameters did not produce the same values. Although most values of mean and median were similar to one another, few instances exhibit differences in mean and median frequency of significance greater than 20% for a given age class. Fall frequency of significance values also indicate that the highest frequency of significant difference in nested within ages 1-3. Frequency of significant difference for mean values in the time series reached maximums of 41% (length), 64% (weight), and 36% (condition factor) while frequencies of the median growth values reached maximums of 39%, 64%, and 32%.

Results of the combined season analysis did not elucidate any trends that were not previously described from Tables 1 and 2. Frequency values in Table IV-3 can be described as the average frequency between spring frequency and fall frequency. Additionally, comparisons between the EGOM and GBK in Tables 1-3 show very similar results to comparisons between the WGOM and GBK. Across all three subsets of data and each of the growth parameters analyzed, mean and median values within the first age class in GOM areas are vastly different from GBK (>50%). In most instances, the degree of difference between the EGOM and GBK or the WGOM and GBK declines with increasing age class, approaching significant difference frequencies for less than 20% of the time series after age 4. This coincides with those age classes that hold the majority of the population biomass.

Overall, results shown in Tables 1-3 illustrate that WGOM and GBK cod are the most dissimilar in their first 3-4 years. EGOM cod are more dissimilar from GBK cod from ages 0-3, but this dissimilarity declines with increasing age class, making EGOM cod almost equally dissimilar to GBK as they are from WGOM. In addition, juvenile GBK cod appear to exhibit unique life history traits in between ages 0-2 as growth parameters are statistically different from GOM cod for a substantial portion of the time series. All large area age-specific percent frequency values of mean and median growth parameter estimates can be found in Tables 1-3.

Table IV-1: Percent frequency of statistically significant differences in spring length, weight, and condition factor between large areas for each age class. Frequency is presented as the percent of the overall time series that age and area-specific growth estimates were significantly different from one another. Please note that the time series for length is 1970-2018 while the time series for weight and condition factor is from 1992-2018. Grey text represents the frequency of median growth parameters while black represents frequency of mean parameter values.

Large Area Frequency (%) of Statistically Significant Differences in Time Series (Spring)										
Age Class	Area	Length (cm)			Weight (g)			Condition Factor		
		East	West	GB	East	West	GB	East	West	GB
1-2	East		40.91	59.09		54.55	63.64		72.73	68.18
1-2	West	27.27		93.18	36.36		90.91	59.09		40.91
1-2	GB	50.00	90.91		54.55	86.36		68.18	31.82	
2-3	East		63.64	47.73		90.91	45.45		90.91	63.64
2-3	West	52.27		40.91	77.27		59.09	72.73		50.00
2-3	GB	27.27	43.18		22.73	59.09		50.00	50.00	
3-4	East		34.09	50.00		77.27	50.00		27.27	36.36
3-4	West	38.64		36.36	90.91		40.91	9.09		90.91
3-4	GB	40.91	13.64		54.55	45.45		27.27	72.73	
4-5	East		4.55	9.09		9.09	4.55		36.36	54.55
4-5	West	2.27		9.09	4.55		0.00	9.09		100.00
4-5	GB	0.00	0.00		0.00	0.00		40.91	95.45	
5-6	East		6.82	11.36		4.55	9.09		45.45	13.64
5-6	West	0.00		18.18	4.55		4.55	22.73		95.45
5-6	GB	0.00	2.27		0.00	4.55		4.55	95.45	

Table IV-2: Percent frequency of statistically significant differences in fall length, weight, and condition factor between large areas for each age class. Frequency is presented as the percent of the overall time series that age and area-specific growth estimates were significantly different from one another. Please note that the time series for length is 1970-2018 while the time series for weight and condition factor is from 1992-2018. Grey text represents the frequency of median growth parameters while black represents frequency of mean parameter values.

Large Area Frequency (%) of Statistically Significant Differences in Time Series (Fall)										
Age Class	Area	Length (cm)			Weight (g)			Condition Factor		
		East	West	GB	East	West	GB	East	West	GB
0-1	East		29.55	72.73		36.36	95.45		13.64	50.00
0-1	West	38.64		88.64	31.82		100.00	31.82		72.73
0-1	GB	81.82	79.55		68.18	95.45		45.45	40.91	
1-2	East		40.91	22.73		36.36	54.55		36.36	81.82
1-2	West	22.73		54.55	31.82		81.82	22.73		59.09
1-2	GB	13.64	56.82		59.09	77.27		77.27	68.18	
2-3	East		36.36	54.55		63.64	36.36		13.64	45.45
2-3	West	20.45		27.27	63.64		54.55	9.09		13.64
2-3	GB	25.00	9.09		27.27	59.09		45.45	13.64	
3-4	East		9.09	13.64		0.00	0.00		22.73	4.55
3-4	West	0.00		29.55	4.55		9.09	13.64		18.18
3-4	GB	0.00	6.82		0.00	4.55		4.55	31.82	
4-5	East		0.00	0.00		0.00	0.00		18.18	0.00
4-5	West	0.00		2.27	0.00		0.00	4.55		40.91
4-5	GB	0.00	2.27		0.00	0.00		0.00	36.36	

Table IV- 3: Percent frequency of statistically significant differences in combined spring and fall length, weight, and condition factor between large areas for each age class. Frequency is presented as the percent of the overall time series that age and area-specific growth estimates were significantly different from one another. Please note that the time series for length is 1970-2018 while the time series for weight and condition factor is from 1992-2018. Grey text represents the frequency of median growth parameters while black represents frequency of mean parameter values.

Large Area Frequency (%) of Statistically Significant Differences in Time Series (Spring and Fall)										
Age Class	Area	Length (cm)			Weight (g)			Condition Factor		
		East	West	GB	East	West	GB	East	West	GB
0-1	East		27.27	63.64		50.00	72.73		50.00	68.18
0-1	West	20.45		75.00	54.55		100.00	59.09		54.55
0-1	GB	52.27	77.27		77.27	100.00		68.18	45.45	
1-2	East		45.45	34.09		54.55	63.64		81.82	72.73
1-2	West	27.27		77.27	54.55		86.36	81.82		63.64
1-2	GB	9.09	65.91		50.00	86.36		68.18	59.09	
2-3	East		40.91	47.73		68.18	40.91		36.36	18.18
2-3	West	29.55		43.18	72.73		54.55	4.55		54.55
2-3	GB	34.09	25.00		45.45	72.73		36.36	54.55	
3-4	East		27.27	52.27		54.55	59.09		50.00	54.55
3-4	West	29.55		40.91	86.36		45.45	31.82		100.00
3-4	GB	27.27	25.00		59.09	36.36		54.55	100.00	
4-5	East		9.09	15.91		4.55	4.55		13.64	18.18
4-5	West	2.27		25.00	22.73		4.55	9.09		95.45
4-5	GB	4.55	20.45		4.55	0.00		13.64	95.45	

Proposed Sub-stock Area Comparison (Eastern GOM, Western GOM, Great South Channel, and George's Bank):

Frequencies of statistically significant difference in age-specific growth estimates from the more spatially restricted sub-stock area analysis showed similar results to the large area analysis regarding EGOM and WGOM comparisons. Results indicate spring values exhibit the highest frequencies of statistically significant differences in the East and West (Tables IV-4:6). Furthermore, frequencies of significant difference in mean and median growth between East and West peak between ages 1-3. Maximum frequencies between East and West peaked at 64% and 52% for mean and median length, 95% and 81% for mean and median weight, and 60% and 23% for mean and median condition factor. Interestingly, mean and median spring cod length estimates in the East were most like those observed in GSC (maximums of 43% and 30%, respectively) and most dissimilar from GBK (maximums of ~ 60%). However, spring cod weight and condition factor in the east are most similar to GBK cod, reaching maximums around 60% for mean and median comparisons while EGOM cod were least similar to GSC cod, reaching maximum frequencies of statistically significant difference for 82% (weight) and 96% (condition factor) of the time series. Overall, spring WGOM cod were most similar to GSC cod, reaching a maximum in the first year-class of 80% before dropping closer to 40% in age 2, and then ultimately remaining under 20% for the remaining year classes.

Once again, fall growth estimates exhibited the lower frequencies of significant difference than those observed in the spring. Fall survey data (Table IV-5) and the combined survey data (Table IV-6) that most of the highest frequencies of significant differences for each age specific growth parameters across all areas is distributed throughout ages 1-3. As was described for spring estimates, EGOM cod length is most similar to GSC cod length for all

evaluated age classes after age 1 (post-age-1 maximum frequency of 25%), but condition factor values from the EGOM are least like those observed in GSC reaching a maximum frequency of difference for 100% of the time series. Fall growth parameter estimates between the EGOM and WGOM reached maximums of 41% (length), 68% (weight), and 68% (condition factor). WGOM and GSC show a high frequency of significantly different values in the first three age class, consistently exhibiting frequencies between 80% and 95 % for weight and condition factor, while maintaining different length values for 70% of the time series from ages 0-2. WGOM cod length, weight, and condition factor were least like GBK cod reaching maximum significant difference frequencies of 89% (mean length), 86% (mean weight), and 96% (median condition factor).

As discussed in the large area analysis, the combination of spring and fall survey data in sub-stock area analysis did not show any different trends in frequency of statistically significant parameter estimates. The majority of high frequencies were contained within the first three age class and frequency declined with increasing age class. Furthermore, and on average, GSC estimates were more similar to GBK estimates for length and weight, maintaining statistically significant values for 30-40% of the time series. However, this trend does not hold true for condition factor. GSC and GBK condition factor were highly significantly different from one another as age-specific values were different for 70-100% in most cases.

Table IV-4: Percent frequency of statistically significant differences in spring length, weight, and condition factor between sub-stock areas for each age class. Frequency is presented as the percent of the overall time series that age and area-specific growth estimates were significantly different from one another. Please note that the time series for length is 1970-2018 while the time series for weight and condition factor is from 1992-2018. Grey text represents the frequency of median growth parameters while black represents frequency of mean parameter values.

Sub-stock Area Frequency (%) of Statistically Significant Differences in Time Series (Spring)													
Age Class	Area	Length				Weight				Condition Factor			
		East	West	GS	GB	East	West	GS	GB	East	West	GS	GB
1-2	East		40.91	36.36	59.09		63.64	72.73	59.09		50.00	95.45	31.82
1-2	West	31.82		79.55	93.18	36.36		81.82	86.36	4.55		45.45	45.45
1-2	GS	22.73	68.18		61.36	50.00	81.82		68.18	50.00	77.27		68.18
1-2	GB	56.82	88.64	47.73		59.09	86.36	54.55		4.55	4.55	63.64	
2-3	East		63.64	43.18	47.73		95.45	36.36	50.00		59.09	68.18	27.27
2-3	West	52.27		43.18	40.91	90.91		59.09	50.00	22.73		31.82	40.91
2-3	GS	29.55	34.09		36.36	13.64	50.00		18.18	95.45	59.09		18.18
2-3	GB	36.36	27.27	13.64		40.91	45.45	9.09		18.18	4.55	36.36	
3-4	East		34.09	27.27	50.00		72.73	36.36	50.00		36.36	18.18	27.27
3-4	West	25.00		11.36	36.36	77.27		31.82	36.36	0.00		59.09	90.91
3-4	GS	11.36	11.36		34.09	36.36	31.82		22.73	63.64	90.91		40.91
3-4	GB	36.36	18.18	11.36		45.45	31.82	0.00		18.18	31.82	100.00	

Table IV-4: Continued.

Sub-stock Area Frequency (%) of Statistically Significant Differences in Time Series (Spring)													
Age Class	Area	Length				Weight				Condition Factor			
		East	West	GS	GB	East	West	GS	GB	East	West	GS	GB
4-5	East		4.55	2.27	9.09		13.64	0.00	9.09		45.45	9.09	54.55
4-5	West	0.00		4.55	9.09	9.09		27.27	0.00	22.73		59.09	100.00
4-5	GS	0.00	0.00		9.09	0.00	27.27		13.64	50.00	22.73		50.00
4-5	GB	0.00	2.27	4.55		0.00	0.00	13.64		0.00	86.36	90.91	
5-6	East		6.82	0.00	11.36		9.09	0.00	22.73		59.09	0.00	4.55
5-6	West	0.00		2.27	18.18	9.09		0.00	18.18	9.09		27.27	95.45
5-6	GS	0.00	0.00		18.18	0.00	4.55		31.82	4.55	13.64		68.18
5-6	GB	6.82	6.82	2.27		13.64	9.09	27.27		0.00	50.00	68.18	

Table IV-5: Percent frequency of statistically significant differences in fall length, weight, and condition factor between sub-stock areas for each age class. Frequency is presented as the percent of the overall time series that age and area-specific growth estimates were significantly different from one another. Please note that the time series for length is 1970-2018 while the time series for eight and condition factor is from 1992-2018. Grey text represents the frequency of median growth parameters while black represents frequency of mean parameter values.

Sub-stock Area Frequency (%) of Statistically Significant Differences in Time Series (Fall)													
Age Class	Area	Length				Weight				Condition Factor			
		East	West	GS	GB	East	West	GS	GB	East	West	GS	GB
0-1	East		29.55	63.64	72.73		36.36	72.73	54.55		9.09	59.09	9.09
0-1	West	27.27		79.55	88.64	27.27		90.91	86.36	54.55		90.91	4.55
0-1	GS	63.64	77.27		56.82	54.55	81.82		13.64	81.82	27.27		81.82
0-1	GB	72.73	75.00	45.45		36.36	77.27	4.55		31.82	40.91	63.64	
1-2	East		40.91	25.00	22.73		59.09	59.09	13.64		27.27	100.00	18.18
1-2	West	27.27		70.45	54.55	59.09		81.82	77.27	36.36		86.36	18.18
1-2	GS	13.64	50.00		20.45	59.09	81.82		27.27	59.09	36.36		72.73
1-2	GB	18.18	50.00	2.27		18.18	77.27	4.55		22.73	40.91	18.18	
2-3	East		36.36	13.64	54.55		68.18	0.00	72.73		4.55	77.27	27.27
2-3	West	22.73		11.36	27.27	63.64		90.91	13.64	4.55		95.45	59.09
2-3	GS	0.00	6.82		47.73	0.00	81.82		86.36	9.09	63.64		100.00
2-3	GB	45.45	11.36	34.09		59.09	22.73	54.55		27.27	72.73	36.36	

Table IV-5: Continued.

Sub-stock Area Frequency (%) of Statistically Significant Differences in Time Series (Fall)													
Age Class	Area	Length				Weight				Condition Factor			
		East	West	GS	GB	East	West	GS	GB	East	West	GS	GB
3-4	East		9.09	13.64	13.64		0.00	0.00	0.00		22.73	72.73	9.09
3-4	West	4.55		22.73	29.55	4.55		0.00	4.55	13.64		36.36	86.36
3-4	GS	4.55	15.91		31.82	0.00	0.00		0.00	9.09	59.09		90.91
3-4	GB	6.82	13.64	22.73		0.00	4.55	0.00		40.91	95.45	45.45	
4-5	East		0.00	4.55	0.00		0.00	0.00	0.00		18.18	22.73	0.00
4-5	West	0.00		6.82	2.27	0.00		4.55	13.64	18.18		13.64	63.64
4-5	GS	0.00	4.55		0.00	0.00	9.09		4.55	4.55	27.27		63.64
4-5	GB	0.00	0.00	0.00		0.00	4.55	0.00		4.55	95.45	50.00	

Table IV-6: Percent frequency of statistically significant differences in combined spring and fall length, weight, and condition factor between sub-stock areas for each age class. Frequency is presented as the percent of the overall time series that age and area-specific growth estimates were significantly different from one another. Please note that the time series for length is 1970-2018 while the time series for weight and condition factor is from 1992-2018. Grey text represents the frequency of median growth parameters while black represents frequency of mean parameter values.

Sub-stock Area Frequency (%) of Statistically Significant Differences in Time Series (Spring and Fall)													
Age Class	Area	Length				Weight				Condition Factor			
		East	West	GS	GB	East	West	GS	GB	East	West	GS	GB
0-1	East		11.36	47.73	54.55		54.55	72.73	63.64		50.00	81.82	36.36
0-1	West	9.09		86.36	81.82	45.45		90.91	77.27	59.09		90.91	13.64
0-1	GS	40.91	70.45		34.09	63.64	77.27		9.09	72.73	86.36		81.82
0-1	GB	52.27	70.45	27.27		59.09	77.27	9.09		50.00	9.09	63.64	
1-2	East		47.73	22.73	29.55		72.73	63.64	27.27		54.55	95.45	54.55
1-2	West	25.00		84.09	72.73	77.27		81.82	86.36	50.00		72.73	45.45
1-2	GS	9.09	72.73		29.55	31.82	81.82		0.00	90.91	40.91		77.27
1-2	GB	15.91	50.00	9.09		27.27	95.45	0.00		45.45	36.36	50.00	
2-3	East		47.73	29.55	47.73		72.73	0.00	72.73		36.36	50.00	54.55
2-3	West	36.36		25.00	36.36	72.73		77.27	18.18	4.55		27.27	86.36
2-3	GS	15.91	22.73		40.91	0.00	63.64		68.18	36.36	31.82		95.45
2-3	GB	38.64	29.55	25.00		54.55	36.36	40.91		50.00	86.36	100.00	

Table IV-6: Continued.

Sub-stock Area Frequency (%) of Statistically Significant Differences in Time Series (Spring and Fall)													
Age Class	Area	Length				Weight				Condition Factor			
		East	West	GS	GB	East	West	GS	GB	East	West	GS	GB
3-4	East		29.55	22.73	45.45		36.36	27.27	45.45		45.45	36.36	63.64
3-4	West	18.18		25.00	38.64	68.18		0.00	40.91	22.73		31.82	100.00
3-4	GS	11.36	11.36		43.18	27.27	13.64		0.00	13.64	27.27		100.00
3-4	GB	29.55	27.27	20.45		36.36	22.73	0.00		59.09	100.00	72.73	
4-5	East		9.09	0.00	13.64		18.18	0.00	4.55		13.64	9.09	31.82
4-5	West	4.55		20.45	20.45	22.73		31.82	9.09	9.09		18.18	95.45
4-5	GS	0.00	2.27		9.09	0.00	40.91		31.82	9.09	9.09		100.00
4-5	GB	2.27	6.82	0.00		4.55	13.64	9.09		18.18	100.00	95.45	

DISCUSSION:

This research evaluated mean and median values of bootstrapped growth parameters in order to develop a more robust understanding of trends over time and differences between geographical areas in the GOM. In many cases, mean and median values were rather dissimilar. Despite this, mean and median values often exhibited the same seasonal trends or in the frequency of difference between two areas (e.g. the same age group exhibiting statistically significant seasonal trends in a given age class and similar distributions in frequency of significant differences between areas). These similarities lend merit to the results observed in this research. However, it should be noted that means and medians should not be treated equally. Although medians are more robust in the presence of outliers, they do not possess a distribution: a feature characteristic to means. Additionally, and as is seen in these results, medians are far more susceptible to higher degrees of variation. Furthermore, bootstrap resampling methods often relieve the impact of outlying values with an increasing number of simulations. As a result, and due to the nature of medians previously discussed, mean values are a more adequate measure of comparison between areas and, henceforth, the discussion of comparisons between areas and over time will be in regard to the bootstrapped mean values of growth.

One purpose of this research is to evaluate allometric parameters for Atlantic cod in the GOM and GBK for temporal trends using data from the NEFSC bottom trawl survey. As previously discussed, phenotypic life history parameters can be used as an indicator of stock structure and population health in which any truncation in length-at-age, weight-at-age, and condition factor may be indicative of fishery-induced evolution or population stress (Devine *et. al.*, 2015; Zemeckis *et. al.*, 2014; Swain, 2010; Begg *et. al.*, 1999). These results indicate that there have been no temporal trends in the aforementioned life history traits between pre- and

post-maturation ages (0-6) in any of the large areas or proposed sub-stock areas in the GOM over the evaluated time series. Fudge and Rose (2008) have suggested that North Atlantic cod (specifically Newfoundland cod) have exhibited substantial shifts in life history traits and maturation timing. In combination with the evidence for the impacts of temperature and salinity on cod growth and fecundity (Zemeckis *et. al.*, 2014; Drinkwater, 2005), it is possible that cod aggregations in the more southerly GOM are not yet noticeably exhibiting adverse effects of changing temperature and salinity in the three growth parameters evaluated in this study.

The only instance in which a temporal trend was observed in cod growth was the truncation in absolute mean weight between ages 1-2 on George's Bank. However, it should be noted that this truncation is not supported by the analysis of median weight values in large areas or by the entirety of the sub-stock area analysis, which makes it difficult to make any conclusions about whether the trend is a true trend or a relic of the subset of data from which it was estimated.

Despite the overall lack of temporal trends that would indicate any statistically significant shifts in cod growth, comparisons of season-specific time series trends appear to be highly significant from one another. Since neither spring nor fall-specific slopes differed significantly from 0 (no temporal change), this means they must exhibit slopes oppose one another with one slope increasing and the other decreasing. Although this does not mean there have been temporal shifts in growth, it does highlight some of the subtle differences in growth within regions, indicating that cod are exhibiting significantly different growth behaviors between seasons *within* areas in addition to the identified differences in growth *between* areas, which adds another level of complexity in regard to assessing and monitoring the overall resources.

Aside from the number of statistically significant differences in spring and fall growth parameters at a number of age classes, it is important to note that the significant difference in trends observed in mean growth values are often corroborated by the plots of median values, which also indicate significant trends for the same age-class in the same area. This provides further evidence that there are, in fact, significant differences regarding trends in season-specific trawl survey data, which brings to light the necessity for closer monitoring and further evaluation of seasonal differences in cod life history.

In addition to the findings of significantly different trends between spring and fall growth parameters, the balance in the number of significant trends across growth parameters were not equal. For example, although all growth parameters showed numerous significant trend differences across different age groups, weight analyses showed the smallest number of differences between spring and fall trends. Both the Eastern and Great South Channel sub-stock showed one age class in which seasonal trend lines were significant from one another while the WGOM and GBK sub-stocks contained more of the variation in weight. Both GBK and WGOM seasonal weight changes included ages around the age of maturation, EGOM and GSC sub-stock showed variation did not, making it difficult to deduce which age classes are most likely to exhibit significant seasonal differences or to tie these differences to other life history parameters such as maturation. On the contrary, length and condition factor seemed to show the largest amount of seasonal variation between areas and sub-stock areas.

With regard to seasonality, bootstrapped mean length estimates in WGOM, GSC, and GBK sub-stock areas indicated seasonality differences from age 2-3. Age 2-3 differences are corroborated by bootstrapped median estimates in GSC and GBK areas. As stated previously, this age class corresponds with the age of reaching sexual maturity, indicating that fall and spring

cod may be reaching sexual maturity at different rates in these areas. Ames (2004) describes the EGOM as once having spawning grounds which have more recently in time become inactive suggesting they are comprised of local population which are now extinct. Furthermore, the NEFSC trawl survey catches the fewest cod in the EGOM ($n = 6,061$) whereas WGOM, GSC, and GBK are all represented by a much larger sample size ($n = 19,991$, $n = 16,667$, $n = 18,428$). As a result, lack of seasonality may be the result of poor representation across certain age-classes. With respect to condition factor, all sub-stocks which exhibited statistically significant seasonal differences showed statistically significant difference in mean and median condition factor of age 2. Most statistically significant differences occurred around age 3, which seems to suggest differences in maturation rates of the spring and fall spawning stocks identified in the GOM.

The other major goal of this study was to evaluate how frequently differences in mean and median absolute growth between ages were statistically significant between areas. It should be stated explicitly that the goal of this research is *not* to generate spatially explicit growth curves or to identify specific life history parameters at age. This was not a simple as saying whether one area was statistically significant from the other, but rather trying to understand how frequently in the time series a growth parameter at given age was statistically significant from its counterpart in another area. As was the case with seasonal trends, most statistically significant differences in growth parameters throughout the time series were nested between ages 1-4. Again, percent frequencies reached maxima in the age 2-3 class pointing toward significant changes around age at maturity.

Pentilla and Gifford (1976) suggest that GOM cod between the ages of 1 and 3 were substantially different from GBK cod. This conclusion is only partially supported by these

results, which indicate that absolute growth of WGOM cod of the same age groups are significantly different from those on GBK anywhere from 45-95% of the years between 1970/1992-2018. However, EGOM cod do not show this significant difference from GBK for these age groups. Results suggest that EGOM cod are much more similar to GBK cod after age one, achieving statistically significant growth values from 9-50% of the years in the time series.

It is well documented that phenotypic life history traits are the direct result of genetic response to fishing effort (Becker and Chen, 2016; Hutchings, 2004; Chen and Mello 1999; Chen and Harvey 1995). Kovach *et. al.* (2010) demonstrated that cod in different regions of the GOM were genetically distinguishable from one another and from GBK. The ability to genetically distinguish cod in geographic regions within the GOM is only possible under reproductive isolation, which inherently violates one of the primary assumptions of the unified stock theory: sufficient mixing through the geographic area of interest. Several studies in recent years have attempted to identify the complex population structure of cod in the GOM (Kovach *et. al.*, 2010 and Breton, 2008), In an unpublished study by Kovach *et. al.* (in prep) EGOM cod are most genetically similar to GBK cod. This corroborates findings from the results here, which indicate that EGOM cod exhibit lower frequencies of statistically significant growth parameters after age 1.

The combination of growth and genetic similarities between EGOM and GBK cod raise important questions about the similarities between EGOM and WGOM cod, which are managed together, or GSC cod, which are spatially split between GBK and the GOM units. Currently, GBK and the GOM are managed independently due to the differences in biology and structural differences in the fisheries in each area. This research demonstrates that absolute cod growth in the EGOM and WGOM are significantly different from one another on expressing statistically

significant differences in the mean from 30-70% of the combined survey time series that were analyzed. Additionally, this research has highlighted substantial differences between spring and fall survey results in which spring differences are far more exacerbated than differences observed in fall growth.

Although results do not allow for the conclusion that phenotypic life history traits have been experiencing a temporal shift in the past 3-5 decades, they do highlight a high degree of difference between the sub-stock areas proposed by Zemeckis (2014), Kovach (2010), and Breton (2008), or as illustrated from the work summarized by Pershing (2013). No comparison between any two large areas or sub-stock areas exhibited consistent frequencies of statistically significant difference. Additionally, all areas in this analysis of growth contained age classes in which absolute growth differed for 50% or more of the last 30-50 years. Ultimately, this suggests that differences between areas can be substantial depending on year class and depending on which seasonal spawning stock the data comes from.

Because 92% of all samples collected between 1970 and 2018 are between the ages of 0 and 5, the analysis methods employed in this study do not allow for a temporal evaluation in maximum theoretical size limits of cod in spatially explicit areas of the GOM. Consequently, a greater sample size of older, larger fish may provide some additional information about temporal changes in cod growth that are missing in this study. Additionally, a study to evaluate any changes in the maturation rates in the areas evaluated in this study would provide a more robust understanding of cod biology in the GOM.

CONCLUSIONS:

Even though the current management units account for spawning time, they do not account for the quantifiable mixing between GOM, GBK, and 4X stocks (Cao and Chen, 2014), the geographic isolation of spawning stocks within management units (Ames, 2004), or the spatially explicit differences in growth identified in this study. All these factors are associated with the genetic uniqueness of spatially explicit spawning stocks identified in other studies. It has been stated that fish populations should be managed independently as long as there exists some degree of geographic isolation that leads to genetic differentiation and significant differences in basic life history traits (Zemeckis, 2014; Ying and Chen, 2011; Ames, 2004; Shaklee, 1998). A failure to account for metapopulation structures, spatial and temporal variation in biology, and movement among metapopulations can lead to an inadequate stock assessment that may be misrepresenting the true status of a fish population.

The results of this study in combination with the available information in the published literature indicate that all of the above sources of variability are present in the Gulf of Maine and George's Bank cod population. However, statistical significance does not necessarily translate to true biological significance. Additionally, there are other parameters of concern that are not analyzed in this study (e.g. spatially explicit maturation schedules or associated biological reference points). As a result, more biological data needs to be collected in order to elucidate the dynamics of spatially explicit cod sub-stocks. Furthermore, one of the inherent issues with modeling natural populations is that there is a fine balance to be struck between model complexity and model simplicity; the simpler the model, the more susceptible it may be to model bias, but more complex models come with greater uncertainty (Lehuta *et. al.* 2016; Collie *et. al.* 2014). As a result, and although more information can be of tremendous benefit, there is a

persistent need to quantify the impacts of including additional information into the current stock assessment in order to assess the merit of doing so.

CHAPTER 5

A SUMMATION OF CONCLUSIONS

Despite several decades of declining cod abundance, spatial constriction of fishing effort, and spatial limitations to state and federal survey methods, the Gulf of Maine (GOM) cod stock is assessed and managed as a single unit stock. This thesis has taken an hour glass approach to elicit robust, fine-scale information from two survey programs in the Gulf of Maine which may better inform the current cod stock assessment process.

Based on the lack of fishing effort and the spatial restrictions to trawl survey gear imposed by complex bathymetry in the EGOM, I have discussed the need for fine-scale fisheries surveys to fill gaps in survey coverage in order to provide data on a sparsely sampled area for inclusion in the stock assessment. However, as stated, it is important to design robust surveys in order to collect accurate data in the EGOM that are representative of the dynamics in the region. In Chapters two and three I evaluated methods and results of the EGOM Sentinel Survey; a jigging and longline survey which targets groundfish in the Eastern Gulf of Maine which is designed to provide data in the survey gaps mentioned.

The purpose of Chapter 2 was to evaluate the role that bycatch of non-target species and gear catchability may play in the calculation of relative abundance indices from the jigging portion of the EGOM Sentinel Survey. Using a sequential model building framework for single-species, single-season occupancy models, the best performing and most appropriate models for the data were those which allowed for temporal heterogeneity in probabilities of detection and occupancy. In conclusion, bycatch of non-target species showed no statistically significant impediment to detecting cod at a given station and no spatially constricted pockets of preferred

habitat with an increased probability of cod detection were observed between years which may have implications in the random station selection design. Although model selection suggests a violation of the assumption that the probability of detection and the probability of occupancy are constant, a common assumption in fisheries surveys, detection probabilities were relatively constant and close to zero, despite observing spatio-temporal trends in the probability of occupancy that are conducive with the known seasonal movements of cod. The consistency in detection in the presence of the variability in occupancy seems to implicate low catchability by jigging gear deployed on the Sentinel Survey. As a result, there is a need for surveys which rely on count-based species detection to incorporate detection probability into estimates of relative abundance as a method of accounting for limited catchability and avoid a potentially large source of bias in abundance indices.

As mentioned, the EGOM Sentinel Survey is designed to fill gaps in current survey coverage in order to provide more information in the stock assessment processes and, thus, improve management. However, the design-based abundance index stemming from Sentinel Survey data have struggled to cope with outlying values of catch and the implications of gear catchability. In Chapter 3 a robust modeling framework was developed with multiple objectives in mind: to assess the impacts of incorporating a metric of catchability into abundance indices, to relieve the impact of outliers and develop a modeling framework to estimate the abundance of groundfish in the GOM, and to understand which factors contribute the greatest influence on groundfish abundance and distributions. Additionally, the documented framework was applied to multiple groundfish species to demonstrate the flexibility of such a framework. It was qualitatively demonstrated that a model-based abundance index could produce highly precise estimates for cod, halibut, and cusk. Additionally, Boosted Regression Tree (BRT) models were

able to produce relative abundance and standardized CPUE trends for cod which were very similar to those calculated from the National Marine Fisheries Service (NMFS) and Massachusetts Department of Marine Fisheries trawl surveys; the major sources of fisheries-independent data incorporated in the cod stock assessment. It was concluded that the BRT-based abundance index is the most robust estimation of relative abundance on the EGOM Sentinel Survey, producing estimates associated with robust CV-values. The EGOM Sentinel Survey should continue to collect data without changing the survey design. However, catchability should be evaluated for its impact on catch and abundance estimates and be incorporated in future estimations of abundance. Additionally, the EGOM Sentinel Survey should seek to quantify catchability of longline gear in order to assess the potential impacts to longline based abundance indices.

Aside from utilizing and evaluating fine-scale surveys to elucidate fine-scale variations in cod abundance and behaviors, it is essential to evaluate the spatio-temporal variability in key phenotypical life history parameters that are inherently linked to maturation and recruitment success. Although the current management units for cod account for spawning time and movement within management stock areas, they do not account for non-negligible mixing between the three management units, geographically isolated spawning stocks within management units, or the spatially explicit differences in cod growth. It is demonstrated in this research that age-specific absolute cod growth varies significantly between spring and fall spawning stocks within proposed sub-stock areas in addition to varying between sub-stock areas. In all instances, length, weight, and condition factor exhibited statistically significant differences between areas for greater than 50% of the last 3-5 decades for at least one age class. Additionally, the most significant growth appears to surround age at maturity, highlighting a

need for more spatially explicit maturation studies in the GOM. Regardless, each of the growth parameters evaluated are congruent with the conclusions drawn from studies which have characterized the genetic uniqueness of spatially explicit spawning stocks in the GOM. Failure to account for metapopulation structures, spatial and temporal variation in biology, and movement among metapopulations can lead to a stock assessment with a potentially biased representation of the fish population. Between the research conducted here and all of the supporting literature, it has been identified and demonstrated that all of the above sources of variability are present in the Gulf of Maine and George's Bank cod population but are not necessarily accounted for in the current stock assessment.

In lieu of the results and conclusions previously stated, the research set forth in this thesis is aimed towards identifying some of the sources of bias in survey efforts and developing a better understanding of the fine-scale and complex dynamics of Atlantic cod in the Gulf of Maine. Although every stock assessment suffers limitations, they are ultimately a rationalized simplification of a complex natural system. As such, there are many ways in which information can be included, excluded, or combined in order to aid in the process of developing a well-informed stock assessment from which a successful management plan can be built. Despite the ability to address many of the confounding challenges that make it inherently difficult to assess and manage a complex system, the question remains as to whether these complexities should, or need, to be addressed in the stock assessment.

Fine-scale surveys can provide invaluable information on the fine-scale dynamics of cod sub-stocks in the GOM so long as survey data results in a robust index of abundance and careful consideration is given to the implications and effects of survey methodology. Additionally, exploiting the data from multiple survey programs and accounting for the fine scale differences

in cod biology across the GOM may aid in the development of a better-informed stock assessment, which may, in turn, lead to future success in rebuilding the cod stock in the Gulf of Maine. However, it has been discussed that adding levels of complexity increases the uncertainty of model output while an oversimplified model can suffer model bias. There remains a constant need for scientists and managers to identify this optimum between complexity and simplicity in order to obtain the most well informed and least biased model with an acceptable margin of uncertainty.

LITERATURE CITED

- Ames, E. 2004. Atlantic Cod Stock Structure in the Gulf of Maine. *J. Fish. Res.* 29 (1): pp. 10-28
- Armstrong, M.P., Dean, M.J., Hoffman, W.S., Zemeckis, D.R., Nies, T.A., Pierce, D.E., Diodati, P.J. and McKiernan, D.J., 2013. The application of small scale fishery closures to protect Atlantic cod spawning aggregations in the inshore Gulf of Maine. *Fisheries Research*, 141, pp.62-69.
- Bayley, P. B., and Peterson, J. T. 2001. An approach to estimate probability of presence and richness of fish species. *Transactions of the American Fisheries Society*, 130(4), 620-633.
- Becker, J. and Chen, Y. 2001. Temporal Variability in Key Life History Traits of Atlantic Herring (*Clupea harengus*) in the Gulf of Maine. Thesis.
- Bigelow, H.B., Schroeder, W.C., 2002. Fishes of the Gulf of Maine. Fishery Bulletin of the Fish and Wildlife Service.
- Boenish, R., & Chen, Y. 2018. Quasi-Stationary Atlantic Cod Bycatch Estimation in the Maine American Lobster *Homarus americanus* Trap Fishery. *North American Journal of Fisheries Management*, 38(1), 3-17.
- Breton, T. S. 2008. Spawning stock identification of Atlantic cod (*Gadus morhua*) in US waters using Pan I and microsatellite genetic markers. Accessed at: <https://scholars.unh.edu/thesis/411/>
- Begg, G. A., Friedland, K. D., and Pearce, J. B. 1999a. Stock identification and its role in stock assessment and fisheries management: an overview. *Fisheries Research*, 43: 1–8.
- Cao, J., Truesdell, S. B., & Chen, Y. 2014. Impacts of seasonal stock mixing on the assessment of Atlantic cod in the Gulf of Maine. *ICES Journal of Marine Science*, 71(6), 1443-1457
- Carlucci, J., Chen, Y. 2018. Eastern Gulf of Maine Sentinel Survey Report.
- Chen, Y., & Mello, L.G. 1998. Growth and maturation of cod (*Gadus morhua*) of different year classes in the Northwest Atlantic, NAFO subdivision 3Ps. *Fisheries Research* 42, 87-101
- Chen, Y., & Mello, L.G. 1999. Developing an overall indicator for monitoring temporal variation in fish size at age. *Fishery Bulletin*, Scientia Marina, 72(2), 221-229.
- Collie, J. S., Botsford, L. W., Hastings, A., Kaplan, I. C., Largier, J. L., Livingston, P. A., Plaganyi, E. E., Rose, K. A., Wells, B. K., Werner, F. E. (2016). Ecosystem models for fisheries management: finding the sweet spot. *Fish and Fisheries*, 17(1), 101-125.

- Davis, A., Hanson, J., Watts, H., MacPherson, H. 2004. Local ecological knowledge and marine fisheries research: the case of white hake (*Urophycis tenuis*) predation on juvenile American lobster (*Homarus americanus*). *Can. J. Fish. Aquat. Sci.* (61): 1191- 1201
- Dean, M.J., Hoffman, W.S. and Armstrong, M.P., 2012. Disruption of an Atlantic cod spawning aggregation resulting from the opening of a directed gill-net fishery. *North American Journal of Fisheries Management*, 32(1), pp.124-134.
- Devine, J., Wright, P., Pardoe, H., Heino, M. 2015. Comparing rates of contemporary evolution in life history traits for exploited fish stocks. Int. Institute for Applied Systems Analysis. Interim Report IR-12-036.
- Drinkwater, K. F. 2005. The response of Atlantic cod (*Gadus morhua*) to future climate change. *ICES Journal of Marine Science*, 62: 1327–1337.
- Elith, J., & Leathwick, J. (2016, January 8). Boosted Regression Trees for Ecological Modeling. Retrieved from <https://cran.r-project.org/web/packages/dismo/vignettes/brt.pdf>
- Elsdon, T.S, Wells, B.K., Campana, S.E., Gillanders, B.M., Jones, C.M., Limburg, K.E., Secor, D.H., Thorrold, S.R., and Walther, B.D. 2008. Otolith chemistry to describe movements and life-history parameters of fishes: Hypotheses, assumptions, limitations, and inferences. *Oceanography and Marine Biology: An Annual Review*, R. N. Gibson, R., J. A. Atkinson, and J. D. M. Gordon, Editors 2008, 46, 297-330.
- Fiske, I., Chandler, R. 2019. Overview of Unmarked: An R Package for the Analysis of Data from Unmarked Animals. Accessed at <https://cran.r-project.org/web/packages/unmarked/vignettes/unmarked.pdf>
- Fudge, S. B., & Rose, G. A. 2008. Life history co-variation in a fishery depleted Atlantic cod stock. *Fisheries Research*, 92(1), 107-113.
- Garrison, L., Link, J. 2000. Dietary guild structure of the fish community in the Northeast United States continental shelf ecosystem. *Mar. Ecol. Prog. Ser.* 202: pp. 231–240
- Garrison, L., and Link, J. 2000. Fishing effects on spatial distribution and trophic guild structure of the fish community in the Georges Bank region. – *ICES Journal of Marine Science*, 57: 723–730
- Guisan, A., Zimmermann, N.E., 2000. Predictive habitat distribution models in ecology. *Ecological Modelling* 135, 147–186.
- Harms, J.H., Wallace, J.R., Stewart, I.J., 2010. Analysis of fishery-independent hook and line-based data for use in the stock assessment of bocaccio rockfish (*Sebastes paucispinis*). *Fisheries Research* 106, 298–309.

- Hilborn, R., Walters, C.J., 1992. Quantitative Fisheries Stock Assessment: Choice, Dynamics and Uncertainty. Kluwer Academic Publishers, Norwell, MA.
- Hinton, M.G., Maunder, M.N., 2003. Methods for standardizing CPUE and how to select among them.
- Hutchings, J. A., & Reynolds, J. D. 2004. Marine fish population collapses: consequences for recovery and extinction risk. *BioScience*, 54(4), 297-309.
- ICES, 2004. Report of the Workshop on Survey Design and Data Analysis (WKSAD). Aberdeen, UK.
- Ichinokawa, M., Oshima, K., Takeuchi, Y., 2012. Abundance indices of young Pacific bluefin tuna derived from catch-and-effort data of troll fisheries in various regions of Japan.
- Jackman, S. 2015. Package “pscl”. Political Science Computational Laboratory. Stanford University. V(1.4.9).
- Jackson, J., Kirby, M., Berger, W., Bjorndal, K., Botsford, L., Bourque, B., Bradbury, R., Cooke, R., Erlandson, J., Estes, J., Hughes, T., Kidwell, S., Lange, C., Lenihan, H., Pandolfi, J., Peterson, C., Steneck, R., Tegner, M., Warner, R. 2001. Historical Overfishing and the Recent Collapse of Coastal Ecosystems. *Science*. 293:5530. Pp. 629-637.
- Jones, C.M. 2002. Age and Growth. In Fisheries Science [ed L.Fuiman and R. Werner] p 30-63. Blackwell Scientific. Oxford. UK. 326 pages
- Kaiser, M. J. 2003, Bigelow and Schroeder's Fishes of the Gulf of Maine, Third Edition. Fish and Fisheries, 4: 372.
- Kovach, A.I., Breton, T.S., Berlinsky, D.L., Maceda, L. and Wirgin, I., 2010. Fine-scale spatial and temporal genetic structure of Atlantic cod off the Atlantic coast of the USA. *Marine Ecology Progress Series*, 410, pp.177-195.
- Lambert, T.C., 1994. The First Report of the 4vn Sentinel Survey. Dartmouth, Nova Scotia Canada.
- Lear W.H., Green J.M. 1984 Migration of the “Northern” Atlantic Cod and the Mechanisms Involved. In: McCleave J.D., Arnold G.P., Dodson J.J., Neill W.H. (eds) Mechanisms of Migration in Fishes. NATO Conference Series (IV Marine Sciences), vol 14. Springer, Boston, MA
- Lehuta, S., Girardin, R., Mahévas, S., Travers-Trolet, M., & Vermard, Y. 2016. Reconciling complex system models and fisheries advice: Practical examples and leads. *Aquatic Living Resources*, 29(2), 208.

- Lokkeborg, S., Pina, T., 1997. Effects of setting time, setting direction and soak time on longline catch rates 32, 213–222.
- MacKenzie, D. I., & Kendall, W. L. 2002. How should detection probability be incorporated into estimates of relative abundance?. *Ecology*, 83(9), 2387-2393.
- MacKenzie, D., Nichols, J., Royle, J., Pollock, K., Bailey, L., Hines, J. 2006. Occupancy Estimation and Modelling: Inferring Patterns and Dynamics of Species Occurrence. Ch. 5: Single Species, Single-Season Models with Heterogenous Detection Probabilities (pp. 133-153) Elsevier. 30 Corporate Drive, Suite 400, Burlington, MA 01803.
- Martin, T.G., Wintle, A., Rhodes, J.R., Field, A., Low-choy, S.J., 2005. Zero tolerance ecology : improving ecological inference by modeling the source of zero observations. *Ecology* 1235–1246.
- Maunder, Mark N., Punt, A.E., 2004. Standardizing catch and effort data: a review of recent approaches. *Fisheries Research* 70, 141–159.
- Minami, M., Lennert-Cody, C.E., Gao, W., Roman-Verdesoto, M., 2007. Modeling shark bycatch: The zero-inflated negative binomial regression model with smoothing. *Fisheries Research* 84, 210–221.
- Murawski, S., Brown, R., Cadrin, S., Mayo, R., O'Brien, L., Overholtz, W., Sosebee, K. 1998. New England Groundfish. *Our Living Oceans. NMFS Northeast Fisheries. Woods Hole.*
- National Marine Fisheries Service. 2014. Gulf of Maine Atlantic Cod: 2014 Assessment Update Report. *Woods Hole, Ma.* 98. Accessed at: https://www.nefsc.noaa.gov/saw/cod/pdfs/GoM_cod_2014_update_20140822.pdf.
- Nelson, G.A., 2013. fishmethods: Fisheries Methods and Models in R.
- Ogura, M., Arimoto, T., Inoue, Y., 1980. Influence of the immersion time on the hooking rate of a small bottom longline in coastal waters. *Bull. Jpn. Sot. Scientific Fish* 46, 963–966.
- Palmer, M. 2014. 2014 Assessment Update Report of the Gulf of Maine Atlantic Cod Stock. Northeast Fisheries Science center. 119. Accessed at: <https://www.nefsc.noaa.gov/publications/crd/crd1414/crd1414.pdf>
- Pennington, M., 1983. Efficient Estimators of Abundance, for Fish and Plankton Surveys. *Biometrics* 39, 281–286.
- Pentilla, J. 2017. FBP: Age Determination Methods: Cod. Accessed at <https://www.nefsc.noaa.gov/fbp/age-man/cod/cod.htm>.

- Pershing, A., Annala, J., Eayrs, S., Kerr, L., Labaree, J., Levin, J., Mills, K., Runge, J., Sherwood, G., Sun, J., Caporossi, S. 2013. The Future of Cod in the Gulf of Maine. Gulf of Maine Research Institute technical report.
- Pollock, K. H., Nichols, J. D., Simons, T. R., Farnsworth, G. L., Bailey, L. L., & Sauer, J. R. (2002). Large scale wildlife monitoring studies: statistical methods for design and analysis. *Environmetrics: The official journal of the International Environmetrics Society*, 13(2), 105-119.
- Poppe, L., Williams, S., Paskevich, V., 2005. USGS east-coast sediment analysis: procedures, database, and GIS data.
- Powles, P. 1958. Studies of Reproduction and Feeding of Atlantic Cod (*Gadus callarias* L.) in the southwestern Gulf of St. Lawrence. *Can. J. Fish. Res. Bd*, 15(6), pp. 1383-1402.
- Reiss, H., Hoarau, G., Dickey-Collas, M., and Wolff, W. J. 2009. Genetic population structure of marine fish: mismatch between biological and fisheries management units. *Fish and Fisheries*, 10: 361–395.
- Robichaud, D. and Rose, G.A., 2001. Multiyear homing of Atlantic cod to a spawning ground. *Canadian Journal of Fisheries and Aquatic Sciences*, 58(12), pp.2325-2329.
- Rodrigue, M., Chen, Y. 2015. Eastern Gulf of Maine Sentinel Survey Report.
- Royle, J. A., & Nichols, J. D. (2003). Estimating abundance from repeated presence–absence data or point counts. *Ecology*, 84(3), 777-790.
- Runge, J.A., Kovach, A.I., Churchill, J.H., Kerr, L.A., Morrison, J.R., Beardsley, R.C., Berlinsky, D.L., Chen, C., Cadrin, S.X., Davis, C.S. and Ford, K.H., 2010. Understanding climate impacts on recruitment and spatial dynamics of Atlantic cod in the Gulf of Maine: Integration of observations and modeling. *Progress in Oceanography*, 87(1-4), pp.251-263.
- Ryan, J. 1979. The Cod Family and its Utilization. *Mar. Fish. Rev.* pp 25-36. Accessed at: <http://spo.nmfs.noaa.gov/mfr4111/mfr41112.pdf>.
- Serchuk, F. M., & Wigley, S. E. 1992. Assessment and management of the Georges Bank cod fishery: an historical review and evaluation. *J. Northw. Atl. Fish. Sci*, 13, 25-52.
- Shaklee, J. B., & Bentzen, P. 1998. Genetic identification of stocks of marine fish and shellfish. *Bulletin of Marine Science*, 62(2), 589-621.
- Steneck, B., Leland, A., McNaught, D., Vavrines, J. 2013. Ecosystem Flips, Locks, and Feedbacks: The Lasting Effects of Fisheries on Maine’s Kelp Forest Ecosystem. *Bul. Mar. Sci.* 89(1): pp. 31-55.

- Swain, D. P., and Foote, C. J. 1999. Stocks and chameleons: the use of phenotypic variation in stock identification. *Fisheries Research*, 43: 113–128.
- Tanaka, K., & Chen, Y. 2016. Modeling spatiotemporal variability of the bioclimate envelope of *Homarus americanus* in the coastal waters of Maine and New Hampshire. *Fisheries Research*, 177, 137-152.
- Walsh, W.A., Chang, Y., Lee, H., 2013. Catch Statistics , Size Compositions , and CPUE Standardizations for Blue Marlin *Makaira nigricans* in the Hawaii-based Pelagic Longline Fishery in 16–23.
- Wenger, S. J., & Freeman, M. C. 2008. Estimating species occurrence, abundance, and detection probability using zero-inflated distributions. *Ecology*, 89(10), 2953-2959.
- Ying, Y., Chen, Y., Lin, L., & Gao, T. 2011. Risks of ignoring fish population spatial structure in fisheries management. *Canadian Journal of Fisheries and Aquatic Sciences*, 68(12), 2101-2120
- Zeileis, A., Kleiber, C., Jackman, S., 2008. Regression Models for Count Data in R. *Journal of Statistical Software* 27.
- Zemeckis, D.R., Dean, M.J. and Cadrin, S.X., 2014. Spawning dynamics and associated management implications for Atlantic cod. *North American Journal of Fisheries Management*, 34(2), pp.424-442.
- Zurr, A., Ieno, E. N., Walker, N., Saveliev, A. A., Smith, G. M. 2009. *Mixed Effects Models and Extensions in Ecology with R*. Springer, New York. pp. (211-248)

APPENDIX

Shortened Longline Justification and Evaluation of Soak Time (as described by Carlucci and Chen, 2017)

In general, catch is expected to increase with soak time. However, the relationship between soak time and catch rate is rarely statistically significant in models (Lokkeborg and Pina, 1997; Lambert, 1994). Additionally, studies of the effectiveness of longline gear have found that most fish are caught between two and three hours. After this time, any additional soak time may result in fish loss due to predation (Ogura et al., 1980; Lokkeborg and Pina, 1997). From 2012 to 2015, the target soak time for the longline gear was two hours, which was then reduced to one hour in 2017.

GAMs with a Tweedie distribution were constructed to analyze the relationship between soak time and catch abundance as well as the effect of hook number on catch between 2012 and 2017. This was done to evaluate whether the change in longline gear and soak time influenced catch abundances on a per-species basis. All models considering count of target species as a response to all variables that influence catch showed no significant relationship between catch abundance and soak time. Models that included hook number excluded soak duration while models that contained soak duration excluded hook number. This was done because hook number and soak duration are directly related with the change in gear and keeping both variables in the same model can mask the true relationships between catch abundance and other explanatory variables in the model. The presence of a statistically significant relationship

between soak time and catch abundance would indicate that soak duration is not sufficient, and the gear is actively fishing while it is being hauled. Since soak duration was found to be insignificant for all target species, it was concluded that target soak time of one hour is enough for the number of hooks on the longline. However, despite the lack of a significant relationship between soak time and target species catch abundance, there was a statistically significant relationship between soak time and the catch abundance of dogfish. Dogfish are not a target species, but they are a schooling, voracious predator that can limit the opportunity for target species to take bait. This can also lead to instances of false zeros – when target species are present but recorded as absent because they were not caught. This information could be useful in the future as the soak time is re-evaluated to optimize catch of target species and minimize catch of non-target species.

Hook number was consistently significant among target species. This is intuitive because the number of hooks is directly related to the number of fish a longline can catch. Because hook number was reduced by a factor of ten in 2017, historic Sentinel Survey data from 2012-2015 has been standardized to account for the change in hook number to calculate comparable abundance estimates between years.

ABOUT THE AUTHOR

John Andrew Carlucci was born August 24, 1995 in Danbury, Connecticut. He has always been an avid outdoorsman, developing an early love for fishing, which then evolved into an insatiable passion for fly-fishing. At the age of ten, John's family vacated to Sanibel Island, Florida. Sharing his love for fishing with his two brothers and his father, the three took one day to go on a fishing trip offshore. Upon catching a juvenile black tip shark off a sandbar, the captain gave John the opportunity to tag the fish, collecting data on its length, weight, age, and location. Having his scientific curiosity shaped by the Saturday morning ocean specials, this excitement of this experience coupled with a pre-existing love for fish prompted John to converge on the decision to become a marine biologist. In 2017, John received his bachelor's in marine science and environmental sciences from the University of Maine. He is a candidate for the Master of Science Degree in Marine Biology from the University of Maine in May 2019.