

On the Dynamic Management of Marine Resources

by

Daniel Carl Dunn

Division of Marine Science and Conservation
Duke University

Date: _____

Approved:

Patrick N. Halpin, Supervisor

Jeffrey A. Buckel

K. David Hyrenbach

David W. Johnston

Andrew J. Read

Dissertation submitted in partial fulfillment
of the requirements for the degree of Doctor of Philosophy
in the Division of Marine Science and Conservation
in the Graduate School of Duke University

2014

ABSTRACT

On the Dynamic Management of Marine Resources

by

Daniel Carl Dunn

Division of Marine Science and Conservation
Duke University

Date: _____

Approved:

Patrick N. Halpin, Supervisor

Jeffrey A. Buckel

K. David Hyrenbach

David W. Johnston

Andrew J. Read

An abstract of a dissertation submitted in partial fulfillment
of the requirements for the degree of Doctor of Philosophy
in the Division of Marine Science and Conservation
in the Graduate School of Duke University

2014

Copyright by
Daniel Carl Dunn
2014

Abstract

Mismatches in the spatiotemporal variability of resource, resource users and management actions breeds inefficiency in the management of marine resources. To date, the spatiotemporal resolution and extent of fisheries management has been largely dictated by logistical and political constraints, and secondarily by the geographic range of the species or meta-population dynamics. Management units are rarely smaller than 1000 km² in developed coastal fisheries, and management measures generally occur at resolutions larger than 100 km². From a temporal perspective, the finest resolution of management measures is at best a month but more generally a year. As such, attempts to manage processes and patterns at sub-10 km, sub-1 month resolution often involve some level of spatiotemporal mismatch. To address the obvious spatiotemporal mismatch between a dynamic ocean and static management, to allow for a comprehensive implementation of ecosystem-based fisheries management, and to minimize inefficiency in our management of marine resources, we must seek to develop more dynamic management measures that allow managers to address scales, processes and patterns occurring under ten kilometers.

In this dissertation I apply point pattern processes, cumulative distribution functions, receiver operator characteristic curves, simulated annealing tools, regression models and clustering techniques to develop examples of two dynamic management

measures and to compare the efficiency of static versus dynamic management measures. I show that autocorrelation analysis can inform the distances and times used in real-time closures based on move-on rules. Further, I identify optimum bottom temperature threshold values to separate individual species within the Northeast Multispecies Fishery from Atlantic cod. Results demonstrate that dynamic spatiotemporal management measures are widely applicable, and more effective and more efficient than static time-area closures. Unexpected trends in some results due to a changing climate indicate possible increasing thermal overlap between Atlantic cod and many other species in the fishery. Implications of scale in fisheries management and the importance of coarse scale (1 – 10km) ecological patterns to fisheries are discussed.

Dedication

To my wife. Life, like the ocean, is mutable. She is not. She is my place.

To my daughter, because balala(la) is an even better word than banana.

To my mom, who asked me if I was being constructive one too many times.

To my dad, because we stand on the shoulders of giants.

Contents

Abstract	iv
List of Tables	xi
List of Figures	xii
Acknowledgements	xiv
1. Introduction: Spatiotemporal management of fisheries to reduce bycatch and increase fishing selectivity	1
1.1 Why mitigate bycatch with spatiotemporal measures?	4
1.2 The analytical framework.....	9
2. Move-on rules and the new objective function in New England fisheries.....	18
2.1 Introduction.....	18
2.1.1 The influence of sector-based management on fishing strategies in New England.....	18
2.1.2 Spatiotemporal autocorrelation in fisheries	22
2.1.3 Move-on rules in fisheries management.....	23
2.2 Methods	29
2.2.1 A collaborative approach	29
2.2.2 Data	30
2.2.3 The space–time K function.....	31
2.3 Results	36
2.4 Discussion.....	42
2.4.1 Actionable & operable results.....	42

2.4.2 Implementation Options	43
2.4.3 Empirical move-on rules	46
2.4.4 Broader applicability of empirical move-on rules	47
3. Temperature-based targeting in a multispecies fishery under climate change	49
3.1 Introduction.....	49
3.1.1 Background	49
3.1.2 Known effects of temperature on species in the Northeast Multispecies Fishery	51
3.2 Methods	53
3.2.1 Data	53
3.2.2 Seasonal variability	55
3.2.3 Empirical cumulative distribution functions	55
3.2.4 Post-hoc analysis	60
3.3 Results	63
3.3.1 Spring clustering analysis	63
3.3.2 Bagged threshold temperature analysis.....	63
3.3.3 Post-hoc analysis	69
3.4 Discussion.....	70
3.4.1 Temperature targeting in a multispecies fishery	70
3.4.2 The influence of climate change on targeting within a multispecies fishery	72
3.4.3 Further considerations.....	75
4. Why do we persist with persistence? A comparison of static and dynamic fishery closures.....	77

4.1 Introduction.....	77
4.1.1 Background	77
4.1.2 The importance of scale in fisheries management.....	78
4.1.3 Dynamic Ocean Management	81
4.2 Methods	85
4.2.1 Development of closures	85
4.2.1.1 Development of annual and seasonal static closures.....	86
4.2.1.2 Development of grid-based “hotspot” closures	89
4.2.1.3 Development of real-time closures based on move-on rules.....	89
4.2.2 Calculation of time and area required by closures	90
4.2.3 The efficiency metric	91
4.3 Results	93
4.3.3 Closure Results	93
4.4 Discussion.....	98
4.4.1 Dynamic management can be more efficient than static	98
4.4.2 Dynamic management can address coactive and social processes	99
5. Conclusions & Future Directions.....	101
5.1 Knowledge and Novelty.....	101
5.2 Gaps and Needs.....	105
5.3 Ecological Considerations	106
Appendix A.....	110
Development of closures based on bottom temperature.....	110

Results	112
ROMS correction results.....	112
Temperature threshold validation	114
Obstacles to the implementation of dynamic management.....	115
Bibliography	118
Biography	138

List of Tables

Table 1: Examples of behaviours or physiology and potential management measures and analytical techniques that may be applied to address them.....	6
Table 2: Minimum, useful and optimal data requirements for the analyses described in the decision tree.....	12
Table 3: Examples of the range in type and geographic scope of fisheries that utilize move-on rules. The literature describing these examples provides little to no explanation for the times and distances employed.....	25
Table 4: Significance test for overall spatiotemporal clustering, move-on distances and performance measures for choke stocks, juvenile catch and depredation events. The sum of $\hat{D}_m(d, t)$ is compared to the 95% quantile of 1000 random labeling permutations of the spatiotemporal K function.	37
Table 5: Results of the explanatory model of the difference in breadth of acceptable threshold values between cold and warm springs.....	69
Table 6: Species meeting all three criteria for successful temperature-based targeting against Atlantic cod (using Breadth > 0.5°C) by season and temperature regime type....	70
Table 7: Results from the simulation of four different closures type spanning a range of dynamism.....	96
Table 8: Mean difference and standard deviation of the ROMS and corrected predicted bottom temperature from in-situ NEFSC Scientific Trawl Survey bottom temperature data.....	112
Table 9: Coefficients and approximate estimates of significance for the GAM model to correct the ROMS.....	114
Table 10: Results of the validation exercise for the optimal temperature threshold.....	115

List of Figures

Figure 1: This decision tree describes some possible analytical tools that may be used to understand and manage bycatch of finfish and protected species through spatiotemporal management measures. The management measures become more targeted as the user moves down the decision tree, however data requirements, uncertainty and the complexity of the management measures generally increase. 11

Figure 2: Spatiotemporal autocorrelation in catch of (a) yellowtail flounder and (b) barndoor skate stocks, and juvenile catches of (c) pollock and (d) cod for large-mesh stand-up gillnet gear. Color values are unitless and represent relative distance above the 95% envelope generated from 1000 random label permutations. Peaks in the surface indicate the spatiotemporal extent of the clustering. I.e., a value of 1 corresponds to the highest autocorrelation value within over the time and distances used in the analysis. . 39

Figure 3: Spatiotemporal autocorrelation in depredation events in sets using large-mesh stand-up gillnet gear: (a) depredation by fleas, (b) depredation by hagfish, (c) depredation by sharks. Color values are unitless and represent relative distance above the 95% envelope generated from 1000 random label permutations. Peaks in the surface indicate the spatiotemporal extent of the clustering. I.e., a value of 1 corresponds to the highest autocorrelation value within over the time and distances used in the analysis. . 40

Figure 4: The Area Under the Curve is calculated by plotting the percentage of biomass of each species available at each 1/4 degree interval, taking the absolute value of the area beneath that curve, and then subtracting the area beneath the line of complete overlap (i.e. slope = 1). 59

Figure 5: Optimum threshold temperatures for separating species within the Northeast Multispecies FMP and species that commonly interact with the fishery from Atlantic cod. All warm spring threshold values were great than cold spring values, and all fall threshold values were greater than warm spring values. 62

Figure 6: The difference in percentage biomass available for Atlantic cod and each comparison species for warm vs cold springs and warm springs vs fall. The dotted line represents a 1-to-1 relationship (i.e., no change) between seasons. Distance from the line indicates strong changes between seasons. 64

Figure 7: Separability by temperature of all species compared to Atlantic cod. A decrease in breadth was found between cold and warm springs, but operable separation was found across each temperature regimes and season. Breadth was generally

categorized into “not operable” (< 0.5°C), “possible” (0.5 – 1.0°C) and operational (>1.0°C).	67
Figure 8: The spatiotemporal extent of: a) fishing gear, intra-annual shifts in fishing effort and traditional static spatiotemporal management measures (i.e., permanent or seasonal time-area closures); and b) dynamic management measures including grid-based closures, real-time closures based on move-on rules and oceanographic closures overlaid on the “Stommel diagram” from Haury et al. 1978 (after Stommel 1963).	79
Figure 9: Dynamic Ocean Management can be seen as a sub-routine within the larger adaptive management framework. While alternate definitions are still being debated, I believe it specifically applies to the where and when a management measure is implemented (i.e., automatically, in near real time and against conditions on the ground).	82
Figure 10: Three efficiency metrics: a) the reduction ratio of bycatch to catch; b) the kilometer days used; and, c) the total efficiency metric (reduction ratio divided by the percent of total kilometer days used. Dynamic management measures are depicted in purple and static measures in blue.	97
Figure 11: Distribution of error (i.e., difference from in-situ measurements) for the ROMS and the predicted bottom temperature from the GAM.	113

Acknowledgements

Overall

I am deeply grateful to the Nippon Foundation – University of British Columbia Nereus program for their full and unwavering support of all of the work that went into this dissertation. I would like to specifically thank Y. Ota, W. Cheung, V. Christiansen and D. Pauly for their leadership in the program, and A. Merrie, M. Metian and A. Boustany for the opportunity to collaborate with them. The NF-UBC Nereus Program is a collaborative initiative conducted by the Nippon Foundation, the University of British Columbia, and five additional partners, including Duke University. This dissertation is only one part of Nereus' international and interdisciplinary effort towards global sustainable fisheries, and I am proud and honored to have been able to work with such a wonderful group of scientists.

Introduction

I am extremely thankful for the contributions of my co-authors on the Fish & Fisheries version of this chapter: A. M. Boustany, J. J. Roberts and P. N. Halpin. I would like to acknowledge the support of the David and Lucile Packard Foundation for their funding of this study. I am also indebted to my colleagues J. Ardron, C. Curtice, and E. Fetherston for their review of the manuscript, and A. Read, K. Gjerde, E. Gilman, E. Brazer, M. Sanderson and J. Dunn for their input and support.

Chapter 1:

I am extremely thankful for the contributions of my co-authors on the Fish & Fisheries version of this chapter: E. Brazer, M. Sanderson, B. Gardner, A. M. Boustany and P. N. Halpin. I gratefully acknowledge the fishermen of the GB Cod Fixed Gear Sector who collaborated with us, as well as B. Martens and the fishermen of the Port Clyde Community Groundfish Sector who participated in the meetings. I am indebted to K. Ryder for her help with the project, and J. Hoey, C. Woodhead, J. Palmer, J. O'Neil and the staff of the Northeast Fisheries Science Center for their support. This chapter was improved by reviews from my colleagues C. Curtice, J. Dunn, J. Moxley and S. Viehman. I deeply appreciate their time and effort. This project was funded by the Cooperative Research Division of the National Marine Fisheries Service and my time was partially supported by the NF-UBC Nereus Program.

Chapter 2:

I am indebted to my co-authors on the manuscript version of this chapter in preparation to be submitted: J. Moxley and P.N. Halpin. I gratefully acknowledge R. Johnston, W. Gabriel and everyone involved with the NEFSC Scientific Trawl Survey for their support. This chapter would not have been possible without the incredible work put into the NEFSC Scientific Trawl Surveys over the last nearly 50 years. The chapter further benefited from constructive reviews by J. Buckel and J. Bonaventura. D.

Johnston also provided strong input into the theory underpinning the methods. I deeply appreciate their time and effort.

Chapter 3:

I gratefully acknowledge the contribution of my co-author on the peer-reviewed manuscript version of this chapter: A. M. Boustany and P. N. Halpin. This chapter would not have been possible without the fishermen of the GB Cod Fixed Gear Sector and E. Brazer and M. Sanderson. The provision of data by J. Hoey, C. Woodhead, J. Palmer, J. O'Neil and the staff of the Northeast Fisheries Science Center was also critical to its success.

1. Introduction: Spatiotemporal management of fisheries to reduce bycatch and increase fishing selectivity¹

Marine environments are currently under stress due to a variety of human influences (Halpern et al., 2008). Fisheries represent one of the greatest anthropogenic stressors on marine ecosystems (Dayton et al., 1995; Goñi, 1998; Jackson et al., 2001). Among the ecosystem effects of fishing, the detrimental impact of bycatch has been increasingly documented in recent years (Crowder and Murawski, 1998; Hall et al., 2000; Lewison et al., 2004; Gilman et al., 2005). For the purposes of this dissertation, I define bycatch as the catch from a fishery that is not landed due to regulatory or economic reasons. The role of fisheries bycatch in the decline of populations of protected species (N. P. Brothers et al., 1999; Spotila et al., 2000; Read et al., 2006; Reeves et al., 2013; Wallace et al., 2013) has led to the enactment of conservation policies (Moore et al., 2009) and costly management measures including fishery closures and gear alterations (Curtis and Hicks, 2000; E. Gilman et al., 2006).

While much attention has been given to the issue of the incidental capture of protected species, bycatch is not merely a protected species issue. Finfish bycatch can be

¹A version of this chapter has been previously published as: Dunn, D.C., A. Boustany, P.N. Halpin. (2011) Spatiotemporal management of fisheries to reduce bycatch and increase fishing selectivity. *Fish and Fisheries* 12:110-119.

discarded by fishers due to regulations (i.e., “regulatory discards”) or lack of commercial value (i.e., “economic discards”). A recent FAO report estimates bycatch to be ~23% of global marine landings, though these levels can be much higher for specific fishing gear (Kelleher, 2005; FAO, 2009). Mortality rates associated with bycatch can be very high. Thus, bycatch represents a sub-optimal use of marine resources: adding to the depletion of already heavily exploited stocks; delaying or preventing the recovery overfished stocks, depleting prey resources for other fisheries, and causing the early closure of fisheries when catch or bycatch quotas of commercial or protected species are exceeded. The economic impact of these effects can be substantial. Rebuilt fisheries have been estimated to be worth approximately three times the value of depleted fisheries (Sumaila and Suatoni, 2006), and the global opportunity cost of depleted and overcapacity fisheries has been projected to be \$50 billion a year (Arnason et al., 2009). Further, the early closure of an otherwise sustainable fishery due to a bycatch quota being exceeded results in unrealized economic gains and places an undesirable financial burden on fishers (Curtis and Hicks, 2000; Chakravorty and Nemoto, 2001). In order to maximize the economic efficiency and limit the ecosystem effects of fishing, bycatch must be minimized and fishing selectivity (i.e., catch to bycatch ratios) must be increased.

As ecosystem-based management approaches are employed and more fisheries are managed through multi-species, multi-objective models, the management of

regulatory bycatch will likely increase. This can already be seen in the importance given to the management of bycatch in the fisheries policy of many governments (e.g. the EU Common Fisheries Policy or the Australian Fisheries Management Act), and recent reforms of such legislation (CEC 2009, or e.g., the Magnuson-Stevens Fishery Conservation and Management Reauthorization Act of 2006). It is also particularly relevant in the United States, as the deadline for setting Annual Catch Limits (ACLs) in fisheries experiencing overfishing passed in 2010, and in all other fisheries in 2011. This has resulted in a dramatic expansion of the number of quotas for which fishers and regulators will have to account (Hall et al., 2000). Quotas are a type of catch management measure that limit the total number of fish that can be taken in a fishery, but this type of measure does not improve fishing selectivity. Typical effort-based management measures (e.g., bag limits or trip limits) also cannot address issues of fishing selectivity. However, operational measures (i.e. how and where fishing occurs) can be used for this purpose. Thus, to ensure that regulations do not result in the early closure of fisheries, it is imperative that managers be given the tools necessary to limit bycatch through operational management measures. Targeted spatiotemporal fishery closures can increase fishing selectivity by prohibiting fishing in areas with high bycatch to catch ratios, and are a possible solution open to managers (Hall, 2002; Hall and Mainprize, 2005). Time-area closures have been used internationally to reduce bycatch

of both protected and commercial species (Hooker and Gerber, 2004; or e.g., AFMA, 2009; PFMC, 2008). However, many methods to identify and manage the spatiotemporal nature of bycatch remain acutely under-utilized. In an effort to synthesize available information before further analyzing individual measures and developing comparisons of static vs. dynamic measures, I present an analytical framework in this introduction for the spatiotemporal management of fisheries to reduce bycatch and increase fishing selectivity.

1.1 Why mitigate bycatch with spatiotemporal measures?

The current movement towards marine spatial planning (MSP) offers an important framework and impetus to examine how we manage fisheries spatially. As plans are put forth, fishers and regulators will want to ensure that areas of persistently high fishing efficiency and selectivity remain open to fisheries. This requires that researchers and regulators first understand the spatiotemporal nature of bycatch within their systems, and then identify and protect economically efficient fishing locations against the potential negative impacts of other industries (i.e. mining, shipping, etc.). The framework put forward in this introduction offers fisheries managers a means to identify such fishing areas, and a first step toward objectively participating in the MSP process.

Ecosystem-based management of biological resources requires that the measures taken be ecologically appropriate and relevant (i.e., related to the biology or ecology of the species in question). Thus, the use of marine spatiotemporal closures to reduce bycatch should be based on clearly quantifiable relationships to behaviors (e.g., foraging) or physiology (e.g. range limits due to salinity or temperature, etc.). To date, fisheries closures have largely been used to prevent catch or to reduce bycatch of sedentary species associated with particular static habitats (e.g., protecting deep-water grouper species or groundfish by protecting deep-water hardbottom habitats; (e.g., AFMA, 2009; SAFMC, 2007). The use of one particular area for multiple life history stages makes such species-environment relationships ideally suited to static spatial management. However, management measures directed at protecting an individual life-history stage (e.g., protection of spawning aggregations) can also effectively limit risk to endangered or overfished species (e.g., AFMA, 2009b; Beets and Friedlander, 1999; Dutton et al., 2005). Further, networks of closures meant to protect successive individual life-history stages may be highly successful where a single spatiotemporal measure meant to protect one life-history stage is not enough to guarantee the sustainability of a population.

Table 1: Examples of behaviours or physiology and potential management measures and analytical techniques that may be applied to address them.

Analytical Technique	Examples of Ecological Relevance (i.e., patterns revealed)
Periodicity analyses	<ul style="list-style-type: none"> • Temporal-regulated behavioral patterns (e.g., foraging)
Local spatial association analyses	<ul style="list-style-type: none"> • Persistent habitat usage (e.g., reef-dependent species)
Combination of periodicity and local spatial association analyses	<ul style="list-style-type: none"> • Migration patterns (both horizontal and vertical) • Seasonal habitat usage
Spatial & temporal autocorrelation analyses	<ul style="list-style-type: none"> • Episodic resource usage • Schooling and social behaviour
Oceanographic correlate analyses	<ul style="list-style-type: none"> • Physiological limits (e.g. to temperature or salinity) • Correlates to behavioural states (e.g. foraging)

Numerous behaviors and physiological traits can be used as the ecological basis for mitigating bycatch with spatiotemporal measures (see Table 1). Persistent habitat usage, the use of one area by resident species throughout multiple life-history stages, was discussed above. Dynamic or ephemeral habitat usage will require different management approaches. Protection of seasonal habitat usage has also been a common objective of fisheries closures, and the use of bycatch rates to focus such time-area closures is not uncommon. Migration patterns have been incorporated in spatiotemporal management through the use of rolling closures meant to protect the species as they move through particular areas during their migration (e.g., NEFMC,

1999). Bycatch of animals engaged in episodic resource usage (i.e., the targeting of static habitats by opportunistic foragers, or specific ephemeral habitats by specialized consumers including depredation events) can be mitigated through event-triggered closures. Schooling or other social behavior among marine organisms also lends itself to such dynamic management measures. Finally, physiological limits or preferences offer clear values that can be used to create oceanographic closures (e.g., Howell et al., 2008; <http://www.pifsc.noaa.gov/eod/turtlewatch.php>) or compared to maps of oceanographic climatologies to optimize the siting of static fishery closures based on the probability that the oceanographic feature will be present in a given cell over a specific time period (i.e., weekly, monthly, annually, etc.; e.g. Hobday and Hartmann, 2006; Hobday et al., 2010). Similarly, oceanographic correlates of various behavioral states, or life-history stages, can be used to delineate and protect such areas.

Although the theoretical ecological relevance of various spatiotemporal management measures is easily defined, there are few examples of the use of biophysical parameters other than benthic habitat type as the basis for selecting the location of a spatiotemporal fishery closure. Event triggered closures are the most common form and are used to close shellfish fisheries due to declines in water quality following storms (e.g., NCDENR, 1987) and are implemented via move-on rules to inform real-time closures in marine fisheries. Move-on rules are reviewed in chapter 1 to provide

background before a theoretical example informed by spatiotemporal autocorrelation analysis is developed.

The spatiotemporal associations between fishing effort, non-target species and observed oceanographic features may also be used to identify critical pelagic areas that can be delimited and managed using static or dynamic fishery closures. Correlations between bycatch rates and dynamic oceanographic features have been elucidated in peer-reviewed literature (Klaer and Polacheck, 1998; N. Brothers et al., 1999; Kobayashi and Polovina, 2005; Dietrich et al., 2009). Oceanographic characterizations of catch rates are even more common (e.g. Bigelow et al., 1999; Seki et al., 2002; Zagaglia et al., 2004) and include a wider variety of variables (e.g. frontal systems, sea-surface height, or salinity). Further, numerous habitat models for commercial and non-target species based on dynamic oceanography have been published (Redfern et al., 2006; Opperl et al., 2012). However, these relationships to dynamic oceanographic features have rarely been incorporated into active resource management planning. In chapter 2, bottom-temperature is used to differentiate biomass of target and non-target species to identify optimum threshold values to inform temperature targeting and temperature-based closures. The rest of this introduction places these management measures within a broader framework, offering a concise description of the management options that might be used based on information gathered by specific analytical techniques.

1.2 The analytical framework

Five questions surround any attempt to designate a fishery closure: (1) What are the specific outcomes to be achieved (e.g. to reduce unintended bycatch of a non-target species during the peak migratory season etc.); (2) How should the closure be constrained in time; (3) how should the closure be constrained in space; (4) how will the implementation be designed and enforced; and (5) how will the benefits and costs be objectively measured?

I propose the use of a general decision tree as a guideline to assist in the definition of appropriate time and space requirements to better meet fisheries management objectives within an MSP context. These approaches aim to reduce bycatch by using the periodicity of bycatch events in space and time, the autocorrelation of the events, and the relationship of events to oceanographic patterns. On the temporal side, fisheries closures may be dynamic (i.e., triggered by an event), seasonal or permanent. When a closure is being implemented to mitigate bycatch the spatial component may be broken down further by three additional questions: 1- how are the bycatch events distributed compared to catch; 2- are the bycatch events spatially autocorrelated to other catch, bycatch or depredation events (i.e., are you more likely to have a second event after an initial one); and 3- are the bycatch events correlated with a spatially explicit

oceanographic variable. Many techniques exist to either describe or analyze bycatch data. These methods may be included in a decision tree (Figure 1) to come to an objective conclusion regarding the appropriate spatiotemporal nature of a fishery closure designed to reduce bycatch.

Decision trees are useful management tools that are commonly utilized in resource management. Regional fishery management councils in the United States are currently using or investigating the use of decision trees to set Allowable Biological Catch (ABC) limits (e.g. Armsworth et al., 2010). The theoretical decision tree offered here classifies the analytical tools available to describe or analyze catch or bycatch data into four types: periodicity analyses, local spatial association analyses, spatiotemporal autocorrelation analyses and oceanographic correlate analyses. It is organized so that the decision tree portrays increasing complexity in the resultant management options as you move down the tree. Similarly, the data required to perform the analyses also tends to increase as you approach the lower nodes (see Table 2). However, this increase in data requirements and management complexity also tends to decrease the time/area affected by the management measure as the tools applied delimit more and more specific times and areas. In other words, the better definition of spatiotemporal relationships provides for more targeted management interventions.

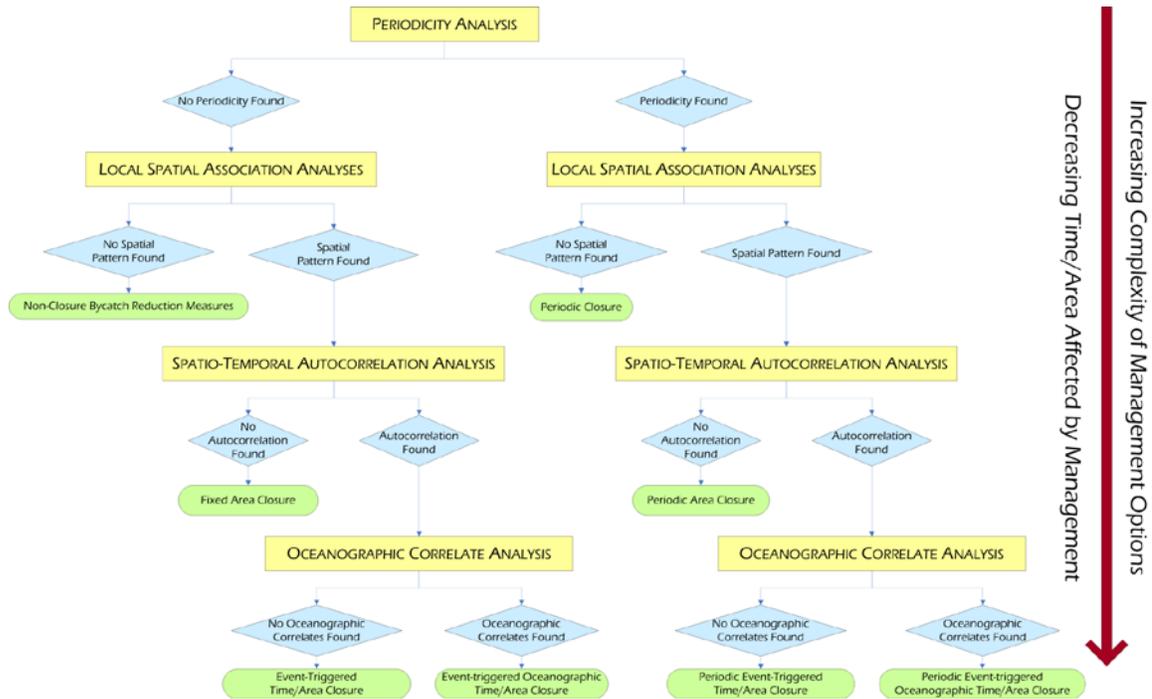


Figure 1: This decision tree describes some possible analytical tools that may be used to understand and manage bycatch of finfish and protected species through spatiotemporal management measures. The management measures become more targeted as the user moves down the decision tree, however data requirements, uncertainty and the complexity of the management measures generally increase.

An easily defined but potentially low precision spatiotemporal management measure is the total closure of a fishery during a particular season. This type of broad management intervention may address a variety of recurring temporal patterns in fisheries bycatch data (e.g., diurnal, lunar, seasonal, and inter-annual), but are not triggered by the specific pattern of bycatch events. Specific recurring periodicities in fisheries bycatch have been found to be explanatory factors affecting bycatch rates

(Barnes et al., 1997; Klaer and Polacheck, 1997; Weimerskirch et al., 2000; Kobayashi and Polovina, 2005; Dietrich et al., 2009; Kot et al., 2010). Numerous statistical methods exist to describe this type of periodicity. Kot et al. (2010) apply four such methods to bycatch data: an analysis of the inter-annual coefficient of variation in bycatch rates by month; a Fast Fourier Transform (FFT); a linear regression of catch per unit effort (CPUE) and bycatch per unit effort (BPUE) data; and a Wilcoxon Signed Rank Test on monthly BPUE. These statistics require significantly less data than all other methods described in this paper, as there is no spatial element to the analysis. However, the resultant management measure, a full fishery seasonal closure, is coarse and will likely have broad socioeconomic impacts. Further analysis to define more specific spatial and temporal patterns in fisheries bycatch may be employed to develop more targeted and effective management efforts.

Table 2: Minimum, useful and optimal data requirements for the analyses described in the decision tree.

	Time	Day	Week	Month	Year	Lat/Long	Oceanography
Periodicity Analyses	Optimal	Useful	Useful	Min			
Local Spatial Association Analyses				Min	Min		
Spatiotemporal Autocorrelation Analyses		Optimal	Useful	Useful	Min	Min	
Oceanographic Analyses		Optimal	Useful	Min		Min	Min

If the CPUE or BPUE data are spatially explicit and have been measured at a resolution relevant to managers, the spatial extent of the closure may be addressed through the use of local spatial association statistics. These statistics identify local spatial clusters (i.e., “hot spots”; Anselin, 1995). When applied to a dataset of spatially explicit catch or bycatch rates, these statistics allow for the identification of areas of persistently high catch or bycatch. Lewison et al. (2009) use a Moran’s scatterplot to identify such clusters. Gi and Gi* statistics (Getis and Ord, 1992), and Local Indicators of Spatial Association (LISA) like the local Moran’s I (Anselin, 1995) may also be used to identify spatial clustering. Perhaps most significantly, these statistics may be applied to bycatch to catch rates or bycatch to catch value ratios to identify areas of low fishing efficiency (i.e., areas where bycatch rates are high relative to the target catch rate; Bartram et al., 2010). The use of systematic conservation planning software (e.g. Marxan; Ball et al., 2009) to optimize site selection based on BPUE or fishing selectivity ratios is another method that can be employed to help define spatiotemporal closures (Grantham et al., 2008). Regardless of whether these methods are applied to bycatch rates or fishing selectivity ratios, they offer a means to create more targeted time-area closures that should consequentially decrease the negative impacts to fishers.

Seasonal and time-area closures are common fisheries management mechanisms. They are well suited to address known ecological and biological characteristics of some

fisheries (e.g., species-habitat relationships, or spawning seasons). As I have indicated, these characteristics make them equally applicable to the reduction of bycatch. I have also suggested how they may be used to increase fishing selectivity. However, these methods are static measures and may not necessarily be ideally suited to dealing with dynamic, ephemeral events such as bycatch. Event-triggered or dynamic oceanographic closures offer a means to address events such as these that otherwise show no predictable spatial or temporal pattern (i.e., clustering in time and/or space).

The use of event-triggered closures to mitigate bycatch is based on the assumption that the likelihood of a bycatch event occurring increases after an initial event. Temporal and spatial autocorrelation analyses may provide a useful method to determine if this assumption is valid. Ripley's K and the O-ring statistic have been applied to bycatch data to measure autocorrelation (Gilman et al., 2007; Gardner et al., 2008; Lewison et al., 2009b). Semivariance analyses (Matheron, 1963; Meisel and Turner, 1998) to define the scale of spatial autocorrelation could also be used for this purpose, though no example of the application of this method using bycatch data exists at this time (though see Ciannelli et al., 2008; Petitgas, 1996 for reviews of geostatistics in fisheries). By determining the temporal and spatial distance at which bycatch events occur, managers should be able to create more targeted closures than might be possible with the previous techniques discussed above. The lack of application of autocorrelation

analyses to inform event-triggered closures to mitigate bycatch is confounding as it requires no more spatiotemporal data than that required to implement time area closures (i.e., the date and location of the bycatch event). The main obstacle to the use of event-triggered closures is likely the need for near real-time management of the fishery for this measure to be effective.

Alternatively, the final node in the decision tree, oceanographic correlate analyses, can be used to define either static or dynamic closures. As mentioned previously, patterns of fisheries target and non-target catch have been shown to be influenced by numerous oceanographic variables. Habitat models (see Guisan and Zimmermann, 2000) generated from observer survey or animal telemetry data may be used to determine the realized niche of a species, and corresponding environmental envelope (i.e. minima and maxima). These values may then be used to regulate fishing above or below the predicted minimum or maximum value in which the bycaught species is commonly found. In other circumstances researchers have used descriptive statistics and regression models to determine the oceanographic correlates of bycatch events themselves (Brothers et al., 1999; Hobday and Hartmann, 2006; Gardner et al., 2008; Zydalis et al., 2011; Reid et al., 2012). The use of oceanographic correlates to create near real-time dynamic closures is proposed, but has not been widely implemented at this point. Sea surface temperature is the basis for a voluntary closure in both the

United States (Howell et al., 2008), and a regulated closure in Australia (Hobday et al., 2010). Although substantial data and analytical capacity that went into the implementation of these two oceanographic closures, the success and targeted nature of the resulting closures in mitigating bycatch provide insight into the utility of these measures and should encourage fisheries managers to move towards the collection of higher resolution data.

The framework presented here is meant to relate spatiotemporal data requirements, analytical techniques and management measures to reduce bycatch. While I believe that many fisheries in developed countries will be able to make use of the whole decision tree, I acknowledge that data availability and resolution will be a limiting factor in many developing regions. However, in such cases this framework should still prove useful in guiding the implementation of data collection policies. It should also be noted that as modelling measures increase in complexity (i.e., as we move further down the decision tree) so does the opportunity for error. Improvements in our ability to focus spatiotemporal management measures are generally tied to increasing model uncertainty. Thus, these measures should not be used in lieu of catch measures that implement hard quotas (i.e., those that close the fishery when the quota is exceeded), but in concert with such measures. Where the exceeding of a bycatch quota

does not result in the closure of the fishery, but in regulations requiring the discard of the bycatch, more precautionary measures are preferable.

2. Move-on rules and the new objective function in New England fisheries²

2.1 Introduction

2.1.1 The influence of sector-based management on fishing strategies in New England

The productivity of waters and fisheries off the coast of New England has been widely recognized (McFarland, 1911; Kurlansky, 1997; Rosenberg et al., 2005; Alexander et al., 2009). The historic economic importance of the Atlantic cod (*Gadus morhua*) fishery to the development and economy of the region cannot be overstated (Ackerman, 1941; Innis, 1954; Doeringer et al., 1986). However, persistent growth and recruitment overfishing leading to sequential depletion of stocks has resulted in trophic cascades and a fundamentally altered ecosystem (Murawski *et al.* 1997; Fogarty and Murawski 1998; NEFMC 2012; for regional examples, see also Myers and Worm 2003; Frank *et al.* 2005). Although some successes at rebuilding stocks have been noted, the latest assessment update listed 80% stocks in the Northeast Multispecies Fishery Management Plan (FMP) as being overfished and/or experiencing overfishing (NEFMC 2012). Recent amendments to the FMP have addressed these problems through a sweeping

² A version of this chapter has been previously published as: Dunn, D.C., A.M. Boustany, J.J. Roberts, P.N. Halpin (2014) Empirical move-on rules to inform fishing strategies: a New England case study. *Fish & Fisheries* 15(3):359–375.

restructuring of the fishery. The main change has been the introduction of a hard quota and catch shares, which have been shown to halt or reverse fishery collapses (Costello et al., 2008). Amendment 16 both expanded the scope of the FMP and allocated quota for 16 groundfish stocks between sectors and a common pool, and ushered in accountability for both landings and discards for the first time (NEFMC 2010). Sector management, whereby fishermen voluntarily formed groups (or “sectors”) with pooled allocations based on their historical fishing and managed primarily under a quota, offered an appealing alternative to the “common pool” which retained input controls such as days-at-sea and trip limits. Fishermen overwhelmingly chose to join sectors: 95% of the historical landings in the multispecies groundfish fishery participated in sectors in FY 2010 (NEFMC 2012).

The potential effects of the new quota system and accountability for discards on the fishing strategies of New England fishermen are enormous. The nature of multispecies fisheries like the New England groundfish fishery is such that healthy and depleted stocks co-exist, which can result in the catch of stocks with very large and very small quotas simultaneously. The smallest allocations are often referred to colloquially as “choke stocks” because once filled they choke off access to other stocks in that area (or require the fishermen to lease more quota). As the amount of quota held by a fisherman

or a sector varies widely, what is considered a choke stock differs among individuals, between individuals and sectors, and among sectors.

Beyond the low-quota “choke” stocks, discards represent another potential cost to fishermen’s profitability. Here we define discards as fish that cannot be landed due to regulatory or market constraints and therefore generate no profit, whereas landings are fish that are landed and sold. After the passing of Amendment 16, minimum size limit regulations are the only regulatory discard permitted under the FMP. Catch of any “allocated” species, including such juvenile discards, are now counted against the sector’s quota. Thus, juvenile catch and market discards (e.g., any fish that is unmarketable due to depredation by sharks, rotting, gear damage, etc.) now have a double cost, as the fishermen are unable to reap a profit from the catch and it also counts against the sector’s quota.

Previously, fishermen in the New England multispecies groundfish fishery sought to land enough of a target stock to fill multiple stock-specific trip limits, while minimizing the operational costs of running a fishing vessel (crew, bait, fuel, etc.). With the implementation of Amendment 16, this equation has fundamentally changed. Landings are no longer constrained by trip limits and as such the incentive to maximize catch of target stocks has increased. However, fishermen now must also factor the cost of leasing more quota and lost quota due to discards into their fishing strategy.

Consequently, sector members have a strong incentive to minimize (1) the catch of choke stocks, (2) regulatory discards largely due to minimum size limits, and (3) depredation events. The use of market measures to enable catch-quota balancing in multispecies fisheries has been well discussed in the economics and policy literature (Buck, 1995; Squires et al., 1998; Dupont and Grafton, 2000; Sanchirico et al., 2006). Work has also been done to examine how fishermen shift effort allocation to target specific mixes of stocks when transferable quota systems are implemented and fishing strategies are altered (Branch and Hilborn, 2008; Poos et al., 2010). However, little work has been done to consider what information might be useful to fishermen to inform their allocation of fishing effort under the new incentive structure. Here, through a cooperative research approach including fisheries biologists, spatial ecologists, sector managers and fishermen, I examine the utility of spatiotemporal autocorrelation analyses to inform “move-on” guidelines to assist a sector to reduce discards and maximize their profit.

I define a move-on rule (also known as “encounter protocols”) as a regulation or guideline that triggers the targeted closure of an area in a fishery to one or more gears for a temporary period when a catch (or bycatch) threshold is reached, without closing the entire fishery. Specifically, such move-on rules provide a distance which fishermen should move, or the amount of time they should wait, to avoid a certain type of catch.

They are commonly implemented to reduce catch of juveniles or non-target species. We differentiate such rules from general event-triggered closures, which are most often applied to a whole fishery and remain in place until the following season (e.g. the closure of a fishery when a bycatch quota is reached). Similarly, they also differ from time-area closures, as time-area closures are generally not dynamically instantiated (i.e., based on the occurrence of a particular event).

2.1.2 Spatiotemporal autocorrelation in fisheries

In the introduction, I presented a framework for minimizing discards and increasing catch selectivity through the use of spatiotemporal management measures (i.e. time-area closures). I put four types of analytical methods (periodicity, local indicators of spatial association, space-time autocorrelation, and oceanographic correlate analyses) in a decision tree where each node adds management complexity, but also decreases the time/area affected. The first two groups of methods can inform seasonal and time/area closures. Seasonal closures and time/area closures have been extensively used to, among other objectives, mitigate bycatch (Dawson and Slooten 1993; Witherell and Pautzke 1997; Murray *et al.* 2000; Hooker and Gerber 2004; Notarbartolo di Sciara *et al.* 2008; PFMC 2008; AFMA 2009a,b). However, in the introduction I suggest that when the goal is to decrease bycatch or discards, these types of closures may be less useful than other types of closures and may result in coarsely targeted management measures.

Alternatively, I indicated that consideration should be given to event-triggered closures or dynamic oceanography-based closures that can more efficiently meet the bycatch or discard mitigation objective (i.e. do so while minimizing lost target fish catch and economic burden for fishermen). Dynamic empirical oceanographic closures have recently been employed in Hawaii and Australia to mitigate bycatch (Hobday and Hartmann, 2006; Howell et al., 2008; Hobday et al., 2010) and the scientific literature contains many examples of how oceanographic habitat models can be used to implement such closures (Palacios et al. 2006; Hyrenbach et al. 2006; Eckert et al. 2008; Louzao et al. 2011; Zydelis et al. 2011; Block et al. 2011; Nur et al. 2011). Although move-on rules have been used longer than oceanographic closures (Kenchington, 2011), they have received far less attention in peer-reviewed literature.

2.1.3 Move-on rules in fisheries management

Move-on rules have been incorporated to varying degrees in the management of a number of fisheries (Table 3). These measures have been utilized from Antarctica to Norway, and in fisheries employing everything from anchored gillnets to pelagic longlines to purse seines. Generally speaking, they are most frequently implemented to reduce bycatch of juveniles or non-target species (including finfish, protected species and corals or sponges). Kenchington et al. (2011) and Shotton and Patchell (2008) offer

non-exhaustive reviews of the use of move-on rules in the context of the development of encounter protocols for deep-sea fisheries.

Table 3: Examples of the range in type and geographic scope of fisheries that utilize move-on rules. The literature describing these examples provides little to no explanation for the times and distances employed.

Management Measure	Fishery	Country	Move-on distance	Move-on time	Frequency of assessment	Threshold (trigger mechanism)
Chinook Salmon Bycatch Reduction Plan and Agreement (i.e., the Voluntary Rolling Hotspot System; Madsen and Haflinger, 2010)	Walleye Pollock Bering Sea and Aleutian Island Fishery	USA	Expert opinion	7+ days, based on vessel bycatch rate	Weekly	Based on an analysis of areas that exceed the base bycatch rate (a moving average)
Scottish Cod Conservation Credits (Holmes et al., 2011; Needle and Catarino, 2011)	Mixed gear, demersal whitefish fishery (targeting cod, haddock and whiting)	Scotland	50 – 225 nm ²	21 days	Daily	Triggered when catch rates exceed 40 juvenile cod per hour of fishing.
Cod juvenile and spawning real time closures (Marine Management Organisation, 2012)	North Sea and Skagerrak fisheries using particular gears	EU & Norway	23 or 64 nm ² , depending on distance from shore	14 days, 21 days or a calendar month, depending on distance from shore	daily for at-sea inspections or voluntary notification by fishermen; also have monthly for LPUE-based closures	Triggered when catch of mature cod (> 50 cm) exceeds 10 per hour of fishing, or 80 cod (all sizes) per hour of fishing.

Juvenile real time closures (European Commission, 2011)	North Sea and Skagerrak fisheries using particular gears	EU & Norway	50 nm ²	21 days	Theoretically upon encounter, but based on country reporting to the EU.	Triggered when catch rates of juveniles exceed 7.5% or 10%, depending on the overall ratio of cod in the catch.
Conservation Measures 33, 41 & 42 (CCAMLR, 2011)	Patagonian toothfish and mackerel icefish fisheries. Some measures affect other Antarctic fisheries.	CCAMLR	5 nm	5 days	Real time (upon encounter)	Various. Used to limit juvenile mackerel icefish catch and bycatch of non-target species in specific statistical areas.
Vulnerable Marine Ecosystem Encounter Protocols (Auster et al., 2010)	Deep sea fisheries in areas beyond national jurisdiction	Various RFMOs	Generally, 1-2 nm ²	Generally, until review	Real time (upon encounter)	Implementation of the protocols is highly variable between the various RFMOs.
Gulf of St. Lawrence groundfish small and incidental catch protocols (DFO, 2008)	Atlantic groundfish fisheries	Canada	Management area	> 10 days, based on catches from a test fishery	Daily, based on at-sea-observer reporting	Triggered when catch of “undersized fish reaches or exceeds 15% of the catch of any of the species [with a minimum size limit] or when incidental catches of a closed species reaches or exceeds the established level for the fleet.”
Gulf of St. Lawrence herring fishery small fish protocols (DFO, 2009)	Atlantic herring fisheries	Canada	Expert opinion	> 5 days, based on catches from a test fishery	Daily, based on dock-side monitoring	Triggered when catch of juvenile herring “exceeds 25% of the total number of herring that were caught and retained during that fishing trip...”

Coral/sponge encounter protocols (DFO, 2011)	British Columbia groundfish trawl fishery	Canada	"Vessels will be encouraged to avoid the area where the bycatch of coral and sponge occurred."	"Vessels will be encouraged to avoid the area where the bycatch of coral and sponge occurred."	Daily, based on at-sea-observer reporting	"This procedure will be followed any time a vessel catches more than 20 kilograms of combined corals or sponges in one tow."
Hoki small fish move-on rule (Shotton and Patchell 2008)	Hoki fishery	New Zealand Hoki Fishery Company (New Zealand)	5 nm	5 days	Real time (upon encounter)	Move-on rule was implemented if 10% of catch (by numbers) were juvenile hoki.
Fish aggregating device (FAD) closures (WCPFC, 2009)	Purse seine fishery for highly migratory fish stocks	Western and Central Pacific Fisheries Commission	50 nm	7 days	Upon retrieval of a FAD	Applies to fishing after retrieval of a FAD during a FAD closure.
Right Whale Dynamic Area Management (DAM; NMFS, 2002)	lobster trap/pot and gillnet	USA	15 nm around a "core area", defined by a polygon encompassing the 15 nm buffer zone.	15 days	Daily, but not applied until "2 days after publication of a notice in the Federal Register."	"A DAM zone will be triggered by a single reliable report from a qualified individual of 3 or more right whales within an area (75 nm ² ; 139 km ²) such that right whale density is equal to or greater than 0.04 right whales per nm ² (1.85 km ²)."

While move-on rules are being used, there are no examples of an empirical approach to determining the times or distances employed. That is, each example appears to have been formulated either by expert opinion, through negotiation with stakeholders, and/or input by enforcement personnel. Although analyses of the underlying spatiotemporal autocorrelation or patch dynamics in the catch data could inform the choice of times and distances employed in move-on rules, I could find no rules generated by such analyses. The origin of existing rules is almost never clear, but some appear to have been generated by assimilating values used in other fisheries (e.g. the CCAMLR examples), or by increasing times or distances when stocks become overfished (e.g., the New Zealand hoki example). Some rules offer no guidance on the time or distance to be moved at all (e.g., the BC groundfish example), while others rely on expert opinion to draw a polygon around hauls with high bycatch rates (e.g., the Bering Sea and Aleutian Islands (BSAI) pollock fishery). Examples like that seen in the BSAI pollock fishery may actually be considered more of a time/area closure, as they don't offer guidance in response to a single event (or encounter), but use a group of events to define an area to be closed.

In this chapter, I develop data-driven move-on guidelines to assist the efficient utilization of multiple quotas. These rules can inform on-the-water decisions by fishermen and enable real-time management of fisheries by providing information on the extent and persistence of negative catch events (i.e., catch of choke species and juveniles or depredation events). I believe that as these guidelines are implemented they

will be the first move-on rules utilizing autocorrelation-based times and distances employed by a fishing industry. Further, in collaboration with Jason Roberts of the Marine Geospatial Ecology Lab, I have implemented this analytical approach in a freely available software tool so that other sectors and fisheries may apply these methods (Marine Geospatial Ecology Tools; <http://mgel.env.duke.edu/mget>).

2.2 Methods

2.2.1 A collaborative approach

This study was conducted through a collaboration between the Cape Cod Commercial Hook Fishermen's Association (CCCHFA), the Georges Bank Cod Fixed Gear Sector and the Marine Geospatial Ecology Lab (MGEL) at Duke University. CCCHFA is a non-profit organization that actively campaigns for a healthy marine environment to support a secure and viable future for sustainable commercial fisheries. The GB Cod Fixed Gear Sector is an organization of commercial fishermen who have come together to collectively manage annual allocations of fish under the Northeast Multispecies FMP. Through a series of meetings in Chatham, Massachusetts, fishermen, sector managers, fishery biologists, spatial ecologists and tool developers sat down to describe fishing activities, outline the problem space, generate research questions, present methods, and vet final results. The Maine Coast Fishermen's Association and the Port Clyde Community Groundfish Sector also participated in these meetings. This

type of collaboration, and the actionable results derived from it, was only possible through the work of the sector manager and the CCCHFA to bridge the gap between scientists and fishermen, and to generate the level of trust required in such a project.

2.2.2 Data

I examined spatiotemporal distribution of catch and discard data using observer data produced by the Northeast Fisheries Observer Program (NEFOP). NEFOP is a program of the Northeast Fisheries Science Center (NEFSC) of the National Marine Fisheries Service (NMFS), and collects, maintains and distributes data for scientific and management purposes in the northwest Atlantic Ocean. After initial meetings describing the project to the fishermen, data waivers for 36 vessels were obtained by the collaborators associated with the GB Cod Fixed Gear Sector, affording access to high-resolution fishing effort and catch data necessary to perform the analyses. Although Fixed Gear Sector fishermen employ handlines, benthic longlines and anchored sink gillnets (both large mesh and extra-large mesh), due to limited sample sizes, only data pertaining to gillnet sets were used. The observer data spanned 6 years (2005-2010) and contained information on 1110 gillnet hauls, including 9343 catch records (i.e., species by haul and disposition of the catch). Records with no catch or no information on species, location, or mesh size were removed. As different species are targeted with different mesh sizes (per National Marine Fisheries Service regulations), I further divided the gillnet sets into two categories: large mesh (< 8 inches; n=455 sets), and extra-large mesh

(≥ 8 inches; $n=541$ sets). This analysis is focused on the large mesh stand-up gillnets that are primarily used to target Atlantic cod and pollock (*Pollachius virens*). Any large mesh gillnet sets employing tie-downs (i.e., a line used to connect the bottom of a gill net to the top, to create a bend or pocket in the net) were discarded ($n=22$), as they were used to target other species.

2.2.3 The space–time K function

Data on catch positions may be thought of as a marked point process (Stoyan 1984a,b; Baddeley 2008). While typical analyses of spatial point processes are evaluated against a null hypothesis of Complete Spatial Randomness, marked point processes consider the distribution of marks compared to an underlying distribution of events to which they belong. For example, from the perspective of this study, I test whether the distribution of gillnet hauls containing catch depredated by hagfish is clustered or over-dispersed in comparison to all gillnet haul positions. The spatial and temporal scales over which the pattern occurs can inform management by indicating the distance in space and time a fisherman must move his/her gear (or wait) to reach an area where the marked point process (e.g., hagfish depredation) no longer exhibits autocorrelation. In this study I am specifically interested in clustering, as the aggregation of events over small distances and short timeframes presents an opportunity for the targeted use of event-triggered closures to avoid such cases.

I follow the methods presented in Gardner et al. (2008) but, given my specific interest in informing move-on rules, focus on clustering in space-time interactions. Here I summarize those methods and concentrate on the specifics of my approach. To analyze spatial and temporal autocorrelation in the marked point processes, I applied a variation on Ripley's K function (Ripley, 1977). Ripley's K compares the expected intensity of events (i.e., fishing sets) based on a global mean from the entire dataset, to the intensity found in the marks (i.e., hauls with catch of choke stocks, regulatory discards or depredation events). The space-time K function can be described by the equation

$$\hat{K}(d, t) = \frac{AT}{N^2} \sum_{i=1}^N \sum_{j \neq i}^N \frac{I(\|s_i - s_j\| \leq d) I(\|h_i - h_j\| \leq t)}{w(s_i, s_j) v(h_i, h_j)}$$

for $t, d > 0$ (Diggle et al., 1995; Gatrell et al., 1996; Gardner et al., 2008). N is the total number of events, A is the total area, T is the total length of the time series (in days), s_i is the spatial location of event i and h_i is the time of event i . The weight $w(s_i, s_j) v(h_i, h_j)$ is an edge-correction factor equal to the proportion of the circle centered at s_i that is inside the study area and the proportion of the time interval centered at h_i that is inside the observed time span. The indicator function $I(\cdot)$ identifies those events s_i, h_j that are within a distance d and time t of the event s_i, h_i . To eliminate purely spatial covariates (e.g. depth gradients) and temporal covariates (e.g. seasonal fluxes in water temperature), I subtract the independent space and time autocorrelation.

$$\hat{K}_{ind}(d, t) = \hat{K}(d, t) - \hat{K}(d)\hat{K}(t)$$

The same is done for the marks. As I am comparing the distribution of marks with the overall distribution of events, the overall distribution is subtracted from the initial K function:

$$\hat{D}_m(d, t) = \hat{K}_m(d, t) - \hat{K}_{ind}(d, t)$$

In doing so, I isolate the effect of only those processes that are correlated in both space and time. I test the null hypothesis that the spatiotemporal autocorrelation in the marks is not significantly different than exhibited by all fishing sets. I use random labeling, a permutation test where points within the overall fisheries dataset are randomly labeled as marks, and compare the distribution of results from the permuted events to those found using the true marks (Kenkel, 1988; Cuzick and Edwards, 1990). I ran one thousand permutations and calculated a test of statistical significance by comparing the overall sum of $\hat{D}_m(d, t)$ across all d and t with the frequency distribution of the sums of each $\hat{D}_i(d, t)$, for $i = 1$ to 1000. As I considered only clustering, I used a one-sided test and considered values of $\hat{D}(d, t)$ above the 95% of the distribution of permuted values ($\alpha = 0.05$) to reject the null hypothesis of no difference in clustering between the marks and the overall dataset (Diggle et al., 1995; Loosmore and Ford, 2006).

Further, to find the scales of the spatiotemporal autocorrelation, I plotted $\widehat{D}_m(d, t)$ against the 95% envelope of the permuted values. Values above the envelope indicate spatial clustering is present. However, since all points within a given distance are used to calculate the K function, \widehat{D} values are correlated to those values at shorter distances. While there are drawbacks to this method of calculating autocorrelation (Wiegand and Moloney, 2004; Lewison et al., 2009a), it is useful for finding threshold distances; the distance up to which the marks are more clustered than the overall dataset. Such thresholds are indicated by peaks in the surface of $\widehat{D}_m(d, t)$; however, these values above the envelope do not infer statistical significance at each separate d and t . For ease of visualization, the 95% envelope is subtracted from $\widehat{D}_m(d, t)$, and normalize the values between 0 and 1 in my figures. Thus any values > 0 indicate a response outside the 95% envelope and those values of 0 show no difference from random. Peaks in spatiotemporal autocorrelation are indicated by a value of 1. All analyses were done using the software program R (R Core Team, 2014) and the *splancs* package (Rowlingson and Diggle, 1993).

I applied the spatiotemporal K function to four types of events: catch of choke, interaction with nuisance stocks, catch of juveniles, and depredation events (Table 4). After discussion with fishermen, it was suggested that yellowtail flounder (*Limanda*

ferruginea) be considered a choke stock. Fishermen and the sector manager were also concerned with avoiding barndoor skate (*Dipturus laevis*), but for slightly different reasons. They suggested barndoor skate could reach such high levels in a given area that it reduced CPUE of target stocks thereby forcing the fishermen to move gear to new fishing grounds (Eric Brazer, personal communication). Since it is not lack of quota, but hyper-aggregation of a non-target species that prevents fishing in the area, I differentiate barndoor skate from yellowtail flounder, and refer to it as a nuisance stock. While I did not consider cod a choke stock in this study, the most recent stock assessment for Gulf of Maine cod reversed previous findings of improvements in the fishery and recommended major reductions in the GOM cod quota (NEFMC, 2012). Given the likely cuts to the GOM cod quota based on the stock assessment, the stock will become a choke stock for GB Cod Fixed Gear Sector fishermen targeting GOM haddock (and any other sectors active in the region). Juvenile catch of target species (cod and pollock) was also investigated. Lastly, I looked at depredation events. There are four main sources of depredation events in the fishery: sharks (generally, spiny dogfish *Squalus acanthias*), gray seals (*Halichoerus grypus*), Atlantic hagfish (*Myxine glutinosa*) and “fleas” (marine amphipods). Depredation by sharks, hagfish and fleas was included in the analysis but, due to a lack of data, depredation by gray seals was not.

I initially limited the analysis of spatiotemporal clustering in catch events to 10 kilometers and 30 days, acknowledging that move-on rules beyond these extents would

be economically infeasible. However, to insure that the maxima visible within the extents of the initial study were not local maxima, I repeated the analysis over 50km. Proposed move-on distances (in time and space) were derived from peaks in the $\hat{D}_m(d, t)$ surface (i.e., the distance and time-lag to the peak). To test the efficacy of the proposed move-on distances, I implemented a script to iterate through the marked hauls by date and time and remove any future hauls within the time and distance specified by the move-on rule. The hauls that were “removed” from the dataset during further iterations represent fishing activities that would have been performed in a different location (or not at all). The number of marked hauls (i.e., those associated with one of the event types considered) and the number of unmarked hauls (i.e., those not associated with the event considered) “removed” were compared to the total number of marked hauls and unmarked hauls to derive event rates inside and outside of the extent of the move-on rule.

2.3 Results

All catch types displayed overall spatiotemporal patterns over 10 kilometers and 30 days, significant at $p < 0.05$, except catch of barndoor skate (Table 4). Space-time interactions were apparent in the $\hat{D}_m(d, t)$ surfaces for each event type considered, including barndoor skate. Both yellowtail flounder and barndoor skate exhibited

Table 4: Significance test for overall spatiotemporal clustering, move-on distances and performance measures for choke stocks, juvenile catch and depredation events. The sum of $\widehat{D}_m(d, t)$ is compared to the 95% quantile of 1000 random labeling

permutations of the spatiotemporal K function.

Group	Species	95% Random Labeling Quantile (*10 ¹⁵)	Sum of D-hat in marks (*10 ¹⁵)	p < 0.05	Move-on Distance (km)	Move- on Time (days)	n _{marks}	Marked Hauls Within Move- on Rule (%)	Unmarked Hauls Within Move-on Rule	Rate of Marked Hauls within Move-on Rule	Rate of Marked Hauls outside Move-on Rule
Choke	Yellowtail Flounder	7.884	13.249	*	6.5	1	31	10 (32.3%)	19 (4.7%)	34.5%	5.2%
Nuisance	Barndoor Skate	9.894	9.149		2	2	20	4 (20.0%)	22 (5.3%)	15.4%	3.9%
Juvenile	Cod	5.059	7.233	*	2.5	1	163	84 (51.5%)	37 (13.7%)	69.4%	20.0%
Juvenile	Pollock	6.119	8.935	*	3.5	1	62	27 (43.5%)	41 (11.1%)	39.7%	8.9%
Depredation	Fleas	6.409	13.186	*	2	2	59	27 (45.8%)	3 (0.8%)	90.0%	7.4%
Depredation	Hagfish	6.109	13.978	*	3	5	69	42 (60.9%)	22 (6.0%)	65.6%	7.1%
Depredation	Shark	10.594	33.035	*	6	1	19	9 (47.4%)	6 (1.4%)	60.0%	2.3%

autocorrelation (Figure 2a & b). While spatiotemporal autocorrelation in barndoor skate catch was not significant over 10 kilometers and 30 days, space-time interaction was still visible at short distances and time-lags (2 kilometers and 2 days). Given the clear and strong peak at a short distance, I recalculated the spatiotemporal K function limited to 5 kilometers and 30 days. The sum of the $\hat{D}_m(d, t)$ values was significant at this shorter distance.

Catch of juveniles also exhibited space-time interaction across both species considered (Figure 2c & d). Juvenile pollock and cod catch demonstrated very clear trends and both had thresholds at very short times and distances (2.5-3.5 kilometers and 1 day). Trends in time were also clear in depredation events though identification of threshold values was slightly more difficult due to indistinct trends over distance (Figure 3). Although flea damage and hagfish damage continued to exhibit local peaks in spatiotemporal autocorrelation out to ~14 kilometers, much of that autocorrelation is due to autocorrelation found at shorter distances (i.e., the distances examined in this study). As such, I am confident that the results (2 kilometers and 2 days for flea damaged catch, and 3 kilometers and 5 days for hagfish depredation) represent operable thresholds. Shark damage exhibited an oddly even trend in space and time, likely due to a small sample size ($n = 19$ shark depredation events). It did, however, have a specific peak at 6 kilometers and 1 day.

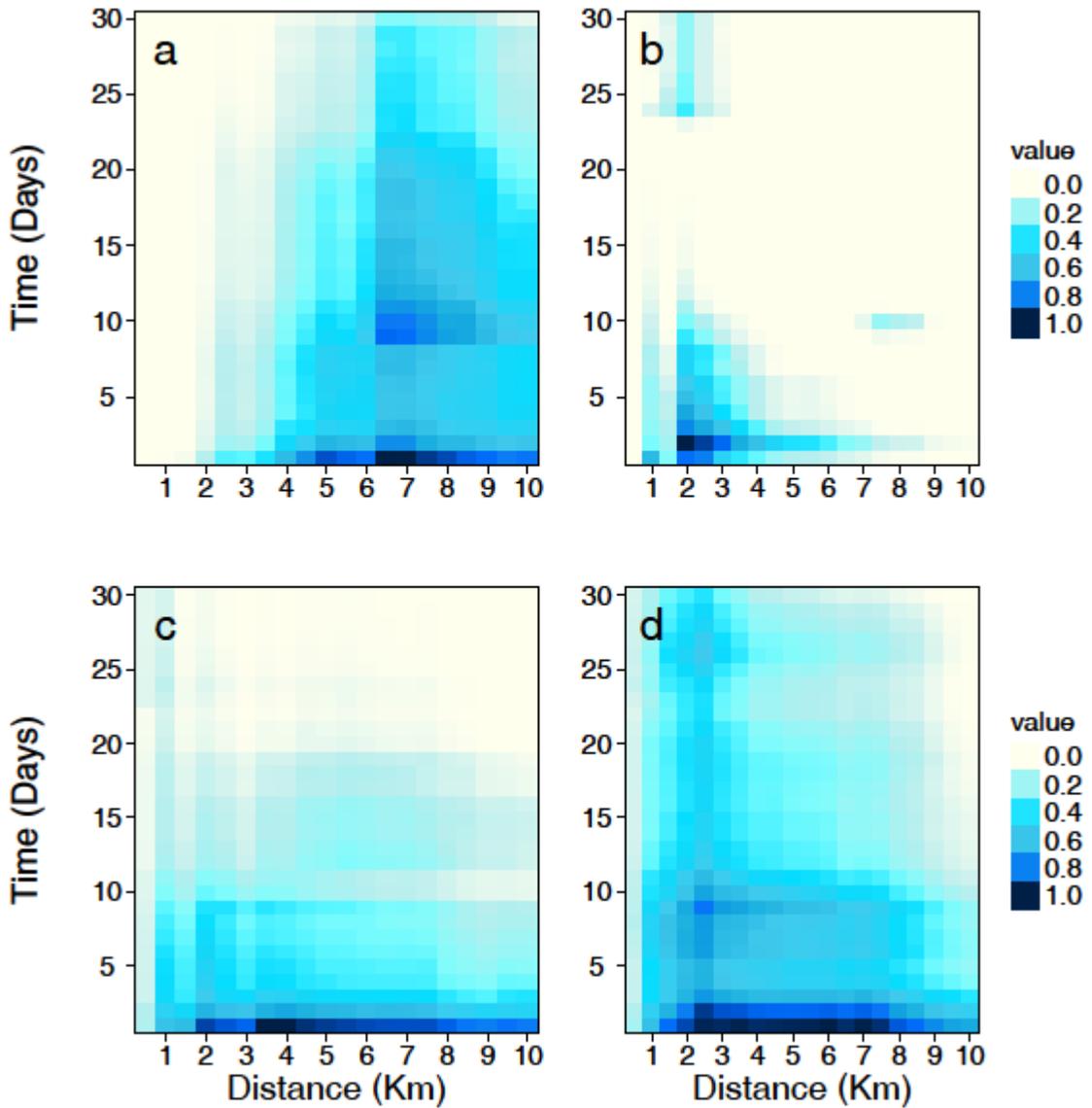


Figure 2: Spatiotemporal autocorrelation in catch of (a) yellowtail flounder and (b) barndoor skate stocks, and juvenile catches of (c) pollock and (d) cod for large-mesh stand-up gillnet gear. Color values are unitless and represent relative distance above the 95% envelope generated from 1000 random label permutations. Peaks in the surface indicate the spatiotemporal extent of the clustering. I.e., a value of 1 corresponds to the highest autocorrelation value within over the time and distances used in the analysis.

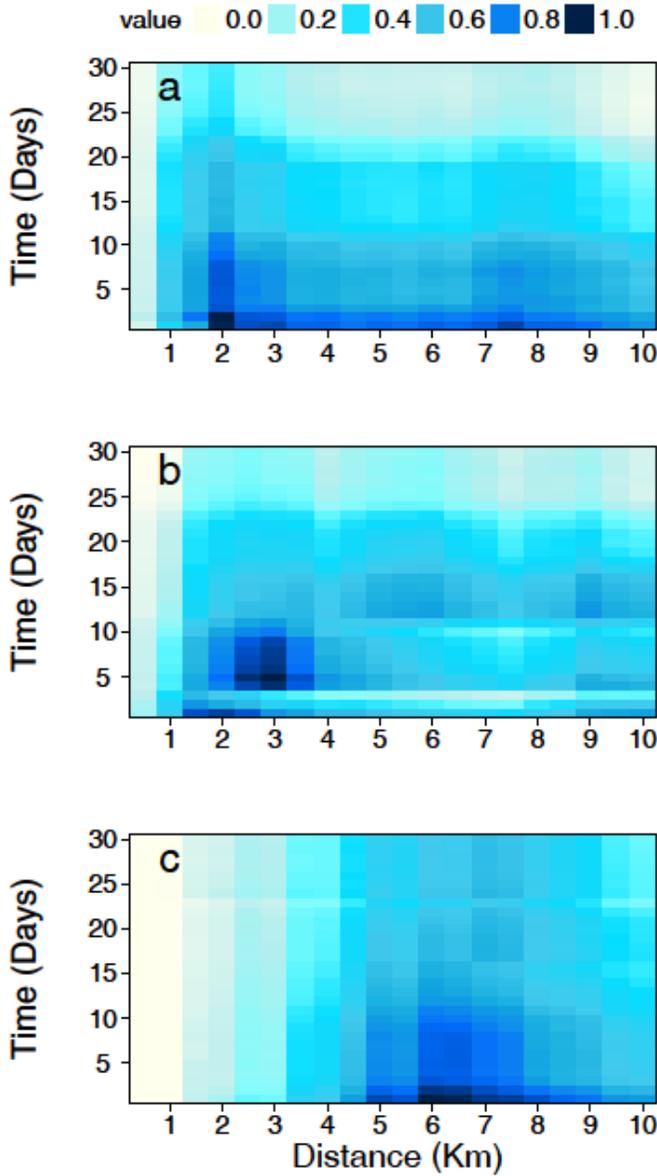


Figure 3: Spatiotemporal autocorrelation in depredation events in sets using large-mesh stand-up gillnet gear: (a) depredation by fleas, (b) depredation by hagfish, (c) depredation by sharks. Color values are unitless and represent relative distance above the 95% envelope generated from 1000 random label permutations. Peaks in the surface indicate the spatiotemporal extent of the clustering. I.e., a value of 1 corresponds to the highest autocorrelation value within over the time and distances used in the analysis.

Analysis of the efficacy of the proposed move-on guidelines offered strong evidence for the utility of move-on rules and the validity of the approach taken in this study (Table 4). An ideal move-on rule would encompass all negative catch events within its limits and as few events without negative catch as possible. The best results were clearly the move-on rules for depredation events. If the recommended move-on rule had been in place, the rate of depredated hauls (depredated hauls/all hauls) would have declined by nearly half (47.1%; $sd=0.063$), while only a small fraction (2.8%) of the non-depredated haul would have been affected. The rate of depredated hauls within the move-on rules was a factor of 9.3 to 25.6 times the rate of depredated hauls outside the move-on rules. The move-on rule for juvenile catch was similarly effective, reducing the juvenile haul rate (hauls with juveniles/all hauls) over 30 percent (32.9%; $sd=0.002$). However, on average, 12.4% of hauls with no juvenile catch were affected, resulting in the juvenile haul rate outside the move-on rule being only 3.5 to 4.5 times higher than the rate inside the bounds of the move-on rule. Choke and nuisance stock catch was the least mitigated by the move-on rule, the rate of hauls with these stocks (hauls with choke or nuisance stocks/all hauls) would have been reduced 21.1% ($sd = 0.088$), but would have affected only 5.0% of the non-choke or nuisance stock hauls. As such, the difference in the rate within the move-on rule was slightly higher than that found for the juvenile catch move-on rule (4.0 to 6.6 times the rate outside the extents of the move-on).

2.4 Discussion

2.4.1 Actionable & operable results

These analyses revealed strong space-time interactions in virtually all of the most important catch types related to the use of quota in the multispecies groundfish fishery in New England. Catch of choke and nuisance stocks, catch of juveniles, and depredated catch all exhibited peaks in spatiotemporal autocorrelation that can inform move-on rules empirically. Most of the threshold values derived from these analyses are at distances under 4 kilometers and at time lags of 2 days or less. Several fall within 2 kilometers and 2 days. These are actionable and operable scales for groundfish fishermen, and adherence to the move-on rules may be less economically detrimental than continued fishing in an area with a higher likelihood of negative catch events. While no attempt was made to determine the ecological underpinning for the move-on times and distances, I suspect they are related to movement behavior of the stocks as well as the persistence of ephemeral oceanographic conditions.

The results of the validation exercise provide strong support for the use of move-on rules to avoid catch of choke and nuisance stocks, juveniles, and particularly in avoiding depredation events. An astounding 90% of hauls within the range of the move-on rule for flea depredation were flea damaged hauls. This figure is all the more dramatic given that the extent of the move-on rule was just 2 kilometers for 2 days. Further, only 0.8% of all unmarked sets were affected by the rule (i.e., 0.8% of all sets

without flea damage would have been re-located to a different area). This efficiency was matched by the effectiveness of the move-on rules, as seen in the potential 54.1% reduction in hauls with hagfish depredation. The move-on rules for choke and nuisance stocks, or juveniles of target stocks, had less effect but still clearly showed the benefit of avoiding the spatiotemporal clustering of these events. In all cases except barndoor skates, employment of empirical move-on rules would have led to at least a 25% reduction in the rate of these negative catch events. Therefore, managers and fishermen can expect significant decreases in discards under these move-on rules. Except for juvenile cod catch ($n = 163$), the sample sizes of depredation, nuisance, choke and juvenile catches were not large ($n = 19-69$). I expect that re-running this analysis with larger sample sizes might increase the efficacy of the move-on rules.

2.4.2 Implementation Options

Although this study follows in the footsteps of initial calls for and efforts to determine empirical move-on rules (Dunn et al., 2011; Gardner et al., 2008a; Lewison et al., 2009b), this is the first time such an autocorrelation study has been done in cooperation with industry. This collaborative approach will provide a direct mechanism whereby the results of the study can be used to directly inform fishing activity. As such, consideration needs to be given to exactly how these move-on rules might be implemented by the sector managers and fishermen. In mobile gear (e.g., trawls or pelagic longlines), fishermen set and haul a single piece of gear consecutively and can

make adaptive decisions based on conditions and the characteristics of the last haul.

However, many stationary gears (e.g., anchored sink gillnets or traps) are often set and hauled at one time, limiting how information on catch from one gillnet may be used in determining where to locate the next set. Under these constraints, there are four possible methods for incorporating move-on rules into the use of anchored sink gillnets:

- (1) Increase “exploratory fishing” before the gillnets are set and apply the move-on rule based on the exploratory fishing;
- (2) For move-on rules with temporal extents > 1 day, apply the rule in deciding where to fish the next day;
- (3) When setting all gillnets, separate them by the distance in the move-on rule;
- (4) If the need to avoid choke species or discards is great enough, investigate the possibility of consecutive sets (i.e., setting and hauling one net at a time).

It is not uncommon for gillnet fishermen to “explore” with a rod and reel before setting their gear. This exploratory fishing is a quick test of the density of target stocks, and sublegal fish or non-target species. Based on what is found, the fishermen may choose to set his or her nets or move to different fishing grounds. This study can be incorporated into the exploratory fishing process to offer some guidelines in how far to move. The main issue with relying solely on this method of implementation is that depredation of catch from a rod and reel is far less likely than depredation of catch that remains in an anchored sink gillnet for hours to days. Therefore, this method can only inform catch of juveniles, choke or nuisance stocks. Option 2 (above) would limit

fishermen to only implementing move-on rules that have a time element greater than 1 day. Several of the move-on rules developed in this study do have temporal extents greater than one day (barndoor skate catch, and flea and hagfish depredation), and could be used in this manner. However, this method would not reduce unwanted catch for all gear deployed at the same time. This would reduce the efficacy of the move-on rule. The third listed option is to proactively separate each gillnet in a trip by the distance specified in the move-on rule. The distribution of distance between consecutive sets in the dataset indicated that 43.9% of sets were greater than 1 kilometer away from the last set, 19.6% were greater than 2 kilometers away, and 12.4% were greater than 3 kilometers away. Five of seven of the move-on rules identified in this study recommend moving 3 kilometers or less. Thus, there is some potential to implement this option, though it would clearly mean increasing the average distance between sets and potentially increasing fuel costs. The last option (4) is a significant departure from the current method of fishing and would require substantial education and outreach for fishermen to accept such a fundamental change. However, if the drawbacks are large enough (e.g. the cost to lease more quota is prohibitive), they may consider multiple, shorter, consecutive sets. This method of fishing would be more precautionary than setting all nets at one time and would incur greater costs (e.g. time, fuel) on the part of the fishermen, but may be necessary as fishermen approach quota limits. While these

implementation options may be viable, further bioeconomic analysis and discussion with fishermen would be necessary to see which, if any, would be optimal.

To facilitate the development and implementation of move-on rules using this approach, I have added tools for performing spatiotemporal analyses of fishery records to the free, open-source Marine Geospatial Ecology Tools software (MGET; Roberts et al., 2010, version 0.8. These tools integrate with the popular ArcGIS software (ESRI, 2010) and allow managers to run the analyses on any fishery that has records of landings or discards that include spatial and temporal data.

2.4.3 Empirical move-on rules

The importance of a data-driven process to determining move-on rules is self-evident. Without knowledge of how the species or events of interest are correlated in time and space, managers and fishermen will likely develop rules that either underestimate the degree of autocorrelation and result in less or no decrease in the negative catch, or overestimate the autocorrelation and cause unnecessary economic burden to fishermen (by overly limiting the time/area they can fish in and increasing fuel and labor costs). If the measure is implemented by managers, such inefficiency may also undermine trust between fishermen and managers. Of note is the difference found in the time/distance of autocorrelation in juvenile cod catch in this study (1 day and 2.5 kilometers or ~5.725 square nautical miles) as compared to the rules in place under the

Scottish conservation credits program (21 days and 50-225 square nautical miles). I do not imply that the rule used in the Scottish program is incorrect or ineffective, but the difference does suggest a need for further research into possible explanations and consideration of multiple scales of autocorrelation.

One potential reason for the difference between my results and the rules employed in Scotland is their use of threshold values of catch to define an “event”. That is, they define a juvenile catch event as being a haul that results in more than 40 juvenile cod per hour of fishing (Holmes et al., 2011; Needle and Catarino, 2011). I define a juvenile catch event as a haul that has any juvenile catch. The development of such catch thresholds should be based on an understanding of the population level effects of the catch, and are beyond the scope of this study. Such thresholds, however, are easily incorporated into an analysis of spatiotemporal autocorrelation and should not limit the use of this technique. Another possible explanation is the different gear examined in the two studies. This analysis was done on anchored sink gillnets, whereas the Scottish studies looked at trawl gear, which inherently covers larger swaths of the seabed.

2.4.4 Broader applicability of empirical move-on rules

In this study I suggest that, due to the implementation of quotas and sector-based management, catch of choke stocks and discards (both regulatory and market-based) will likely play an increasingly important role in the fishing strategies of New

England fishermen. More broadly, they also affect, or are likely to affect, all US fisheries following the passing of the Reauthorization of the Magnuson-Stevens Act of 2006 with its requirements to implement Annual Catch Limits for all fisheries by 2011, and globally as discards policies are reconsidered (e.g. the ban on discards under the EC's Common Fisheries Policy). This is particularly true given the continued movement toward catch shares (Arnason 2002; Chu 2009; Jardine and Sanchirico 2012). In an effort to help fishermen and managers deal with these new factors, I offer analyses of spatiotemporal autocorrelation to generate empirical move-on rules that will aid in the efficient fulfillment of quotas. Such rules can simultaneously benefit the fishermen by minimizing lost opportunities for revenue, and benefit the target stock by minimizing overages in quotas and capture of juveniles that could lead to growth and recruitment overfishing. The utility of this method is not limited to efficient use of target stocks, but can also be applied to avoid protected species and may offer a much more targeted method of approaching the issue of protected species bycatch than simple time area closures.

3. Temperature-based targeting in a multispecies fishery under climate change¹

3.1 Introduction

3.1.1 Background

Multispecies fisheries, where less productive “weak” stocks mix with more productive “strong” stocks, present a challenge to both fishermen and fisheries managers. Under a multispecies quota system, fishermen must avoid weak stocks (with small overall quotas) or choke stocks (i.e., stocks for which they have little quota), and target strong stocks or those for which they have relatively higher quotas. We intuitively know, and research confirms, that fishermen can target and avoid species within a multispecies fishery (Pascoe et al., 2007; Branch and Hilborn, 2008; Gillis et al., 2008; Quirijns et al., 2008). However, even in systems with strong individual incentives (i.e., catch shares), efforts to match catches to quotas and avoid weak stocks have proven problematic (Copes, 1986; Squires et al., 1998; Sanchirico et al., 2006; Pascoe et al., 2007). This has led to research on fishermen behavior (including discarding and targeting of different catch compositions) under multispecies ITQ systems (Branch, 2006; Branch et al., 2006; Pascoe et al., 2007; Branch and Hilborn, 2008; Poos et al., 2010). However, correlations between catches and oceanographic variables have rarely been considered

¹ A version of this chapter is being submitted to Fisheries Oceanography as: Dunn, D.C., J.H. Moxley, P.N. Halpin. Temperature-based targeting in a multispecies fishery under climate change. Fisheries Oceanography.

in efforts to manage weak stocks or improve targeting through spatiotemporal measures.

Spatiotemporal associations between target or non-target species and observed oceanographic features may be used to identify critical areas that can be delimited and managed using static or dynamic measures (Hobday and Hartmann 2006, Dunn et al. 2011, Lewison et al. *in review*, Maxwell et al. *in review*). Correlations between bycatch rates and dynamic oceanographic features have been elucidated in peer-reviewed literature (e.g., Klaer and Polacheck 1998, Brothers et al. 1999b, 1999a, Kobayashi and Polovina 2005, Dietrich et al. 2009). Oceanographic characterizations of catch rates are even more common, and have been examined for a wide range of fisheries from lobsters to tunids (e.g. Beardsley 1969, Laurs et al. 1984, Evans et al. 1995, Bigelow et al. 1999, Waluda and Rodhouse 2001, Seki et al. 2002, Campana and Joyce 2004, Zagaglia et al. 2004, Drinkwater et al. 2006, Mourato et al. 2014), and include a wide variety of variables (e.g. frontal systems, sea surface height or salinity). However, these relationships are rarely translated into active spatiotemporal resource management. Here, in an effort to inform targeting and spatiotemporal management in the US Northeast Multispecies fishery, I seek to determine if bottom temperature can be used to separate Atlantic cod (*Gadus morhua*) from other species within the Fishery Management Plan (FMP) and three species that commonly interact with this fishery: spiny dogfish (*Squalus acanthias*), silver hake (*Merluccius bilinearis*) and Barndoor skate (*Dipturus laevis*).

3.1.2 Known effects of temperature on species in the Northeast Multispecies Fishery

Temperature controls important physiological processes in fish (Fry 1971; reviewed for Atlantic cod in Drinkwater 2005) and thus it is likely an important factor in determining their niches and resulting distribution. In particular, the distribution of fish in the Northeast U.S. Continental Shelf Large Marine Ecosystem has been shown to be based on temperature and depth (Murawski and Finn, 1988; Gabriel, 1992; Perry and Smith, 1994; Methratta and Link, 2006). Many studies have described the thermal preference and found significant correlations between the distribution of Atlantic cod and bottom temperature (Coutant, 1977; Scott, 1982; Murawski, 1993; Perry and Smith, 1994; Castonguay et al., 1999; Rose, 2005; Ruppert et al., 2009; Tamdrari et al., 2012; Shackell et al., 2014). Several studies have also found direct effects of temperature not just on the distribution of cod, but also the degree of aggregation in cod as well (Swain et al., 1998; Dutil et al., 1999; Tamdrari et al., 2012). Drinkwater (2005) reviewed the effects of temperature on cod more broadly including effects on growth, body condition, spawning, reproduction, distribution, migration, abundance and recruitment.

One common method to examine habitat associations of target species has been the use of empirical cumulative distribution functions (CDF) of biomass by bottom temperature. In the Northwest Atlantic, Perry and Smith (1994) use CDFs to identify associations between yellowtail flounder (*Limanda ferruginea*), haddock (*Melanogrammus aeglefinus*), silver hake and Atlantic cod and depth, temperature and salinity on the

eastern Scotian Shelf. The authors only found a statistically significant relationship between cod and temperature during summer. In my study area, cumulative distribution functions were also employed by Helser & Brodziak (1996) and Methratta and Link (2006) based on the Northeast Fisheries Science Center (NEFSC) scientific bottom trawl survey data. Helser & Brodziak (1996) analyzed cumulative distribution functions of temperature across all strata in the Northeast Multispecies Fishery and compare them to catch weighted CDFs to determine if there were statistically significant relationships between three species (cod, yellowtail flounder and haddock) and temperature. It is reassuring to know that, unlike Perry and Smith (1994), Helser & Brodziak (1996) did find a significant relationship between cod and bottom temperature in my study region in 19 out of 27 spring surveys and 15 out of 32 fall surveys. I draw further comfort from the results of Methratta and Link (2006) who found that cod stayed in relatively cooler waters in both fall and spring. However, the variability of these findings, and the findings for other species in the region (e.g. yellowtail flounder), indicate that there may be significant differences in the utility of temperature-based targeting and closures across species and seasons (Perry and Smith, 1994; Helser and Brodziak, 1996; Methratta and Link, 2006).

I build on these studies by investigating the utility of temperature thresholds generated from CDFs to separate target species in the Northeast Multispecies fishery. The methods are similar in that both utilize CDFs and examine distances between CDFs

across a spectrum of temperatures. Yet, this study is distinguished by its focus on the utility of using temperature as a dynamic management tool, rather than solely focusing on identifying statistically significant relationships between species and temperature.

3.2 Methods

3.2.1 Data

To examine the potential for using bottom temperature to reduce non-target catches, I analyzed 16 years (1998-2013) of data from the NEFSC Scientific Trawl Surveys. The surveys collect data from 350 to 400 sampling stations using a stratified random sampling design (NEFSC 1988). Within each stratum, 2.0° latitude by 2.5° longitude rectangular sampling units are randomly selected and each station is sampled with a standardized bottom trawl deployed for 30 min at a tow speed of 3.5 km/h (Azarovitz 1981, Despres-Patanjo et al. 1988, NEFSC 1988). Measurements of bottom temperature and depth, among other variables, are also recorded.

The Multispecies Groundfish Fishery Management Plan (FMP) includes 13 species, and governs groundfish from the Gulf of Maine to Cape Hatteras. Fishermen in this fishery generally employ trawls, but gillnets and hook and line gear are also present. To remove regional differences and potential metapopulation effects and to attempt to offer results directly applicable to a specific group of fishermen, I limit the extent of the study to the area off of Cape Cod and Georges Bank used by the Fixed Gear Sector of the

Northeast Multispecies fishery (i.e., between 67.67° and 70.91° West and 39.99° to 42.42° North; n=51,319 species catch records). My analyses required records with information on the species type, depth, bottom temperature and expected catch weight. Therefore, any record missing this information was removed from the dataset, resulting in a final dataset of 37,214 species catch records from 2,480 tows.

To more clearly convey the implications of this study, I divide species into three categories: top catches, no retention species and others. I again try to make this study as applied as possible and define the top catches as the top three catches by weight in the Fixed Gear Sector (specifically, the large-mesh gillnet component of that sector). While top catches differ slightly by season and year, they are dominated by Atlantic cod, spiny dogfish, haddock and pollock (*Pollachius virens*). No retention species are those for which the quota is set at 0. Current no retention species are windowpane flounder (*Scophthalmus aquosus*), ocean pout (*Zoarces americanus*) and Atlantic wolffish (*Anarhichas lupus*). Other species are neither top catches nor no retention species and include: Acadian redfish (*Sebastes fasciatus*), witch flounder (*Glyptocephalus cynoglossus*), winter flounder (*Pseudopleuronectes americanus*), American plaice (*Hippoglossoides platessoides*), yellowtail flounder, white hake (*Urophycis tenuis*), and Atlantic halibut (*Hippoglossus hippoglossus*). For the purpose of this study, I include two further species that commonly interact with the fishery but are not in the FMP as part of this “other” group: silver hake and barndoor skate. When I refer to target/non-target species, I refer to this on an

individual fishermen level, not at the level of the entire fishery. Given the nature of a multispecies fishery with quotas for each species, any species may be a target or bycatch at some point in time.

3.2.2 Seasonal variability

Variability in seasonal temperatures will strongly affect the utility of a seasonal temperature threshold to separate two species. That is, the greater the inter-annual variability in seasonal temperatures, the less likely that any single threshold value will work well across all years. To address such inter-annual variation, I standardized bottom temperatures from the fall and spring surveys for the day of year of the survey and the depth of the survey using a linear regression (bottom temperature \sim day of year + depth of tow). I then calculated the standard deviation of the median temperature across all years in that season. The median bottom temperature was used because the distribution of standardized bottom temperatures were not normally distributed in 12 of 16 years (Shapiro-Wilk Test, $p < 0.05$). Spring bottom temperatures exhibited strong variability, so I applied K-means clustering to identify two clusters of years corresponding to those with “warm” springs ($n = 6$) and those with “cold” springs ($n = 10$).

3.2.3 Empirical cumulative distribution functions

The empirical cumulative distribution function plots discussed in the introduction describe the percent of biomass for a species caught in the scientific trawl

surveys up to a given temperature. Specifically they may be described with the following equation:

$$\hat{F}(t) = \frac{1}{B} \sum_{i=1}^n I(T_i < t) B_i \quad \text{where: } I(T_i < t) = \begin{cases} 1 & \text{if } T_i < t \\ 0 & \text{if } T_i > t \end{cases}$$

Where B is biomass (in weight or numbers of individuals caught), n is the sample size for the year/season subset of the data, T is the temperature associated with a single trawl in the survey, and t is the range of temperatures over which the species was caught. I is an identity function which determines whether the set is included in the cumulative total (1) or left out (0) based on the temperature of the trawl. The objective of this analysis was to find the temperature at which the percentage of target biomass available to fishermen is maximized, while the percentage of non-target biomass is minimized. To identify the optimal temperature to maximize this objective function I used a bagged approach to remove any trends across years (e.g., an overall increase in water temperatures between 1998 and 2013). Specifically, based on the k -means clustering of spring-time temperatures, for each iteration ($n=1000$) I randomly sampled 7 of 10 “cold” years and 4 of 6 “warm” years to train the model. For each season / year combination in a bag, I calculated an empirical CDF for biomass of cod and an interacting species at 0.25°C temperature intervals. Species/season/year combinations that had less than 5 records were removed from the analysis (Atlantic wolffish, $n_{\text{total}} = 2$; and Atlantic halibut, $n_{\text{total}} = 20$). Next, I calculated the absolute value of the difference

between the cumulative percentages of the target and non-target biomasses available at each temperature.

Since a variety of threshold values may provide very similar results, I opted to identify a range of “acceptable” threshold values for each species/season/year combination. I arbitrarily defined “acceptable” as any temperature that resulted in a difference in percentage biomass available between target and non-target species greater than or equal to 90% of the maximum difference found in that species/season/year subset. The acceptable threshold values for each species/season/year combination across all iterations were aggregated together by species and the median of these values was selected as the optimal threshold value for that species/season. The median was used rather than the mean because the threshold values were not normally distributed. The result of this approach was three threshold values for each cod/interacting species combination per bag (i.e., one for each: “cold” springs and “warm” springs, and one for fall). These thresholds values were then validated using the 4 years that were not included in the training data bag.

Validation of the threshold values involved a very similar process as was used to generate the optimum threshold value. For each model iteration, empirical distribution functions were developed for both target and non-target species. In an effort to generate operable results I looked at two easily implementable scenarios: the ability to fish at all temperatures above a specific value, or the ability to fish at all temperatures below the

value. To implement this, I took the maximum of the absolute value of the difference between the percent available biomass of cod and the interacting species above and below the threshold temperature.

To help describe the feasibility of the threshold values, I created several other performance metrics to help describe the validation results. Specifically, I calculated the “breadth” of the acceptable threshold values as the mean number of acceptable threshold values divided by 4 to give a value in °C (the values were in .25° intervals). The breadth indicates the buffer around the threshold value that will still generate similar results (i.e., 90% of the maximum difference found). This is of particular interest in relation to the standard deviation of the optimum threshold value. A standard deviation less than half the breadth is a likely indicator that the threshold value is robust to interannual variability. Mean Breadth is given in °C. Due to spatiotemporal variability in water masses, I view values of Breadth < 0.5°C as inoperable, values between 0.5°C and 1°C to be challenging to implement, and values >1°C to be operable. Since percentage of biomass does not offer any information on the quantity of catch of that species, I also include total weight in the supplementary materials to give the reader an overall idea of the magnitude of the catch in question.

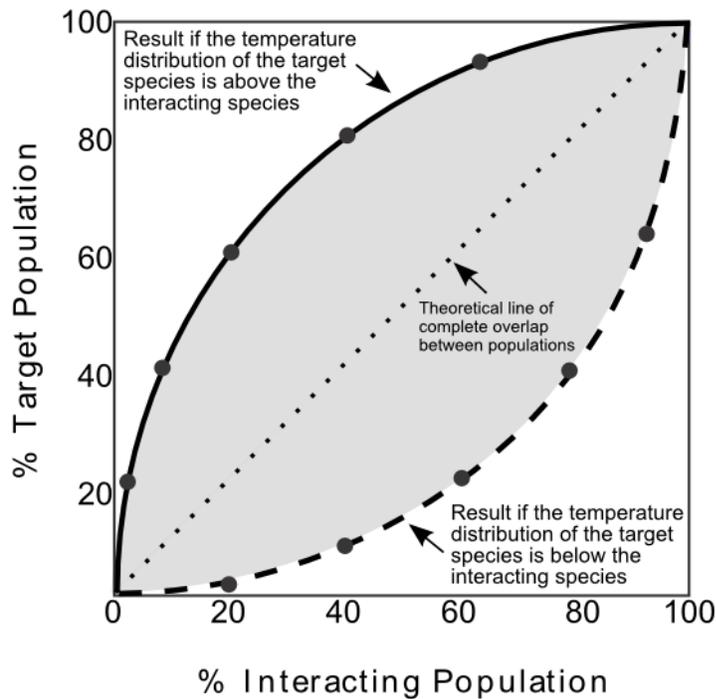


Figure 4: The Area Under the Curve is calculated by plotting the percentage of biomass of each species available at each 1/4 degree interval, taking the absolute value of the area beneath that curve, and then subtracting the area beneath the line of complete overlap (i.e. slope = 1).

I offer one final metric to describe the overall biological separability of the two species by temperature: the Area Under the Curve. Specifically, I used the previously calculated CDFs of each species to produce a form of a Receiver Operator Characteristic (ROC) curve (Figure 4). Estimating the area under the curve (AUC) using the Mann-Whitney approach follows naturally from estimating the ROC curve as a step-function based on empirical cumulative distribution functions (Green and Swets, 1966; Hanley and McNeil, 1982). The CDF of the target species was used as the true positive

(sensitivity), while the CDF of the non-target species was used as the true negative (specificity). Since the worst case scenario is completely overlapping thermal responses (indicated by an ROC curve with slope = 1), I subtract the area under this line from the ROC curve and take the absolute value of the Area Under the Curve (for cases in which the non-target species is found at temperatures colder than the target species). The median AUC value for each season indicates the likely thermal separation between two species based solely on thermal preference of the two species. I consider values of AUC > 0.75 to indicate strongly separable species, $0.50 < \text{AUC} < 0.75$ to suggest reasonably separable species and $\text{AUC} < 0.50$ to be poorly separable species.

The analytical approach outlined above results in: (1) an optimum temperature value to use in targeting or avoiding specific catch events; (2) a value indicating the maximum difference in the percentage of the target to non-target species biomass available above (or below) the threshold temperature; and (3) two descriptive metrics to help describe the feasibility and utility of applying the threshold value.

3.2.4 Post-hoc analysis

The main purpose of this study was to describe how useful bottom temperatures are in separating species within the Northeast Multispecies Fishery compared to Atlantic cod. However, the results from this analysis indicated that separability was not static either between or within years. While I expected shifts across seasons based on previous studies (Perry and Smith, 1994; Helser and Brodziak, 1996; Methratta and Link, 2006), I

did not expect changes across years (i.e., between years with cold and warm springs). To help explain the spring results, I developed a linear model of the difference in breadth for each species between warm and cold spring. I used the species' mean minimum temperature, mean maximum temperature, mean range of temperatures and the mean median temperature (i.e., the mean of the median seasonal temperature across all years) in cold springs as explanatory variables as well as the standard deviation of those variables. I ran a stepwise (backward and forward) regression with model selection by Akaike information criteria.

All analyses described above were conducted using the R statistical software package (R Core Team, 2014). Data was manipulated using the plyr (Wickham, 2011) and reshape2 (Wickham, 2007) packages. Empirical distribution functions were generated using the spatstat package (Baddeley and Turner, 2005), and AUCs were calculated using the flux package (Jurasinski et al., 2014). The stepwise linear regression was done via the MASS package (Venables and Ripley, 1999). Figures were developed using ggplot2 (Wickham, 2009) and plotrix (Lemon, 2006).

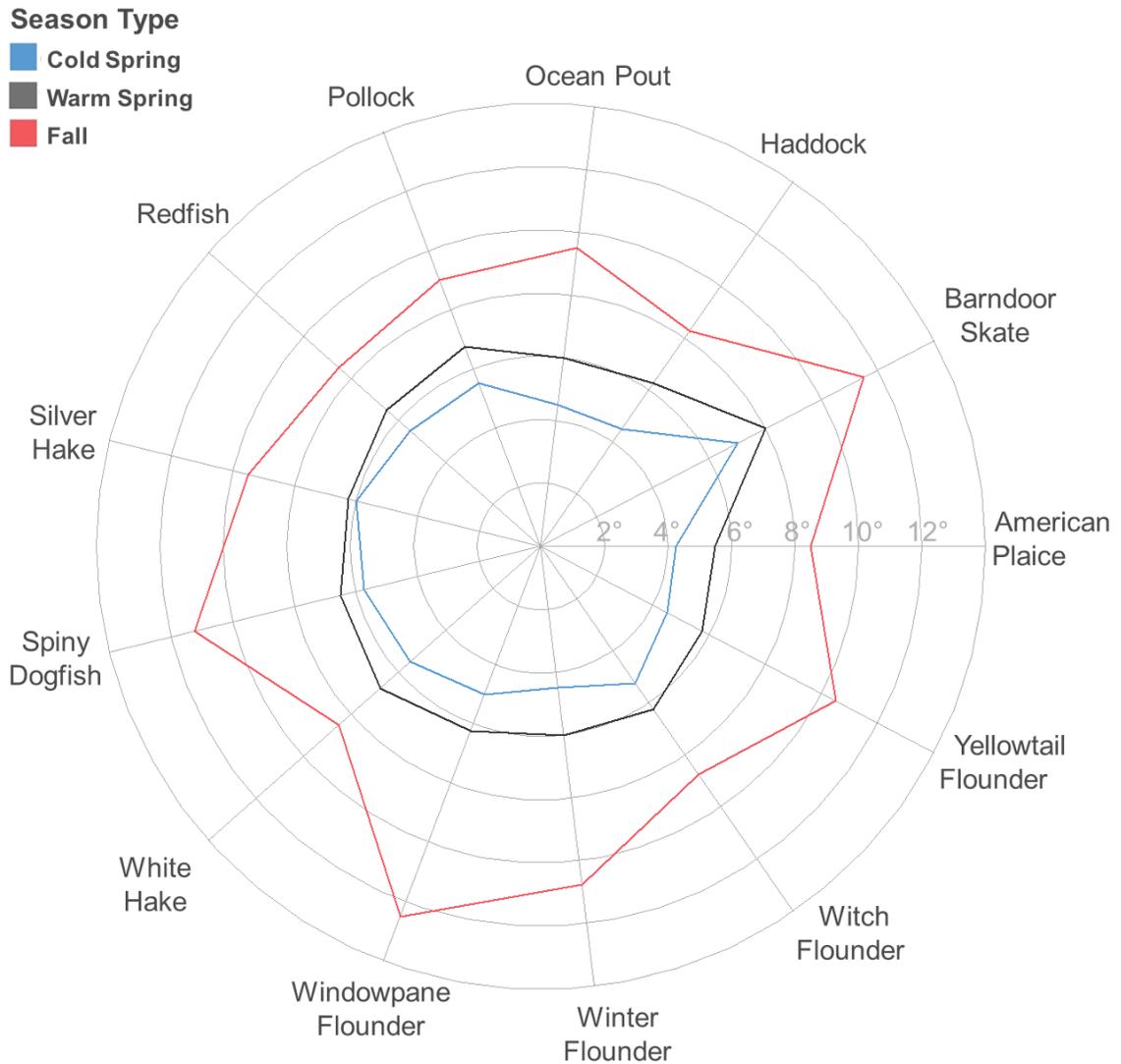


Figure 5: Optimum threshold temperatures for separating species within the Northeast Multispecies FMP and species that commonly interact with the fishery from Atlantic cod. All warm spring threshold values were greater than cold spring values, and all fall threshold values were greater than warm spring values.

3.3 Results

3.3.1 Spring clustering analysis

Spring temperature distributions were characterized by high variability of the median temperature when compared to the fall. The K-means clustering analysis to reduce interannual variability in mean spring bottom temperature was constrained to two clusters. The analysis resulted in a “cold” cluster of 10 years (1998, 1999, 2001, and 2003-2009; standardized cluster mean = -0.968) and a “warm” cluster of 6 years (2000, 2002, and 2010-2013; standardized cluster mean = 0.813). Deviance was largely explained by the difference between the clusters rather than by differences within each cluster (between sum of squares/total sum of squares ratio = 0.793), indicating a good fit of the K-means clustering in spite of the 2-group constraint.

2.3.2 Bagged threshold temperature analysis

The optimum threshold temperatures (**Figure 5**) found for cold springs (range = 4.25 – 7.00°C) were always lower than warm springs threshold temperatures (range = 5.50 – 8.00°C), and warm springs always produced lower threshold values than fall (range = 8.25 – 12.50°C). The mean difference in optimum threshold temperatures between cold and warm springs was 1.15° C (sd = 0.38°C), while optimum threshold temperatures in fall averaged 3.40°C (sd = 1.37°C) higher than warm springs.

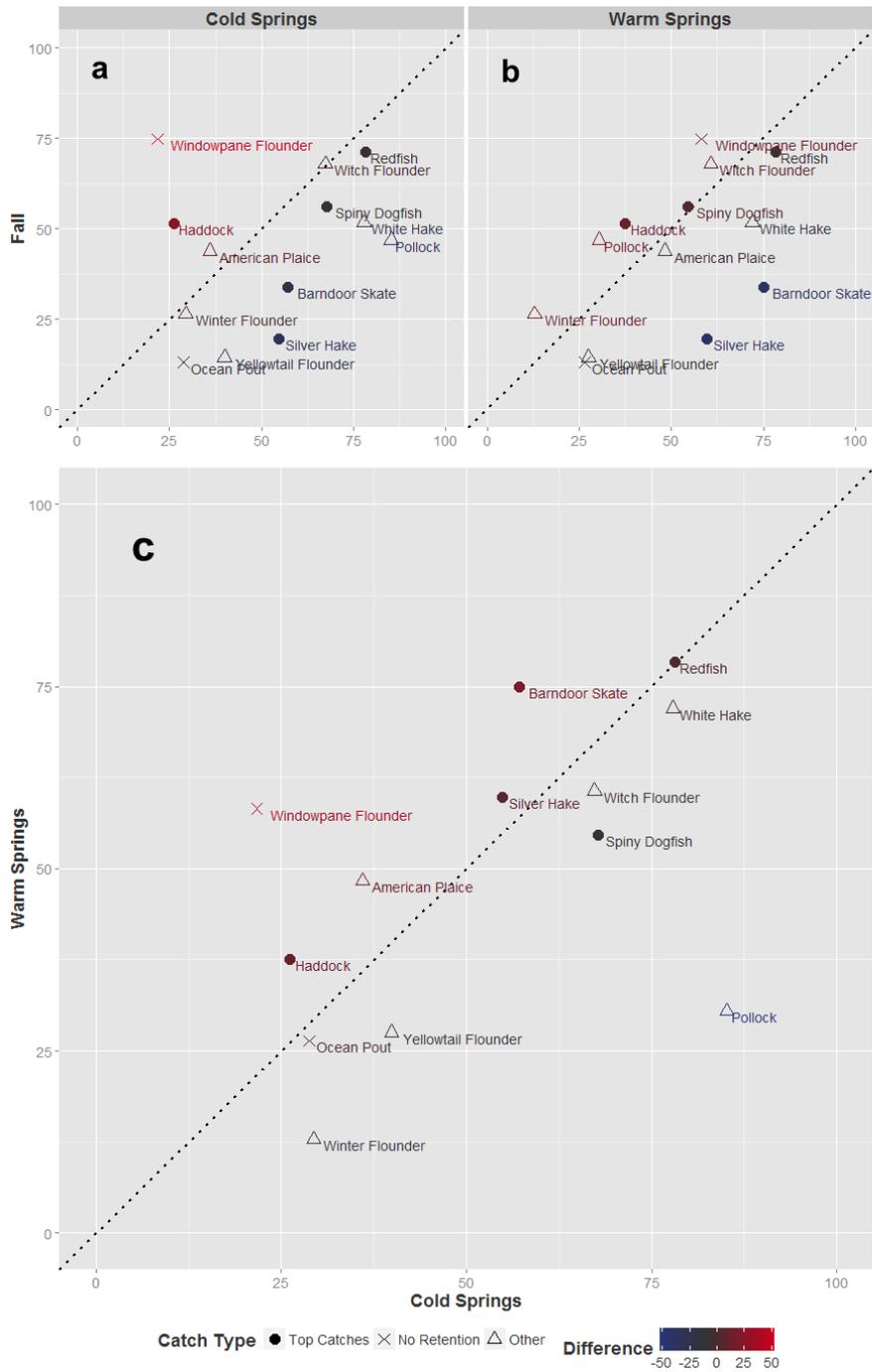


Figure 6: The difference in percentage biomass available for Atlantic cod and each comparison species for warm vs cold springs and warm springs vs fall. The dotted line represents a 1-to-1 relationship (i.e., no change) between seasons. Distance from the line indicates strong changes between seasons.

To better understand the implications of the results, I report them in the three categories mentioned in the methods: top catches, no retention species and others. All four of the species that made up the top catches in cold and warm springs displayed strong differences from Atlantic cod in the percentage of their biomass available at or below the optimum threshold temperature (Figure 6; mean = 65.95, sd = 10.53).

Alternatively, the percentage of biomass of no retention species were poorly distinguished from Atlantic cod in cold springs (windowpane flounder = 21.70; ocean pout = 28.76). Windowpane flounder was more strongly differentiated in warm springs (58.22), while ocean pout remained difficult to separate by temperature (26.38). Spring results for “other” species ranged widely with white hake and witch flounder displaying strong differentiation (>50 in both cold and warm springs), while American plaice, pollock, yellowtail flounder and winter flounder were less differentiated (<50). Of note, pollock and windowpane flounder were highly variable between cold and warm springs (85.18 *vs.* 30.44 and 21.70 *vs.* 58.22).

Results for the top caught species in the fall season ranged in the difference of the percentage of biomass available at the threshold temperature (as compared to Atlantic cod) with spiny dogfish and haddock being easily differentiated (>50), while silver hake was poorly differentiated by temperature (19.60). The no retention species also displayed mixed results (windowpane flounder = 78.85, ocean pout = 13.04). Of the “other” species, only witch flounder and white hake were strongly distinguished from

cod (67.97 and 51.67, respectively), while American plaice and pollock faired almost as well (43.87 and 46.90, respectively). Yellowtail flounder and winter flounder were again poorly distinguished from cod by temperature (14.44 and 26.37, respectively). There were strong seasonal differences between warm springs and fall for both barndoor skate and silver hake with both becoming less distinguished from cod by temperature (barndoor skate = 75.00 to 33.72; silver hake = 59.74 to 19.60). White hake was also less easily separated in fall, but was still well distinguished from cod (72.00 to 51.67).

The initial results above describe the maximum differentiation between the percentage of cod biomass available above (or below) an optimum threshold temperature as compared to a suite of other species. Essentially these results describe the utility of trying to differentiate species with threshold temperatures. However, they do not offer insight into how feasible it is to separate the species. Results of analysis into the AUC and mean threshold temperature breadth lend insight into the feasibility of the optimal temperature threshold reported above. That is, while the maximum difference in percentage of available biomass at the threshold temperature may be very large (i.e., most of the target biomass is available and only a fraction of the interacting biomass), a very small shift in temperature may radically shift this ratio and result in a far greater portion of the interacting population becoming available. The breadth metric offers some insight into this, but is meant to focus on how much variability captains will have around targeting the threshold temperature. The AUC metric offers insight into the

biological separability of the two species; using one value to describe differences in percent biomass available across all temperatures. Alternatively, breadth describes operational feasibility of separating the species.

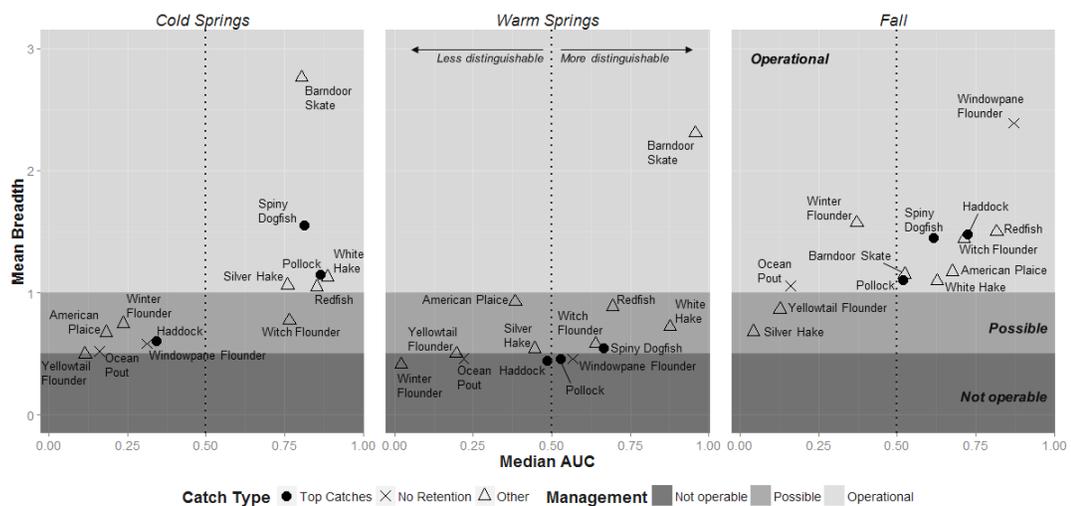


Figure 7: Separability by temperature of all species compared to Atlantic cod. A decrease in breadth was found between cold and warm springs, but operable separation was found across each temperature regimes and season. Breadth was generally categorized into “not operable” (< 0.5°C), “possible” (0.5 – 1.0°C) and operational (>1.0°C).

For the top three catches in cold springs, spiny dogfish and pollock were strongly separable by AUC (>0.81; Figure 7), while haddock was poorly separated (AUC = 0.34). Warm springs exhibited a reduction in the AUC of the well distinguished top catches: spiny dogfish ($\Delta AUC = -0.15$) and pollock ($\Delta AUC = -0.38$). Conversely, haddock separability increased ($\Delta AUC = 0.19$). All three top catches were well distinguished from cod by temperature in fall (AUC > 0.52). While the two no retention species were both

poorly separated from cod by temperature in cold springs (AUC < 0.31), they differed in their response to warming waters. While ocean pout remained poorly distinguished in warm springs (AUC = 0.22) and falls (AUC = 0.16), windowpane flounder became reasonably separable in warm springs (AUC = 0.57) and was the most distinguished species from cod in fall in this study (AUC = 0.87).

In cold springs, the “other” species were divided between being well separated (AUC > 0.76; witch flounder, barndoor skate, Acadian redfish, silver hake and white hake) and poorly separated (AUC < 0.25; winter flounder, American plaice, yellowtail flounder). Warm springs distributed “other” species more widely across AUC values, with two in each quartile. Acadian redfish was strongly separable from cod in fall (AUC > 0.81), while 3 species exhibited poor separation (winter flounder yellowtail flounder and silver hake < 0.37). Strong decreases in seasonal AUC values were seen in barndoor skate (Δ AUC = -0.44) and silver hake (Δ AUC = 0.41), which became indistinguishable from the cod distribution across temperatures (AUC = 0.04).

Very strong differences were found in mean breadth across both springs and fall. In general, I found mixed operational separability in cold springs, poor operational separability in warm springs, and good operational separability in fall (Figure 7). Breadth change in a similar manner for all top catches. All three had breadth >0.5°C in cold springs, all three experienced declines in breadth in warm springs (resulting in 2 of 3 with breadth < 0.5°C), and all three had strong operational separation from cod by

temperature in fall (breadth > 1°C). Both of the no retention species reacted in exactly the same manner as the top catches (cold spring breadth >0.5°C; warm spring breadth <0.5°C; and fall breadth >1°C). The “other” species had a similar response. All had breadth >0.5°C in cold springs, all but one had breadth <1°C in warm springs (winter flounder), and all but 2 had breadth >1°C in fall (yellowtail flounder and silver hake). Decreases in breadth were seen in 11 out of 13 species between cold and warm springs. Two of the three top catches, spiny dogfish and pollock, showed very large decreases in breadth (>0.71°C). Only two species saw any increase in breadth from cold to warm springs (yellowtail flounder, 0.01°C; and American plaice, 0.25°C).

Table 5: Results of the explanatory model of the difference in breadth of acceptable threshold values between cold and warm springs.

	Estimate	Std. Error	t value	Pr(> t)	Significance
(Intercept)	0.729	0.272	2.678	0.023	*
Weighted Median Temp	-0.221	0.054	-4.058	0.002	**
SD of Min Temp	0.371	0.190	1.955	0.079	.

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

3.3.3 Post-hoc analysis

To reiterate, breadth describes the thermal extent of “acceptable” threshold temperature values. The smaller the breadth of acceptable threshold values that separate two species, the more difficult it would be to efficiently target one or the other

species based on temperature. The final model of the difference in breadth between cold and warm springs included the weighted median temperature and the standard deviation of the minimum temperature (Table 5). Weighted median temperature had a negative effect on difference in breadth between cold and warm springs, while the standard deviation of the minimum temperature had a positive effect. The final model explained 62% of the null deviance with just two variables.

Table 6: Species meeting all three criteria for successful temperature-based targeting against Atlantic cod (using Breadth > 0.5°C) by season and temperature regime type.

Cold Springs	Warm Springs	Fall
Barndoor skate	Barndoor skate	Haddock
Pollock	Redfish	Pollock
Redfish	Spiny Dogfish	Redfish
Silver hake	White hake	Spiny Dogfish
Spiny Dogfish	Witch flounder	White hake
White hake		Witch flounder
Witch flounder		Windowpane flounder

3.4 Discussion

3.4.1 Temperature targeting in a multispecies fishery

For temperature based closures or targeting to be useful three elements must coincide: 1) the magnitude of the difference between the percentage biomass available above (or below) the threshold temperature must be strong (Difference > 50); 2) the species should be biologically generally separable across the range of temperatures they inhabit (AUC > 0.50); and (3) the threshold temperature must have a reasonable buffer

which offer similar results (Breadth > 0.5°C and probably > 1°C). Warm spring had the lowest number of top catches that met these criteria (1, spiny dogfish; Table 6). Two of three top catches met the criteria in cold springs and all three met the criteria in fall.

While low-quota species in this fishery will vary by license holder, it is highly likely that Atlantic cod will become a choke species for many fishermen. This study suggests that, although temperature targeting of top catches will be difficult in warm springs, temperature can be used to separate a choke species (cod) from more abundant species in cold springs and during the fall. This is particularly crucial for the common pool fishermen who are under a trimester TAC system (i.e., the fishery can be closed three times during the year when the trimester TAC is reached).

Of the two no retention species, only windowpane flounder in fall appears to be well suited for temperature targeting. While not a no retention species, barndoor skate, which is managed under the Northeast Skate Complex fishery, is considered a nuisance species by some fishermen in the Northeast Multispecies fishery as it can cluster in areas in very high densities and prevent the targeting of other species. Barndoor skate met all three conditions in both cold and warm springs. Thus, I find utility (on a species by species basis) in temperature targeting to reduce catch of choke species, no retention species, and nuisance species. It is important to note, however, that the utility of temperature targeting in each of these cases is highly seasonal. Interestingly, given the increased correlation between cod and temperature in spring found by Helser &

Brodziak (1996), there was little difference between the total number of species meeting the criteria for temperature targeting against cod in the cold (n=7) or warm (n=5) springs and the fall (n=7).

3.4.2 The influence of climate change on targeting within a multispecies fishery

While some species experienced drastic decreases in the difference in percentage biomass available compared to cod at the optimum threshold temperature between cold and warm springs, there was no significant trend across all species. However, a clear declining trend was visible in the breadth of acceptable threshold values. While not the initial focus of this study, the implications of the changes in breadth between cold and warm springs for selectivity in multispecies fisheries under a warming climate are disturbing. I discuss them below.

The effect of climate change on the distribution of fish stocks has been a major area of research for fisheries scientists and ecologists for decades (DeAngelis and Cushman, 1990; Frank et al., 1990; Glantz, 1990; Murawski, 1993). However, the main focus of this research has been on climate-induced shifts in latitude or depth (Murawski, 1993; Drinkwater, 2005; Perry et al., 2005; Rose, 2005; Fogarty et al., 2007; Nye et al., 2009; Pinsky et al., 2013) and resultant impacts on growth and productivity (Fogarty et al., 2007; Brander, 2010; Mantzouni et al., 2010; Shackell et al., 2012) with less attention paid to consequent changes in interspecific interactions and effects on fishery selectivity. The shift in the mean breadth of the threshold values between cold and warm springs found

in this study indicate a significant (Wilcoxon signed rank test, $p = 0.003$) and substantial (mean = -0.30°C , sd = 0.33°C) change in how virtually every species in the Northeast Multispecies fisheries is distributed across bottom temperature compared to Atlantic cod. Only one species meaningfully increased the breadth of acceptable threshold values in warm springs compared to cold springs (American plaice = $+0.25^{\circ}\text{C}$). These results indicate that the ability to selectively fish in the Northeast Multispecies fishery will become more difficult under a warming ocean. While, selectivity in a multispecies fishery has always been a problem, its importance has been amplified with the introduction of catch share systems with quotas for individual species within the fishery.

Specifically, the post-hoc analysis indicated that the breadth of acceptable threshold values for species caught at higher median temperatures were more strongly affected by the shift in bottom temperature than those caught at lower median temperature values. It also suggested that the breadth was affected by standard deviation of the minimum bottom temperature at which the species was caught. These results are curious in that they suggest two separate mechanisms affecting the breadth of acceptable threshold values. First, the influence of high median temperatures might be explained by Atlantic cod being forced into a distribution across bottom temperatures previously largely occupied by species with higher median temperatures, including all three top catches (i.e., spiny dogfish, haddock, pollock, and barndoor skate, silver hake, white hake, witch flounder, windowpane flounder and redfish). The mean change in

the range of acceptable threshold values for species with median temperatures higher than cod was -0.41°C , compared to just -0.03°C for species with lower median temperatures than cod. Three of the four highest changes in breadth were also the three highest median temperature species (i.e., spiny dogfish, barndoor skate and silver hake). This narrowing of the temperature window in which these species are well separated from cod indicates that, as the Northeast US shelf continues to warm under climate change, it will become more difficult to target these warm-temperature species while avoiding cod.

The second mechanism is driven by the relative weight of a species' temperature and depth preferences. Several previous studies have suggested that species with strong depth or substrate preferences ("depth-keepers") are likely to be exposed to a wider range of temperatures across seasons (Murawski, 1993; Methratta and Link, 2006). Although my linear model is solely based on variables derived from species distributions in spring, the connection between standard deviation of (minimum) temperature and strong depth or habitat preference remains evident. Three out of the four species with the highest standard deviation of minimum temperature were depth-keeper: windowpane flounder (a shallow depth-keeper), witch flounder and white hake; barndoor skate was the only temperature-keeper (Scott, 1982; Gabriel, 1992; Murawski, 1993; Methratta and Link, 2006). Conversely, the three out of four of the species with the lowest standard deviation of minimum temperature were temperature-keeper (spiny

dogfish, American plaice, and haddock; Scott 1982, Gabriel 1992, Murawski 1993, Methratta and Link 2006). The other, silver hake, is widely distributed but generally considered to be a deep-water species (Methratta and Link, 2006). However, unlike the median temperature variable, only one of the three species with the three lowest standard deviations of minimum temperature exhibited the expected strong decrease in breadth between cold and warm springs (spiny dogfish). The second lowest standard deviation, American plaice, was actually the only species to exhibit a significant increase in breadth. This indicates the importance of standard deviation in minimum bottom temperature variable in explaining the very strong decrease in breadth of spiny dogfish, and any extrapolation of these findings to suggest a decreased ability to target temperature-following species and not catch cod under climate change needs further study. The findings relative to climate change in this study warrant serious consideration and follow-up using the full temporal and spatial extent of the NEFSC Scientific Trawl Surveys.

3.4.3 Further considerations

It is also important to note that, as with numerous previous studies (e.g., Murawski 1993 or Methratta and Link 2006) I did not take into account stock structure, ontogenetic shifts or differences in distribution based on sex. While these variables may be significant factors affecting the distribution of various species across temperature (Murawski and Finn, 1988) I believe that this study provides insight into the main trends

in temperature targeting in the region and potential effects of climate change on selectivity in the Northeast Multispecies fishery. It is also important to note that I have considered the percent biomass available for a species at a given temperature, not the total biomass available. It is feasible that I may be comparing 90% of 1,000 tons of one species and 90% of 10 tons of another. For this reason I have included the weight of catch of each species in each season / year combination in the Supplementary materials. I believe that any implementation of the methods used here by management must also include a trade-off evaluation of the total biomass of both target and non-target species. For temperature targeting to reach its full utility in this fishery, seasonal gaps in the temporal extent of the NEFSC Scientific Trawl Survey data need to be filled (e.g. through the use of the NEFSC study fleet).

4. Why do we persist with persistence? A comparison of static and dynamic fishery closures²

4.1 Introduction

4.1.1 Background

At the turn of the millennium, Hyrenbach *et al.* (2000) presented a thought piece in *Aquatic Conservation: Marine & Freshwater Ecosystems* that fundamentally altered the scope of what many thought could be accomplished with time-area closures. The stated purpose of the piece was to “stimulate discussion and research on the implementation of pelagic protected areas... [and] to argue that in principle large-scale reserves can be applied to highly dynamic marine habitat...” With their Viewpoint piece, Hyrenbach *et al.* achieved something arguably greater- it was the first real discussion of dynamic ocean management in general (Elliott Norse, personal communication). Unfortunately, the intervening period has resulted in few real world examples of the concept of dynamic ocean management (see Dunn *et al.* 2014, Little *et al.* 2014, Lewison *et al.* in review for non-exhaustive reviews of existing measures). The vast majority of spatiotemporal management measures (i.e., marine protected areas or time-area closures) remain static in either time or space, and more often than not they are static in both (Hyrenbach *et al.*, 2000; Norse, 2005; Game *et al.*, 2009). We persist in

² A version of this chapter will be submitted as: Dunn, D.C., A.M. Boustany, P.N. Halpin. Why do we persist with persistence? A comparison of static and dynamic fishery closures.

clinging to the idea that resources or biodiversity must be spatially or temporally persistent for managers to effectively address them using spatiotemporal measures.

4.1.2 The importance of scale in fisheries management

While ocean management is principally static, the ocean itself is fundamentally dynamic. Primary production on land is dominated by large static flora in habitats that change on the order of decades to millennia, but primary production in the ocean is almost entirely driven by planktonic organisms whose abundance and distribution change on the order of minutes to months. Plankton abundance is a function of highly variable factors influencing growth (light, temperature and nutrient availability) and the equally variable physical forcing driving their distribution (e.g., molecular processes, internal and surface waves and tides, fronts and eddies, wind-driven mixing, biophysical coupling, or basinal or decadal/multidecadal oscillations) (Bainbridge 1957, Haury et al. 1978, Smith 1978, Steele 1978, Denman and Gargett 1983, Mackas et al. 1985; reviewed in Legendre and Demers 1984a, Martin 2003). The first attempt to describe how these physical forces interact across spatial and temporal scales came from Henry Stommel (1963). Stommel's intent in developing his seminal spectral analysis diagram was to point out that the scale at which an oceanographic process is measured is extremely important and to differentiate realizable from intractable goals. Haury et al. (1978) followed Stommel's lead and adapted his diagram to describe drivers and variability of plankton biomass.

If the causes of heterogeneity in the distribution of phytoplankton are different on different spatial and temporal scales, it should come as no surprise that the spatiotemporal distributions of higher trophic level organisms are also patchy and forced by diverse scale-dependent drivers (Mann, 1993; Langton et al., 1995; Bertrand et al., 2002; Croll et al., 2005). Perhaps only slightly less obvious is that the distribution of fishing effort is in no way exempt from these factors. If variability in the distribution and abundance of target species and fishing effort are based on multiple drivers across multiple scales, we can also assume that fisheries management should be a multiscale process, capable of addressing drivers at all tractable scales.

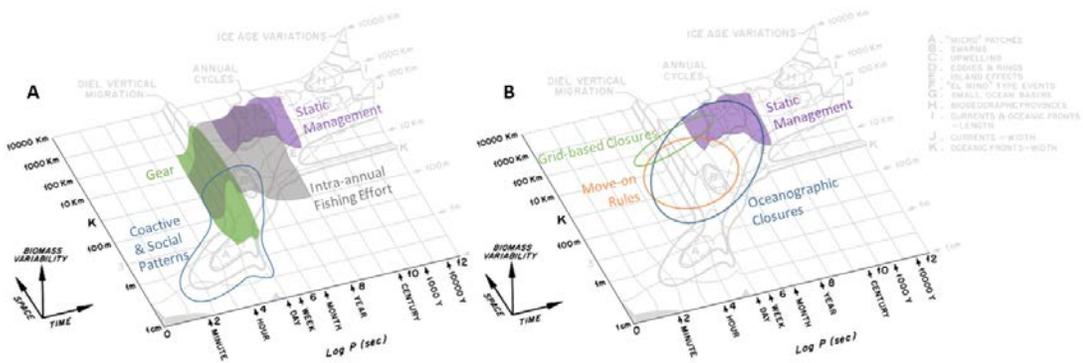


Figure 8: The spatiotemporal extent of: a) fishing gear, intra-annual shifts in fishing effort and traditional static spatiotemporal management measures (i.e., permanent or seasonal time-area closures); and b) dynamic management measures including grid-based closures, real-time closures based on move-on rules and oceanographic closures overlaid on the “Stommel diagram” from Haury et al. 1978 (after Stommel 1963).

When scales associated with various elements of fisheries management are overlaid on Haury’s diagram, we can begin to understand what ecological processes fisheries management is capable of addressing (Figure 8). Process leads to pattern and

Haury *et al.* also describe dominant patterns at each scale. Scales smaller than 10km differ from larger scales by including coactive and social patterns as dominant forces. Coactive patterns, as defined by Hutchinson (1953), arise from interactions between species (e.g., competition, niche partitioning, predation and parasitism) while social patterns are “determined by signalling of various kinds, leading either to spacing or aggregation”. This general ~10km threshold is important in fisheries management because it is approximately the minimum resolution of spatiotemporal management measures.

The spatiotemporal resolution and extent of fisheries management has been largely dictated by logistical and political constraints, and secondarily by the geographic range of the species or meta-population dynamics (Langton et al., 1995). Management units are rarely smaller than 1000 km² in developed coastal fisheries, and management measures generally occur at resolutions larger than 10km². From a temporal perspective, the resolution of management measures is at best a month and generally a year. As such, attempts to manage processes and patterns at sub-10 km, sub-1 month resolution likely involves some level of spatiotemporal mismatch. This is troubling as inefficiency in the management of marine resources is born of mismatches in the spatiotemporal variability of resource, resource users and management actions. Further, it raises some doubt as to whether (and at what cost due to the inefficiency of the measures) we can meet commitments to implement ecosystem-based fisheries

management (EBFM) with spatiotemporal measures that may be fundamentally mismatched in space and time to address coactive and social patterns. To address the obvious spatiotemporal mismatch between an incredibly mutable ocean and static management, to allow for a comprehensive implementation of EBFM, and to minimize inefficiency in our management of marine resources, we must seek to develop more dynamic management measures that allow managers to address scales, processes and patterns occurring under ten kilometers.

4.1.3 Dynamic Ocean Management

In the past few years, interest in the concept of Dynamic Ocean Management has accelerated (DOM; Hobday et al., 2014; Lewison et al., *in review*; Maxwell et al., *in review*). Maxwell *et al.* defined DOM as “management that changes in space and time in response to the shifting nature of the ocean and its users based on the integration of new biological, oceanographic, social and/or economic data”. While this generally describes the intent, it is too broad to allow for appropriate differentiation between DOM and other forms of management. I believe DOM should specifically be focused on how management is implemented (Figure 9). That is, *dynamic ocean management is any coordination of activities related to the marine environment in which the time and/or location of the implemented measure is dependent on spatiotemporally variable conditions (e.g., oceanography, the contents of a haul or market signals), and is updated in near-real time with the objective of increasing efficiency by aligning the temporal and spatial scales of the resource,*

resource users, management, and markets. Specificity with regard to how the implementation of the management measure is defined (i.e., automatically, in near real time and against conditions on the ground) is critical, as it is only through the automatic changing of the time and location of implementation that increases in the spatiotemporal resolution of management are achieved and spatiotemporal mismatches are overcome.

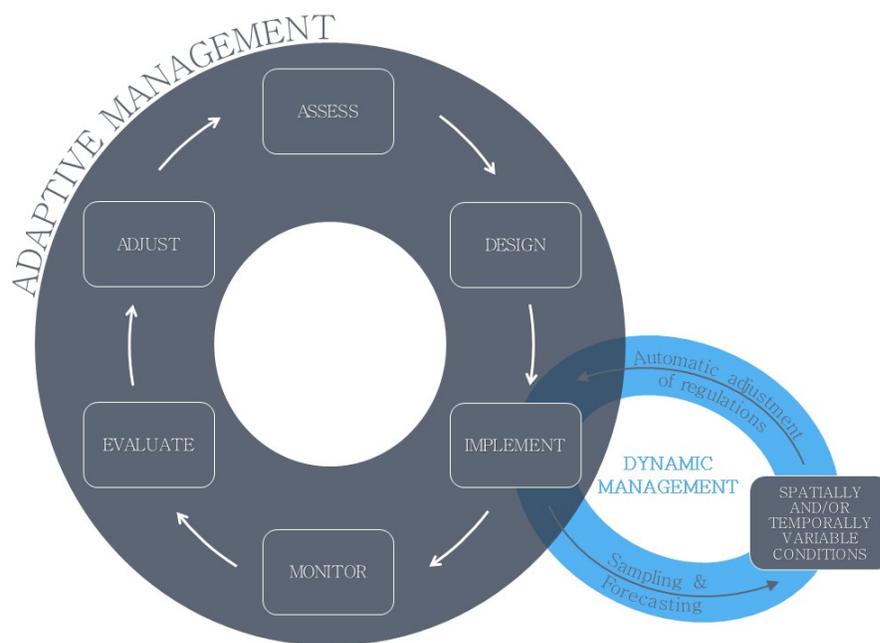


Figure 9: Dynamic Ocean Management can be seen as a sub-routine within the larger adaptive management framework. While alternate definitions are still being debated, I believe it specifically applies to the where and when a management measure is implemented (i.e., automatically, in near real time and against conditions on the ground).

In the introduction, I describe a framework for mitigating bycatch with spatiotemporal management measures. The recent work on dynamic ocean management largely focuses on three types of examples that fall within that framework: grid-based hotspot closures, real-time closures based on move-on rules and

oceanographic closures. Each of these types of measures offers the opportunity to manage fisheries at finer spatiotemporal scales than traditional static management. Grid-based hotspot closures (e.g., Bethoney et al. 2013, O'Keefe and DeCelles 2013) have been implemented on a weekly basis with cell sizes as small as $\sim 5 \times 10$ km. As mentioned in chapter 1, move-on rules have been widely implemented with real-time closures lasting days to weeks over distances as short as 2-10 km (in radius). In that chapter, I showed that empirically-based move-on rules should be operable down to 1 km and 1 day in the US Northeast Multispecies Fishery. With more and finer resolution catch data, it is likely that the temporal component could actually be hourly. Oceanographic closures, specifically closures based on sea-surface temperature, have been implemented on a daily (Howell et al., 2008) and monthly (Hobday and Hartmann, 2006; Hobday et al., 2010) basis. The spatial resolution of oceanographic closures can be subjective, as in voluntary programs it is implemented by captains testing the temperature of the water they are in (resolution = meters), while regulated examples require designation of cells or areas as being closed and are coarser. Hobday et al. (2010) base their model for a dynamic closure to reduce bycatch of southern bluefin tuna (*Thunnus maccoyii*) on 5 km resolution temperature data, but the final management measure is implemented at a coarser scale. The resolution of the dynamic closures described above suggests that dynamic management should allow fisheries managers to expand the scope of the

processes and patterns they can address down to the kilometer and day scale (Figure 8b).

While we are seeing a growing number of dynamic management measures and some coalescing around a definition of DOM, there is a near total lack of concrete studies comparing static and dynamic management measures - either theoretical or existing. O'Keefe et al. (2013) evaluate the effectiveness of time/area closures, quotas/caps, and fleet communications to reduce fisheries bycatch against a set of five criteria. Evaluation criteria include "(1) reduced identified bycatch or discards, (2) no or minimal negative effect on the catch of target species, (3) no or minimal negative effect on the catch of other non-target species or sizes, (4) no or minimal spatial or temporal displacement of bycatch, and (5) economically viable for the fisher." Their results indicated that four of the five static time-area closures studied failed to meet even two of the criteria, while all of the more dynamic measures used were able to meet at least three criteria (mean = ~4.125).

The one example of a study looking at the efficiency of using static and dynamic closures to reduce bycatch, Grantham et al. (2008), examined permanent full fishery closures, seasonal full fishery closures and a series of temporary time-area closures. While this effort represented a major step forward in considering the utility of quasi-dynamic management measures, it did not incorporate many of the aspects of what it might mean for a closure to be "dynamic" (e.g., either of the examples from the two

prior chapters- dynamic instantiation or dynamic delineation). In the introduction, I set out a specific framework based on the idea that more dynamic fishery closures might result in more targeted (i.e. efficient) management than commonly results from static closures. In this study, I seek to build on Grantham's effort and compare the efficiency of the forms of spatiotemporal management described in the introduction. In chapters 1 and 2, I simulated two types of dynamic closures (i.e., move-on rules and dynamic oceanographic closures). Here, I compare the efficacy and efficiency of dynamic measures to optimized static monthly and annual closures developed through the use of a spatial conservation prioritization tool (i.e., Marxan; Ball, Possingham, & Watt, 2009; *sensu* Grantham et al., 2008).

4.2 Methods

4.2.1 Development of closures

Five types of closures were simulated: 1) seasonal full-fishery closures; 2) static annual time-area closures; 3) seasonal time-area closures; and 4) grid-based "hotspot" closures; and 5) real-time closures based on move-on rules. In each case the objective of the closure is to minimize catch of juvenile cod while maximizing the percent of adult cod catch taken. An attempt was made to develop an oceanographic closure based on threshold bottom temperatures, but due to poor performance of the threshold and high

standard error between modeled bottom temperatures and in-situ bottom temperatures, it is not included in this study (see Appendix A).

4.2.1.1 Development of annual and seasonal static closures

I developed optimized annual and monthly static closures using Marxan (Ball et al., 2009; no software was necessary to determine the optimal monthly full-fishery closure). Marxan is a conservation planning software tool that attempts to efficiently solve a minimum set reserve design problem (though see Ball et al., 2009 for other more recent and novel uses). That is, it attempts to efficiently select reserve sites that include various types of features such that targets for those features are met while a cost is minimized. Ball *et al.* describe this function mathematically as:

$$\min \sum_i^{N_s} x_i c_i + b \sum_i^{N_s} \sum_h^{N_s} x_i (1 - x_h) cv_{ih}$$

subject to:

$$\sum_i^{N_s} x_i r_{ij} \geq G_j \forall j \quad \text{and} \quad x_i \in \{0,1\} \forall i$$

The first term represents the cost c of including site i in the reserve set, across all sites N_s . This value is multiplied by a binomial variable x for site i (i.e., 0 or 1) representing whether the site was included in the reserve set. The second term adds a penalty based on the configuration of the reserve set. A boundary multiplier b is applied to a penalty generated relative to the connectivity cv between any two sites (i, h)

contained in the reserve set. The terms $x_i(1-x_i)$ again use a binomial control variable to ensure that only distances between pairs of sites included in the reserve set are included in the penalty. Marxan attempts to minimize these costs subject to the need to meet a specific goal G for feature j , across all sites N_s . Following the previous examples, it does this by summing the quantity r of feature j in site i , and multiplying it by the binomial control variable x_i .

While the reserve configuration penalty (boundary length modifier; i.e., a penalty based on the sum of the lengths of the perimeters of all areas in the reserve network) is important for reserves sets considering larval transport or other movement patterns, or that need to cluster sites to make compliance and enforcement easier, there are circumstances that may not require such constraints. For instance, in their comparison of various quasi-dynamic closures, Grantham *et al.* (2008) do not include the configuration penalty. Their reserve set was meant to capture a target level of the overall bycatch occurring in the fishery while minimizing any effect on the catch of commercial species. Neither the feature (bycatch) nor the cost (target catch) have movement characteristics that were meant to be considered in the reserve set, and as such it may have been ecologically reasonable for the authors to ignore the configuration penalty. However, their reserves would still require enforcement, and thus the study might have benefited from the use of a configuration penalty (as use of the penalty would result in smaller, more compact reserve sets).

In the present study, I consider a range of configuration penalties to determine whether a boundary length modifier improves the efficiency metric proposed below. So while this study follows Grantham *et al.* (2008) in adding a monthly time step t (for the seasonal closures), we keep the configuration penalty:

$$\text{Min} \sum_i^{N_S} \sum_t^{N_T} c_{it} x_{it} + b \sum_i^{N_S} \sum_h^{N_S} \sum_t^{N_T} x_{it} (1 - x_{ht}) c v_{iht}$$

subject to:

$$\sum_i^{N_S} \sum_t^{N_T} x_{it} r_{itj} \geq G_j \forall j \quad \text{and} \quad x_i \in \{0,1\} \forall i$$

The new variable t has been added referencing the time t at which the site i was selected. Grantham *et al.* (2008) use a monthly time step for t . The temporal resolution used in this study is a trade-off between the ability to make fair comparisons with the methods used in the previous chapters which have time steps as fine as 1 day, and the validity of using such a fine time-step considering the potentially large inter-annual variability in when bycatch occurs.

The target was a percent of total juvenile catch in the dataset. Juvenile catch is recorded in the NEFOP data with a specific disposition code (“RegsSmall”) and is thus easily identifiable. Cost was calculated as the percentage of target catch forgone. This assumes that fishing effort is reduced by the closures rather than shifted. This assumption is difficult to justify in most implementations of time-area closures, but in

this circumstance we are comparing closures using the same assumption across the board. Thus we assume not that fishing effort is reduced, but that the shift in fishing effort due to any of the closures would have similar results. Since we are only considering a single gear type over a small area, we believe this assumption is reasonable.

4.2.1.2 Development of grid-based “hotspot” closures

Development of grid-based “hotspot” closures was similar to the validation method used to identify the effect of real-time closures based on move-on rules in chapter 1 and were meant to mimic (to the degree possible) the methods employed by O’Keefe and DeCelles (2013). A 5km by 10km grid was overlaid on the cleaned Fixed Gear Sector large-mesh anchored gillnet data (excluding those using tie-downs) from 2005 to 2010. I then developed an R script to iteratively go through the data sorted by date. When a set with a catch of juvenile cod greater than a predefined threshold was encountered, the cell in which it occurred was closed to fishing the next day. Multiple juvenile catch thresholds were tested: 0 lbs, 0.1 lbs, 1 lb, 5 lbs and 10 lbs. Similarly, I tested one-day closures and weeklong closures. Lastly, I tested the same scenarios on the 10 km by 10 km grid used for the Marxan-based closures.

4.2.1.3 Development of real-time closures based on move-on rules

The methods used here to implement real-time closures based on move-on rules follow those in chapter 1. I again used the cleaned Fixed Gear Sector large-mesh

anchored gillnet data (excluding those using tie-downs) from 2005 to 2010. The move-on distance (2.5 kilometers) and time (1 day) for avoiding juvenile cod were also taken directly from chapter 1. Rather than using number of events as our metric for performance, we used weight of catch. As in chapter 1, closure effect was calculated by iterating through the dataset by time and day and removing any future sets within the time and distance indicated by the move-on rule of a set marked as containing any juvenile catch (i.e., bycatch threshold = 0 lbs).

4.2.2 Calculation of time and area required by closures

Before comparisons between the various types of closures can be drawn, the time-area required by each method must first be calculated. The function used to calculate the time-area required for each type of closure will differ. For move-on rules, the total time-area required is simply the number of instances the move-on rules was implemented over the course of iterating through the dataset multiplied by the time and area used in the rule. The area of a move-on rule is found by calculating the area of a circle with radius equal to the distance employed in the move-on rule. This relationship is captured by the following equation:

$$R = \sum_k^{N_k} \pi s_{kj}^2 t_{kj}$$

Where k is an implementation of the move-on rule, N_k is the total number of implementations, s is the distance of the move-on rule, and t is the time-lag of the move-

on rule. Grid-based closures are defined similarly, but the area of an individual closure is the gridcell size (i.e., 5x10 or 10x10 km).

The time-area requirements for the static closures were based on the area within the study site that was within the selected “reserve”. However, unlike the dynamic closures, the area of the static closures vary with each time step, not with each instantiation of a rule. Thus, continuing to use the same notation, the time and area required by the closure may be described:

$$R = \sum_t^{N_t} \sum_i^{N_s} x_{it} a_i t \quad \text{subject to: } x_i \in \{0,1\} \forall i$$

Thus, the time requirement for the a static closure is found by summing the area a of site i multiplied by a control variable describing whether the site was within the reserve set, across all sites N_s within the bounds of the study and all timesteps N_t .

4.2.3 The efficiency metric

To compare the three types of closures, I examined the percentage of bycatch reduced (by weight), the percentage target catch forgone (by weight) and the time and area required to achieve the bycatch reduction. Each of these values separately has information useful to managers, but a single metric of efficiency is also useful.

Therefore, I generated a metric that includes all three values. The metric may be described as:

$$\sum_f^{N_f} x_f u_f / \sum_f^{N_f} u_f \times \frac{\sum_f^{N_f} x_f u_f / \sum_f^{N_f} u_f}{\sum_f^{N_f} x_f v_f / \sum_f^{N_f} v_f} / \frac{R()}{\sum_i^{N_s} a_i * \sum_t^{N_t} t} \quad \text{subject to: } x_f, x_i \in \{0,1\}$$

The first term is simply the total reduction in bycatch, the second is the reduction ratio (percent bycatch reduction divided by percent catch reduction) and the last term is the percent area used. More specifically, the total reduction in bycatch is the ratio non-target catch u in set f contained within the closure (represented by the control term x_f) to the total weight of non-target catch, where N_f is total number of fishing sets. I multiply this term by the ratio of the same term to total catch reduction (notated as with the non-target catch, except v represents the target catch weight). The denominator is the ratio of time and area used in the closure (denoted as the function R), to the product of all time N_t and area N_a considered. The numerator describes the magnitude and efficiency of the closure, while the denominator describes how efficient the closure was in time and space. Finally, due to the large range of values displayed by the efficiency metric, I take the log of one plus the efficiency metric. As the ratio of bycatch reduced to catch forgone increases and the time-area used decreases, the metric goes to infinity. Alternatively, as bycatch reduction efficiency decreases and the time-area required increases, it goes to zero. This equation can easily be weighted to ascribe more importance to one or another element within the metric, but such weighting would likely differ between any two fishermen or managers. As such, we do not weight any aspect of the metric.

All analyses described above were run in R (R Core Team, 2014). Data was manipulated using the `plyr` (Wickham, 2011) and `reshape2` (Wickham, 2007) packages. Spatial analyses were completed using the `sp` and `rgdal` packages (Bivand et al., 2013, 2014). Figures were developed using `ggplot2` (Wickham, 2009).

4.3 Results

4.3.3 Closure Results

The real-time closures based on move-on rules reduced juvenile cod bycatch 62.17% by weight (Table 7). To draw comparisons between the real-time closures and less dynamic monthly and annual time-area closures, a general target of 60% reduction in bycatch biomass was set for the Marxan runs. The time-area required per individual closure can be considered the resolution of the management measure. For instance, each real-time closure based on move-on rules had an approximate area of 20km² and was closed for 1 day, resulting in a 20km²-days/closure resolution. Seen this way, the measures can be ordered by resolution: high resolution (i.e., move-on rules, 20km²-days per closure; grid-based closures, 50km²-days per closure), medium resolution (monthly time-area closures; 3000km²-days per closure), and 2 low resolution closures (annual time-area closures, 36500 km²-days per closure; and monthly total closures, 78000 km²-days per closure). Trends in the best results from each closure type based on achieving a 60% bycatch reduction target were monotonic (Table 7, Figure 10). Percent catch forgone increased linearly as the resolution of the management measure decreased

(slope = 9.13, $R^2 = 0.932$). Consequently, the reduction ratio (inversely related to the percent catch forgone) decreased linearly with resolution (slope = -1.76, $R^2 = 0.816$).³ The total kilometer-days used to achieve the target portrayed a log-linear increase as resolution decreased (slope = 0.832, $R^2 = 0.987$). The combination of the increase in catch forgone and the decreases in the reduction ratio and kilometer-days per year resulted in a log-linear decrease in efficiency as resolution decreased (slope = -1.07, $R^2 = 0.953$). While the best grid-based closure had a higher reduction ratio and used relatively less space than the move-on rule, the eight-fold higher reduction in bycatch afforded by the move-on rule resulted in a higher efficiency value.

The initial Marxan runs were all parameterized with a zero boundary length modifier and a target of 60% reduction of bycatch to be able to compare them to the efficacy of the move-on rules. Results for runs where the target was allowed to vary between 10% and 100% bycatch reduction and where the BLM was allowed to range between 0.00001 and 100 were also run. In both cases where the BLM was allowed to vary (i.e., monthly and annual time-area closures), the efficiency of the closure improved (0.1 and 0.41 log units, respectively; Table 7), even though the percent catch forgone also increased (11.5% and 21.6%, respectively). Similarly, the reduction ratio improved when the target was not constrained (monthly time-area = 44.0%; annual time-area = 46.1%;

³ The percent catch forgone and kilometer-days of closure trends exclude grid-based closures that could not meet this target. However, reduction ratios can be calculated regardless of the target and they are included in this trend and in the efficiency metric)

monthly full fishery closure = 7.5%), but the overall percent bycatch reduction was lower in each case as well (66.8%, 25.8% and 46.0%, respectively).

Table 7: Results from the simulation of four different closures type spanning a range of dynamism.

ClosureType	BLM or Weight Threshold (in lbs)	Target	Percent Bycatch Reduction	Percent Catch Forgone	Reduction Ratio	Number of Closures Per Year	Area Of Closure	Days Closed	Km-Days Of Closure Per Year	Km Day Ratio	Efficiency Metric
Move-On Rules	NA	NA	62.17	8.57	7.25	8	19.63	1	157	0.0002	6.4
5x10 Daily Grid-based	10 lbs	NA	8.31	1.02	8.17	1	50	1	50	0.00005	6.1
5x10 Daily Grid-based	5 lbs	NA	8.51	1.93	4.41	1	50	1	50	0.00005	5.9
5x10 Daily Grid-based	1 lbs	NA	9.12	2.10	4.34	1	50	1	50	0.00005	5.9
5x10 Daily Grid-based	0.1 lbs	NA	9.12	2.10	4.34	1	50	1	50	0.00005	5.9
5x10 Daily Grid-based	0 lbs	NA	14.78	12.43	1.19	2	50	1	100	0.00011	5.2
5x10 Weekly Grid-based	1 lbs	NA	9.64	7.07	1.36	2	50	7	700	0.00074	4.3
Monthly Time-Area	0	Best (20)	20	3.88	5.15	3	100	30	9000	0.0095	4.0
	1	60	60.44	18.77	3.22	5	100	30	15000	0.0158	4.1
	0	60	60.22	16.84	3.58	7	100	30	21000	0.0221	4.0
Annual Time-Area	0	Best (40)	44.96	15.64	2.87	1	100	365	36500	0.0385	3.5
	0.001	60	68.72	37.47	1.83	2	100	365	73000	0.0769	3.2
	0	60	60.63	30.81	1.97	5	100	365	182500	0.1923	2.8
Monthly Total	NA	Best (30)	36.99	21.73	1.70	1	2600	30	78000	0.0822	2.9
Monthly Total	NA	60	68.54	43.28	1.58	4	2600	30	312000	0.3288	2.5

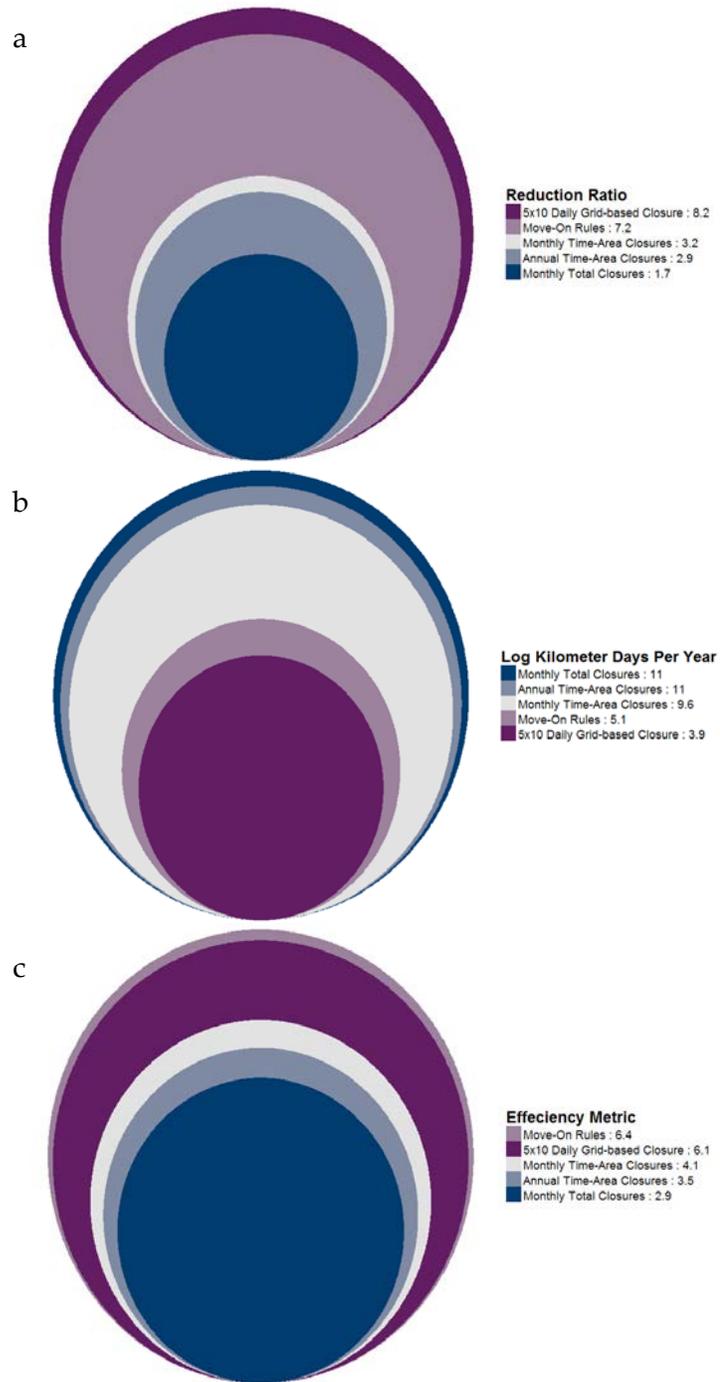


Figure 10: Three efficiency metrics: a) the reduction ratio of bycatch to catch; b) the kilometer days used; and, c) the total efficiency metric (reduction ratio divided by the percent of total kilometer days used). Dynamic management measures are depicted in purple and static measures in blue.

4.4 Discussion

4.4.1 Dynamic management can be more efficient than static

The results of this simulation study paint a clear picture about how the use of more dynamic measures affects key aspects of fisheries management (i.e., the cost in lost catch to achieve bycatch reduction targets and the time-area required). As the resolution of the closures decreases (reading down Table 7):

- 1- the percent of target catch forgone increases
- 2- the reduction ratio (bycatch/catch) decreases
- 3- the total time-area required increases; and
- 3- the efficiency of the closures significantly decreases

The coarser management measures (annual time-area closures and monthly full fishery closures) resulted in 4-5x the lost catch and required 100-200x the time-area of the dynamic measures (grid-based closures and move-on rules). Dynamic management measures were expected to be more efficient, but the magnitude of the difference was a surprise. Similarly, the monotonic decrease in efficiency as we move from more dynamic to less dynamic closures was also surprising. I expected the differences in efficiency to be relatively small and thus there to be some possibility that coarser closures might be more efficient than a higher resolution closure in certain instances. However, across all boundary length modifiers and weight thresholds, and even when the closures were not constrained to the same reduction target, there was essentially no

overlap in the efficiency of the various closure types (Table 7). Overlap was seen in the reduction ratios, but this was largely the result of testing sub-optimal grid-based closure scenarios (i.e., weekly closures with low threshold values that generated lower bycatch reduction at a greater cost in the time-area used).

The results of this study are not an artifact of the efficiency metric used. It is clear that the range of time-area required across all closure types (i.e., 4 orders of magnitude) is far greater than the range in the reduction ratio. Thus, the time-area used likely has an outsized effect on the efficiency metric. However, the reduction ratio displayed the same monotonic increase with little overlap in the best solutions as measures became more dynamic. Thus, while further consideration should be given to the optimal method to describe closure efficiency, the results of this study are not sensitive to changes in that metric.

4.4.2 Dynamic management can address coactive and social processes

In chapter 1, I demonstrated how move-on rules can effectively address predation and competition. In chapter 2, I showed how bottom temperature can be used to separate species by considering how they partition their thermal niches. In this study I showed how, by managing at scales more relevant to coactive and social processes, dynamic management can be significantly more efficient than traditional static spatiotemporal management. By improving the minimum resolution of spatiotemporal management measures, dynamic management affords fisheries managers the opportunity to address

vital coactive and social processes affecting their stocks (e.g., competition, niche partitioning, predation, parasitism, aggregation and social interactions).

This is the first study to include dynamically instantiated closures (grid-based and move-on rule-based) in a direct analysis of the efficiency of different closure types. Further comparisons of the efficiency of dynamic versus static closures will be necessary before broad generalization can be drawn. However, it is self-evident that the area required to encompass a spatiotemporally dynamic process is inversely proportional to the temporal resolution at which it is viewed. For example, the area required to encompass a sea surface temperature front that aggregates fish increases as the front moves over a span of days or weeks. Attempting to manage activities around all locations of the front on a monthly basis will take more space than if it is done daily. This is the draw of dynamic ocean management. The near real-time nature of the management measures affords managers the opportunity to use higher resolution measures, and the ability to use higher resolution measures allows managers to better address specific patterns (i.e., coactive and social) and processes that were previously intractable.

5. Conclusions & Future Directions

5.1 Knowledge and Novelty

With this dissertation I set out to implement and build on a framework for the spatiotemporal management of bycatch and describe how more dynamic forms of management (i.e., Dynamic Ocean Management) can increase the efficiency of attaining management goals. In chapters 1 and 2, I offered two novel methods for developing dynamic closures. In chapter 3, I compared dynamic management measures to static measure and quantified differences in efficiency between the two types of measures. Further, I offered a theoretical ecological basis for why dynamic management not only increases efficiency but also affords managers the opportunity manage patterns and processes that were previously intractable to them. While this dissertation provides a more specific definition of dynamic ocean management, new methods for the development of dynamic management measures and the first quantification of the efficiency gained by using dynamic measures, it only scratches the surface of what fishermen, researchers, managers and policy makers need to know to fully implement DOM. Here, I summarize the novelty and nature of the work in the previous three chapters and discuss gaps in knowledge and future research directions to advance the dynamic management of oceanic systems.

Chapter 1 included the first attempt to generate real-time closures based on move-on rules based on autocorrelation analysis. While the connection between how far

in time and space a fishermen should “move-on” and clustering of the species/events they are attempting to avoid is entirely intuitive, no effort had been made before this work to inform such closures with point-pattern analyses. In transitioning from move-on rules to temperature-based targeting and closures, it became clear that the degree and scales of patchiness in many species is dependent on temperature. One logical direction for further research on move-on rules would be to develop and compare temperature-dependent spatial (distances) and temporal (times) scales defining these aggregations. In a paper I co-authored based on the R script I produced for chapter 1, Bjorkland et al. (*in revision*) found differences in move-on rule times and distances seasonally and regionally. This work needs to be followed-up with more analyses to determine how temperature affects the aggregation and the degree of overlap (e.g., predators and prey) in target and non-target species, and to incorporate that knowledge to define the time/distance lags for move-on rules. Further, research needs to continue linking the ecology of species being exploited or impacted by fisheries and the scales of these dynamic management measures.

In chapter 2, I examined temperature-based targeting to separate target / non-target species within the Northeast Multispecies Fishery Management Plan (FMP). The basic method used in chapter 2 was not novel. Several authors had previously used cumulative distribution functions to describe an individual species thermal response curves (e.g, Perry and Smith, 1994; Helser and Brodziak, 1996; Methratta and Link,

2006)). However, I took that method a step further by examining how differences in two species' thermal response curves could be used to identify optimal temperature thresholds to separate them. Further, I developed novel metrics for describing how differentiable the species were based on the magnitude of the difference, the range of temperature values that produced near-optimal results and a novel use of receiver operator characteristic curves to describe the overall environmental separability of the two species. The results underscored the validity of this method to help targeting or to define time-area closures to protect a number of species within the FMP. An unexpected outcome from this work was evidence that the thermal overlap between cod and other species within the FMP is likely increasing under climate change. If borne out by further studies, this has serious implications for management of an ever-dwindling stock of Atlantic cod in the Gulf of Maine and Georges Bank.

While an attempt was made to test an optimal threshold temperature in chapter 3, a number of factors confounded the effort (see Appendix A). An obvious next step with respect to the development of bottom-temperature closures is to test other combination of species and circulation models to determine what the sensitivity of results are to temperature threshold breadth and modeled bottom temperature error. Of particular interest is the Finite-Volume Community Ocean Model and Surface WAVE model (FVCOM-SWAVE) which has a variable resolution unstructured grid that approximates 10km resolution in the study area (Chen et al., 2003; Qi et al., 2009) and

has been put forward as the best option for the development of these temperature thresholds (J. Hare, pers. comm.). Further work also needs to be done to bring the temporal variability of bottom temperature into any quantification of what breadth may be deemed operational.

The development of a comparison of static and dynamic management measures in chapter 3 was meant to put the specific work done in chapters 1 and 2 into a broader context. The comparison shines a harsh light on the lack of efficiency inherent in managing a highly dynamic environment with mesoscale measures at monthly or annual time scales. That is not to say that the understanding and integration of mesoscale, macroscale and megascale processes and patterns into fisheries management is not critical. Rather, it simply points out that interactions between fishermen and the marine environment generally happen at scales smaller than the minimum resolution of our current fisheries management. While the meso and macro scales are, have been, and will continue to be, the dominant scales of strategic fisheries management, managers must develop finer scale (1 – 10 km) management measures to ensure that the tactical implementation of those strategies is done as efficiently as possible.

The novelty of chapter 3 lies in the quantitative comparison of efficiency between static and dynamic measures. While two previous studies of efficiency of dynamic measures were cited in the chapter (i.e., Grantham et al., 2008; O’Keefe et al., 2013), one does not include truly dynamic measures (i.e., dynamically instantiated or dynamically

defined) and the other does not draw comparisons between measures but rates them against criteria. Significant further work needs to be done to test whether the results of chapter 3 are general rules or fishery-specific.

5.2 Gaps and Needs

The most obvious overall gap in existing DOM measures and theory is how these measures work in a multispecies / multiobjective environment. While the examples put forward in this dissertation are from a multispecies fishery, I have only offered solutions to the interaction of two species or two different age-classes of the same species. A key question is how do real-time closures based on move-on rules work toward the end of a season, when fishermen, operating in a fishery with 13 choke points based on 13 different quotas, may be trying to avoid the majority of species in the FMP? When the catch includes multiple species to be avoided, which move-on rule should be used? Further, the Northeast Multispecies fishery is an excellent example of a fishery that overlaps with multiple other fisheries in the same region and frequently catches species that are managed under a different FMP. How do we ensure that spatial management of one fishery in a region does not impinge on the ability of another fishery to meet its objectives (both conservation and catch related)? To answer these questions DOM must be scaled up with multispecies and multifishery (i.e., regional) examples.

Another important question stems from considerations of the data required to implement dynamic ocean management measures. The framework set forth in the

introduction was largely constructed in the context of developing spatiotemporal management measures for developed fisheries. When not viewed from this perspective it sets up a false dichotomy: that of requiring more data to manage more dynamically. I suspect there are many examples of dynamic management in small-scale fisheries with little or no formal data collection. As has been repeatedly shown throughout the history of modern fisheries management, we frequently find ourselves “discovering” management measures that actually have been used for millennia but were pushed aside by industrial fishing and industrial fisheries management (e.g., tenure systems and marine protected areas). A significant effort should be made by advocates of DOM to reach out to groups like Too Big To Ignore (<http://toobigtoignore.net>) to encourage the development of a review of dynamic management measures in small-scale fisheries.

5.3 Ecological Considerations

In the introduction to chapter 3, I posed a question with implications far beyond the scope of the chapter: Can we meet commitments to implement ecosystem-based fisheries management (EBFM) with spatiotemporal measures that may be fundamentally mismatched in space and time to address coactive and social patterns? Since its inception, calls for EBFM have contained requirements to account for other ecosystem components including non-target species, protected species, habitat and trophic interactions, and to incorporate spatiotemporal management (Pikitch et al., 2004). The COMPASS Scientific Consensus statement on Marine Ecosystem-based

Management outlines a number of “key elements” including accounting for dynamic changes in ecosystems, and states that “ecosystem processes operate over a range of spatial scales, and thus appropriate scales for management will be goal specific” (McLeod et al., 2005). Similarly, one of the “ten commandments” of ecosystem-based fisheries management according to Francis et al. (2007) is to “characterize and maintain the natural spatial structure of fish stocks.” It is critical that we recognize that scale does not stop at 10km and that the marine realm is a complex adaptive system where large-scale dynamics can be driven by fine-scale interactions (Levin, 1998; Levin and Lubchenco, 2008). To implement EBFM we must understand the linkages among these scales and we must have the ability to address our management to all the scales of the natural environment we influence. To do so efficiently and in a manner that is most likely to maintain ecosystem and stock structure, we need to be able to manage at the spatiotemporal scale of those effects. While I believe this dissertation has raised this issue, there is a large amount of work ahead of us to better understand cross-scale linkages and the ecosystem effects of our choice of resolution and scale in fisheries management.

Beyond the question of scale, there are a number of other important ecological factors to consider as we move forward with Dynamic Ocean Management. An argument is made in chapter 3 that as the vagility of an organism or process increases, the amount of space required to encapsulate it within a management scheme is inversely

proportional to the temporal resolution used. This implies that dynamic management may be more useful for the management of highly mobile pelagic species or processes (e.g. sea turtles and tuna, or fronts and eddies), and has limited the consideration of dynamic management of more sessile species. However, the work in this dissertation shows that dynamic management can more efficiently meet management targets in demersal species as well. Considered together with the work of Bjorkland et al. (*in revision*) and O'Keefe and DeCelles (2013), a trend begins to appear indicating that the utility of dynamic management to demersal fisheries may be the norm, not an anomaly. Further work needs to be done examine how dynamic management fares against a continuum of species life-histories (benthic *vs.* pelagic, central place foragers *vs.* wanderers, migratory *vs.* local populations, etc.). Only through the production of more example analyses examining the efficiency of spatiotemporal management measures under various scenarios can we develop an idea of whether the findings here are general rules.

It is not enough to simply think about how much fishing effort or fishing mortality is being applied in a fishery. To maintain ecosystem structure and integrate ecosystem impacts into management, we must also understand how and when that effort and mortality is occurring. Further, we need management measures that are targeted at the spatiotemporal scales of fishing effort at the time and point it occurs. I sincerely hope that this dissertation has contributed significantly to how we think about

space and time in fisheries management and provided concrete examples of how we can manage at finer scales and benefit from employing Dynamic Ocean Management.

Appendix A

Development of closures based on bottom temperature

The Northeast Fisheries Science Center Scientific Trawl Survey data from chapter 2 were also used in this study and cleaned following the methods found in that chapter. However, the objective was the separation of adult and juvenile cod rather than two distinct species. To identify juvenile catch within the scientific trawl survey data we defined all cod smaller than the regulatory limit of 19 inches (48.3 cm) as juveniles¹. Expected catch weight had been summed across all catch sizes in the NEFSC database, so we established catch weight by length by applying NEFSC season-specific length-weight equations and multiplying the modeled weight by the expected number of fish caught at that length. Length-weight ratios for Atlantic cod on Georges Bank are given in the 55th Northeast Regional Stock Assessment Workshop (SAW 55) Assessment Report (NEFSC 2013). The SAW 55 reports the following season-specific length-weight conversions:

$$\text{Quarter 1 and 2 : } \ln(W) = -11.6913 + 3.0291 \cdot \ln(L)$$

$$\text{Quarter 3 and 4: } \ln(W) = -11.9883 + 3.1221 \cdot \ln(L)$$

¹ [69 FR 22974, Apr. 27, 2004, as amended at 71 FR 46876, Aug. 15, 2006; 72 FR 11276, Mar. 12, 2007; 75 FR 18328, Apr. 9, 2010; 76 FR 42585, July 19, 2011; 78 FR 26158, May 3, 2013]

Where W is live weight in kilograms and L is total length. These weights were used to calculate the effectiveness of closures in reducing non-target catch and their impact on target catches.

Sets affected by bottom temperature-based closures were identified by removing any set that occurred above the threshold bottom temperature. We derived bottom temperature for each set by sampling a 3-D Regional Ocean Modeling System (ROMS; (Shchepetkin and McWilliams, 2005; Haidvogel et al., 2008; Kang and Curchitser, 2013) with the Fixed Gear large-mesh gillnet data. The ROMS run used for this study extended from January 2005 through 2011, and had a horizontal resolution of 7 km. The ROMS does not assimilate temperature data, so corrections were required. I corrected the ROMS by developing a generalized additive model (GAM) with a Gaussian link function to predict in-situ bottom temperature values from the Scientific Trawl Surveys using the ROMS bottom temperature, latitude, longitude, month and year as explanatory variables. Two interaction terms were also included, individually combining month and year with latitude and longitude. The ROMS bottom temperature, latitude, longitude and the interaction terms were smoothed with a spline function. Model selection was performed by minimizing the generalized cross validation (GCV; an estimate of the mean square prediction error based on a leave-one-out cross validation estimation process).

Table 8: Mean difference and standard deviation of the ROMS and corrected predicted bottom temperature from in-situ NEFSC Scientific Trawl Survey bottom temperature data.

Month	Mean ROMS Difference	SD of ROMS Difference	Mean Predicted Temp Difference	SD of Predicted Temp Difference
3	0.345	1.838	0.0005	1.114
4	1.144	2.112	-0.0004	1.110
5	2.230	1.443	0.0020	0.570
9	2.059	3.005	-0.0044	0.955
10	1.052	2.588	0.0013	1.164
11	0.634	1.798	-0.0026	1.047
Means	1.244	2.131	-0.0006	0.993

Results

ROMS correction results

I compared the original ROMS model output to the in-situ bottom temperatures recorded by the NEFSC Scientific Trawl Surveys (Table 8, Figure 11). The ROMS run had a mean error (i.e., difference from in-situ measurements) of $>1^{\circ}\text{C}$, and the standard deviation of the difference was $>2^{\circ}\text{C}$. The final generalized additive model chosen to correct this error through minimization of GCV dropped the year term (though year was kept in an interaction term) and explained 91.4% of the deviance in the Trawl Survey bottom temperatures (Table 9). The mean difference between the corrected bottom temperature and the in-situ data was approximately 0 ($\sim 0.0006^{\circ}\text{C}$), but the standard deviation was still $\sim 1^{\circ}\text{C}$ (0.993°C ; Figure 11).

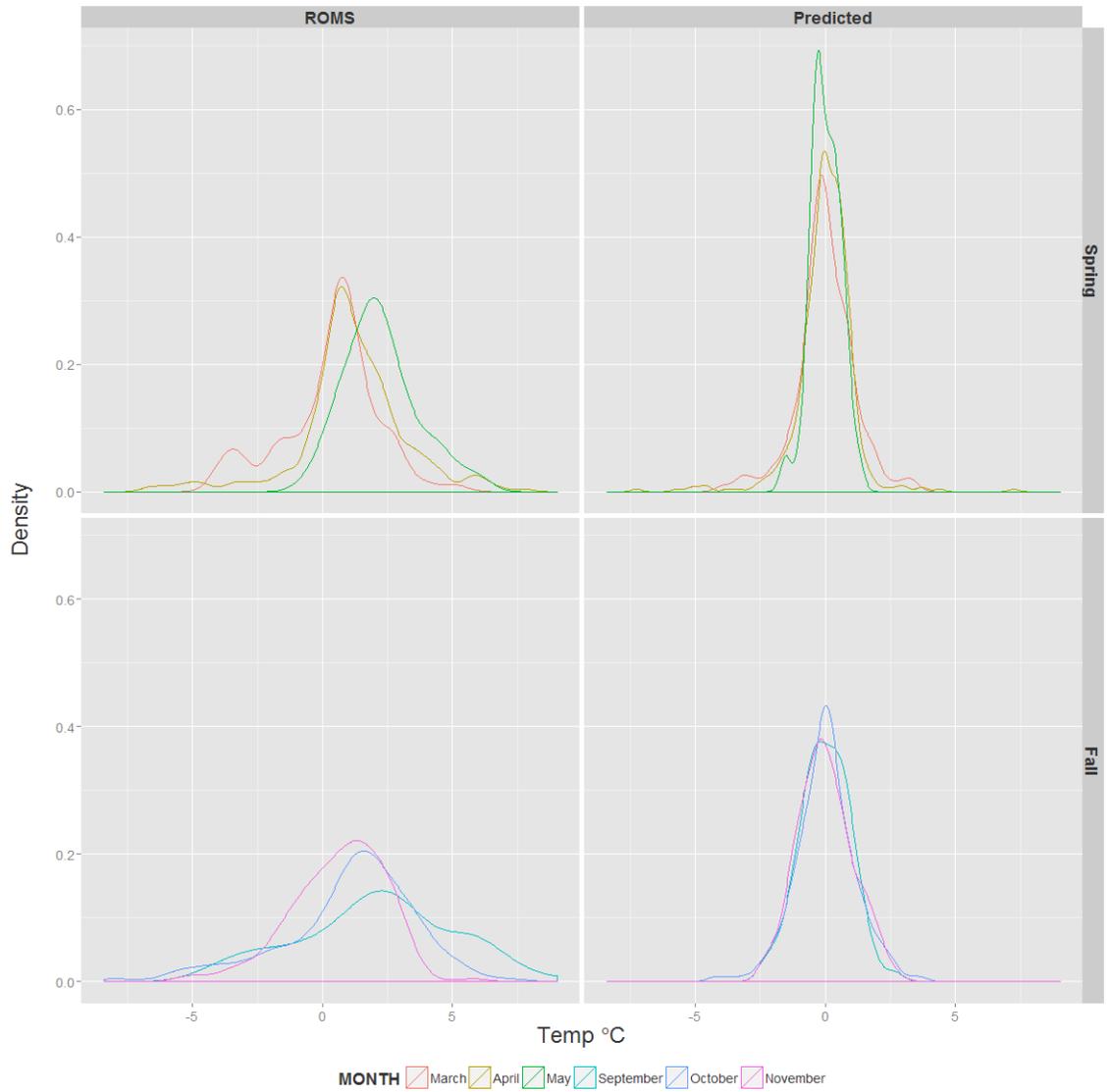


Figure 11: Distribution of error (i.e., difference from in-situ measurements) for the ROMS and the predicted bottom temperature from the GAM.

Table 9: Coefficients and approximate estimates of significance for the GAM model to correct the ROMS

Parametric coefficients:	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	4.0286	1.5676	2.57	0.01029	*
Month	0.7093	0.2274	3.119	0.00186	**
Approximate significance of smooth terms:	Effective Degrees of Freedom	Ref.df	F	p-value	
s(ROMS Bottom Temperature)	7.828	8.636	16.828	< 2e-16	***
s(Latitude)	8.898	8.986	8.39	3.08e-12	***
s(Longitude)	8.572	8.823	2.905	0.00231	**
s(Month, Latitude, Longitude)	95.245	101.679	9.82	< 2e-16	***
s(Year, Latitude, Longitude)	74.536	87.528	5.093	< 2e-16	***

Temperature threshold validation

Development of the optimum threshold temperature indicated that the threshold would likely not perform well. In chapter 2, I described a set of criteria that would qualify a threshold as likely being useful to managers and fishermen: difference in percent biomass available of > 50 units; mean breadth of at least 0.5°C and probably 1°C; and an AUC > 0.5. The threshold used to separate juvenile and adult cod failed all three of these criteria in each temperature regime and season except the mean breadth criteria for cold springs and falls (Table 10). Validation by applying the threshold to the Fixed Gear sector data using the corrected ROMS bottom temperature resulted in a 16.89% reduction of juvenile bycatch reduction at the cost of a 47.97% decrease in adult cod catch (reduction ratio = 0.35). These results appear better than they actually were, as spring results independently were either 0% bycatch reduction and 0% catch forgone

(cold springs, n=5), or 100% bycatch reduction and 77.53% catch forgone (warm springs, n=1). Even given the poor performance of the threshold value during development, it is clear that there were issues with the accuracy of the corrected ROMS. These and other obstacles to the implementation of dynamic management are discussed below.

Table 10: Results of the validation exercise for the optimal temperature threshold

Season Type	Median Threshold	SD of Median Threshold	Median Difference	SD of Median Difference	Mean Breadth	SD of Mean Breadth	Median AUC	SD of Median AUC
Cold Spring	4.75	0.0056	13.71	6.92	0.75	0.67	-0.082	0.29
Warm Spring	5.75	0.0040	16.38	11.46	0.42	0.12	0.028	0.29
Fall	9.5	0.0000	21.86	12.29	1.16	0.86	-0.029	0.21

Obstacles to the implementation of dynamic management

The failure to implement a theoretical temperature-based closure in this analysis affords an opportunity to discuss obstacles and limits to the implementation of dynamic management. The dynamic approaches analyzed in this dissertation all require high-resolution data. That is not the case for all dynamic management measures (see Lewison et al., *in review*). However, other than fleet communication strategies (E. L. Gilman et al., 2006; O’Keefe et al., 2013), dynamic management measures in developed fisheries require at least high resolution fishing set location data. The pervasiveness of GPS recorders has made high-resolution location data a low bar to meet.

The need for high-resolution temperature data to drive temperature-based closures presents a larger obstacle, particularly in the case of bottom temperature.

Accessibility is not an issue for sea surface temperatures that can be remotely sensed, but bottom temperatures are virtually always based on circulation models which are far less accessible than remotely sensed products. The output from circulation models are not generally made openly available, though frequently the model framework is made available (e.g., the ROMS used in this study).

Beyond data accessibility, there is the question of how well these models fit in-situ conditions and whether and at what spatiotemporal resolution it is feasible to use them for management purposes. In chapter 2, I developed optimum threshold temperature values to separate Atlantic cod from other species within the Northeast Fisheries Management Plan. The breadth of the threshold values that produced results greater than 90% of the maximum was used as a metric to determine how operationally feasible it might be to implement the thresholds. Breadth values between 0.5°C and 1°C were defined as “possible”, while values greater than 1°C were defined as “operational”. These values were put forward as being well within the error margin of inexpensive temperature sampling equipment that could be used by fishermen. From this perspective, the categories make sense. However, to test the efficacy and efficiency of bottom temperature-based closures for fishing data with no bottom temperature records, we need regional models of bottom temperature. Managers would also require such models if they chose to implement bottom temperature-based closures in a top down fashion (e.g., Hobday et al., 2010). If circulation models are used to develop or

implement temperature-based closures, the error associated with those models must also be considered in determining what breadth of threshold values is “operational”.

In this study, I used a ROMS that had both a systematic bias in spring values and a large standard error when compared to in-situ data (Table 8, Figure 11). While the correction I applied was able to remove the systematic bias entirely and halve the standard error, there remained a $\sim 1^{\circ}\text{C}$ standard error. For the temperature threshold to be effective when applied to fishing data based on the ROMS, the breadth would have to be greater than 2°C . The mean breadth for the threshold temperature separating adult and juvenile cod did not exceed 1°C in spring and was 1.16°C in fall. Between the poor performance of the threshold in separating the two life history stages and the large standard error in the model bottom temperatures, no operable results were found for the temperature closure.

These results are not generalizable to the use of all circulation models. The ROMS used in this study covers the entire northwest Atlantic including the Gulf of Mexico at a 7km resolution. It is highly likely that a local circulation model, or even a smaller regional circulation model could have performed better. Further, the ROMS used in this study did not assimilate sea surface temperature values to force the model. That is, it was initiated using a set of conditions and then allowed to run. Use of a temperature-assimilative model would also likely have produced better results.

Bibliography

- Ackerman, E.A., 1941. New England's fishing industry. The University of Chicago Press, Chicago.
- AFMA (Australian Fisheries Management Authority), 2009a. Southern and eastern scalefish and shark fishery (Closures) Direction No. 1 [WWW Document]. URL [http://www.comlaw.gov.au/Details/F2009L01123/Explanatory Statement/Text](http://www.comlaw.gov.au/Details/F2009L01123/ExplanatoryStatement/Text) (accessed 12.20.12).
- AFMA (Australian Fisheries Management Authority), 2009b. The school shark rebuilding strategy 2008 [WWW Document]. URL http://www.afma.gov.au/wp-content/uploads/2010/07/school_shark_rebuild.pdf (accessed 12.20.12).
- Alexander, K.E., Leavenworth, W.B., Cournane, J., Cooper, A.B., Claesson, S., Brennan, S., Smith, G., Rains, L., Magness, K., Dunn, R., Law, T.K., Gee, R., Jeffrey Bolster, W., Rosenberg, A. a., 2009. Gulf of Maine cod in 1861: historical analysis of fishery logbooks, with ecosystem implications. *Fish Fish.* 10, 428–449. doi:10.1111/j.1467-2979.2009.00334.x
- Anselin, L., 1995. Local Indicators of Spatial Association-LISA. *Geogr. Anal.* 27, 93–115. doi:10.1111/j.1538-4632.1995.tb00338.x
- Armsworth, P.R., Block, B.A., Eagle, J., Roughgarden, J.E., 2010. The role of discounting and dynamics in determining the economic efficiency of time-area closures for managing fishery bycatch. *Theor. Ecol.* 4, 513–526. doi:10.1007/s12080-010-0093-x
- Arnason, R., Kelleher, K., Willmann, R., 2009. The sunken billions: the economic justification for fisheries reform, The World Bank. The World Bank & The UN Food and Agriculture Organization, Washington, D.C.
- Auster, P.J., Gjerde, K., Heupel, E., Watling, L., Grehan, A., Rogers, A.D., 2010. Definition and detection of vulnerable marine ecosystems on the high seas: problems with the “move-on” rule. *ICES J. Mar. Sci.* 68, 254–264. doi:10.1093/icesjms/fsq074
- Azarovitz, T.R., 1981. A brief historical review of Woods Hole Laboratory trawl survey time series, in: Doubleday, W.G., Rivard, D. (Eds.), *Bottom Trawl Surveys: Proceedings of a Workshop Held at Ottawa, November 12-14, 1980*. Volume 58 of

- Canadian Special Publication of Fisheries and Aquatic Sciences. Dept. of Fisheries and Oceans, Ottawa, pp. 62–67.
- Baddeley, A., Turner, R., 2005. spatstat: An R package for Analyzing Spatial Point Patterns. *J. Stat. Softw.* 12, 1–42.
- Bainbridge, R., 1957. The size, shape and density of marine phytoplankton concentrations. *Biol. Rev.* 32, 91–115.
- Ball, I., Possingham, H.P., Watt, M.E., 2009. Marxan and relatives: software for spatial conservation prioritisation, in: *Spatial Conservation Prioritisation: Quantitative Methods and Computational Tools*. Oxford University Press, Oxford, UK, pp. 185–195.
- Barnes, K.N., Ryan, P.G., Boix-Hinzen, C., 1997. The impact of the hake *Merluccius* spp. longline fishery off South Africa on procellariiform seabirds. *Biol. Conserv.* 82, 227–234. doi:10.1016/S0006-3207(97)00020-7
- Bartram, P.K., John Kaneko, J., Kucey-Nakamura, K., 2010. Sea turtle bycatch to fish catch ratios for differentiating Hawaii longline-caught seafood products. *Mar. Policy* 34, 145–149. doi:10.1016/j.marpol.2009.05.006
- Beardsley, G.L.J., 1969. Distribution and apparent relative abundance of yellowfin tuna (*Thunnus albacares*) in the eastern tropical Atlantic in relation to oceanographic features. *Bull. Mar. Sci.* 19, 48–56.
- Beets, J., Friedlander, A., 1999. Evaluation of a conservation strategy: a spawning aggregation closure for red hind, *Epinephelus guttatus*, in the U.S. Virgin Islands. *Environ. Biol. Fishes* 55, 91–98. doi:10.1023/A:1007404421518
- Bertrand, A., Josse, E., Bach, P., Gros, P., Dagorn, L., 2002. Hydrological and trophic characteristics of tuna habitat: consequences on tuna distribution and longline catchability. *Can. J. Fish. Aquat. Sci.* 59, 1002–1013. doi:10.1139/f02-073
- Bethoney, N.D., Schondelmeier, B.P., Stokesbury, K.D.E., Hoffman, W.S., 2013. Developing a fine scale system to address river herring (*Alosa pseudoharengus*, *A. aestivalis*) and American shad (*A. sapidissima*) bycatch in the U.S. Northwest Atlantic mid-water trawl fishery. *Fish. Res.* 141, 79–87. doi:10.1016/j.fishres.2012.09.003

- Bigelow, K., Boggs, C., He, X., 1999. Environmental effects on swordfish and blue shark catch rates in the US North Pacific longline fishery. *Fish. Oceanogr.* 8, 178–198.
- Bivand, R., Keitt, T., Rowlingson, B., 2014. rgdal: Bindings for the Geospatial Data Abstraction Library. R package version 0.9-1. [WWW Document]. URL <http://cran.r-project.org/package=rgdal>
- Bivand, R.S., Pebesma, E., Gomez-Rubio, V., 2013. Applied spatial data analysis with R, 2nd ed. Springer, New York, NY.
- Bjorkland, R., Dunn, D.C., McClure, M., Bellman, M., Jannot, J., Schiffers, K., McVeigh, J., Gleason, M., n.d. Spatiotemporal patterns of rockfish bycatch in US west coast groundfish fisheries: opportunities for reducing incidental catch of depleted species. *Can. J. Fish. Aquat. Sci.*
- Branch, T., 2006. Discards and revenues in multispecies groundfish trawl fisheries managed by trip limits on the US west coast and by ITQs in British Columbia. *Bull. Mar. Sci.* 78, 669–689.
- Branch, T. a., Rutherford, K., Hilborn, R., 2006. Replacing trip limits with individual transferable quotas: implications for discarding. *Mar. Policy* 30, 281–292. doi:10.1016/j.marpol.2004.12.003
- Branch, T.A., Hilborn, R., 2008. Matching catches to quotas in a multispecies trawl fishery: targeting and avoidance behavior under individual transferable quotas. *Can. J. Fish. Aquat. Sci.* 65, 1435–1446.
- Brander, K., 2010. Impacts of climate change on fisheries. *J. Mar. Syst.* 79, 389–402. doi:10.1016/j.jmarsys.2008.12.015
- Brothers, N., Gales, R., Reid, T., 1999. The influence of environmental variables and mitigation measures on seabird catch rates in the Japanese tuna longline fishery within the Australian Fishing Zone, 1991–1995. *Biol. Conserv.* 88, 85–101. doi:10.1016/S0006-3207(98)00085-8
- Brothers, N.P., Cooper, J., Lokkeborg, S., Al., E., 1999. The incidental catch of seabirds by longline fisheries: worldwide review and technical guidelines for mitigation. FAO Fisheries Circular No. 937. Rome.
- Buck, E., 1995. Individual transferable quotas in fishery management. US Congressional Research Report 95-849 ENR. Washington, D.C.

- Campana, S., Joyce, W., 2004. Temperature and depth associations of porbeagle shark (*Lamna nasus*) in the northwest Atlantic. *Fish. Oceanogr.* 52–64.
- Castonguay, M., Rollet, C., Fréchet, A., Gagnon, P., Gilbert, D., Brêthes, J.-C., 1999. Distribution changes of Atlantic cod (*Gadus morhua* L.) in the northern Gulf of St Lawrence in relation to an oceanic cooling. *ICES J. Mar. Sci.* 56, 333–344. doi:10.1006/jmsc.1999.0471
- CCAMLR (Commission for the Conservation of Antarctic Marine Living Resources), 2011. Conservation Measures 33-02, 41-02 & 42-01.
- CEC (Commission of the European Community), 2009. Green paper on a reform of the Common Fisheries Policy. COM (2009) 163 final. [WWW Document]. URL <http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52009DC0163&from=EN>
- Chakravorty, U., Nemoto, K., 2001. Modeling The Effects Of Area Closure And Tax Policies: A Spatial-Temporal Model Of The Hawaii Longline Fishery. *Mar. Resour. Econ.* 15, 179–204.
- Chen, C., Liu, H., Beardsley, R., 2003. An unstructured grid, finite-volume, three-dimensional, primitive equations ocean model: application to coastal ocean and estuaries. *J. Atmos. Ocean. Technol.* 20, 159–186.
- Ciannelli, L., Fauchald, P., Chan, K.S., Agostini, V.N., Dingsør, G.E., 2008. Spatial fisheries ecology: Recent progress and future prospects. *J. Mar. Syst.* 71, 223–236. doi:10.1016/j.jmarsys.2007.02.031
- Copes, P., 1986. A critical review of the individual quota as a device in fisheries management. *Land Econ.* 62, 278–291.
- Costello, C., Gaines, S.D., Lynham, J., 2008. Can catch shares prevent fisheries collapse? *Science* (80-.). 321, 1678–81. doi:10.1126/science.1159478
- Coutant, C.C., 1977. Compilation of Temperature Preference Data. *J. Fish. Res. Board Can.* 34, 739–745.
- Croll, D.A., Marinovic, B., Benson, S., Chavez, F.P., Black, N., Ternullo, R., Tershy, B.R., 2005. From wind to whales: trophic links in a coastal upwelling system. *Mar. Ecol. Prog. Ser.* 289, 117–130. doi:10.3354/meps289117

- Crowder, L., Murawski, S., 1998. Fisheries bycatch: implications for management. *Fisheries* 37–41.
- Curtis, R., Hicks, R.L., 2000. The Cost of Sea Turtle Preservation: The Case of Hawaii's Pelagic Longliners. *Am. J. Agric. Econ.* 82, 1191–1197. doi:10.1111/0002-9092.00119
- Cuzick, J., Edwards, R., 1990. Spatial clustering for inhomogeneous populations. *J. R. Stat. Soc. Ser. B* 52, 73–104.
- Dawson, S.M., Slooten, E., 1993. Conservation of Hector's dolphins: The case and process which led to establishment of the Banks Peninsula Marine Mammal Sanctuary. *Aquat. Conserv. Mar. Freshw. Ecosyst.* 3, 207–221. doi:10.1002/aqc.3270030305
- Dayton, P.K., Thrush, S.F., Agardy, M.T., Hofman, R.J., 1995. Environmental effects of marine fishing. *Aquat. Conserv. Mar. Freshw. Ecosyst.* 5, 205–232. doi:10.1002/aqc.3270050305
- DeAngelis, D.L., Cushman, R.M., 1990. Potential application of models in forecasting the effects of climate changes on fisheries. *Trans. Am. Fish. Soc.* 119, 224–239.
- Denman, K.L., Gargett, A.E., 1983. Time and space scales of vertical mixing and advection of phytoplankton in the upper ocean. *Limnol. Oceanogr.* 28, 801–815.
- Despres-Patanjo, L., Azarovtitz, T., Byrne, C., 1988. Twenty five years of fish surveys in the northwest Atlantic: The NMFS Northeast Fisheries Center's bottom trawl survey program. *Mar. Fish. Rev.* 50, 69–71.
- DFO (Fisheries and Oceans Canada), 2008. Procedures for Monitoring and Control of Small Fish Catches and Incidental Catches in Atlantic Groundfish Fisheries.
- DFO (Fisheries and Oceans Canada), 2009. Procedures for monitoring and control of small fish catches in the southern gulf herring mobile gear fishery.
- DFO (Fisheries and Oceans Canada), 2011. Pacific region integrated fisheries management plan groundfish.
- Dietrich, K.S., Parrish, J.K., Melvin, E.F., 2009. Understanding and addressing seabird bycatch in Alaska demersal longline fisheries. *Biol. Conserv.* 142, 2642–2656. doi:10.1016/j.biocon.2009.06.013

- Diggle, P.J., Chetwynd, A.G., Häggkvist, R., Morris, S.E., 1995. Second-order analysis of space-time clustering. *Stat. Methods Med. Res.* 4, 124–136.
doi:10.1177/096228029500400203
- Doeringer, P.B., Moss, P.I., Terkla, D.G., 1986. *The New England fishing economy: Jobs, income, and kinship.* The University of Massachusetts Press, Boston.
- Drinkwater, K., 2005. The response of Atlantic cod (*Gadus morhua*) to future climate change. *ICES J. Mar. Sci.* 62, 1327–1337. doi:10.1016/j.icesjms.2005.05.015
- Drinkwater, K.F., Tremblay, M.J., Comeau, M., 2006. The influence of wind and temperature on the catch rate of the American lobster (*Homarus americanus*) during spring fisheries off eastern Canada. *Fish. Oceanogr.* 15, 150–165.
doi:10.1111/j.1365-2419.2005.00349.x
- Dunn, D.C., Boustany, A.M., Halpin, P.N., 2011. Spatio-temporal management of fisheries to reduce by-catch and increase fishing selectivity. *Fish Fish.* 12, 110–119.
doi:10.1111/j.1467-2979.2010.00388.x
- Dunn, D.C., Boustany, A.M., Roberts, J.J., Brazer, E., Sanderson, M., Gardner, B., Halpin, P.N., 2014. Empirical move-on rules to inform fishing strategies: a New England case study. *Fish Fish.* 15, 359–375. doi:10.1111/faf.12019
- Dupont, D.P., Grafton, R.Q., 2000. Multi-species individual transferable quotas: the Scotia-Fundy mobile gear groundfishery. *Mar. Resour. Econ.* 15, 205–220.
- Dutil, J.-D., Castonguay, M., Gilbert, D., Gascon, D., 1999. Growth, condition, and environmental relationships in Atlantic cod (*Gadus morhua*) in the northern Gulf of St. Lawrence and implications for management strategies in the Northwest Atlantic. *Can. J. Fish. Aquat. Sci.* 56, 1818–1831. doi:10.1139/f99-140
- Dutton, D.L., Dutton, P.H., Chaloupka, M., Boulon, R.H., 2005. Increase of a Caribbean leatherback turtle *Dermodochelys coriacea* nesting population linked to long-term nest protection. *Biol. Conserv.* 126, 186–194.
doi:http://dx.doi.org/10.1016/j.biocon.2005.05.013
- ESRI (Environmental Systems Research Institute), 2010. *ArcGIS.* Environmental Systems Research Institute, Redlands, CA.
- European Commission, 2011. Commission Implementing Regulation (EU) No 783/2011 of 5 August 2011 amending Regulation (EU) No 724/2010 laying down detailed

rules for the implementation of real-time closures of certain fisheries in the North Sea and Skagerrak. *Off. J. Eur. Union* L 203, 7–8.

Evans, C.R., Lockwood, A.P.M., Evans, A.J., 1995. Associations between sea temperature, catch per unit of fishing effort, and yield in the Bermuda spiny lobster fishery, 1975–1989. *Mar. Freshw. Res.* 46, 809–818.

FAO, 2009. *The State of World Fisheries and Aquaculture 2008*, FAO. Rome. Rome.

Fogarty, M., Incze, L., Hayhoe, K., Mountain, D., Manning, J., 2007. Potential climate change impacts on Atlantic cod (*Gadus morhua*) off the northeastern USA. *Mitig. Adapt. Strateg. Glob. Chang.* 13, 453–466. doi:10.1007/s11027-007-9131-4

Fogarty, M.J., Murawski, S.A., 1998. Large-scale disturbance and the structure of marine systems: Fishery impacts on Georges Bank. *Ecol. Appl.* 8, S6–S22. doi:10.1890/1051-0761(1998)8[S6:LDATSO]2.0.CO;2

Francis, R.C., Hixon, M.A., Clarke, M.E., Murawski, S.A., Elizabeth, M., 2007. Ten commandments for ecosystem-based fisheries scientists. *Fisheries* 32, 217–233. doi:10.1577/1548-8446(2007)32

Frank, K.T., Perry, R.I., Drinkwater, K.F., 1990. Predicted response of Northwest Atlantic invertebrate and fish stocks to CO₂-induced climate change. *Trans. Am. Fish. Soc.* 119, 353–365.

Frank, K.T., Petrie, B., Choi, J.S., Leggett, W.C., 2005. Trophic cascades in a formerly cod-dominated ecosystem. *Science* 308, 1621–3. doi:10.1126/science.1113075

Fry, F.E.J., 1971. *The Effect of Environmental Factors on the Physiology of Fish*. *Fish Physiol.* 6, 1–98.

Gabriel, W.L., 1992. Persistence of Demersal Fish Assemblages Between Cape Hatteras and Nova Scotia, Northwest Atlantic. *J. Northwest Atl. Fish. Sci.* 14, 29–46.

Game, E.T., Grantham, H.S., Hobday, A.J., Pressey, R.L., Lombard, A.T., Beckley, L.E., Gjerde, K., Bustamante, R., Possingham, H.P., Richardson, A.J., 2009. Pelagic protected areas: the missing dimension in ocean conservation. *Trends Ecol. Evol.* 24, 360–9. doi:10.1016/j.tree.2009.01.011

- Gardner, B., Sullivan, P., Epperly, S., Morreale, S., 2008. Hierarchical modeling of bycatch rates of sea turtles in the western North Atlantic. *Endanger. Species Res.* 5, 279–289. doi:10.3354/esr00105
- Gardner, B., Sullivan, P.J., Morreale, S.J., Epperly, S.P., 2008. Spatial and temporal statistical analysis of bycatch data: patterns of sea turtle bycatch in the North Atlantic. *Can. J. Fish. Aquat. Sci.* 65, 2461–2470. doi:10.1139/F08-152
- Gatrell, A.C., Bailey, T.C., Diggle, P.J., Rowlingson, B.S., 1996. Spatial point pattern analysis and its application in geographical epidemiology. *Trans. Inst. Br. Geogr.* 21, 256–274.
- Getis, A., Ord, J.K., 1992. The Analysis of Spatial Association. *Geogr. Anal.* 24, 189–206.
- Gillis, D.M., Rijnsdorp, A.D., Poos, J.J., 2008. Behavioral inferences from the statistical distribution of commercial catch: patterns of targeting in the landings of the Dutch beam trawler fleet. *Can. J. Fish. Aquat. Sci.* 65, 27–37. doi:10.1139/f07-147
- Gilman, E., Brothers, N., Kobayashi, D.R., 2005. Principles and approaches to abate seabird by-catch in longline fisheries. *Fish Fish.* 6, 35–49. doi:10.1111/j.1467-2679.2005.00175.x
- Gilman, E., Kobayashi, D., Swenarton, T., Brothers, N., Dalzell, P., Kinankelly, I., 2007. Reducing sea turtle interactions in the Hawaii-based longline swordfish fishery. *Biol. Conserv.* 139, 19–28. doi:10.1016/j.biocon.2007.06.002
- Gilman, E., Zollett, E., Beverly, S., Nakano, H., Davis, K., Shiode, D., Dalzell, P., Kinan, I., 2006. Reducing sea turtle by-catch in pelagic longline fisheries. *Fish Fish.* 7, 2–23. doi:10.1111/j.1467-2979.2006.00196.x
- Gilman, E.L., Dalzell, P., Martin, S., 2006. Fleet communication to abate fisheries bycatch. *Mar. Policy* 30, 360–366. doi:10.1016/j.marpol.2005.06.003
- Glantz, M.H., 1990. Does History Have a Future? Forecasting Climate Change Effects on Fisheries by Analogy. *Fisheries* 15, 39–44. doi:10.1577/1548-8446(1990)015<0039:DHHAFF>2.0.CO;2
- Goñi, R., 1998. Ecosystem effects of marine fisheries: an overview. *Ocean Coast. Manag.* 40, 37–64. doi:http://dx.doi.org/10.1016/S0964-5691(98)00037-4

- Grantham, H., Petersen, S., Possingham, H., 2008. Reducing bycatch in the South African pelagic longline fishery: the utility of different approaches to fisheries closures. *Endanger. Species Res.* 5, 291–299. doi:10.3354/esr00159
- Green, D.M., Swets, J.A., 1966. *Signal Detection Theory and Psychophysics*. Wiley, New York.
- Guisan, A., Zimmermann, N.E., 2000. Predictive habitat distribution models in ecology 135, 147–186.
- Haidvogel, D.B., Arango, H., Budgell, W.P., Cornuelle, B.D., Curchitser, E., Di Lorenzo, E., Fennel, K., Geyer, W.R., Hermann, a. J., Lanerolle, L., Levin, J., McWilliams, J.C., Miller, a. J., Moore, a. M., Powell, T.M., Shchepetkin, a. F., Sherwood, C.R., Signell, R.P., Warner, J.C., Wilkin, J., 2008. Ocean forecasting in terrain-following coordinates: Formulation and skill assessment of the Regional Ocean Modeling System. *J. Comput. Phys.* 227, 3595–3624. doi:10.1016/j.jcp.2007.06.016
- Hall, M.A., Alverson, D.L., Metuzals, K.I., 2000. By-Catch: Problems and Solutions. *Mar. Pollut. Bull.* 41, 204–219. doi:http://dx.doi.org/10.1016/S0025-326X(00)00111-9
- Hall, S.J., 2002. Area and Time Restrictions., in: Cochrane, K. (Ed.), *Fisheries Managers Handbook: Management Measures and Their Application*. FAO Fisheries Technical Paper No. 424. Food and Agricultural Organization of the United Nations, Rome.
- Hall, S.J., Mainprize, B.M., 2005. Managing by-catch and discards: how much progress are we making and how can we do better? *Fish Fish.* 6, 134–155. doi:10.1111/j.1467-2979.2005.00183.x
- Halpern, B.S., Walbridge, S., Selkoe, K.A., Kappel, C. V, Micheli, F., D'Agrosa, C., Bruno, J.F., Casey, K.S., Ebert, C., Fox, H.E., Fujita, R., Heinemann, D., Lenihan, H.S., Madin, E.M.P., Perry, M.T., Selig, E.R., Spalding, M., Steneck, R., Watson, R., 2008. A global map of human impact on marine ecosystems. *Science* (80-). 319, 948–52. doi:10.1126/science.1149345
- Hanley, J.A., McNeil, B.J., 1982. The Meaning and Use of the Area under a Receiver Operating (ROC) Curvel Characteristic. *Radiology* 143, 29–36.
- Haury, L.R., McGowan, J.A., Wiebe, P.H., 1978. Patterns and processes in the time-space scales of plankton distributions, in: Steele, J.H. (Ed.), *Spatial Pattern in Plankton Communities*. Plenum Press & NATO Scientific Affairs Division, New York, pp. 277–327.

- Helser, T., Brodziak, J., 1996. Influence of temperature and depth on distribution and catches of yellowtail flounder, Atlantic cod, and haddock in NEFSC bottom trawl surveys. Northeast Fisheries Science Center Reference Document 96-05e. Woods Hole, MA.
- Hobday, A.J., Hartmann, K., 2006. Near real-time spatial management based on habitat predictions for a longline bycatch species. *Fish. Manag. Ecol.* 13, 365–380. doi:10.1111/j.1365-2400.2006.00515.x
- Hobday, A.J., Hartog, J.R., Timmiss, T., Fielding, J., 2010. Dynamic spatial zoning to manage southern bluefin tuna (*Thunnus maccoyii*) capture in a multi-species longline fishery. *Fish. Oceanogr.* 19, 243–253. doi:10.1111/j.1365-2419.2010.00540.x
- Hobday, A.J., Maxwell, S., Forgie, J., McDonald, J., Darby, M., Seto, K., Bailey, H., Bograd, S.J., Briscoe, D.K., Costa, D.P., Crowder, L.B., Dunn, D.C., Fossette, S., Halpin, P.N., Hartog, J.R., Hazen, E.L., Lascelles, B.G., Lewison, R.L., Poulos, G., Powers, A., 2014. Dynamic ocean management: Integrating scientific and technological capacity with law, policy and management. *Stanford Environ. Law J.* 33, 125–165.
- Holmes, S.J., Bailey, N., Campbell, N., Catarino, R., Barratt, K., Gibb, A., Fernandes, P.G., 2011. Using fishery-dependent data to inform the development and operation of a co-management initiative to reduce cod mortality and cut discards. *ICES J. Mar. Sci.* 68, 1679–1688. doi:10.1093/icesjms/fsr101
- Hooker, S.K., Gerber, L.R., 2004. Marine reserves as a tool for ecosystem-based management: The potential importance of megafauna. *Bioscience* 54, 27. doi:10.1641/0006-3568(2004)054[0027:MRAATF]2.0.CO;2
- Howell, E.A., Kobayashi, D.R., Parker, D.M., Balazs, G.H., Polovina, J.J., 2008. TurtleWatch: a tool to aid in the bycatch reduction of loggerhead turtles *Caretta caretta* in the Hawaii-based pelagic longline fishery. *Endanger. Species Res.* 5, 267–278. doi:10.3354/esr00096
- Hutchinson, G., 1953. The concept of pattern in ecology. *Proc. Acad. Nat. Sci.* ... 105, 1–12.
- Hyrenbach, K.D., Forney, K.A., Dayton, P.K., 2000. Marine protected areas and ocean basin management. *Aquat. Conserv. Mar. Freshw. Ecosyst.* 10, 437–458. doi:10.1002/1099-0755(200011/12)10:6<437::AID-AQC425>3.0.CO;2-Q

- Innis, H.A., 1954. The cod fisheries: history of an international economy. 2nd edn. University of Toronto Press, Toronto.
- Jackson, J.B.C., Kirby, M.X., Berger, W.H., Bjorndal, K.A., Botsford, L.W., Bourque, B.J., Bradbury, R.H., Cooke, R., Erlandson, J., Estes, J.A., Hughes, T.P., Kidwell, S., Lange, C.B., Lenihan, H.S., Pandolfi, J.M., Peterson, C.H., Steneck, R.S., Tegner, M.J., Warner, R.R., 2001. Historical Overfishing and the Recent Collapse of Coastal Ecosystems. *Sci.* 293 , 629–637. doi:10.1126/science.1059199
- Jurasinski, G., Koebisch, F., Guenther, A., Beetz, S., 2014. flux: Flux rate calculation from dynamic closed chamber measurements. R.
- Kang, D., Curchitser, E.N., 2013. Gulf Stream eddy characteristics in a high-resolution ocean model. *J. Geophys. Res. Ocean.* 118, 4474–4487. doi:10.1002/jgrc.20318
- Kelleher, K., 2005. Discards in the world's marine fisheries: an update. FAO Fisheries Technical Paper No. 470. Rome.
- Kenchington, T.J., 2011. Encounter protocols for avoidance of harm to vulnerable marine ecosystems: A global review of experience to 2010. DFO Can. Sci. Advis. Sec. Res. Doc. 2011/009.
- Kenkel, N., 1988. Pattern of self-thinning in jack pine: testing the random mortality hypothesis. *Ecology* 69, 1017–1024.
- Klaer, N., Polacheck, T., 1997. By-catch of albatrosses and other seabirds by Japanese longline fishing vessels in the Australian Fishing Zone from April 1992 to March 1995. *Emu* 97, 150–167.
- Klaer, N., Polacheck, T., 1998. The Influence of Environmental Factors and Mitigation Measures on By-Catch Rates of Seabirds by Japanese Longline Fishing Vessels in the Australian Region. *EMU* 98, 305. doi:10.1071/MU98042
- Kobayashi, D.R., Polovina, J.J., 2005. Evaluation of time-area closures to reduce incidental sea turtle take in the Hawaii-based longline fishery: generalized additive model (GAM) development and retrospective examination. NOAA Technical Memorandum NMFS-PIFSC-4, 39. Honolulu.
- Kot, C.Y., Boustany, A.M., Halpin, P.N., 2010. Temporal patterns of target catch and sea turtle bycatch in the US Atlantic pelagic longline fishing fleet. *Can. J. Fish. Aquat. Sci.* 67, 42–57. doi:10.1139/F09-160

- Kurlansky, M., 1997. Cod. Knopf, Canada.
- Langton, R.W., Auster, P.J., Schneider, D.C., 1995. A spatial and temporal perspective on research and management of groundfish in the northwest Atlantic. *Rev. Fish. Sci.* 3, 201–229. doi:10.1080/10641269509388572
- Laurs, R.M., Fiedler, P.C., Montgomery, D.R., 1984. Albacore tuna catch distributions relative to environmental features observed from satellites. *Deep Sea Res. Part A. Oceanogr. Res. Pap.* 31, 1085–1099. doi:10.1016/0198-0149(84)90014-1
- Legendre, L., Demers, S., 1984. Towards dynamic biological oceanography and limnology. *Can. J. Fish. ...* 41, 2–19.
- Lemon, J., 2006. Plotrix: a package in the red light district of R. *R-News* 6, 8–12.
- Levin, S.A., 1998. Ecosystems and the biosphere as complex adaptive systems. *Ecosystems* 1, 431–436.
- Levin, S.A., Lubchenco, J., 2008. Resilience, Robustness, and Marine Ecosystem-based Management. *Bioscience* 58, 27–32.
- Lewison, R., Hobday, A.J., Maxwell, S., Hazen, E., Hartog, J.R., Dunn, D.C., Briscoe, D., O’Keefe, S.F.C.E., Barnes-Mauthe, M., Abecassi, M., Bograd, S., Bethoney, N.D., Bailey, H., Wiley, D., Andrews, S., Howell, E., Hazen, L., Crowder, L.B., n.d. *Dynamic Ocean Management: 21st century approaches for marine resource management and conservation.* Bioscience.
- Lewison, R.L., Crowder, L.B., Read, A.J., Freeman, S.A., 2004. Understanding impacts of fisheries bycatch on marine megafauna. *Trends Ecol. Evol.* 19, 598–604. doi:http://dx.doi.org/10.1016/j.tree.2004.09.004
- Lewison, R.L., Soykan, C.U., Franklin, J., 2009a. Mapping the bycatch seascape: multispecies and multi-scale spatial patterns of fisheries bycatch. *Ecol. Appl.* 19, 920–30.
- Lewison, R.L., Soykan, C.U., Franklin, J., 2009b. Mapping the bycatch seascape: multispecies and multi-scale spatial patterns of fisheries bycatch. *Ecol. Appl.* 19, 920–30.
- Loosmore, N., Ford, E., 2006. Statistical inference using the G or K point pattern spatial statistics. *Ecology* 87, 1925–1931.

- Mackas, D.L., Denman, K.L., Abbot, M.R., 1985. Plankton patchiness: biology in the physical vernacular. *Bull. Mar. Sci.* 37, 652–674.
- Madsen, S., Haflinger, K., 2010. Application for an Incentive Plan Agreement (IPA) and list of IPA participants.
- Mann, K.H., 1993. Physical oceanography, food chains, and fish stocks: a review. *ICES J. Mar. Sci.* 50, 105–119.
- Mantzouni, I., Sørensen, H., O'Hara, R.B., MacKenzie, B.R., 2010. Hierarchical modelling of temperature and habitat size effects on population dynamics of North Atlantic cod. *ICES J. Mar. Sci. J. du Cons.* 67, 833–855. doi:10.1093/icesjms/fsp291
- Marine Management Organisation, 2012. Real time closures (sampling) [WWW Document]. URL http://www.marinemanagement.org.uk/fisheries/monitoring/closures_rtc.htm
- Martin, A.P., 2003. Phytoplankton patchiness: the role of lateral stirring and mixing. *Prog. Oceanogr.* 57, 125–174. doi:10.1016/S0079-6611(03)00085-5
- Matheron, G., 1963. Principles of geostatistics. *Econ. Geol.* 58, 1246–1266. doi:10.2113/gsecongeo.58.8.1246
- Maxwell, S.M., Lewison, R.L., Hazen, E.L., Dunn, D.C., Bailey, H., Bograd, S.J., Hobday, A.J., Bennett, M., Benson, S., Briscoe, D.K., Caldwell, M., Costa, D.P., Dewar, H., Eguchi, T., Fossette, S., Hazen, L., Kohin, S., Sippel, T., Crowder, L.B., n.d. Dynamic Oceans Need Dynamic Management. *Proc. Natl. Acad. Sci. U. S. A.*
- McFarland, R., 1911. A history of New England fisheries, with maps. J. F. Tapley Co., New York.
- McLeod, K., Lubchenco, J., Palumbi, S., Rosenberg, A., 2005. Scientific consensus statement on marine ecosystem-based management.
- Meisel, J.E., Turner, M.G., 1998. Scale detection in real and artificial landscapes using semivariance analysis. *Landsc. Ecol.* 13, 347–362.
- Methratta, E.T., Link, J.S., 2006. Seasonal variation in groundfish habitat associations in the Gulf of Maine –Georges Bank region. *Mar. Ecol. Prog. Ser.* 326, 245–256. doi:10.3354/meps326245

- Moore, J.E., Wallace, B.P., Lewison, R.L., Žydelis, R., Cox, T.M., Crowder, L.B., 2009. A review of marine mammal, sea turtle and seabird bycatch in USA fisheries and the role of policy in shaping management. *Mar. Policy* 33, 435–451. doi:<http://dx.doi.org/10.1016/j.marpol.2008.09.003>
- Mourato, B.L., Hazin, F., Bigelow, K., Musyl, M., Carvalho, F., Hazin, H., 2014. Spatio-temporal trends of sailfish, *Istiophorus platypterus* catch rates in relation to spawning ground and environmental factors in the equatorial and southwestern Atlantic Ocean. *Fish. Oceanogr.* 23, 32–44. doi:10.1111/fog.12040
- Murawski, S.A., 1993. Climate change and marine fish distributions: forecasting from historical analogy. *Trans. Am. Fish. Soc.* 122, 647–658.
- Murawski, S.A., Finn, J.T., 1988. Biological bases for mixed-species fisheries: species co-distribution in relation to environmental and biotic variables. *Can. J. Fish. Aquat. Sci.* 45, 1720–1735.
- Murawski, S.A., Maguire, J.J., Mayo, R.K., Serchuk, F.M., 1997. Groundfish stocks and the fishing industry, in: Boreman, J., Nakashima, B.S., Wilson, J.A., Kendall, R.L. (Eds.), *Northwest Atlantic Groundfish: Perspectives on a Fishery Collapse*. American Fisheries Society, Bethesda, MD., pp. 27–70.
- Murray, K.T., Read, A.J., Solow, A.R., 2000. The use of time/area closures to reduce bycatches of harbour porpoises: lessons from the Gulf of Maine sink gillnet fishery. *J. Cetacean Res. Manag.* 2, 135–141.
- Myers, R.A., Worm, B., 2003. Rapid worldwide depletion of predatory fish communities. *Nature* 423, 280–283.
- NCDENR (North Carolina Department of Environment and Natural Resources), 1987. Standards for an approved shellfish growing area.
- Needle, C.L., Catarino, R., 2011. Evaluating the effect of real-time closures on cod targeting. *ICES J. Mar. Sci.* 68, 1647–1655. doi:10.1093/icesjms/fsr092
- NEFMC (New England Fishery Management Council), 1999. Framework Adjustment 27 to the Northeast Multispecies Fishery Management Plan.
- NEFSC (Northeast Fisheries Science Center), 1988. An Evaluation of the bottom trawl survey program of the Northeast Fisheries Center. NOAA Technical Memorandum NMFS-F/NEC-52. Woods Hole, MA.

- NEFSC (Northeast Fisheries Science Center), 2012. Assessment or data updates of 13 Northeast groundfish stocks through 2010. Northeast Fisheries Science Center Reference Document 12-06.
- NEFSC (Northeast Fisheries Science Center), 2013. 55th Northeast Regional Stock Assessment Workshop (55th SAW) Assessment Report. Northeast Fisheries Science Center Reference Document 13-11. Woods Hole, MA.
- NMFS (National Marine Fisheries Service), 2002. Taking of marine mammals incidental to commercial fishing operations; Atlantic Large Whale Take Reduction Plan regulations. Fed. Regist. 67, 1113–1142.
- NMFS (National Marine Fisheries Service), 2010. Final amendment 16 to the Northeast (NE) Multispecies Fishery Management Plan. Fed. Regist. 75, 18262–18353.
- Norse, E., 2005. Pelagic protected areas: the greatest parks challenge of the 21st century. Prot. Areas Program. 15, 32–39.
- Notarbartolo di Sciara, G., Agardy, T., Hyrenbach, D., Scovazzi, T., Van Klaveren, P., 2008. The Pelagos sanctuary for Mediterranean marine mammals. Aquat. Conserv. Mar. Freshw. Ecosyst. 18, 367–391. doi:10.1002/aqc
- Nye, J., Link, J., Hare, J., Overholtz, W., 2009. Changing spatial distribution of fish stocks in relation to climate and population size on the Northeast United States continental shelf. Mar. Ecol. Prog. Ser. 393, 111–129. doi:10.3354/meps08220
- O’Keefe, C.E., Cadrin, S.X., Stokesbury, K.D.E., 2013. Evaluating effectiveness of time/area closures, quotas/caps, and fleet communications to reduce fisheries bycatch. ICES J. Mar. Sci. 71, 1286–1297.
- O’Keefe, C.E., DeCelles, G.R., 2013. Forming a Partnership to Avoid Bycatch. Fisheries 38, 434–444. doi:10.1080/03632415.2013.838122
- Oppel, S., Meirinho, A., Ramírez, I., Gardner, B., O’Connell, A.F., Miller, P.I., Louzao, M., 2012. Comparison of five modelling techniques to predict the spatial distribution and abundance of seabirds. Biol. Conserv. 156, 94–104. doi:http://dx.doi.org/10.1016/j.biocon.2011.11.013
- Pascoe, S., Koundouri, P., Bjørndal, T., 2007. Estimating targeting ability in multi-species fisheries: a primal multi-output distance function approach. Land Econ. 83, 382–397.

- Perry, A.L., Low, P.J., Ellis, J.R., Reynolds, J.D., 2005. Climate change and distribution shifts in marine fishes. *Science* (80-.). 308, 1912–5. doi:10.1126/science.1111322
- Perry, R., Smith, S., 1994. Identifying habitat associations of marine fishes using survey data: an application to the Northwest Atlantic. *Can. J. Fish. Aquat. Sci.* 51, 589–602.
- Petitgas, P., 1996. Geostatistics and their applications to fisheries survey data, in: Moksness, B.A.M. and E. (Ed.), *Computers in Fisheries Research*. Chapman and Hall, London, U.K., pp. 113–142.
- PFMC (Pacific Fishery Management Council), 2008. Pacific Coast Groundfish Fishery Management Plan for the California, Oregon, and Washington Groundfish Fishery.
- Pikitch, E.K., Santora, C., Babcock, E.A., Bakun, A., Bonfil, R., Conover, D.O., Dayton, P., Doukakis, P., Fluharty, D., Heneman, B., Houde, E.D., Link, J., Livingston, P.A., Mangel, M., McAllister, M.K., Pope, J., Sainsbury, K.J., 2004. EBFM: Ecosystem-Based Fishery Management. *Science* (80-.). 305, 346–347. doi:10.1126/science.1098222
- Pinsky, M.L., Worm, B., Fogarty, M.J., Sarmiento, J.L., Levin, S.A., 2013. Marine taxa track local climate velocities. *Science* (80-.). 341, 1239–42. doi:10.1126/science.1239352
- Poos, J.J., Bogaards, J.A., Quirijns, F.J., Gillis, D.M., Rijnsdorp, A.D., 2010. Individual quotas, fishing effort allocation, and over-quota discarding in mixed fisheries. *ICES J. Mar. Sci. J. du Cons.* 67, 323–333.
- Qi, J., Chen, C., Beardsley, R.C., Perrie, W., Cowles, G.W., Lai, Z., 2009. An unstructured-grid finite-volume surface wave model (FVCOM-SWAVE): Implementation, validations and applications. *Ocean Model.* 28, 153–166. doi:10.1016/j.ocemod.2009.01.007
- Quirijns, F.J., Poos, J.J., Rijnsdorp, A.D., 2008. Standardizing commercial CPUE data in monitoring stock dynamics: Accounting for targeting behaviour in mixed fisheries. *Fish. Res.* 89, 1–8. doi:10.1016/j.fishres.2007.08.016
- R Core Team, 2014. *R: A Language and Environment for Statistical Computing*.
- Read, A.J., Drinker, P., Northridge, S., 2006. Bycatch of Marine Mammals in U.S. and Global Fisheries. *Conserv. Biol.* 20, 163–169. doi:10.1111/j.1523-1739.2006.00338.x

- Redfern, J., Ferguson, M., Becker, E., 2006. Techniques for cetacean–habitat modeling. *Mar. Ecol. Prog. Ser.* 310, 271–295.
- Reeves, R., McClellan, K., Werner, T., 2013. Marine mammal bycatch in gillnet and other entangling net fisheries, 1990 to 2011. *Endanger. Species Res.* 20, 71–97. doi:10.3354/esr00481
- Reid, T., Hindell, M., Wilcox, C., 2012. Environmental determinants of the at-sea distribution of encounters between flesh-footed shearwaters *Puffinus carneipes* and fishing vessels. *Mar. Ecol. Prog. Ser.* 447, 231–242. doi:10.3354/meps09449
- Ripley, B.D., 1977. Modelling spatial patterns. *J. R. Stat. Soc. Ser. B* 39, 172–212.
- Roberts, J.J., Best, B.D., Dunn, D.C., Treml, E.A., Halpin, P.N., 2010. Marine Geospatial Ecology Tools: An integrated framework for ecological geoprocessing with ArcGIS, Python, R, MATLAB, and C++. *Environ. Model. Softw.* 25, 1197–1207. doi:10.1016/j.envsoft.2010.03.029
- Rose, G., 2005. On distributional responses of North Atlantic fish to climate change. *ICES J. Mar. Sci.* 62, 1360–1374. doi:10.1016/j.icesjms.2005.05.007
- Rosenberg, A.A., Bolster, W.J., Alexander, K.E., Leavenworth, W.B., Cooper, A.B., Mckenzie, M.G., 2005. The history of ocean resources: modeling cod biomass using historical records. *Front. Ecol. Environ.* 3, 78–84.
- Rowlingson, B.S., Diggle, P.J., 1993. Splanx: Spatial point pattern analysis code in S-plus. *Comput. Geosci.* 19, 627–655. doi:10.1016/0098-3004(93)90099-Q
- Ruppert, J.L.W., Fortin, M.-J., Rose, G.A., Devillers, R., 2009. Atlantic cod (*Gadus morhua*) distribution response to environmental variability in the northern Gulf of St. Lawrence. *Can. J. Fish. Aquat. Sci.* 66, 909–918. doi:10.1139/F09-049
- SAFMC (South Atlantic Fishery Management Council), 2007. Final Amendment Number 14 to the Snapper-Grouper Fishery Management Plan. National Marine Fisheries Service.
- Sanchirico, J.N., Holland, D., Quigley, K., Fina, M., 2006. Catch-quota balancing in multispecies individual fishing quotas. *Mar. Policy* 30, 767–785.
- Scott, J.S., 1982. Depth, temperature and salinity preferences of common fishes of the Scotian Shelf. *J. Northwest Atl. Fish. Sci.* 3, 29–39.

- Seki, M.P., Polovina, J.J., Kobayashi, D.R., Bidigare, R.R., Mitchum, G.T., 2002. An oceanographic characterization of swordfish (*Xiphias gladius*) longline fishing grounds in the springtime subtropical North Pacific. *Fish. Oceanogr.* 11, 251–266. doi:10.1046/j.1365-2419.2002.00207.x
- Shackell, N.L., Bundy, A., Nye, J.A., Link, J.S., 2012. Common large-scale responses to climate and fishing across Northwest Atlantic ecosystems. *ICES J. Mar. Sci.* 69, 151–162. doi:10.1093/icesjms/fsr195
- Shackell, N.L., Ricard, D., Stortini, C., 2014. Thermal habitat index of many northwest Atlantic temperate species stays neutral under warming projected for 2030 but changes radically by 2060. *PLoS One* 9, e90662. doi:10.1371/journal.pone.0090662
- Shchepetkin, A.F., McWilliams, J.C., 2005. The regional oceanic modeling system (ROMS): a split-explicit, free-surface, topography-following-coordinate oceanic model. *Ocean Model.* 9, 347–404. doi:10.1016/j.ocemod.2004.08.002
- Shotton, R., Patchell, G., 2008. The Proposed “5-Mile” Move-on-rule in Deep-sea Trawl Fisheries of the Southern Indian Ocean: An Analysis of its Origins and the Basis for the Requirement. SIODFA Tech. Rep. 08/02.
- Smith, P., 1978. Biological effects of ocean variability: time and space scales of biological response. *Rapp. Proces Verbaux des Reun.* 173, 117–127.
- Spotila, J.R., Reina, R.D., Steyermark, A.C., Plotkin, P.T., Paladino, F. V, 2000. Pacific leatherback turtles face extinction. *Nature* 405, 529–30. doi:10.1038/35014729
- Squires, D., Campbell, H., Cunningham, S., Dewees, C., Grafton, R.Q., Herrick, S.F., Kirkley, J., Pascoe, S., Salvanes, K., Shallard, B., Turris, B., Vestergaard, N., 1998. Individual transferable quotas in multispecies fisheries. *Mar. Policy* 22, 135–159.
- Steele, J.H. (Ed.), 1978. Spatial pattern in plankton communities. Plenum Press, New York.
- Stommel, H., 1963. Varieties of Oceanographic Experience. *Science* (80-.). 139, 572–576.
- Sumaila, U.R., Suatoni, L., 2006. Economic benefits of rebuilding US ocean fish populations. Working Paper Series #2006-04, Fisheries Centre, the University of British Columbia, Vancouver, BC, Canada. Vancouver, B.C.

- Swain, D.P., Chouinard, G.A., Morin, R., Drinkwater, K.F., 1998. Seasonal variation in the habitat associations of Atlantic cod (*Gadus morhua*) and American plaice (*Hippoglossoides platessoides*) from the southern Gulf of St. Lawrence. *Can. J. Fish. Aquat. Sci.* 55, 2548–2561. doi:10.1139/f98-122
- Tamdrari, H., Castonguay, M., Brêthes, J., Galbraith, P.S., Duplisea, D.E., 2012. The dispersal pattern and behaviour of Atlantic cod (*Gadus morhua*) in the northern Gulf of St. Lawrence : results from tagging experiments 121, 112–121. doi:10.1139/F2011-137
- Venables, W., Ripley, B., 1999. *Modern applied statistics with S*, 4th ed. Springer, New York.
- Wallace, B., Kot, C., DiMatteo, A., Lee, T., Crowder, L.B., Lewison, R.L., 2013. Impacts of fisheries bycatch on marine turtle populations worldwide: toward conservation and research priorities. *Ecosphere* 4, 1–49.
- Waluda, C., Rodhouse, P., 2001. Remotely sensed mesoscale oceanography and the distribution of *Illex argentinus* in the South Atlantic. *Fish. Oceanogr.* 207–216.
- WCPFC (Western and Central Pacific Fisheries Commission), 2009. Conservation and management measure on the application of high seas FAD closures and catch retention. Conservation and Management Measure 2009-02.
- Weimerskirch, H., Capdeville, D., Duhamel, G., 2000. Factors affecting the number and mortality of seabirds attending trawlers and long-liners in the Kerguelen area. *Polar Biol.* 23, 236–249. doi:10.1007/s003000050440
- Wickham, H., 2007. Reshaping Data with the reshape Package. *J. Stat. Softw.* 21, 1–20.
- Wickham, H., 2009. *ggplot2: elegant graphics for data analysis*. Springer, New York.
- Wickham, H., 2011. The Split-Apply-Combine Strategy for Data Analysis. *J. Stat. Softw.* 40, 1–29.
- Wiegand, T., Moloney, K.A., 2004. Rings, circles, and null models for point pattern analysis in ecology. *Oikos* 104, 209–229.
- Witherell, D., Pautzke, C., 1997. A brief history of bycatch management measures for Eastern Bering Sea Groundfish Fisheries. *Mar. Fish. Rev.* 59, 15–22.

Zagaglia, C.R., Lorenzzetti, J.A., Stech, J.L., 2004. Remote sensing data and longline catches of yellowfin tuna (*Thunnus albacares*) in the equatorial Atlantic. *Remote Sens. Environ.* 93, 267–281. doi:10.1016/j.rse.2004.07.015

Zydelis, R., Lewison, R.L., Shaffer, S.A., Moore, J.E., Boustany, A.M., Roberts, J.J., Sims, M., Dunn, D.C., Best, B.D., Tremblay, Y., Kappes, M.A., Halpin, P.N., Costa, D.P., Crowder, L.B., 2011. Dynamic habitat models: using telemetry data to project fisheries bycatch. *Proc. R. Soc. B* 278, 3191–3200. doi:10.1098/rspb.2011.0330

Biography

BORN

August 11, 1972
Singapore, The Republic of Singapore

EDUCATION

- Doctor of Philosophy, Marine Science & Conservation, (2014)
Nicholas School of the Environment and Earth Sciences, Duke University, Durham, NC
- Master of Environmental Management, 2005
Nicholas School of the Environment and Earth Sciences, Duke University, Durham, NC
- Master of Fine Arts, Photography, 2001
Savannah College of Art & Design, Savannah, GA
- Bachelor of Arts, Philosophy, Human & Natural Ecology, 1995
Emory University, Atlanta, GA

PEER-REVIEWED PUBLICATIONS

In review

1. Morato, T., P.I. Miller, **D.C. Dunn**, S. Nicol, J. Bowcott, P.N. Halpin, (in review) A perspective on the importance of oceanic fronts in promoting aggregation of visitors to seamounts. *Fish & Fisheries*
2. Maxwell, S.M., R. Lewison, H. Bailey, M. Bennett, S. Benson, S. Bograd, D.K. Briscoe, M. Caldwell, D.P. Costa, H. Dewar, **D.C. Dunn**, T. Eguchi, S. Fossette, E.L. Hazen, L. Hazen, A.J. Hobday, S. Kohin, T. Sippell, L. Crowder. (in review) Dynamic ocean environments require dynamic management. *Proceedings of the National Academy of Sciences*.
3. Lewison, R., A.J. Hobday, S. Maxwell, E. Hazen, J.R. Hartog, **D.C. Dunn**, D. Briscoe, S.F.C.E. O'Keefe, M. Barnes-Mauthe, M. Abecassi, S. Bograd, N.D. Bethoney, H. Bailey, D. Wiley, S. Andrews, E. Howell, L. Hazen, L.B. Crowder. (in review) *Dynamic Ocean Management: 21st century approaches for marine resource management and conservation*. *Bioscience*.
4. Bjorkland, R., **D.C. Dunn**, M. McClure, M. Bellman, J. Jannot, K. Schiffers, J. McVeigh, M. Gleason (in revision) Spatiotemporal patterns of rockfish bycatch in US west coast groundfish fisheries: opportunities for reducing incidental catch of depleted species. *Canadian Journal of Fisheries and Aquatic Sciences*.

In print

1. Merrie, A., **D.C. Dunn**, M. Metian, A.M. Boustany, Y. Takei, Y. Ota, V. Christensen, P.N. Halpin, H. Österblom. (2014) Human use trends and potential surprise in the global marine common. *Global Environmental Change* 27:19-31.

2. Lewison, R., L.B. Crowder, B. Wallace, J. Moore, T. Cox, R. Zydalis, S. McDonald, A. DiMatteo, **D.C. Dunn**, K. Stewart, C. Soykan, M. Sims, R. Bjorkland, C. Kot, S. Kelez, A. Boustany, A. Read, P.N. Halpin, W.J. Nichols, C. Safina. (2014) Global patterns of marine megafauna bycatch. *Proceedings of the National Academy of Sciences* 111(14):5271-5276.
3. Hobday, A.J., S.M. Maxwell, H. Bailey, D. Costa, L. Crowder, **D.C. Dunn**, K.M. Gjerde, B. Lascelles, G. Poulos, H. Possingham, P.N. Halpin, J. Hartog, E.L. Hazen, R. Lewison, A. Powers, J. McDonald, K. Seto, M. Hall, K. Gordon. (2014) Dynamic marine management: Integrating scientific and technological capacity with law, policy and management. *Stanford Environmental Law Journal* 33(2):125-168.
4. **Dunn, D.C.**, J. Ardron, N. Bax, P. Bernal, J. Cleary, I. Cresswell, B. Donnelly, P. Dunstan, K.M. Gjerde, D. Johnson, K. Kaschner, B. Lascelles, J. Rice, H. von Nordheim, L. Wood, P. N. Halpin. (2014) The Convention on Biological Diversity's Ecologically or Biologically Significant Areas: origins, development, and current status. *Marine Policy* 49:137-145.
5. Ban, N.C., S.M. Maxwell, **D.C. Dunn**, N.J. Bax, K.M. Gjerde, R. Devillers, P.K. Dunstan, A.J. Hobday, D., Kaplan, R.L. Pressey, J.A. Ardron, E.T. Game, P.N. Halpin. (2014) Better integration of sectoral planning and management approaches for the interlinked ecology of the open oceans. *Marine Policy* 49: 127-136.
6. Ban, N.C., N.J. Bax, K.M. Gjerde, R. Devillers, **D.C. Dunn**, P.K. Dunstan, A.J. Hobday, S.M. Maxwell, D. Kaplan, R.L. Pressey, J.A. Ardron, E.T. Game, P.N. Halpin. (2013) Systematic Conservation Planning: A new recipe for managing the High Seas. *Conservation Letters* 7(1):41-54.
7. **Dunn, D.C.**, A.M. Boustany, J.J. Roberts, P.N. Halpin (2014) Empirical move-on rules to inform fishing strategies: a New England case study. *Fish & Fisheries* 15(3):359-375.
8. Curtice, C., **D.C. Dunn**, J.J. Roberts, P.N. Halpin. (2012) Ecosystem-Based Management May Fail Without Changes to Tool Development Financing. *Bioscience* 62(5):508-515.
9. Garcia, S.M., J. Kolding, J. Rice, M-J Rochet, S. Zhou, T. Arimoto, J.E. Beyer, L. Borges, A. Bundy, **D.C. Dunn**, N. Graham, M. Hall, M. Heino, R. Law, M. Makino, A.D. Rijnsdorp, F. Simard, and A.D.M Smith (2012) Balanced harvesting: reconsidering the consequences of selective fisheries. *Science* 335:1045-1047.
10. Van Dover C.L., C. Smith, J. Ardron, **D.C. Dunn**, K. Gjerde, L. Levin *et al.* (2012) Designating networks of chemosynthetic ecosystem reserves in the deep sea. *Marine Policy* 36:378-381
11. Curtice, C., R.S. Schick, **D.C. Dunn**, and P.N. Halpin. (2011) Home range analysis of Hawaiian Monk Seals (*Monachus schauinslandi*) based on colony, age and gender. *Aquatic Mammals* 37(3):360-371.
12. Gilman, E., **D.C. Dunn**, A. Read, R. Warner, K.D. Hyrenbach. (2011) Designing criteria suites to identify sites and networks of high value across manifestations of biodiversity. *Biodiversity and Conservation* 20(14):3363-3383.

13. Žydelis, R., D.P., Costa, B.D. Best, A.M. Boustany, L.B. Crowder, **D.C. Dunn**, M.A. Kappes, R.L. Lewison, J.E. Moore, J.J. Roberts, S.A. Shaffer, M. Sims, Y. Tremblay (2011) Dynamic habitat models: a new perspective in analyzing fisheries bycatch. *Proceedings of the Royal Society B* 278:3191-3200.
14. **Dunn, D.C.**, A. Boustany, P.N. Halpin. (2011) Spatio-temporal management of fisheries to reduce bycatch and increase fishing selectivity. *Fish and Fisheries* 12:110-119.
15. Stewart, K., R. Lewison, **D.C. Dunn**, R. Bjorkland, S. Kelez, P.N. Halpin, L.B. Crowder (2010) Characterizing fishing effort and spatial extent for coastal fisheries. *PLoSOne* 5(12): e14451.
16. Roberts, J.J., B.D. Best, **D.C. Dunn**, E.A. Treml, P.N. Halpin (2010) Marine Geospatial Ecology Tools: an integrated framework for ecological geoprocessing with ArcGIS, Python, R, MATLAB, and C++. *Ecosystem Modeling & Software* 25(10):1197-1207
17. **Dunn, D.C.**, K. Stewart, R. Bjorkland, M. Haughton, S. Singh-Renton, R. Lewison, L. Thorne, P.N. Halpin. (2010) A regional analysis of coastal and domestic fishing effort in the wider Caribbean. *Fisheries Research* 102:60–68
18. **Dunn, D.C.**, P.N. Halpin (2009) Rugosity-based regional modeling of hard-bottom habitat. *Marine Ecology Progress Series* 377:1–11. *Feature Article*.
19. **Dunn, D.C.**, C.Y. Kot, P.N. Halpin (2008) A comparison of methods to spatially represent pelagic longline fishing effort in catch and bycatch studies. *Fisheries Research* 92:268-276
20. Eckert, S., J.E. Moore., **D.C. Dunn**, R. Sagarminaga, K. Eckert, P.N. Halpin (2008) Hierarchical state-space models of loggerhead sea turtle movement in relation to size and oceanographic features in the western Mediterranean Sea. *Ecological Applications* 18(2):290-308.
21. Koch, V., J.M.M. Suástegui, F. Sinsel, M.R. Mungaray, **D.C. Dunn** (2005) Lion's paw scallop (*Nodipecten subnodosus*, Sowerby 1835) aquaculture in Bahía Magdalena, Mexico: effects of population density and season on juvenile growth and mortality. *Aquaculture Research* 36 (5), 505–512.

AWARDS

Nippon Foundation Doctoral Fellowship, Nippon Foundation
James B. Duke Fellowship, Duke University