UiT The Arctic University of Norway

Faculty of Biosciences, Fisheries and Economics

# Assessing the impacts of climate change and spatial dynamics on the Canadian lobster fishery (*Homarus americanus*)

Insights into harvest, catch rates, and production risks

Dana Elizabeth Wright

A dissertation for the degree of Philosophiae Doctor (PhD) February 2025

# Table of Contents

# List of Tables



# List of Figures

# Acknowledgements

I would like to express my deepest gratitude to my supervisor, Dr. Yajie Liu. This thesis would not have been possible without her unwavering support throughout my Ph.D. journey, and the final product is immeasurably improved under her guidance. Her vast knowledge, dedication, and passion for the field of natural resource economics continues to be an inspiration to me.

Sincere thanks as well to the members of the Marine Resource Economics (MRØ) research group for welcoming me with open arms and for the helpful feedback and critiques during seminars. My appreciation also extends to the faculty and staff in the Faculty of Biosciences, Fisheries and Economics who were always so helpful and kind. Starting my Ph.D. program in the strange and uncertain times of the pandemic wasn't ideal, but I felt truly supported and cared for.

Thank you to my peers for their camaraderie and willingness to commiserate over a well-deserved lønningspils. I would like to thank TODOS for all they do to support Ph.D. students and for the events they organize (the writing retreat I attended in Malangen was one of the highlights of my experience) as well as ESN Tromsø for the social gatherings and trips – who would have thought I'd get to visit Santa's Village in Finland and stay on a reindeer farm?!

Sincere thanks to my former managers at Fisheries and Oceans Canada, Dr. Barbara Best and Dr. Gisele Magnusson, for their encouragement and advice when I was making the decision to pursue the Ph.D., and for their ongoing assistance including invaluable advice and manuscript review. I would also like to thank my current manager at Seafish Jennifer Robson, and Chief Economist Arina Motova-Surmava, for their patience with me as I slowly crept towards the finish line.

I am endlessly grateful for my friends and family for always believing in me even when I doubted myself. A few shout-outs: Bettina Pribek for always offering a moment of levity and a healthy dose of realism, and Sophie Lorius, for our heart-to-hearts and her adventurous spirit which inspired me to embark on this international journey. I am forever grateful for my wonderful mother Barbara Wright, my biggest cheerleader and proofreader extraordinaire, who instilled in me a deep sense of resilience and tenacity. I wouldn't have been able to prevail without her unending support and pep-talks.

Last but not least, heartfelt thanks to my brilliant and patient husband Christopher Law for his consistent support and encouragement. I know that no matter how difficult things get, he is always in my corner and I'm excited about sharing together in all the joys, challenges and celebrations that life brings.

# Summary


This thesis offers a comprehensive analysis of how climate change affects fishery production, presenting empirical evidence and methodological innovations that contribute to the development of adaptive management strategies. In particular, it seeks to understand how warming waters, distributional species shifts, and extreme weather events are disrupting fishery dynamics and undermining the stability of fishers' livelihoods. Different facets of production are examined such as expected output, variance in harvest, and production risk. Using the lobster (*Homarus americanus*) fishery in Atlantic Canada as a case study, this research provides insights that are applicable to other fisheries, particularly those with input-controlled management systems.

The first study in this thesis (Chapter 2) utilizes a panel dataset of individual fishing vessels to investigate the impact of ocean temperature variation on fish harvests. A generalized linear mixed model (GLMM) is applied, accounting for heterogeneity among fishers, gear types, vessels, and fishing areas. The GLMM demonstrates superior performance and more accurate estimations compared to alternative models. As anticipated, the analysis reveals a significant positive relationship, further supporting the growing body of evidence on the effects of warming temperatures on the lobster fishery. Additionally, the study highlights the utility of GLMMs as an effective empirical tool for analyzing hierarchical data structures.

The second paper (Chapter 3) employs emerging hotspot analysis to explore how changes in lobster catch rates correlate with warming trends in Atlantic Canada. This method identifies areas undergoing significant temperature changes, along with the direction and intensity of these trends within each region. A generalized linear model (GLM) is applied to assess the relationship between catch rates and the proportion of each fishing area affected by these warming or cooling hotspots. The analysis reveals strong evidence that emerging hotspots are linked to higher catch rates, with the intensification of warming trends showing a substantial positive association.

The third study (Chapter 4) applies a Just-Pope production framework to assess production risk in an input-controlled fishery exposed to environmental variability. The analysis incorporates data on landings, effort, vessel characteristics, and weather conditions. A generalized linear model with two-way random effects is utilized, and the findings indicate that extreme weather conditions negatively impact fishing operations. Specifically, fluctuations in wind speed are inversely related to expected harvests, while mean wind speed increases harvest variance. Additionally, wave height above a certain threshold significantly reduces the expected monthly catch. The study highlights the critical need to account for extreme weather conditions in fishing operations and decision-making, emphasizing the importance of adaptive management strategies.

# 1 Introduction

## 1.1 The consequences of climate change for global fisheries

Climate change poses a serious threat to fisheries, and its impacts are being felt at alarming rates across the globe. Warming waters are altering marine ecosystems and biota, and those who depend on fishing for their livelihood are vulnerable to these changes. Although the severity of these impacts depends on many different factors such as location, target species, management, and adaptability, it is inevitable that most fisheries will need to adapt to these changes. To effectively mitigate worst-case scenarios and enhance management strategies and measures, sound scientific and data-driven approaches are essential. Research on the impacts of climate change on marine resources often emphasizes the biological facets rather than the experiences of fish harvesters. This overlooks a key cog in the machine: as harvesters adapt to shifting conditions they adjust their fishing strategies. This interplay can have a significant impact on both retrospective analyses and forecasts. Understanding fishing behaviour, and recognizing and incorporating the adaptive strategies of fish harvesters, is vital for developing comprehensive and effective management responses to climate change.

Fisheries are affected by climate change in a myriad of ways, but the most profound impacts arise from changes in environmental conditions that affect fish populations, ecosystems, and the effectiveness of management strategies. As ocean temperatures rise, many fish stocks are shifting their range toward cooler waters, often towards the poles or deeper waters (Perry et al. 2005, Cheung et al. 2009, Pinsky et al. 2013). This can alter the availability of fish in areas that have traditionally been targeted by fisheries. Fishers that target specific species may find that they move beyond their managed areas, leading to reduced catch rates and possible economic loss. The productivity of a stock in a given area is also affected by warming waters, and this could have either a positive or negative effect depending on the scenario. Warmer temperatures can affect fish breeding and the survival rates of fish larvae (Munday et al. 2008, Rijnsdorp et al. 2009, Pörtner and Peck 2010, Pankhurst and Munday 2011). Changes in the timing and abundance of fish recruitment can lead to periods of low fish stocks, affecting fishers' ability to maintain catch levels. Climate change also alters ecosystems, damaging critical habitats and altering the species' composition. Variation in the availability of plankton and other prey species affects food availability, which in turn affects species' growth rates, survival, and migration patterns (Richardson and Schoeman 2004, Hays et al. 2005, Beaugrand et al. 2008).

## 1.2 Climate risks for input-controlled fisheries

Climate change presents unique challenges to input-controlled fisheries in which the level of fishing effort such as the number of vessels, fishing gear, or hours spent fishing is regulated. As climate change causes fish populations to fluctuate or move, existing input controls such as fishing zones or seasonal closures may not be as effective. It might be the case that these input controls no longer align with current location or abundance of the target species, leading to inefficiencies and potential economic losses. Fisheries also contend with increased uncertainty and variability in catch; as environmental conditions become more unpredictable (e.g., more frequent and intense storms, temperature extremes), fishery yields may become more variable. Input-controlled systems may struggle to adjust to these changes, especially if fisheries managers rely on historical norms to determine fishing effort limits. For instance, inflexible fishing seasons might lead some to fish despite inclement weather, posing safety risks and incentivizing "race-to-fish" competition. This situation raises questions about the effectiveness of input controls as a management tool. The success of input controls depends on reliable, relevant data, and increased uncertainty makes it harder for managers to set appropriate limits on fishing effort or catch. Managers may find it more difficult to predict optimal fishing times and locations, and the ability to enforce these regulations may be reduced due to changes in fisheries dynamics. Adapting to these challenges will require more flexible and dynamic approaches to fisheries management. Empirical studies can provide valuable insights to guide fishers and policymakers to find the best path forward.

## 1.3 History and importance of the Canadian lobster fishery

The American lobster (*Homarus americanus*) fishery is a pillar of many coastal communities in Atlantic Canada. The fishery has a rich history: Indigenous groups harvested lobsters for centuries, followed by European settlers. The fishery and the industry has undergone many changes, but it has remained a mainstay and a source of livelihood for these communities. The commercial industry formed in the mid-19th century, with humble beginnings in the form of small canneries. The number of canneries in seaside communities rose from 44 in 1872 to 900 by 1900 and continued to increase through the early part of the century. In the latter part of the century, industrialization led to larger scale production, and consumers started demanding fresh, live, and frozen lobster. Today, it is one of the most valuable fisheries in Canada, with landings valued at CAD $1.8 billion in 2022 (DFO 2024). Given the high value of lobster and the many people who are employed in the industry, communities in Atlantic Canada are highly dependent on the fishery.

The lobster fishery is regulated by Fisheries and Oceans Canada (DFO), the Canadian governmental body responsible for managing Canada's oceans and inland waters. Various rules and regulations have been introduced since the advent of the commercial fishery, mostly aimed at conservation of lobster stocks. In the Bay of Fundy, fishing seasons were introduced as early as 1879, with size restrictions being introduced two decades later. In the late 1960s, a number of initiatives were introduced that form the basis for the present-day fishery. Most notably, DFO established a limited entry policy for licenses. Prior to that, no restrictions were in place for who could obtain a lobster license. Around this time DFO also introduced trap limits, minimum size limits, fishing seasons, and defined boundaries for most of the lobster fishing areas (LFAs) that delimit the current management zones. Other regulations were introduced over the next few decades including a license buyback program, changes in minimum size, and v-notching for egg-bearing females (Figure 1.1).

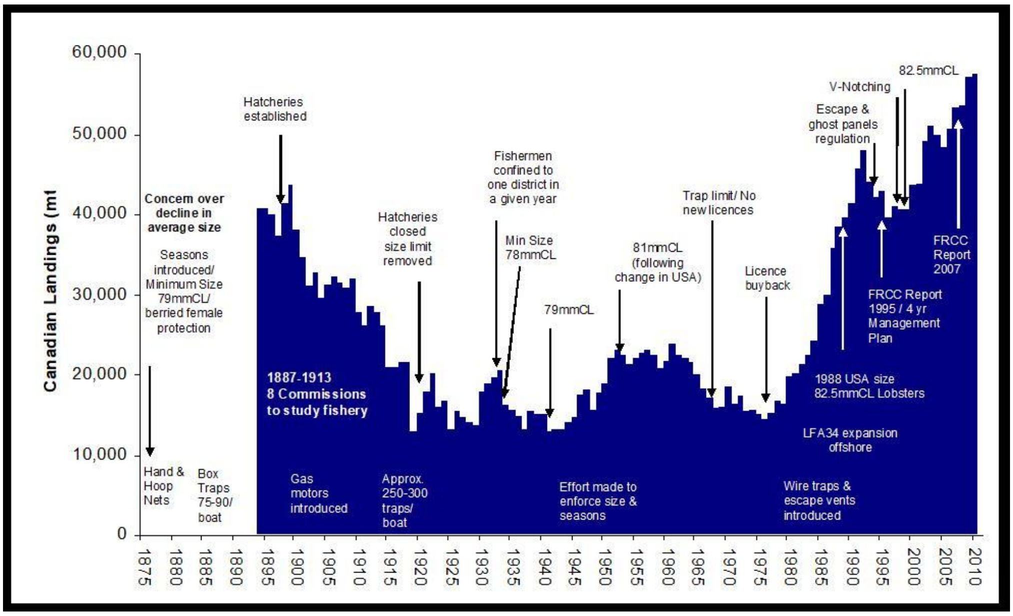


**Figure 1.1: A timeline of regulations and landings in the Canadian lobster fishery (DFO 2022)**

Lobster fishing occurs in five provinces in Atlantic Canada: Nova Scotia, New Brunswick, Prince Edward Island, Newfoundland, and Quebec. There are 41 lobster fishing areas (LFAs), each with its own fishing season that varies from eight weeks to six months (Figure 1.2). Seasonal timings are based on summer molting and reproductive schedules, and are staggered to balance stock availability. Each license holder has an allotted number of traps ranging from 200 to 375 that they can fish during each season. All of the LFAs are inshore (usually within 15 km of the coast) with the exception of one – LFA 41 which is an offshore year-round fishery.

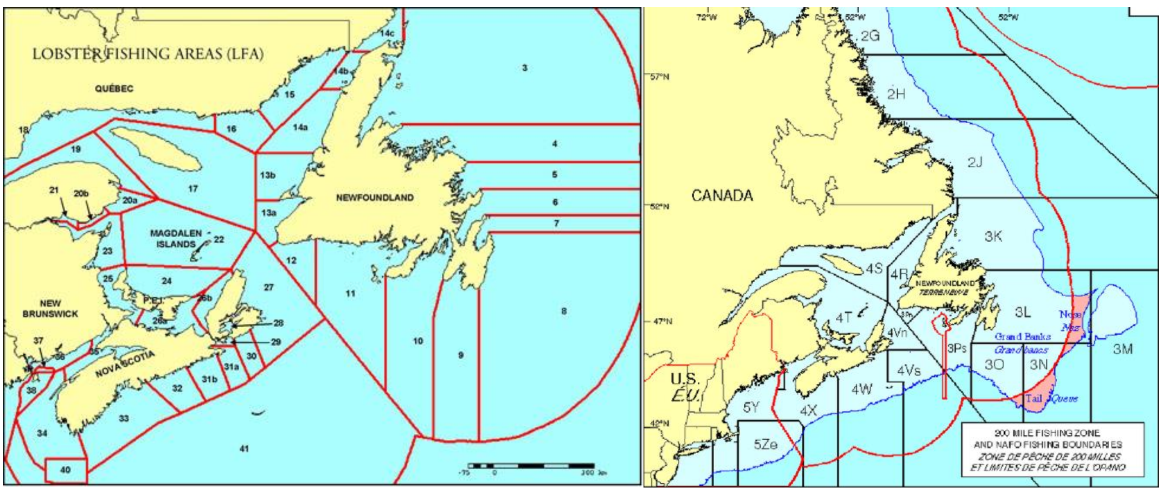


**Figure 1.2: Lobster fishing areas (LFAs) in Atlantic Canada (left) and NAFO divisions (right)**

The American lobster is distributed throughout the northwest Atlantic Ocean from Labrador to Cape Hatteras, North Carolina but are most abundant in the Gulf of Maine and the Gulf of St. Lawrence. Juvenile lobsters tend to stay in shallower water and build and maintain burrows in rocks to shelter from predators, while older lobsters tend to be found in deeper waters. Lobsters molt once a year, which eventually decreases to once every two or three years when they are larger. It takes 6-10 years for a lobster to reach market weight, although lobsters mature at various sizes based on environmental factors such as temperature. Lobsters are opportunistic feeders and feed on whatever prey is most available, so their diet varies regionally. Larvae and postlarvae are carnivorous and prey upon zooplankton during their first year, while adults are omnivorous, feeding on crabs, mollusks, worms, sea urchins, sea stars, fish, and algae. A variety of bottom-dwelling species feed on lobster, including fish, sharks, rays, skates, octopuses, and crabs. Young lobsters are especially vulnerable to predators while large, hard-shelled lobsters are mostly immune to predators.

Total landings has increased over time, with a rapid rise occurring in recent years (Figures 1.3 and 1.4). The most productive areas for lobster fishing are the Bay of Fundy, Scotian Shelf, and the Gulf of St. Lawrence. In the Scotia-Fundy region (also known as the Maritimes region) the majority of landings occur in LFA 34, although landings in LFA 33 have increased significantly in recent years (Figure 1.3). Most LFAs are spring fisheries that last between two to three months in duration, while in LFAs 33 and 34 the fishing season opens in late November and lasts for six months. Landings have also increased in the Bay of Fundy (LFAs 35-38) which similarly have a fall fishery and a spring fishery, albeit with a two-month closure window in between.

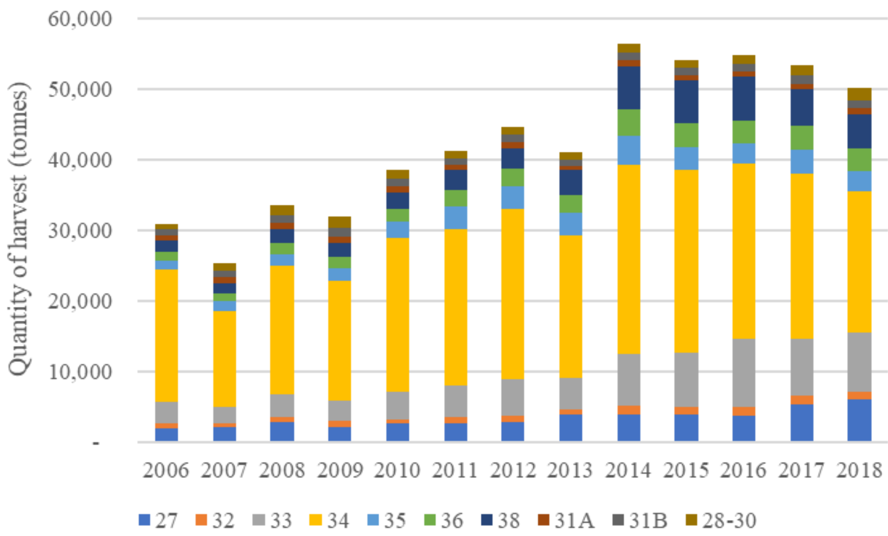


**Figure 1.3: Lobster landings by LFA in the Scotia-Fundy region, 2006-2018**

The Gulf region also accounts for a significant proportion of landings, although the available data do not permit a breakdown by LFA. Figure 1.4 shows a breakdown of historical landings by Northwest Atlantic Fisheries Organization (NAFO) divisions (Figure 1.2). The Maritimes region is mostly enclosed within NAFO divisions 4V, 4W, and 4X. The Gulf region is approximately represented by NAFO division 4T, and accounts for almost half of the landings in 2018. Overall, landings in the lobster fishery have increased threefold since 1986, with most regions seeing gains. While the Maritimes region saw a steady increase in landings over most of the time series, landings started to decrease in the last four years for which disaggregated data are available. On the other hand, while landings in the Gulf region remained relatively constant for much of the time series, it has experienced marked increases in recent years.

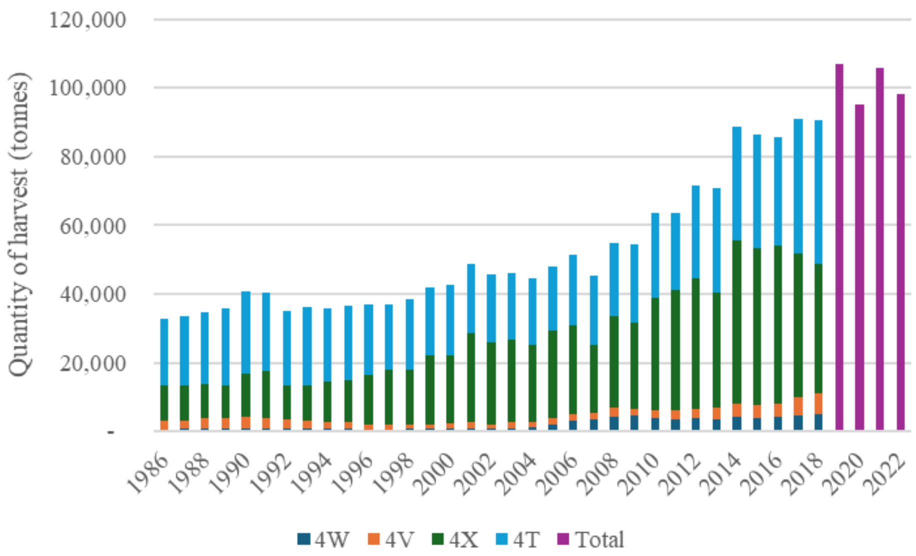


**Figure 1.4: Lobster landings by NAFO area, 1986-2018**

As will be explored in this thesis, these regions have felt the effects of climate change in differing ways. Warming waters have in part led to increases in landings, however these warming effects are not uniform across the different regions (Figure 1.5). Warmer-than-average temperature anomalies have consistently been detected in the last decade, coinciding with a boom in lobster landings. Catch per unit effort (CPUE) as a whole has experienced an unprecedented rise (Figure 1.6), and while efficiency gains and technological advancements in fishing methods might partially explain this, it is impossible to ignore the likely warming impacts. This has thus far been a win for the lobster industry in Canada, but it cannot be overstated that this is unlikely to be the case in perpetuity. If temperatures continue to rise and exceed a certain threshold, it will have serious negative impacts on the species resulting in depletion of stocks and the collapse of the lobster industry.

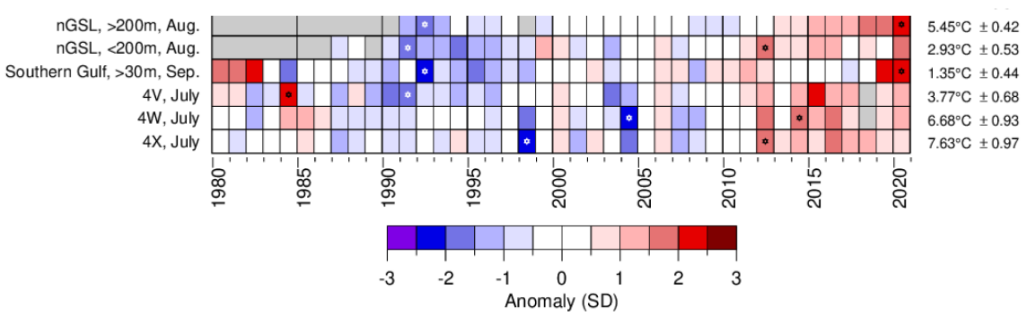


**Figure 1.5: Anomalies in bottom temperature relative to long-term average (DFO 2021)**

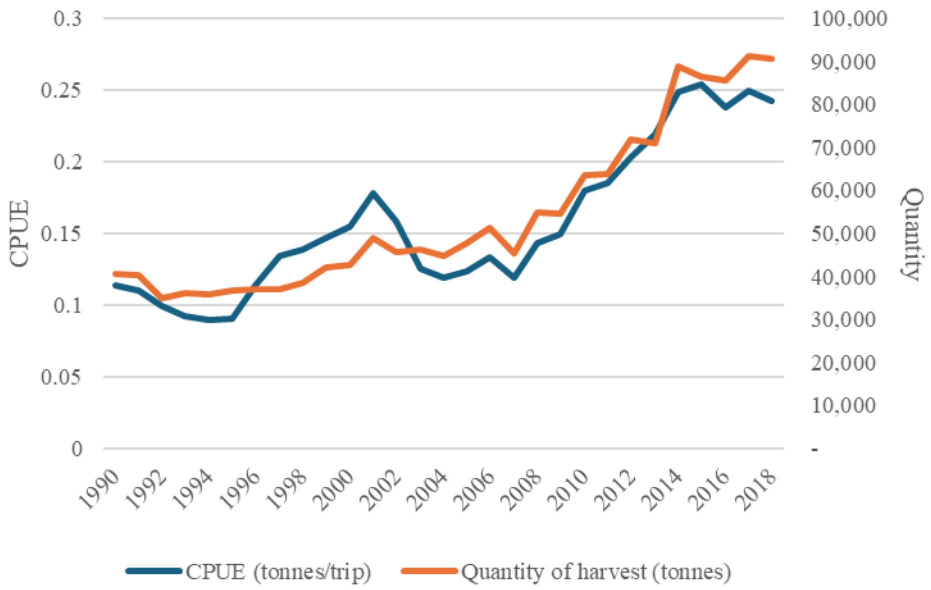


**Figure 1.6: CPUE and landings in Canadian lobster fishery, 1990-2018**

## 1.4 Literature Review

Economic methods were first incorporated into fisheries research around the mid-20th century, with the first works seeking to answer questions related to the "tragedy of the commons." These earlier studies focused on topics such as stock depletion, economic rents, property rights, and optimal levels of effort and harvest (e.g., for details see the review paper by Squires and Walden 2022). By the late 1960s and early 1970s, attention shifted away from the analysis of aggregate fisheries to individual vessel data, in which vessels were treated akin to firms in modern production theory. For instance, some of the earlier works of this nature were those by Comitini and Huang (1967), Carlson (1973 and 1975), Huang and Lee (1976), and Anderson (1976). The pathbreaking work of Hannesson (1983) brought modern production economics concepts such as technological change, technical efficiency, and frontier functions into the fisheries context. More data-driven models prompted the use of more sophisticated econometric methods, particularly the use of panel data and time series methods. The field continued to evolve in the next decades as various levels of complexity were added to models, and computational power allowed for more rigorous analyses.

In the 1990s and into the 2000s, climate change increasingly became a part of public discourse, and research began to focus on how these outcomes might affect fisheries worldwide. Literature aimed at investigating these impacts falls into two broad categories of modelling techniques: bioeconomic simulation models and econometric models. While there is a breadth of studies that seek to determine the biological and ecological consequences on species and habitats, less attention has been paid to the human dimension. Capture fisheries add an additional layer of complexity that confounds modeling exercises – fisheries dynamics are intrinsically linked to ecological systems, and the interplay between the present-day activity of a fishery and the future state of the environment is fraught with uncertainty. Estimating the bioeconomic impacts of climate change on capture fisheries necessitates an understanding of population dynamics in addition to fleet dynamics. Knowler (2002) provides a comprehensive review of some of the early examples of models that incorporate biophysical and economic concepts to assess how environmental change affects fisheries. Static and dynamic bioeconomic models are described and extended to account for the influence of environmental quality on habitat. Foley et al. (2012) also describe some notable developments in the study of the connection between habitat change and fishery dynamics.

Environmental variability can be included in fisheries models in various ways, the inclusion of which depends on research objectives, biological and ecological characteristics of the targeted species, and available data. In terms of the classical Gordon-Schaefer (GS) model, climate-related factors can alter biological parameters such as the carrying capacity (Kahn and Kemp 1985), the intrinsic growth rate (Knowler et al. 2003, Shephard et al. 2012), or both (Kahn 1987, Anderson 1989). They also affect the environmental quality of habitats that are essential for the growth and survival of species (Lynne et al. 1981, Swallow 1990, Barbier and Strand 1998, Foley et al. 2010, Kahui and Armstrong 2010) Other studies assume that changes in habitat quality directly influence the harvest function (Ellis and Fisher 1987, Freeman 1991, Sathirathai and Barbier 2001). In the GS model, this would manifest through changes in the catchability coefficient, the proportion of the biomass that can be caught for each unit of effort. For example, warmer ocean temperatures might result in either higher or lower densities of fish in an area, leading to a change in catchability of the targeted species.

As environmental variables started being incorporated into fisheries production functions, the lobster fisheries in Canada and the United States became the setting for many early examples given the commercial importance of these fisheries. For example, Bell and Fullenbaum (1972) used seawater temperature as a proxy for environmental quality in an analysis of the United States lobster fishery. The results suggested that temperature is positively associated with growth of the lobster stock, and that declining lobster landings could be attributed to lower seawater temperatures at that time. Henderson and Tugwell (1979) used current and lagged bottom temperature to show that temperature affects the catchability of lobster in the Nova Scotia lobster fishery. Drinkwater et al. (2006) used temperature as well as wind to investigate the relationship between catch and environmental conditions in the Baie des Chaleurs and off Cape Breton Island in Eastern Canada. They found evidence of a positive association between bottom temperature and catch rates, and that wind has an influence on catch rates through its effect on bottom temperatures.

## 1.5 Summary and structure of thesis chapters

Studying the impacts of climate change on fisheries is no easy feat as it involves disentangling many different complex and interconnected processes. This thesis attempts to investigate three consequences of climate change on fisheries: how it might affect harvest expectations, variation, and distribution. While there are infinitely many considerations that are beyond the scope of this thesis, this research presents an empirical analysis that boils down convoluted concepts into more straightforward associations between harvesters and natural resources. Benefitting from a substantial dataset of commercial fishing observations, it does not try to make assumptions about reality, but rather to use best practices in econometrics and statistics to extract useful insights from the data. In a period of intensifying uncertainty, these insights based on real world data can help fisheries managers develop realistic adaptation strategies.

This thesis attempts to answer some of the questions that plague fisheries researchers. For example, are rising ocean temperatures behind the increases in landings that are being observed? Biological studies suggest that temperature influences biomass for many species, and there is anecdotal evidence suggesting this affects the economic performance of fisheries. However, lack of available fishery-dependent data and high-resolution environmental data often impedes empirical efforts. Combining landings data with sampled bottom temperature data enables us to make valuable inferences. Extending this analysis further, spatiotemporal trends in environmental data can be evaluated in order to locate hot spots where warming effects are more prominent or more rapid. With this evidence, we can try to ascertain whether changes in catch rates (CPUE) track spatially with the emergences of these hot spots. Lastly, climatic uncertainty poses significant risks to those who rely on fishing for their livelihood. Besides the occupational risks that fishers face, they also contend with production risk in that adverse weather affects their ability to reliably catch a certain amount in their allotted fishing time. Determining which drivers increase or decrease variability in harvest can make the case for more flexible management strategies.

### 1.5.1 Paper 1: Assessing the Impact of Environmental Variability on Harvest in a Heterogeneous Fishery: A Case Study of the Canadian Lobster Fishery

The lobster fishery in Canada is particularly vulnerable to climate change and susceptible to risk in several different ways. Lobsters thrive in cold, temperate waters and although they can survive in a wide range of temperatures, lobsters' physiology is sensitive to temperature (Crossin et al. 1998, Jury and Watson 2000, Klymasz-Swartz et al. 2019). Warmer waters are found to affect their growth rates, molting cycles, and reproductive success (McMahan 2016, Waller et al. 2017, Quinn 2017, Harrington 2019). Due to this thermal preference, lobsters are being forced to migrate to cooler, deeper areas (Tanaka and Chen 2015, Greenan et al. 2019). This shift can affect traditional fishing areas as populations decline due to unsuitable conditions (Wahle et al. 2015, Goode et al. 2019) but can also lead to increased catch volumes in other regions. This is the focus of the first chapter in this thesis, in which an empirical model is developed that investigates the relationship between temperature changes and catch volumes. It seeks to achieve this by estimating a production function which directly includes bottom temperature as an input in production. It emphasizes the presence of heterogeneity amongst individual fishers and fishing areas, as pitfalls of estimation arise when we treat all entities with the same weight. To mitigate this, a generalized linear mixed model (GLMM) with random effects is employed to account for heterogeneity among fishing vessels and locations. Temperature change is represented by anomalies in ocean bottom temperature, and these are isolated from other production inputs in an attempt to measure this effect. This chapter finds evidence of a significant relationship between temperature and catch, and also finds that the mixed-effects model performs better in estimation than a standard pooled model.

### 1.5.2 Paper 2: Emerging Hotspot Analysis as a Tool for Understanding Climate Impacts: A Spatiotemporal Study of Catch Rates in the Canadian Lobster Fishery

One aspect of the lobster fishery that has been studied less intensively is the spatial dynamics of the fishery. As competition for limited space and resources intensifies, the growing emphasis on the spatial distribution of fishing activity has become a key element in modern fisheries management. This is particularly relevant when considering climate change impacts, as rising ocean temperatures are altering marine ecosystems and causing certain species to migrate. These shifts may force fishers to reassess their strategies, such as adjusting fishing grounds or altering their effort levels. Monitoring spatiotemporal trends in catch rates provides valuable insights into the direction and extent of changes in species distribution. This will not only deepen our understanding of catch dynamics but also contribute to more informed and effective management and policy decisions. The second chapter of this thesis utilizes a novel geostatistical approach called Emerging Hotspot Analysis to identify areas that are experiencing significant environmental changes over time. It first identifies patches that are experiencing notable trends in ocean temperature changes, e.g. persistent or intensifying phenomena rather than acute fluctuations. A generalized linear model (GLM) is then used to assess how catch per unit effort (CPUE) tracks with these warming trends. Our findings provide strong evidence that emerging hotspots are associated with higher catch rates, particularly for areas that are experiencing intensifying warming effects.

### 1.5.3 Paper 3: Analyzing Production Risk Under Environmental Variability: A Case of the Canadian Lobster Fishery

The lobster fishery in Canada is input-controlled, with limits on the number of traps per license holder, seasonal limits, and spatial boundaries. These regulations have remained relatively the same for decades, despite the biological changes the region has endured. Warmer water temperatures are altering lobster population dynamics, and the allowed fishing seasons may not reflect the true conservation strategies they were put in place to protect. For example, some fisheries have already observed earlier landings as lobsters become active earlier in the year. In addition, the frequency of severe storms and other extreme weather events is increasing due to climate change. These events can disrupt fishing operations and force temporary closures. Besides being detrimental to fisher safety and their ability to harvest lobsters during certain times of the year, this can lead to increased competition and greater variation in harvest. The third chapter in this thesis centers on this growing concern and discusses it in the framework of production risk. The concept of risk in fisheries has long interested researchers and while there are many ways to measure production-related risk, the Just and Pope (1978 and 1979) production model is particularly popular and convenient due to its flexibility. The key benefit of this model is that in addition to the usual deterministic production function, it enables us to assess production risk through the variation in harvest (it serves as a proxy for risk). This dual capability allows us to assess not only how the intensity of inputs contributes to overall harvest, but also how they increase or decrease production risk. It identifies risk factors present in production which fall into two general categories: effort and vessel-related variables (number of trips, vessel length, vessel tonnage) and environmental risk (wind speed and wave height).

## 1.6 References


Anderson, L.G. (1976) The relationship between firm and fishery in common property fisheries. Land Economics 52(2): 179–191.

Anderson E. E. (1989) Economic benefits of habitat restoration: seagrass and the Virginia hard-shell blue crab fishery. North American Journal of Fisheries Management 9(2): 140–149.

Barbier, E. B., Strand I. (1998) Valuing mangrove-fishery linkages. A case study of Campeche, Mexico. Environmental and Resource Economics 12(2): 151–166.

Beaugrand, G., Edwards, M., Brander, K., Luczak, C., Ibanez, F. (2008) Causes and projections of abrupt climate-driven ecosystem shifts in the North Atlantic. Ecology Letters 11(11): 1157-1168.

Bell, F.W., Fullenbaum, R.F. (1972) Economic Impact of Alternative Management Strategies for the Northern Lobster Fishery. National Marine Fisheries Service 108.

Carlson, E.W. (1973) Cross Section Production Functions for North Atlantic Groundfish and Tropical Tuna Seine Fisheries- Measures of Fishing Power and Their Use in the Measurement of Fishing Effort. United States National Marine Fisheries Service, Economic Research Division, number 233336, January.

Carlson, E.W. (1975) The measurement of relative fishing power using cross section production functions. In: Pope, J.A. (ed) Measurement of fishing effort. Rapports et procès-verbaux des réunions, vol. 168, The International Council for the Exploration of the Sea, Charlottenlund.

Cheung, W.W.L., Lam, V.W.Y., Sarmiento, J.L., Kearney, K., Watson, R., Zeller, D., Pauly, D. (2009) Large-scale redistribution of maximum fisheries catch potential in the global ocean under climate change. Global Change Biology 16(1): 24-35.

Comitini S., Huang D.S. (1967) A study of production and factor shares in the halibut fishing industry. Journal of Political Economy 75(4): 366–372.

Crossin, G.T., Al-Ayoub, S.A., Jury, S.H., Hunting Howell, W., Watson, W.H. III (1998) Behavioral Thermoregulation in the American Lobster *Homarus Americanus*. Journal of Experimental Biology 201(3): 365-374.

DFO (2021) Fisheries and Oceans Canada, Oceanographic Conditions in the Atlantic Zone in 2020. Canadian Science Advisory Secretariat, Sciency Advisory Report 2021/026.

DFO (2022) Fisheries and Oceans Canada, Lobster Fishing Areas 27 – 38: Integrated Fisheries Management Plan https://www.dfo-mpo.gc.ca/fisheries-peches/ifmp-gmp/maritimes/2022/inshore-lobster-homard-cotiere-eng.html

DFO (2024) Fisheries and Oceans Canada, Seafisheries landed value by province, 2022 https://www.dfo-mpo.gc.ca/stats/commercial/land-debarq/sea-maritimes/s2022pv-eng.htm.

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. Fisheries Oceanography 15(2): 150-165.

Ellis, G.M., Fisher, A.C. (1987) Valuing the environment as input. Journal of Environmental Management 25(2): 149–156.

Foley, N.S., Kahui, V., Armstrong, C.W., van Rensburg, T.M. (2010) Estimating linkages between redfish and cold water coral on the Norwegian Coast. Marine Resource Economics 25(1): 105–120.

Foley, N.S., Armstrong, C.W., Kahui, V., Mikkelsen, E., Reithe, S. (2012) A Review of Bioeconomic Modelling of Habitat-Fisheries Interactions. International Journal of Ecology 2012(1): 1-11.

Freeman, A.M. (1991) Valuing environmental resources under alternative management regimes. Ecological Economics 3(3): 247–256.

Goode, A.G., Brady, D.C., Steneck, R.S., Wahle, R.A. (2019) The brighter side of climate change: How local oceanography amplified a lobster boom in the Gulf of Maine. Global Change Biology, 25(11): 3906-3917.

Greenan, B.J.W., Shackell, N.L., Ferguson, K., Greyson, P., Cogswell, A., Brickman, D., Wang, Z., Cook, A., Brennan, C.E., Saba, V.S. (2019) Climate Change Vulnerability of American Lobster Fishing Communities in Atlantic Canada. Frontiers in Marine Science, 6: 579.

Hannesson, R. (1983) Bioeconomic Production Function in Fisheries: Theoretical and Empirical Analysis. Canadian Journal of Fisheries and Aquatic Sciences 40:968–982.

Harrington, A.M., Tudor, M.S., Reese, H.R., Bouchard, D.A., Hamlin, H.J. (2019) Effects of temperature on larval American lobster (*Homarus americanus*): Is there a trade-off between growth rate and developmental stability? Ecological Indicators 96(1): 404-411.

Hays, G.C., Richardson, A.J., Robinson, C., (2005) Climate change and marine plankton. Trends in Ecology and Evolution 20(6): 337-344.

Henderson and Tugwell (1979) Exploitation of the lobster fishery: Some empirical results. Journal of Environmental Economics and Management 6(4): 287-296.

Huang, D.S., Lee, C.W. (1976) Toward a general model of fishery production. Southern Economic Journal 43(1): 846-854.

Jury, S.H., Watson, W.H. III (2000) Thermosensitivity of the lobster, *Homarus americanus*, as determined by cardiac assay. The Biological Bulletin 199(3): 257-264.

Just, R.E. and Pope, R.D. (1978) Stochastic specification of production functions and economic implications. Journal of Econometrics, 7: 67-86.

Just, R.E. and Pope, R.D. (1979) Production function estimation and related risk considerations. American Journal of Agricultural Economics, 61(2): 276-284.

Kahn, J.R., Kemp, W.M. (1985) Economic losses associated with the degradation of an ecosystem: the case of submerged aquatic vegetation in Chesapeake Bay. Journal of Environmental Economics and Management 12(3): 246–263.

Kahn, J.R. (1987) Measuring the Economic Damages Associated with Terrestrial Pollution of Marine Ecosystems. Marine Resource Economics 4(3): 193-209.

Kahui, V., Armstrong, C. (2010) Fishing on Cold Water Coral Reefs: A Bioeconomic Model of Habitat-Fishery Connections, 2010, University of Tromsø, Working Paper Series in Economics and Management: No. 06/08, November 2008.

Klymasz-Swartz, A.K., Allen, G.J.P., Treberg, J.R., Yoon, G.R., Tripp, A., Quijada-Rodriguez, A.R., Weihrauch, D. (2019) Impact of climate change on the American lobster (*Homarus americanus*): Physiological responses to combined exposure of elevated temperature and pCO2

Knowler, D. (2002) A Review of Selected Bioeconomic Models with Environmental Influences in Fisheries. Journal of Bioeconomics, 4: 163-181.

Knowler, D.J., MacGregor, B.W., Bradford, M.J., Peterman, R.M. (2003) Valuing freshwater salmon habitat on the west coast of Canada. Journal of Environmental Management 69(3): 261–273.

Lynne, G.D., Conroy, P., Prochaska, F.J. (1981) Economic valuation of marsh areas for marine production processes. Journal of Environmental Economics and Management 8(2): 175–186.

McMahan, M.D., Cowan, D.F., Chen, Y., Sherwood, G.D., Grabowski, J.H. (2016) Growth of juvenile American lobster *Homarus americanus* in a changing environment. Marine Ecology Progress Series 557: 177-187.

Munday, P.L., Jones, G.P., Pratchett, M.S., Williams, A.J. (2008) Climate change and the future for coral reef fishes. Fish and Fisheries 9(3): 261-285.

Pankhurst, N.W., Munday, P.L. (2011) Effects of climate change on fish reproduction and early life history stages. Marine and Freshwater Research 62(9): 1015-1026.

Perry, A.L., Low, P.J., Ellis, J.R., Reynolds, J.D. (2005) Climate Change and Distribution Shifts in Marine Fishes. Science 308(5730): 1912-1915.

Pinsky, M.L., Worm, B., Fogarty, M.J., Sarmiento, J.L., Levin, S.A. (2013) Marine Taxa Track Local Climate Velocities. Science 341: 1239-1242.

Pörtner, H.O., Peck, M.A. (2010) Climate change effects on fishes and fisheries: towards a cause-and-effect understanding. Journal of Fish Biology 77(8): 1745-1779.

Quinn, B.K. (2017) Threshold temperatures for performance and survival of American lobster larvae: A review of current knowledge and implications to modeling impacts of climate change. Fisheries Research 186(1): 383-396.

Richardson, A.J., Schoeman, D.S. (2004) Climate Impact on Plankton Ecosystems in the Northeast Atlantic. Science 305(5690): 1609-1612.

Rijnsdorp, A.D., Peck, M.A., Engelhard, G.H., Möllmann, C., Pinnegar, J.K. (2009) Resolving the effect of climate change on fish populations. ICES Journal of Marine Science 66(7): 1570–1583.

Sathirathai, S., Barbier, E.B. (2001) Valuing mangrove conservation in Southern Thailand. Contemporary Economic Policy 19(2): 109–122.

Shephard, S., Brophy, D., Reid, D.G. (2010) Can bottom trawling indirectly diminish carrying capacity in a marine ecosystem? Marine Biology 157(11): 2375–2381.

Squires, D., Walden, J. (2022) The Economics of Production in Marine Fisheries. In: Ray, S.C., Chambers, R.G., Kumbhakar, S.C. (eds) Handbook of Production Economics. Springer, Singapore.

Swallow, S.K. (1990) Depletion of the environmental basis for renewable resources: the economics of interdependent renewable and nonrenewable resources. Journal of Environmental Economics and Management 19(3): 281–296.

Tanaka, K., Chen, Y. (2015) Spatiotemporal Variability of Suitable Habitat for American Lobster (*Homarus americanus*) in Long Island Sound. Journal of Shellfish Research 34(2): 531-543.

Wahle, R.A., Dellinger, L., Olszewski, S., Jekielek, P. (2015) American lobster nurseries of southern New England receding in the face of climate change. ICES Journal of Marine Science, 72: i69-i78.

Waller, J.D., Wahle, R.A., McVeigh, H., Fields, D.M. (2017) Linking rising pCO2 and temperature to the larval development and physiology of the American lobster (*Homarus americanus*). ICES Journal of Marine Science 74(4): 1210–1219.

# 2 Paper 1: Assessing the Impact of Environmental Variability on Harvest in a Heterogeneous Fishery: A Case Study of the Canadian Lobster Fishery

*Wright, D., Liu, Y. (2023) Assessing the impact of environmental variability on harvest in a heterogeneous fishery: a case study of the Canadian lobster fishery. Journal of Environmental Economics and Policy, 13(1): 55-69. doi: 10.1080/21606544.2023.2207535*

## Abstract

Global fisheries face significant challenges in the coming years due to climate change. Understanding and anticipating the impacts of climate change is a necessity for implementing appropriate fisheries management. This study uses a panel dataset of individual fishing vessels to examine how variation in ocean temperature affects fish harvest. Using the American lobster (*Homarus americanus*) fishery in the Maritimes region of Canada as a case study, this paper employs a generalized linear mixed model (GLMM) taking into account heterogeneity amongst fishers, gear, vessels, and fishing areas. The GLMM is found to have better performance and estimations when compared against alternative specifications. As expected, a significant and positive relationship was found, further contributing to the existing evidence of warming impacts on the lobster fishery. The implications of this study are twofold: first, it provides further evidence that environmental change does have a significant positive impact on harvest. This information should be considered by fishing industry and fisheries authorities when implementing appropriate adaptive management strategies and measures in their decision making. Second, it illustrates that allowing for mixed-effects using GLMMs is a valuable empirical tool when dealing with hierarchical data structures.

## 2.1 Introduction

Global fisheries face significant challenges in the coming years, many of which are caused either directly or indirectly by climate change. According to the Intergovernmental Panel on Climate Change (IPCC)'s special report on the ocean and cryosphere, the world's oceans are becoming warmer and more acidic, impacting the productivity, abundance, and distribution of marine species (IPCC 2019). As waters warm beyond species' optimal range, species that once inhabited certain areas may begin to move their distribution northward and into deeper waters, while some may begin to die out entirely. A global study revealed that climate change extensively affects the distribution of global catch potential leading to changes in fisheries productivity, with increase in the polar regions and a loss in the tropics (Cheung et al. 2010). Harvesters and communities that are heavily reliant on fisheries revenue are the most vulnerable to these changes. This is especially true for the ones who cannot diversify the species they catch or obtain alternative employment. Climate-induced changes in productivity and distribution pose challenges to fisheries management (Bryndum-Buchholz et al. 2020). Thus, anticipating the consequences of climate change on fishing operations and advancing our understanding of these impacts is crucial for developing appropriate mitigation and adaptation measures.

This paper seeks to empirically investigate the impacts of changing environmental conditions on a fishery resource using a panel dataset of harvest and fishing effort of commercial vessels. The inclusion of environmental variables in the harvest production function is a convenient way to estimate the relative effects on harvest by treating the environmental variable as an additional input in production. However, this is not without its limitations – there are several pitfalls that can arise when attempting this type of modeling exercise. For example, the model can suffer from omitted variables such as missing stock size data or unobserved characteristics between subjects. These latent variables may be correlated with the explanatory variables, violating the key assumption of independence that is required for ordinary linear regression. While traditional fisheries production models assume homogeneity among fishers, vessels, and fishing areas, more recent research confronts the issue of how to incorporate heterogeneity among these factors of production. This is a key issue that is explored in depth in this paper.

A generalized linear mixed model (GLMM) with both fixed and random effects is employed to account for heterogeneity among fishing vessels and fishing locations. It will attempt to isolate the effect of ocean bottom temperature on annual harvest from other production inputs; this effect is disentangled from the operational and effort-based measures such as number of fishing days, vessel size, and vessel power. Exploiting the hierarchical structure of the data, we are able to mitigate some of the common pitfalls that are often encountered, and to show that efficiency in estimation is improved. Compared against a model without mixed effects, we find that the mixed-effects model performs better in estimation. As a case study, we use the American lobster (*Homarus americanus*) fishery in Canada to explore how ocean bottom temperature affects harvest, but it is important to note that this method can also be applied to other fisheries and to other environmental variables. The main contribution of this paper is to provide a robust econometric framework for empirical estimation of environmental elasticities as an input in production of a natural resource.

#### 2.1.1 Case study: the American lobster fishery in Atlantic Canada

The American lobster (*Homarus americanus*) is geographically distributed along the coast of the northwestern Atlantic, ranging from North Carolina to Newfoundland and Labrador (Squires 1990). The most abundant populations are found in the Gulf of Maine, the Nova Scotian shelf, and the southern Gulf of St. Lawrence. The lobster fishery is the most commercially important fishery in Atlantic Canada, with annual landed value exceeding CAD $1 billion (DFO 2021a).[1] The fishery in the Scotia-Fundy region alone provides employment for approximately 7,500 people and generates many other direct and indirect economic benefits (DFO 2020a). It has become the backbone for the inshore commercial fisheries in the region. It is ecologically important to the biodiversity of the area, and it is an intrinsic part of the culture and identity of the East Coast of Canada (Greenan et al. 2019). Although the Canadian lobster fishery has seen record landings in recent years, the future of the fishery is uncertain due to risks posed by climate change. It is difficult to predict the net effects of climate change on lobster populations

---

[1] Annual landed values in the last five years were consistently above $1 billion with the exception of 2020, which was valued at $761 million.

as stocks will be influenced by changes at both the regional level and larger scale changes in ocean conditions (DFO 2020a).

Lobster fisheries in Canada are primarily located in inshore waters of the Maritimes region. This paper focuses on the lobster fisheries in the Scotia-Fundy region of Canada, which includes the eastern coast of Nova Scotia and the Bay of Fundy. These correspond to lobster fishing areas (LFAs) 27-34 and 35-38, respectively (Figure 2.1). This region encompasses the inshore waters from the northern tip of Cape Breton to the New Brunswick-Maine border and is one of the most productive regions for lobster fishing in Canada. This paper focuses only on the inshore lobster fishery, as the offshore lobster fishery (LFA 41) is managed separately and accounts for a small amount of annual landings.

The inshore lobster fisheries are managed through effort-based controls with limits on number of licenses and traps, delimited seasons and zones, and protection of juvenile and ovigerous females. The fishing areas (LFAs) are the primary management tool to control fishing effort for each designated area, and the opening and length of fishing season vary across different LFAs (Reid-Musson et al. 2022). There are also restrictions on number of traps per licence holder that also varies by licence type and LFA. Fishing effort is fully competitive, and this type of management may potentially create a "race to fish" scenario and intensify harvesters' safety risks (Munro and Clark 2003, Reid-Musson et al. 2022).

In the North Atlantic, air temperatures are rising and ocean circulation patterns are changing, leading to higher temperatures both at the surface and in deeper waters of the ocean (DFO 2021b). It has been well-established that rising ocean temperature has an impact on lobsters' habitat preference, coincided with the species' range shifting further north (Le Bris et al. 2018, Greenan et al. 2019, Goode et al. 2019, Tanaka et al. 2020). As ocean temperatures are cooler in the Scotian Shelf and Gulf of Maine than in areas that have experienced stock depletion such as New England, warming ocean temperatures have increased lobster habitat suitability in these regions (ASMFC 2020). Higher temperatures also have an impact on lobsters' growth, size at maturity, and reproduction. It affects molting phenology making them more vulnerable to predators, and it increases susceptibility to epizootic shell disease (Groner et al. 2018). These climate-induced changes in habitat and biological functions present challenges for the management of lobster fisheries in the region.


**Figure 2.1: Inshore lobster fishing areas (LFAs) in the Scotia-Fundy region of Canada. The shaded regions depict average annual landings in thousand tonnes for the years 2014-2018**

## 2.2 Literature review

There are two broad categories of economic production models to analyze fisheries: optimal or simulated bioeconomic production models (e.g. the classical Gordon-Schaefer model) and empirical econometric modeling. The former combines biological/ecological and economic components in the optimal or simulation setting for homogenous fisheries, while the latter applies econometric techniques based on cross-sectional, time-series, and panel data on individual fishing vessels. A detailed review of fisheries production models can be found in Squires and Walden (2021).

It has long been acknowledged that ocean biophysical conditions such as water temperature, salinity, waves, wind, and storms have effects on fish stocks (IPCC 2019). Given the uncertainty and complexity of the linkages between environmental conditions and fish stocks, the incorporation of environmental variables in fisheries production models has been sporadic. Population dynamics are influenced by environmental characteristics in many complex, and often nonlinear ways. The limitations in methodologies and availability of data have impeded researchers' abilities to empirically assess the impacts of climate change on fishery resources and fishing sectors. The inherent complexity of ecological systems lends to interactions with the environment in bioeconomic modeling being simplistic. Despite this, there are some notable examples of economic models being applied to estimate production in the midst of a changing environment.

Environmental variables might be included as an input in production (Barbier 2000), but alternatively they might enter the biomass growth function, or alter consumers' utility functions. Lynne et al. (1981) examined the Florida Gulf Coast blue crab fishery, which relies on the threatened mangrove forests as habitat. In this case, the extent of mangrove forest is the environmental input and the relationship between catch and mangrove area is modeled. Similarly, Barbier and Strand (1998) modeled catch against mangrove area in the shrimp fishery in the Bay of Campeche, Mexico. Kahn and Kemp (1985) estimate the economic losses from the destruction of submerged aquatic vegetation on the commercial striped bass fishery in Chesapeake Bay. They estimated industry supply and demand functions where environmental degradation enters the supply function, and the equations are solved to find the bioeconomic equilibrium catch under different levels of degradation. Foley et al. (2010a, 2010b) examine the bioeconomic interplay between cold water coral as habitat for fish species and the impacts of habitat reduction on these species. Cheung et al. (2010) used a dynamic bioclimate envelope model to project the maximum exploitable catch of a species under climate change scenarios, and the findings suggest that the polar region is benefiting while the tropics are losing from climate change.

Several empirical studies have linked environmental variables to harvest in the lobster fisheries of Canada and the United States. Bell and Fullenbaum (1972) were one of the first to include a variable for environmental quality in the analysis of the inshore lobster fishery in the United States. In this case study, seawater temperature appeared directly in the production function. The results indicated that seawater temperature has a positive effect on the growth of the lobster stock, citing trends that suggest that declining seawater temperature is partially responsible for declining coastal lobster catches. Henderson and Tugwell (1979) estimated a production function for two lobster fishing areas in Nova Scotia that included both current and lagged bottom temperature. The assumption is that temperature affects the catchability of lobster, as lobsters tend to move around more and cover more territory when temperature rises. Several other studies found correlations between lobster harvest and ocean temperature, such as McCleese and Wilder (1958), Dow (1961), and Flowers and Saila (1972). Hudon

(1994) and Drinkwater et al. (2006) similarly found correlations between harvest and temperature, and in addition found wind to be a significant determinant of catch amounts.

As with some of the existing studies, this current paper incorporates environmental values by having the environmental variable enter the model as an input directly in the harvest production function. With the increasing availability of panel data and more advanced econometric techniques, empirical vessel-level analysis in response to environmental issues has garnered more interest. Huang, Smith, and Craig (2010) used a differenced bioeconomic framework and individual fishing data combined with oxygen monitoring data to quantify the economic effects of hypoxia on the brown shrimp fishery in North Carolina. Later, Huang and Smith (2014) applied a restricted Cobb-Douglas production function to model harvest which is determined by both fishing inputs and other inputs such as season closure, wind, waves, and stock size. Autoregressive models combined with Seemingly Unrelated Regression (SUR) models were applied to estimate an output production function. Nguyen (2022) used a partial equilibrium analysis with combined production, demand, and aggregate supply functions to project welfare impacts of climate change on fisheries in Vietnam. In this study, the production function included sea surface temperature, precipitation, number of typhoons, maximum wind speeds of typhoons, and the Southern Oscillation Index. An autoregressive distributed lag model (ARDL) was used to predict fishery yields.

When the panel data are complex and nested, e.g., fishers operating within fishing areas, multilevel modeling (otherwise known as mixed-effects or hierarchical modeling) is a powerful tool that can accommodate various data structures and improve inference (Gelman 2006, Gelman and Hill 2006). Generalized linear models (GLMs) are a generalization of linear regression that allow a linear model to be related to the response variable via a link function (Nelder and Wedderburn 1972). Generalized linear mixed models (GLMMs) are an extension of GLMs that allow for both fixed and random effects to be estimated when data has a hierarchical structure (Breslow and Clayton 1993). The fixed effect is the population-averaged effect, while the random effects are the subject-specific effects that manifest through variances that represent individual-specific heterogeneity. Mixed-effects modeling can be a useful tool in fisheries research because there are often many unobserved characteristics that confound estimation (Hyun et al. 2014, Thorson and Minto 2015), but this method has also been widely applied in disciplines such as ecology (Venables and Dichmont 2004, Bolker et al. 2009, Harrison et al. 2018), psychology (Moscatelli et al. 2012, Meteyard and Davies 2020, Bono et al. 2021), and medicine (Dean and Nielsen 2007, Casals et al. 2014).

## 2.3 Material and methods

### 2.3.1 Methodology

A Cobb-Douglas harvest production function is specified, the goal of which is to estimate and assess the relative effects of an environmental variable (ocean temperature) as well as technical and effort-based variables (number of days fished, length of vessel, and vessel tonnage) on lobster harvest. The hope is that the model yields reliable coefficient estimates that can allow us to glean something about the relationship between environmental variability and harvest without undue complexity.

First, we consider the following basic model,

$$y_{ijt} = \beta_0 + \beta_1 d_{ijt} + \beta_2 l_{ijt} + \beta_3 g_{ijt} + \beta_4 t_{jt} + \varepsilon_{ijt} \tag{1}$$

where $y$ is harvest, $d$ is days fished, $l$ is length of vessel, g is gross tonnage, t is temperature anomaly, and $\varepsilon$ is the idiosyncratic error term. The subscript $i$ corresponds to each vessel, $j$ to LFA, and $t$ to year. Since the data have a hierarchical structure (vessels operating within fishing areas), we exploit this by using a generalized linear mixed model (GLMM) that allow for random effects to be specified. In matrix form, the specification is given by,

$$g\{E(y|X,u)\} = X\beta + Zu \tag{2}$$

where the dependent variable $y$ is an $n \times 1$ vector. $X$ is an $n \times k$ design matrix for the fixed effects $\beta$. This contains the explanatory variables and their associated coefficients. $Z$ is an $n \times m$ design matrix for the random effects $u$. $g$ is the invertible link function which can take on many different functional forms. In our case, the outcome variable is annual harvest of individual fishing vessels, which is a continuous and repeated variable and is heavily right-skewed, not normally distributed (Figure 2.2). Different distributions can be used to deal with this, but log-normal is chosen as we suspect this most closely approximates the data-generating process. Therefore, we choose a log link function and a Gaussian distributional family.

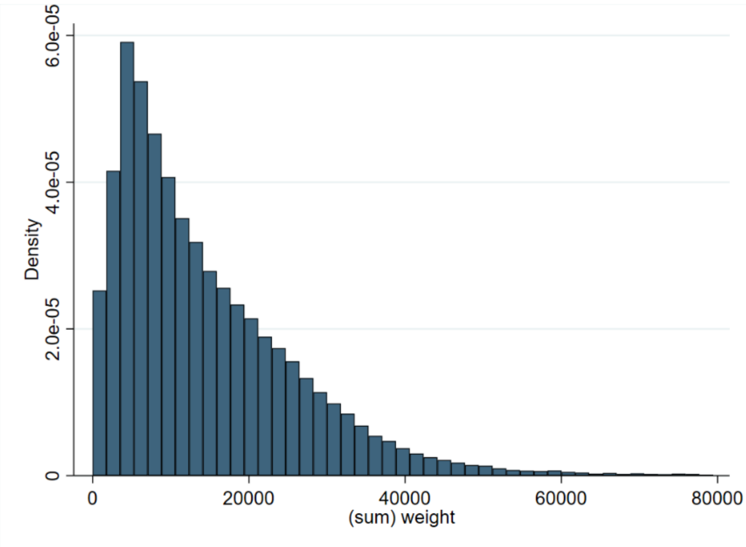


**Figure 2.2: Histogram of harvest observations (kg)**

Taking the hierarchical structure of the data into consideration and allowing for random intercepts, we consider the following extended model,

$$y_{ijt} = \beta_0 + \beta_1 d_{ijt} + \beta_2 l_{ijt} + \beta_3 g_{ijt} + \beta_4 t_{jt} + u_{ij} + u_j + \varepsilon_{ijt} \quad (3)$$

where the first six terms represent the fixed component and are equivalent to equation 1. This is the dependent variable, the explanatory variables, and their estimated coefficients. The last three terms represent the random component which are two additional random intercepts and the error term. To illustrate the intuition behind the three levels of effects, consider the following equations,

$$y_{ijt} = \gamma_{0j} + \gamma_{0ij} + \beta_1 d_{ijt} + \beta_2 l_{ijt} + \beta_3 g_{ijt} + \beta_4 t_{jt} + u_{ij} + u_j + \varepsilon_{ijt} \quad (4)$$
$$\gamma_{0j} = \beta_{00} + u_{oj} \quad (5)$$
$$\gamma_{0ij} = \beta_{000} + u_{oij} \quad (6)$$

The equation for the intercept $\gamma_{0j}$ consists of the LFA-level mean intercept $\beta_{00}$ and an LFA-specific random intercept $u_{oj}$. The equation for the intercept $\gamma_{0ij}$ consists of the overall mean intercept $\beta_{000}$ and a vessel-specific random intercept $u_{oij}$. Rearranging and collapsing to one intercept for the fixed portion of the model, we are left with equation 2 where $u_j$ represents the LFA-level unobserved effects and $u_{ij}$ represents the vessel-within-LFA unobserved effects.

The reasoning behind this choice of model is that in addition to stochastic effects, there are unobserved effects that are particular to LFAs and vessels. At the vessel level, there may be technological inputs or crew skill that are not accounted for. At the LFA level, there are oceanographic, biological, and ecological influences that are difficult to observe or quantify. Accounting for multilevel structures in the data can improve statistical inferences. As opposed to ordinary linear regression which treats all explanatory variables as independent and calculates standard errors using only the residual variance, mixed-effects models allow subjects at each level to deviate by its own mean and calculates standard errors using both the residual variance and the variance between the higher levels of the hierarchy. By not accounting for the variances at the different levels when hierarchical structures exist, coefficient estimates are likely to be biased upward and can lead to a type I error, i.e. finding statistical significance when none exists.

This method enables us to obtain reliable estimates despite missing pertinent data. Perhaps most importantly, biomass data are not directly observed, and this creates difficulties for this type of modeling exercise. Biomass is a crucial component of the traditional harvest function, however data on population size is often unavailable or spotty across space and time. Since all vessels operating in the same LFA share the same stock in each time period, the biomass can be treated as a random intercept. Although not a perfect solution, this method should still allow us to obtain coefficient estimates for the environmental variables, which is what we are interested in.

### 2.3.2 Estimation procedure

To justify the application of a multilevel model, we analyze the variance components by calculating the intraclass correlation coefficient (ICC). Assuming that our model is correctly specified, conditional on the explanatory variables (the fixed part of the model), the ICC calculates the dispersion of harvest weight around a mean value for each level of the hierarchy (the random intercepts $u_i$ and $u_{ij}$). The intuition behind this is that the higher the correlation is within the clusters (the larger the ICC) the lower the variability is within the clusters and the higher the variability is between the clusters. Having a high degree of correlation within clusters can lead to biased estimates if regular pooled regression is used, as it violates the assumption of independence.

The ICC is calculated and the level-3 intraclass correlation, which is the correlation of observations between the same LFA, is estimated to be 0.21. The level-2 intraclass correlation, which is the correlation between yearly observations for each vessel, is estimated to be 0.68. Therefore, conditional on the covariates, we find that annual harvest is only weakly correlated within the same LFA, but strongly correlated across year classes for each vessel. A rule of thumb can be used to determine if the hierarchical structure should be taken into consideration. The literature defines the design effect of a sample statistic as the ratio of the actual variance of a sample to the variance of a simple random sample of the same number of elements (Kish 1965). In multilevel modeling, the design effect (DE) is estimated as a function of the ICC and the average size of the clusters (c) (Muthen and Satorra 1995):

$$DE = 1 + (c - 1) * ICC \tag{7}$$

The rule of thumb is that when the design effect is less than 2, the multilevel structure can be ignored. The average number of vessels in each LFA is calculated and it equals 598.9. This leads to a design effect of ~127, and thus the multilevel structure of the data cannot be ignored. The coefficients for the mixed-effects model with random intercepts are estimated using maximum likelihood.

In addition to the mixed-effects model, two other versions of the model are employed for comparison (Table 2.2). The first column is the model with only the fixed component (equation 1). The second column is the mixed-effects model but with random effects only at the vessel level, and the last column is the mixed-effects model with random effects at both the vessel and the LFA level (equation 3).

### 2.3.3 Data collection

#### *2.3.3.1 Logbook data*

The landings data used for this analysis are from commercial fisheries logbook data collected by Fisheries and Oceans Canada (DFO). The variables retrieved from the logbook data are catch in kilograms, date landed, lobster fishing area (LFA), vessel identifier, vessel length, and vessel tonnage. The data span the years 2006–2018. The logbook data is geographically delineated by NAFO division, subdivision, and LFA, but LFA was chosen as the fishery is managed at the LFA level. LFAs 28 and 29 were excluded as sampled temperature data points were sparse in this area, and LFA 37 is a small area shared by LFAs 36 and 38. All variables are continuous except for tonnage class which is a dummy variable that is coded 1 if the vessel is greater than 25 tons and 0 if the vessel is less than 25 tons. The reason for this is that it is a categorical variable in the logbook data. After compiling the logbook data, we are left with 10 fishing areas and 4,064 vessels operating over the 13 years analyzed. The data have a hierarchical structure in that each LFA contains vessel observations, and each vessel contains repeated observations for each year. The panel is balanced in the spatial dimension in that there are observations for each year for each LFA, but highly unbalanced at the fleet level. Some vessels drop in and out, some are retired, and some are newly added. A total of 36,672 observations will be used for the analysis.

#### *2.3.3.2 Bottom temperature data*

Complete ocean temperature profiles at all depths were retrieved from DFO's Marine Environmental Data Section (MEDS) (DFO 2021c). To determine which profiles reached the seafloor, these data were cross-referenced with the Canadian Hydrographic Service Non-Navigational (NONNA) Bathymetric Data (DFO 2021d). Although there are a large number of observations that span the study area, the locations sampled are not consistent from year to year. Therefore, bottom temperature data are expressed in terms of anomalies from their long-term mean. Present climate data were retrieved from DFO's Bedford Institute of Oceanography North Atlantic model (BNAM) (Wang et al. 2018). Bottom temperature in the model are monthly averages for the years 1990–2015 on a spatial grid of 1/12 degrees. Each real temperature observation was matched with its nearest geodetic neighbour from the BNAM long-term averages, and the differences between these points were calculated by subtracting the long-term average observation from each real temperature observation. Shapefiles that delineate the LFAs' polygons were used to determine which observations fall into which LFA and the observations were grouped accordingly. The average temperature anomalies for each LFA for each year were then calculated, and these anomalies are proxies for temperature change. A negative observation represents a colder-than-average anomaly, and a positive observation represents a warmer-than-average anomaly. The minimum temperature anomaly is -2.9 degrees Celsius and the maximum is 6. Since logarithms cannot be taken for negative values, the temperature anomalies are rescaled so that the minimum is zero and the maximum is 100. All of the variables used in the analysis and their associated summary statistics are given in Table 2.1.

**Table 2.1: Variables and associated summary statistics**

| | Mean | S.D. | Min | Max |
|---|---|---|---|---|
| **Bottom temperature anomaly** | | | | |
| Degrees Celsius | 1.62 | 1.61 | -2.88 | 6.03 |
| Rescaled | 50.56 | 18.02 | 0.28 | 99.997 |
| **Vessel and effort variables** | | | | |
| Weight landed (kg) | 14,796 | 12,564 | 6 | 170,994 |
| Number of days fished per vessel | 42 | 23 | 1 | 624* |
| Length of vessel (feet) | 38.08 | 6.08 | 0 | 64 |
| Vessel tonnage ≥25 tons (dummy) | 0.07 | 0.25 | 0 | 1 |

**Since number of logbook entries is used as a proxy for days fished, there are some instances where fishers record multiple entries per day. There are two instances in which the number of a vessel's logbook entries exceeds the number of calendar days: 624 in 2006, and 397 in 2013*.

## 2.4 Results and discussion

For all model specifications the coefficients are statistically significant at the 1% level, with the exception of vessel tonnage ≥25 tons (Table 2.2). The model that achieves the best fit according to the Akaike information criterion (AIC) is the mixed-effects model with random effects at both the vessel and LFA level. All variables except vessel tonnage are continuous, therefore the log-transformed variables are elasticities. Vessel tonnage ≥25 tons is a dummy variable, so the exponentiated coefficient is the ratio of the mean harvest weight for vessels ≥25 tons to the mean harvest weight for vessels <25 tons. Therefore, this would give an estimate of the expected percent increase in mean harvest weight that would result when going from vessels <25 tons to vessels ≥25 tons, holding other variables constant. However, the estimated coefficients are statistically insignificant for all four models. The negative coefficients for two of the three models suggest that an increase in tonnage would decrease output which is contrary to what would be expected. The statistical insignificance could be because harvest is inelastic to vessel tonnage, but it should be noted that the vast majority of vessels (93%) are < 25 tons.

**Table 2.2: Maximum likelihood estimation results**

| | Fixed component only (eq. 1) | Mixed-effects model (random effects only at vessel level) | Mixed-effects model (random effects at both vessel and LFA, eq. 3) |
|---|---|---|---|
| **Variable** | **Coeff. ( St. error)** | **Coeff. (St. error)** | **Coeff. ( St. error)** |
| Intercept | -3.4821 (0.0807)*** | -2.0762 (0.1806)*** | 0.1789 (0.2228) |
| Days fished | 0.5354 (0.0045)*** | 0.5729 (0.0046)*** | 0.5726 (0.0047)*** |
| Vessel length | 2.8232 (0.0221)*** | 2.498 (0.0495)*** | 1.9138 (0.0526)*** |
| Vessel tonnage ≥25 tons | -0.0115 (0.0147) | 0.0261 (0.0334) | -0.0273 (0.0298) |
| Bottom temperature anomaly | 0.1564 (0.0072)*** | 0.0558 (0.0054)*** | 0.0476 (0.0054)*** |
| **Random effects** | | | |
| LFA | | | 0.1301 (0.0598)** |
| Vessel | | 0.3707 (0.0092)*** | 0.2994 (0.0075)*** |
| Overall variance | 0.4833 (0.0036) | 0.2105 (0.0017) | 0.2015 (0.0016) |
| AIC | 76388.45 | 57931.53 | 56197.42 |
| BIC | 76439.42 | 57991.00 | 56265.40 |
| Log-likelihood | -38188.22 | -28958.76 | -28090.71 |

*** p < 1%; ** p < 5%; * p < 10%

Most coefficients have the expected signs, and reasonably plausible magnitudes. The results from the estimation of our chosen models using the historical data available suggest that a 1% increase in ocean bottom temperature anomaly results in a 4.8 – 15.6% increase in harvest by weight, depending on model specification. The directional signal tracks with previous studies that found positive correlation between bottom temperature and harvest. However, it is important to note that the precision of the estimated coefficients rely heavily upon the transformation of the temperature data to anomalies. Although this was chosen as the least problematic method given inconsistencies in the sampling areas, this makes interpretation difficult and we would be better served by using raw temperature data if this was possible.

As expected, number of days fished and vessel length have a large and positive impact on harvest. Thus, controlling for technical efficiency of the fleet is crucial as changes in harvest can be attributed to changes in biomass or changes in the amount of fishing pressure that is applied. The increase in landings seen in recent years may be caused by an increase in abundance, which could be linked to climate-related factors, but could also be the result of increased fishing capacity. Although the number of license holders has decreased and the number of traps allocated to each license holder has stayed relatively constant, it is likely that effort capacity and fishing efficiency has effectively increased. According to the 2007 report by the Fisheries Resource Conservation Council (FRCC), there is general agreement that harvesters' ability to catch lobster has improved due to improved gear, vessels, and technology.

Results from the mixed-effects models are compared with results from the model with only the fixed component. Since the portion of the variance attributed to LFA is fairly small, a mixed-effects model with random effects only at the vessel level was also compared. It is useful to compare the fixed coefficients that are estimated under the different specifications as it provides insight into what exactly mixed-effects modeling does, how it is different, and why it is useful. The coefficient for number of days fished does not change significantly with the different specifications. Meanwhile, the coefficient for vessel length decreases from 2.8 with the fixed model to 1.9 with the mixed-effects model. This suggests that not accounting for the variance at the vessel level results in an over-estimation of the coefficient for vessel length.

The difference in the coefficients between the fixed model and the mixed-effects model can be attributed to the concept of partial pooling, otherwise known as shrinkage. When the data are pooled, each observation has an equal chance of success. With partial pooling, each unit (vessel in our case) has a different chance of success and this is informed by the vessel-specific characteristics. This allows vessels with less observations and more extreme values to borrow strength from vessels with more observations and less extreme values, and therefore "shrinks" the estimated coefficient back to a more reasonable value. It acknowledges that each unit has characteristics in common, while also placing less importance on extreme values within each unit (Clark 2019).

A notable takeaway is that the estimated bottom temperature anomaly elasticities vary substantially across the models. It decreases from 15.6% in the fixed-only model to 5.6% in the model with random effects at the vessel level only to 4.8% in the model with random effects at both the vessel and area levels. It makes sense that the coefficient does not differ significantly between the latter two, as the variance at the LFA level is not very large. The difference between the coefficients from the fixed and mixed-effects models can again be attributed to the idea of partial pooling. The influence of bottom temperature on harvest may be higher when considering each unit separately, but when imposing a normal distribution on each vessel's observations this makes extreme values less probable, thus shrinking the coefficients back toward a more reasonable value.

This empirical exercise is useful for investigating the historical impact of bottom temperatures on harvest as well as illustrating the merits of mixed-effects models. However, it is important to note that this alone cannot be used to make predictions of future harvest. Lobsters' tolerance to temperature exhibits a bell-shaped curve. Although lobster abundance has increased steadily as temperatures have increased, it is still at the ascending part of the curve. Once temperatures reach a certain point, productivity will start to decline and distribution will be shifted offshore and into deeper water (Oppenheim et al. 2019). Additionally, there are many complex interactions at play that are not accounted for by this convenient production framework. Although there is a well-established link between landings and temperature, there are different pathways through which this is realized. For example, temperature can impact landings through changes in recruitment, likelihood to enter traps, availability of food sources, etc. Models that contain these interactions are complex and are beyond the scope of this paper. Making predictions based on future environmental scenarios would involve a much more complex model, and this would be interesting to explore as future research.

### 2.4.1 Model validation

In addition to the coefficient estimates, best linear unbiased predictions (BLUPs) are retrieved for the random effects (Henderson 1950). Usually, random effects are only reported in terms of variance components, but BLUPs can also be estimated in addition to coefficients as another form of model selection. By inserting BLUPs into the estimation equation and solving, fitted values can be obtained. To assess goodness of fit, we plot the log-transformed harvest weight observations against the fitted values. We compare the fitted values of the model with the fixed component only with the mixed-effects model with random effects at both the vessel and area level (Figure 2.3). We also plot the residuals from these models against the fitted values (Figure 2.4).

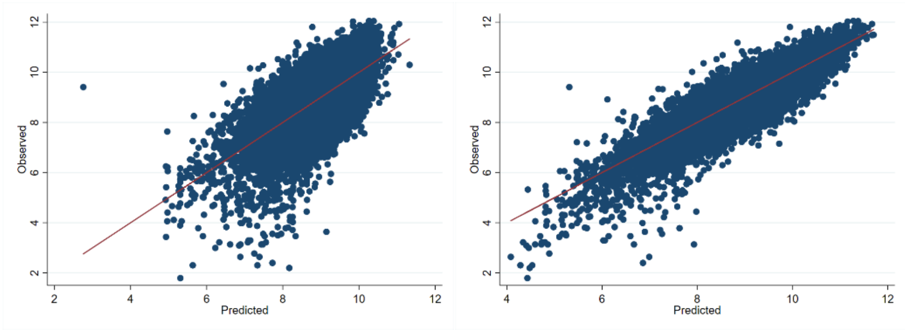


**Figure 2.3: Observed log-transformed harvest versus fitted values from the model with the fixed component only (left) and the mixed-effects model (right)**

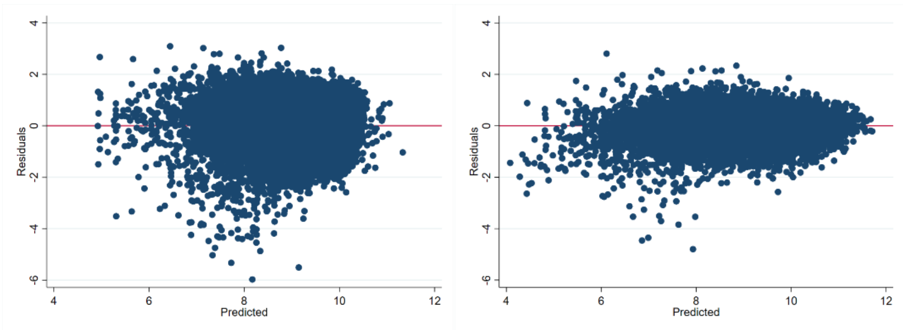


**Figure 2.4: Residuals versus fitted values from the model with the fixed component only (left) and the mixed-effects model (right)**

Visualizing the fitted values and the residual errors allows us to see how the model performs with and without the random effects. Figure 2.3 clearly shows that the GLMM results in a better goodness-of-fit than the model without mixed effects. Figure 2.4 shows that the residuals are more tightly centered around zero with the GLMM; they are dispersed fairly evenly above and below zero, although they tend more toward negative values. This implies that our model tends to over-estimate, but this is made much less severe with the GLMM.

### 2.4.2 Random effects estimates

It is also helpful to look at how the estimated random effects change over time. The median vessel-level random effects hover around zero but there is a significant amount of dispersion (Figure 2.5, left panel). The estimated unobserved effects at the vessel level also appear to be increasing over the time period analyzed. This suggests that indeed there are unobservable effort-related factors at play such as more crew or more advanced technology, and that these are increasing over time. This is consistent with the FRCC report's suggestions that harvesters' ability to catch lobster is improving. This can muddy the waters for estimation because the traditional effort-based measures will be under-estimating the operational influences on harvest. Consequently, this makes incorporating environmental variables into the analysis difficult as the true effect will be harder to isolate from the noise. The random effects at the fishing area level remain relatively constant over the time period, suggesting that unobserved effects at these larger spatial scales are time-invariant and less problematic for estimation (Figure 2.5, right panel). Perhaps most importantly, how much of the increase in harvest is attributed to increasing stock size rather than increased fishing pressure or technological change remains a mystery for now. Catch per unit of effort (CPUE) in terms of catch per fishing trip in the logbook data displays an increasing trend. but with the available data it is not possible to say conclusively what is driving this. Further research that uses more detailed effort data such as number of trap hauls may be able to uncover this. Unfortunately, the number of trap hauls per fishing trip is not available in the data that were available to us.

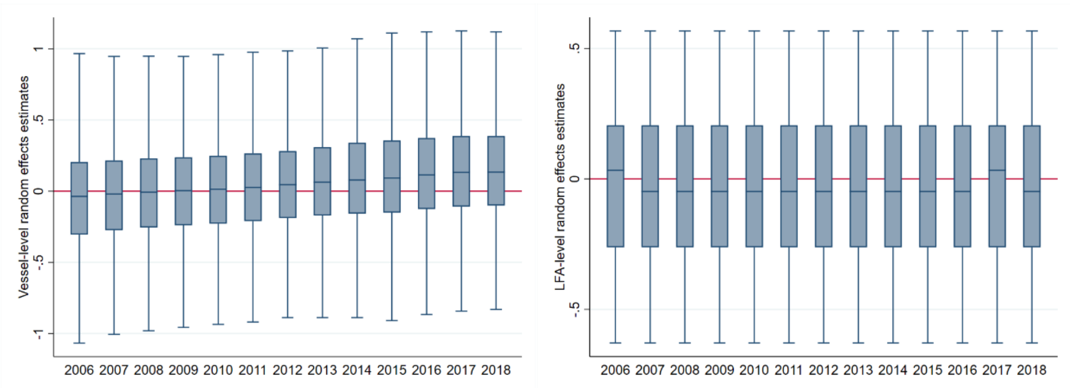


**Figure 2.5: Box and whisker plots of vessel-level random effects estimates (left) and LFA-level random effects estimates (right)**

## 2.5 Conclusions

The aim of this paper was to examine the economic consequences of ocean temperature increases on the lobster fishery in Atlantic Canada. This study pulled data from multiple sources and set up an empirical econometric framework that models annual lobster harvest as a function of environmental and operational variables. Coefficients were estimated using a maximum-likelihood mixed-effects estimator and these were compared with two other model specifications to see which model fits the best. The mixed-effects model was selected as the best fitting model according to the AIC, and goodness-of-fit plots visually substantiated this. All coefficients were statistically significant at the 5% level apart from vessel tonnage. The estimated coefficients suggest that a 1% increase in bottom temperature anomaly results in approximately a 5% increase in harvest weight with the chosen model specification, and this was the most conservative estimate of the three models. The estimated coefficients for the effort-related variables vessel size and number of fishing days are large and positive, as expected. Best linear unbiased predictions (BLUPs) were estimated for the random effects at the vessel level. The unobserved effects at the vessel level are significant and have increased over the years 2006 – 2018. This complicates matters when trying to isolate the relative effects of environmental variables, and suggests that finding a way to incorporate technological progress would improve estimation. There is a vast body of research that aims to measure technical efficiency in fisheries (i.e., stochastic frontier analysis) and incorporating this would be a boon to future research.

The implications of this study are twofold: first, it provides further evidence that environmental change does have a significant impact on harvest. Although this empirical framework does not capture all of the intricate ecological systems at play, it is highly likely that the significant and positive effect of temperature on harvest is reflective of real-world phenomena. As fisheries are confronted with considerable environmental uncertainty in the coming years, there is a fear that warming waters will exacerbate other issues such as excess fishing pressure and competition. This must be considered by policymakers when implementing management measures, as distributional changes may tempt increases in allowances or access. In the case of the Canadian lobster fishery, the current management measures include designated fishing areas, fishing seasons, and limits on the number of traps per license holder. This management regime incentivizes a race to fish the most productive areas, and fishers have the incentive to outcompete others by increasing vessel power, size, speed, number of crew, or make other capital investments aimed at maximizing catch (Pfeiffer and Gratz 2016). As lobsters' preferred habitat shifts, the existing management measures may not be adequate to mitigate excess capacity. In the colder parts of lobsters' range, increasing temperatures may lead to greater abundance, and these areas might become more attractive for fishing. In warmer areas that are approaching the upper limit of lobsters' thermal range, the negative impacts on the species' physiology will begin to manifest. The strong relationship between harvest and temperature underscores that conservation measures should be taken while temperatures are still at a manageable level. This analysis is more exploratory than prescriptive, and caution must be taken when making assumptions about the future of the fishery based on historical trends. However, it calls attention to something that must be delved into deeper.

The second implication of this analysis is one of a more technical nature: that mixed-effects modeling can be a useful part of the natural resource economist's toolbox when the data are hierarchically structured. Given that fisheries management is often area-based, mixed-effects models are surprisingly under-utilized in fisheries economics research. Models that combine both fixed and random effects provide a more flexible approach for analyzing the data that are not normally distributed. In this case, we find that the model that most closely resembles reality is the model with random effects at the vessel level and the fishing area level. On the other hand, a pooled model with only fixed effects that ignores the hierarchical structure of the data resulted in a poorer model fit. This is a lesson in the importance of accounting for heterogeneity when these data structures exist.

## Acknowledgements

We thank Barbara Best and Gisele Magnusson at Fisheries and Oceans Canada (DFO) for their gracious assistance in data collection and manuscript review. We also thank Luc Bujold at DFO's Marine Environmental Data Section for providing bottom temperature data, Zeliang Wang at DFO's Bedford Institute of Oceanography for providing BNAM model output, and Christine Irwin at DFO's Economic Analysis and Statistics group for providing shapefiles.

## 2.6 References

ASMFC (2020) American Lobster Benchmark Stock Assessment and Peer Review Report. Atlantic States Marine Fisheries Commission.

Barbier, E.B., Strand, I. (1998) Valuing Mangrove-Fishery Linkages – A Case Study of Campeche, Mexico. Environ. Resour. Econ., 12: 151–166.

Barbier E.B. (2000) Valuing the environment as input: review of applications to mangrove-fishery linkages. Ecol. Econ., 35: 47–61.

Bell, F.W., Fullenbaum, R.F. (1972) Economic Impact of Alternative Management Strategies for the Northern Lobster Fishery. United States National Marine Fisheries Service, Economic Research Division, number 233538.

Bolker, B.M., Brooks, M.E., Clark C.J., Geange, S.W., Poulsen, J.R., Stevens, M.H., White, J.S. (2009) Generalized linear mixed models: a practical guide for ecology and evolution. Trends Ecol. Evol., 24: 127–135.

Bono, R., Alarcón, R., Blanca, M.J. (2021) Report Quality of Generalized Linear Mixed Models in Psychology: A Systematic Review. Front. Psychol., 12: 666182.

Breslow, N.E., Clayton, D.G. (1993) Approximate Inference in Generalized Linear Mixed Models. J. Am. Stat. Assoc., 88: 9–25.

Bryndum-Buchholz, A., Boyce, D.G., Tittensor, D.P., Christensen, V., Bianchi, D., Lotze, H.K. (2020) Climate-change impacts and fisheries management challenges in the North Atlantic Ocean. Mar. Ecol. Prog. Ser., 648: 1–17.

Casals, M., Girabent-Farrés, M., Carrasco, J.L. (2014) Methodological Quality and Reporting of Generalized Linear Mixed Models in Clinical Medicine (2000–2012): A Systematic Review. PLOS ONE 9: e112653.

Cheung, W.W., Lam, V.W., Sarmiento, J.L., Kearney, K., Watson, R.E.G., Zeller, D., Pauly, D. (2010) Large-scale redistribution of maximum fisheries catch potential in the global ocean under climate change. Glob. Change Biol., 16: 24–35.

Clark, M. (2019) Shrinkage in Mixed Effects Models. https://m-clark.github.io/posts/2019-05-14-shrinkage-in-mixed-models/.

Dean, C.B., Nielsen, J.D. (2007) Generalized linear mixed models: a review and some extensions. Lifetime Data Anal., 13: 497–512.

Dow, R.L. (1961) Some Factors Influencing Maine Lobster Landings. Commer. Fish. Rev. 23: 1–11

Drinkwater, K.F. et al. (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.

Fisheries Resource Conservation Council (2007) Sustainability Framework for Atlantic Lobster 2007: report to the Minister of Fisheries and Oceans. Fisheries and Oceans Canada, Ottawa.

DFO (2020a). Fisheries and Oceans Canada Lobster Fishing Areas 27 – 38 Integrated Fisheries Management Plan, https://www.dfo-mpo.gc.ca/fisheries-peches/ifmp-gmp/maritimes/2019/inshore-lobster-eng.html.

DFO (2020b). Fisheries and Oceans Canada Seafisheries Landed Quantity, Zonal Interchange File, Ottawa.

DFO (2021a) Fisheries and Oceans Canada Seafisheries Landed Value, Zonal Interchange File, Ottawa.

DFO (2021b) Fisheries and Oceans Canada Oceanographic Conditions in the Atlantic Zone in 2020. Canadian Science Advisory Secretariat, Science Advisory Report 2021/026.

DFO (2021c) Marine Environmental Data Section Archive, https://meds-sdmm.dfo-mpo.gc.ca, Ecosystem and Oceans Science, Fisheries and Oceans Canada. Data obtained on 2021/09/07.

DFO (2021d) The Canadian Hydrographic Service CHS NONNA bathymetric data, https://www.charts.gc.ca/data-gestion/index-eng.html, Fisheries and Oceans Canada. Data obtained on 2021/10/03.

Flowers, J.M., Saila, S.B. (1972) An Analysis of Temperature Effects on the Inshore Lobster Fishery. J. Fish. Res. Board Can., 29: 1221–1225.

Foley, N.S., Van Rensburg, T.M., Armstrong, C.W. (2010a) The ecological and economic value of cold-water coral ecosystems. Ocean. Coast. Manag., 53: 313–326.

Foley, N.S., Kahui, V., Armstrong, C.W., Van Rensburg, T.M. (2010b) Estimating Linkages between Redfish and Cold Water Coral on the Norwegian Coast. Mar. Resour. Econ., 25: 105–120.

Gelman, A. (2006) Multilevel (Hierarchical) Modeling: What It Can and Cannot Do. Technometrics, 48: 432–435.

Gelman, A., Hill, J. (2006) Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge University Press.

Goode, A.G., Brady, D.C., Steneck, R.S., Wahle, R.A. (2019) The brighter side of climate change: How local oceanography amplified a lobster boom in the Gulf of Maine. Glob. Change Biol., 25: 3906–3917.

Greenan, B.J.W., Shackell, N.L., Ferguson, K., Greyson, P., Cogswell, A., Brickman, D., Wang, Z., Cook, A., Brennan, C.E., Saba, V.S. (2019) Climate Change Vulnerability of American Lobster Fishing Communities in Atlantic Canada. Front. Mar. Sci., 6: article 579.

Groner, M.L., Shields, J.D., Landers, D.F., Swenarton, J., Hoenig, J.M. (2018) Rising Temperatures, Molting Phenology, and Epizootic Shell Disease in the American Lobster. Am. Nat., 192: E163–E177.

Harrison, X.A., Donaldson, L., Correa-Cano, M.E., Evans, J., Fisher, D.N., Goodwin, C.E., Robinson, B.S., Hodgson, D.J., Inger, R. (2018) A brief introduction to mixed effects modelling and multi-model inference in ecology. PeerJ, 6: e4794.

Henderson, C.R. (1950) Estimation of genetic parameters. Ann. Math. Stat., 21: 309–310.

Henderson, J.V., Tugwell, M. (1979) Exploitation of the Lobster Fishery: Some Empirical Results. J. Environ. Econ. Manag., 6: 287–296.

Huang, L., Smith, M.D., Craig J.K. (2010) Quantifying the Economic Effects of Hypoxia on a Fishery for Brown Shrimp *Farfantepenaeus aztecus*. Mar. Coast. Fish., 2: 232–248.

Huang, L., Smith, M.D. (2014) The dynamic efficiency costs of common-pool resource exploitation. Am. Econ. Rev., 104: 4071–4103.

Hudon, C. (1994) Large-Scale Analysis of Atlantic Nova Scotia American Lobster (Homarus americanus) Landings with Respect to Habitat, Temperature, and Wind Conditions. Can. J. Fish. Aquat. Sci., 51: 1308–1321.

Hyun, S.Y., Cadrin, S.X., Roman, S. (2014) Fixed and mixed effect models for fishery data on depth distribution of Georges Bank yellowtail flounder. Fish. Res., 157: 180-186.

IPCC (2019) H.-O. Pörtner, D.C. Roberts, V. Masson-Delmotte, P. Zhai, M. Tignor, E. Poloczanska, K. Mintenbeck, A. Alegría, M. Nicolai, A. Okem, J. Petzold, B. Rama, N.M. Weyer (eds.) IPCC Special Report on the Ocean and Cryosphere in a Changing Climate. In press.

Kahn, J.R., Kemp, W.M. (1985) Economic losses associated with the degradation of an ecosystem: The case of submerged aquatic vegetation in Chesapeake Bay. J. Environ. Econ. Manag., 12: 246–1263.

Kish, L. (1965) Survey Sampling. John Wiley & Sons, Inc., New York, London.

Le Bris, A., Mills, K.E., Wahle, R.A., Chen, Y., Alexander, M.A., Allyn, A.J., Schuetz, J.G., Scott, J.D., Pershing, A.J. (2018) Climate vulnerability and resilience in the most valuable North American fishery. Proc. Natl. Acad. Sci., 115: 1831–1836.

Lynne, G.D., Conroy, P., Prochaska, F.J. (1981) Economic valuation of marsh areas for marine production processes. J. Environ. Econ. Manag., 8: 175–186.

McCleese, D.W., Wilder, D.G. (1958) The Activity and Catchability of the Lobster (Homarus americanus) in Relation to Temperature. J. Fish. Res. Board Can., 15: 1345–1354.

Meteyard, L., Davies, R.A. (2020) Best practice guidance for linear mixed-effects models in psychological science. J. Mem. Lang., 112: 104092.

Moscatelli, A., Mezzetti, M., Lacquaniti, F. (2012) Modeling psychophysical data at the population-level: The generalized linear mixed model. J. Vis., 12: 1–17.

Munro, G.R., Clark, C.W. (2003) Fishing capacity and resource management objectives. In: Pascoe, S. and Gréboval, D. (eds.) Measuring Capacity in Fisheries. FAO Fisheries Technical Paper No. 445. Rome, Italy: Food and Agriculture Organization of the United Nations.

Muthen, B.O., Satorra, A. (1995) Complex Sample Data in Structural Equation Modelling. Sociol. Methodol., 25: 267–316.

Nguyen, T.V.H. (2022) Welfare impact of climate change on capture fisheries in Vietnam. PLOS ONE, 17: e0264997.

OECD (2011) The Economics of Adapting Fisheries to Climate Change, OECD Publishing, Paris.

Pfeiffer, L., Gratz, T. (2016) The effect of rights-based fisheries management on risk taking and fishing safety. Proc. Natl. Acad. Sci., 113: 2615–2620.

Reid-Musson, E.R., Neis, B. (2022) Fishing safety and timed openings in Atlantic Canada's lobster fisheries: the mediating role of local management systems. Marit. Stud., 21: 1–12.

Squires, D., Walden, J. (2021) The Economics of Production in Marine Fisheries. In: Ray, S.C., Chambers, R.G., Kumbhakar, S.C. (eds.) Handbook of Production Economics. Springer, Singapore.

Tanaka, K.R., Torre, M.P., Saba, V.S., Stock, C.A., Chen, Y. (2020) An ensemble high-resolution projection of changes in the future habitat of American lobster and sea scallop in the Northeast US continental shelf. Divers. Distrib., 26: 987–1001.

Thakur K.K., Revie C., Stryhn H., Tibbetts S.S., Lavallée J., Vanderstichel R. (2017) Risk factors associated with soft-shelled lobsters (Homarus americanus) in southwestern Nova Scotia, Canada. FACETS, 2: 15–33.

Thorson, J.T., Minto, C. (2015) Mixed effects: a unifying framework for statistical modelling in fisheries biology. ICES J. Mar. Sci., 72: 1245–1256.

Tran, N., Shikuku, K.M., Peart, J., Chan, C.Y., Chu, L., Bailey, C., Valdivia, R. (2022) A Review of economic analysis of climate change impacts and adaptation in fisheries and aquaculture. SocArXiv zctxn, Center for Open Science.Venables, W.N., Dichmont, C.M. (2004) GLMs, GAMs and GLMMs: an overview of theory for applications in fisheries research. Fish. Res., 70: 319–337.

Wang, Z., Lu, W., Greenan, B., Brickman, D., DeTracey, B. (2018) BNAM: An eddy-resolving North Atlantic Ocean model to support ocean monitoring. Fisheries and Oceans Canada, Canadian Technical Report of Hydrography and Ocean Sciences 327.

# 3 Paper 2: Emerging Hotspot Analysis as a Tool for Understanding Climate Impacts: A Spatiotemporal Study of Catch Rates in the Canadian Lobster Fishery

*Submitted to Fish and Fisheries for review.*


## Abstract

Spatial management of fisheries has gained attention in recent years, as competition for space intensifies and the effects of climate change are felt ununiformly across different regions. For the lobster fisheries in the North Atlantic, it is undeniable that warming ocean waters are causing distributional shifts. However, lack of sufficient data has meant that few studies have attempted to uncover how this affects the performance of fisheries. This paper uses a novel approach (emerging hotspot analysis) to examine how changes in lobster catch rates track with warming trends in Atlantic Canada. We use emerging hotspot analysis to identify areas which are experiencing significant trends in temperature changes, and the direction and intensity associated with each patch. We then use a generalized linear model (GLM) regressing catch rates on the percentage of each fishing area that experienced these hot or cold spots. We find clear evidence that emerging hotspots are associated with higher catch rates but moreover, the intensification of these warming effects have a large positive association.



**Keywords:** Spatial analysis, emerging hotspot analysis, generalized linear model, CPUE, hot and cod spots

**JEL codes:** C13, C33, C55, Q22, C54

## 3.1 Introduction

Recently, the increasing focus on the spatial distribution of fishing activity is a critical aspect of modern fisheries management. The competition for limited space and resources calls for management approaches that consider spatial and temporal dynamics. This becomes particularly critical in the context of the impacts of climate change. Warming ocean temperatures are transforming marine ecosystems and driving the migration of certain species into deeper and cooler waters. Weather patterns also appear to be changing, and extreme weather events are becoming more and more prevalent. These climate events are likely to compel fishers to rethink their fishing strategies; for example, they might change their fishing grounds or how much effort they allocate spatially. As vessel technology advances, fishers may invest in larger and more powerful boats in order to travel farther distances, or to be able to fish safely in inclement weather. These changing conditions require management that can keep abreast of these developments, and current management measures might not be efficient if they fail to account for spatial heterogeneity.

To effectively address the challenges posed by climate change, it is essential to develop and implement adaptation and mitigation strategies. Fisheries management must evolve to account for shifting populations and changing environmental conditions. One approach is to enhance the monitoring and assessment of fish populations and their habitats. Improved data collection and analysis can help identify shifts in distribution, growth rates, and reproductive patterns, therefore facilitating more informed management decisions. Catch per unit effort (CPUE) has traditionally been used as a proxy for stock biomass, which is rarely observed directly. In the classic Gordon-Schaefer (GS) model, CPUE is assumed to be proportional to the portion of a fish population that is vulnerable to fishing gear, provided that fishing technology remains relatively unchanged. However, it is well-known that CPUE is an imperfect proxy, as there are many different factors that influence catch rates. The GS model assumes homogeneity of the stock while in reality, non-standardized CPUE is rarely proportional to abundance over a species' whole range. Changes in CPUE also represent fishing efficiency, as advances in technology allows fishers to harvest more in the same number of trips.

Many factors need to be considered when investigating why the spatial distribution of catch rates is changing over time. There are complex biological processes that govern the productivity of a particular species in an area, and other branches of research seek to study the movement of fish populations over time. However, empirically examining how catch rates might be influenced by environmental variables is another way to infer changes in fish abundance that result from climate change. This is particularly useful when a rich dataset spanning many years and encompassing a large geographic region is utilised. It is clear that intricate systems are at play that leave the lobster fishery vulnerable, and having knowledge of these spatial linkages can help ensure management measures are tailored toward these realities. This study makes an important contribution to the literature as, to our knowledge, emerging hotspot analysis has not previously been used as a tool for investigating spatiotemporal changes in productivity in the Canadian lobster fishery.

Analyzing spatiotemporal trends in catch rates allows us to glean important information about the direction and magnitude of changes in species distribution. Given the well-documented changes in ocean temperatures and the observed shifts in weather patterns, it is crucial to investigate the relationship between these distributional shifts in catch rates and our changing environment. This will not only enhance our understanding of catch dynamics but it also supports more informed and effective management and policy decisions. For our case study, we focus on the American lobster (*Homarus americanus*) fisheries in Atlantic Canada. This study aims to delve into rich fisheries-dependent data to track trends and make inferences about distributional changes in lobster population and harvest rates. Specifically, the focus will be on analyzing patterns of fishing success (measured by CPUE), examining how these patterns have evolved over time and space, and how they might relate to climate-driven factors.

## 3.2 Literature review

Spatial econometrics has gained popularity in recent years as data have become available on finer spatial and temporal resolutions. For example, spatial panel models (i.e., spatial autoregressive models or SARs) extend the standard panel data model to account for spatial dependence and heterogeneity (Belotti et al. 2017). Besides improving precision in estimation, spatial panel models allow the measurement of spatial spillovers on neighbouring areas. This technique is valuable and has many potential applications for fisheries research. However, it has limitations that inhibit its use: it requires a balanced panel (each spatial unit cannot have any missing observations for any time period) and often necessitates aggregating the data to a higher level, losing valuable variation at the vessel-level. One notable exception is a study by Sampson (2018) who developed a spatial econometric model for the Great Barrier Reef coral trout fishery. Feng et al. (2018) use an SAR model to investigate how the distribution and catch per unit effort (CPUE) of the jumbo flying squid in Peru is influenced by environmental factors, and Aminizadeh et al. (2024) use a spatial econometric model to examine the spatial footprint of fishing grounds in 156 countries. Despite these examples, the use of spatial econometrics in the fisheries setting continues to be sparse with researchers often opting to use fixed or random effects models to account for spatial heterogeneity.

### 3.2.1 Emerging hotspot analysis

Emerging hotspot analysis is a spatial statistical method designed to identify areas that are experiencing significant changes in a particular phenomenon over time (Esri 2024). This technique is commonly applied in fields such as crime, public health, and urban planning to detect trends and inform decision-making processes (Columbia Public Health 2024). It combines spatial statistics, e.g. Getis-Ord Gi* (Getis and Ord 1992) or local indicators of spatial association (LISA) (Anselin 1995) and temporal analysis, which involves comparing data across different time periods to identify areas where activity is increasing or decreasing (Esri 2024). The results can then be visually represented on maps highlighting hotspots, facilitating the identification of areas requiring attention. The impetus of this approach is that it focuses on emerging trends rather than static hotspots, thereby enhancing proactive planning and responses to dynamic changes.

Hotspot analysis has become increasingly popular in marine research, as researchers grapple with spatially heterogeneous effects of climate change. For example, Hobday and Pecl (2014) analyzed 50 years of sea surface temperature data to identify marine hotspots where ocean warming is fastest.

Identifying these key regions of concern is invaluable as it helps to pinpoint where to focus attention for future research. This method is also being used more often in fisheries research: for example, Everett et al. (2021) used emerging hotspot analysis to investigate spatiotemporal changes in CPUE and fishing effort in a deepwater crustacean trawl fishery off the east coast of South Africa. They discovered a contraction of fishing effort over time and converging to a smaller fishing area, providing valuable insights into a fishery that has not been subject to any official stock assessments. Vlietstra and Thoenen (2024) analyzed Vessel Monitoring System (VMS) data to investigate whether changes in fishing activity track with poleward shifts in fish stocks on the Bering Sea Shelf. They identified regions with increasing vessel activity (emerging hot spots) and decreasing activity (emerging cold spots). They found evidence of northward shifts in vessel distribution, particularly during certain months. These studies highlight how climate change is influencing the distributional shifts of fish stocks, and subsequently reshaping commercial fishing effort. As such, emerging hotspot analysis proves to be a valuable tool in guiding resource allocation, policy-making, and targeted interventions as the impacts of climate change intensify.

### 3.2.2 Case study and empirical setting

Lobster fisheries are the cornerstone of many coastal communities in Atlantic Canada and as both a lucrative industry and a vital source of employment, ensuring their longevity is vital. In the Northwest Atlantic climate change is altering marine environments in profound ways, and the region is experiencing some of the fasting warming waters (Pershing et al. 2015, Saba et al. 2016). Lobsters are cold-water species and as global temperatures rise, they are forced to migrate towards cooler waters, often moving northward to maintain their preferred thermal habitat (Tanaka et al. 2018, Goode et al. 2019, Greenan et al. 2019, Mazur et al. 2020). This shift disrupts established fishing grounds and necessitates adjustments in fishing practices (Le Bris et al. 2018, Young et al. 2019, McClenachan et al. 2019, Oppenheim et al. 2019, Mason et al. 2024). Furthermore, warmer waters can lead to increased metabolic rates in lobsters (Harrington et al. 2020, Watson et al. 2023) affecting their growth rates and reproductive cycles (McLeese 1956, Hughes et al. 1972, Aiken and Waddy 1986, Waller et al. 2017). High temperatures can accelerate the growth of lobsters to some extent (Quinn et al. 2013, McMahan et al. 2016, Le Bris et al. 2017), but this comes with the cost of potentially reducing their lifespan and overall health (Harrington et al. 2019). It can result in a decreased size and quality of the catch, impacting both the economic value and sustainability of the fishery.

One of the dominant harvest strategies in the lobster fishery aims at maximizing catch per unit effort (CPUE) through the movement of effort between the various grounds and tracking lobster movements (Pezzack et al. 2015). As rising ocean temperatures cause distributional shifts in the lobster populations, fishers must adapt, which may involve changing their fishing grounds and moving further offshore. This necessitates more travel time as well as greater fuel costs to reach those fishing grounds. Moreover, fishers are confined by the boundaries of the lobster fishery area (LFA) for which they have a license to fish, so they do not have full freedom of movement. As the climate situation worsens and continues to reshape the landscape, current regulations (which in large part have not changed in several decades) will need to be revised to reflect changing environmental and economic conditions. The biological health of the stocks must be appropriately balanced with the economic importance of the fishery in these communities. However, if the status quo is maintained, rigid restrictions could result in excess competition and overcrowding, and ultimately overfishing. Implementing adaptive management practices, such as adjusting fishing grounds, quotas and regulations based on real-time data, can help sustain lobster populations and ensure the long-term viability of the fishery.

The choice of the Canadian lobster fishery as the setting for our case study is twofold. First, the dataset provides repeated observations across different spatial units, capturing catch and effort data for each fishing area over an extensive time series from 1990 to 2018. The precise harvest locations for each vessel within their designated fishing areas are unknown, but landings are demarcated by NAFO subdivisions, enabling us to explore spatial patterns in the data. Second, the lobster fishery has faced significant environmental uncertainty in recent years, leaving it particularly vulnerable. These environmental changes are not homogeneous across the whole fishery, providing a unique opportunity to investigate how fleet activity evolves in response to diverse conditions across different geographic areas.

While warming waters around the species' southern range (particularly in Southern New England, USA) have led to depletion of stocks, lobster has thus far thrived in its northern range (Wahle et al. 2015, Greenan et al. 2019, Goode et al. 2019). As the species has an optimal temperature of between 12°C to 18°C (Crossin et al. 1998), it benefits from the colder Canadian waters. However, certain regions are warming much faster than others, and it is not uncommon for temperatures in the semi-closed Bay of Fundy to exceed this maximum threshold. Although warming waters have likely contributed to the boom in landings in recent decades, when the temperature surpasses 24°C, larvae become stressed or die (Quinn 2017). In addition, rapid warming in the Gulf of Maine has posed other challenges for the lobster fishery. The critically endangered North Atlantic right whales have begun to migrate into Canadian waters as their main food source, the copepod *Calanus finmarchicus* moves north (Reygondeau and Beaugrand 2010, Grieve et al. 2017). This shift has led to increased whale fatalities and injuries from collisions with vessels and entanglements in fishing gear. In response, the Canadian government has implemented mitigation measures including static and dynamic fishing area closures when whales have been sighted in the area. These measures are necessary for the protection of the species, but these closures have negative repercussions for fisheries resulting in revenue loss and marine spatial squeeze.

## 3.3 Methods

We use the Emerging Hot Spot Analysis (space time pattern mining) tool in ArcGIS to identify spatiotemporal trends in the data. To use this tool, we first create a space-time cube by aggregating temperature anomaly points based on location and time stamp. In each bin of the cube, the points are counted and the mean temperature anomaly is calculated. For each bin, the Getis-Ord Gi* statistic (Getis and Ord 1992) is calculated, which is used to identify statistically significant spatial clusters of high values (hot spots) and low values (cold spots). The statistic is given by:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{x} \sum_{j=1}^{n} w_{i,j}}{s\sqrt{\frac{(n\sum_{j=1}^{n} w_{i,j}^2 - (\sum_{j=1}^{n} w_{i,j})^2)}{n-1}}} \tag{1}$$

Where $x_j$ is the attribute value for feature $j$, $w_{i,j}$ is the spatial weight between feature $i$ and $j$, $n$ is equal to the number of features, and

$$\bar{x} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{2}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2 - (\bar{x})^2}{n}} \tag{3}$$

Next, the hot and cold spot trends are measured using the Mann-Kendall statistic (Mann 1945, Kendall 1975, Gilbert 1987), a statistic which is used to determine if a time series has a monotonic upward or downward trend. For a time series $x_1, \ldots x_n$,

$$K = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(x_j - x_i) \tag{4}$$

If $K > 0$ the trend is found to be monotonically increasing, and if $K < 0$ the trend is found to be monotonically decreasing. These calculations result in z-scores and p-values and using these, the tool assigns each study area a category (Table 3.1).

**Table 3.1: Hot and cold spot classifications and criteria**

| | Pattern name | Definition |
|---|---|---|
| | No Pattern Detected | Does not fall into any of the hot or cold spot patterns defined below. |
| | New Hot Spot | A location that is a statistically significant hot spot for the final time step and has never been a statistically significant hot spot before. |
| | Consecutive Hot Spot | A location with a single uninterrupted run of at least two statistically significant hot spot bins in the final time-step intervals. The location has never been a statistically significant hot spot prior to the final hot spot run and less than 90 percent of all bins are statistically significant hot spots. |
| | Intensifying Hot Spot | A location that has been a statistically significant hot spot for 90 percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of high counts in each time step is increasing overall and that increase is statistically significant. |
| | Persistent Hot Spot | A location that has been a statistically significant hot spot for 90 percent of the time-step intervals with no discernible trend in the intensity of clustering over time. |
| | Diminishing Hot Spot | A location that has been a statistically significant hot spot for 90 percent of the time-step intervals, including the final time step. In addition, the intensity of clustering in each time step is decreasing overall and that decrease is statistically significant. |

| | Pattern name | Definition |
|---|---|---|
| | Sporadic Hot Spot | A statistically significant hot spot for the final time-step interval with a history of also being an on-again and off-again hot spot. Less than 90 percent of the time-step intervals have been statistically significant hot spots and none of the time-step intervals have been statistically significant cold spots. |
| | Oscillating Hot Spot | A statistically significant hot spot for the final time-step interval that has a history of also being a statistically significant cold spot during a prior time step. Less than 90 percent of the time-step intervals have been statistically significant hot spots. |
| | Historical Hot Spot | The most recent time period is not hot, but at least 90 percent of the time-step intervals have been statistically significant hot spots. |
| | New Cold Spot | A location that is a statistically significant cold spot for the final time step and has never been a statistically significant cold spot before. |
| | Consecutive Cold Spot | A location with a single uninterrupted run of at least two statistically significant cold spot bins in the final time-step intervals. The location has never been a statistically significant cold spot prior to the final cold spot run and less than 90 percent of all bins are statistically significant cold spots. |
| | Intensifying Cold Spot | A location that has been a statistically significant cold spot for 90 percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of low counts in each time step is increasing overall and that increase is statistically significant. |
| | Persistent Cold Spot | A location that has been a statistically significant cold spot for 90 percent of the time-step intervals with no discernible trend in the intensity of clustering of counts over time. |
| | Diminishing Cold Spot | A location that has been a statistically significant cold spot for 90 percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of low counts in each time step is decreasing overall and that decrease is statistically significant. |
| | Sporadic Cold Spot | A statistically significant cold spot for the final time-step interval with a history of also being an on-again and off-again cold spot. Less than 90 percent of the time-step intervals have been statistically significant cold spots and none of the time-step intervals have been statistically significant hot spots. |
| | Oscillating Cold Spot | A statistically significant cold spot for the final time-step interval that has a history of also being a statistically significant hot spot during a prior time step. Less than 90 percent of the time-step intervals have been statistically significant cold spots. |
| | Historical Cold Spot | The most recent time period is not cold, but at least 90 percent of the time-step intervals have been statistically significant cold spots. |

*Source: Esri (2024)*

### 3.3.1 Empirical strategy

We exploit the hierarchical structure of the data (vessels operating within fishing areas) by using a generalized linear mixed model (GLMM), allowing for random effects to be specified at multiple levels. We consider the following model,

$$y_{it} = \beta_0 + \beta_k \sum_{k=1}^{K} X_{it} + u_i + u_j + \varepsilon_{it} \quad (5)$$

where $y_{it}$ is CPUE for vessel $i$ at year $t$, $X_{it}$ is a vector of explanatory variables for vessel $i$ at year $t$, $u_i$ is a vessel-level random effect, $u_j$ is an area-level random effect, and $\varepsilon_{it}$ is the disturbance term. The benefit of using this type of model is the ability to account for unobserved heterogeneity for vessels and fishing areas. For example, there are likely to be differences in vessel technology or innate skill that are not accounted for. Accounting for this heterogeneity can improve statistical inference and mitigate bias in estimation.

### 3.3.2 Data

#### *3.3.2.1 Fisheries-dependent data*

Fisheries-dependent data form the basis of our study, and we observe commercial lobster fishing data for the years 1990-2018. We use annually aggregated vessel-level data, and we use catch per unit effort (CPUE) as the dependent variable. CPUE is defined as harvest in kilograms per fishing trip. For the purpose of our study, we use Northwest Atlantic Fisheries Organization (NAFO) subdivisions to delimit fishing areas, and these fall within the larger NAFO divisions 4T, 4V, 4W, and 4X. These areas have the finest spatial resolution that is available for the whole length of the time series. It should be noted that the Canadian lobster fishery is managed at the lobster fishing area (LFA) level, however this has a shorter time series (only back to 2006) and LFA is missing for some regions even in later years. Our study area encompasses 18 fishing areas in the Bay of Fundy (4Xr and 4Xs), the Nova Scotian coast (4Xm-q, 4Wk, 4Wd, and 4Vn), and the Gulf of St. Lawrence (4Tf-o) (Figure 3.1). Smaller amounts are landed in Newfoundland and Northern Quebec but these only account for 0.3% of the landings over this time period. There are 24 annual time steps totalling 191,306 observations.

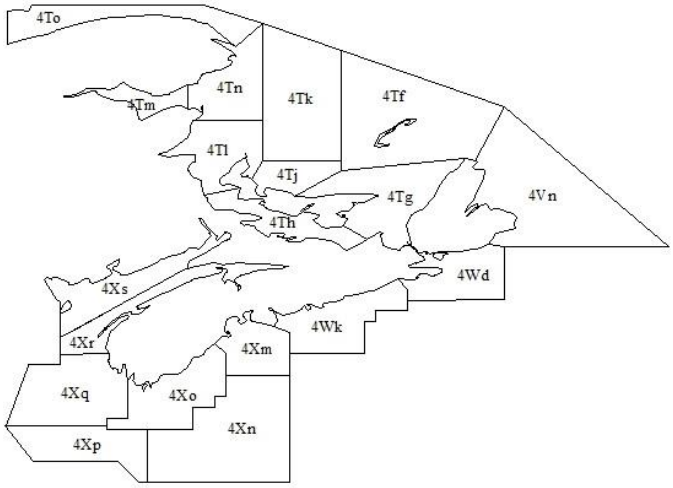


**Figure 3.1: NAFO subdivisions in Atlantic Canada**

### *3.3.2.2 Ocean temperature data*

Ocean temperature observations at all depths were retrieved from Fisheries and Oceans Canada (DFO)'s Marine Environmental Data Section (MEDS) (DFO 2021a). These data were then cross-referenced with bathymetric data (DFO 2021b) and only the bottom temperature observations are retained. Although there are a large number of observations that span the study area over each year (n=91,231) the locations sampled are not consistent from year to year. Therefore, temperature data are expressed in terms of anomalies from their long-term mean. Bottom temperature averages for the years 1990-2015 on a spatial grid of 1/12 degrees were retrieved from DFO's Bedford Institute of Oceanography North Atlantic model (BNAM) (Wang et al. 2018). Each temperature observation was matched with its nearest neighbor from the BNAM long-term averages, and the difference between these points were calculated. Shapefiles that delineate the fishing areas' polygons were used to determine which observations fall into which area. The average temperature anomalies for each area and each year were then calculated. A negative observation represents a colder-than-average anomaly, and a positive observation represents a warmer-than-average anomaly.

The explanatory variables we use are length of vessel, gross tonnage, mean temperature anomaly, and the percentage of each fishing area that falls into each hot/cold spot classification. Length of vessel is measured in feet, and gross tonnage is a categorical variable that takes on values according to the criteria below (Table 3.2).

**Table 3.2: Gross tonnage and associated factor variables**

| Value | Tonnage |
|---|---|
| 1 | 1-24.9 T |
| 2 | 25-49.9 T |
| 3 | 50-149.9 T |
| 4 | 150-499.9 T |
| 5 | 500-999.9 T |
| 6 | 1000-1999.9 T |

The variables and their associated summary statistics are given in Table 3.3. The minimum and maximum CPUE are omitted for anonymity so as not to highlight the catch rate of a particular vessel.

**Table 3.3: Variables and associated summary statistics**

| Variable | Mean | St. dev. | Min. | Max. |
|---|---|---|---|---|
| CPUE (kg/trip) | 373.1 | 646.9 | | |
| Length of vessel (ft) | 38.6 | 7.0 | 10 | 141 |
| Tonnage (T) | 0.8 | 0.5 | 1 | 6.0 |
| Mean temperature anomaly (°C) | -0.6 | 1.9 | -6.3 | 4.6 |
| New hot spot (%) | 0.2 | 1.3 | 0 | 27.6 |
| Intensifying hot spot (%) | 1.4 | 5.4 | 0 | 47.6 |
| Persistent hot spot (%) | 7.1 | 15.9 | 0 | 76.3 |
| Consecutive hot spot (%) | 0.3 | 1.6 | 0 | 18.4 |
| Diminishing hot spot (%) | 5.7 | 16.0 | 0 | 70.7 |
| Sporadic hot spot (%) | 7.9 | 16.7 | 0 | 74.5 |
| Oscillating hot spot (%) | 0.5 | 1.9 | 0 | 21.0 |
| Historical hot spot (%) | 0.6 | 3.0 | 0 | 32.4 |
| New cold spot (%) | 0.6 | 3.6 | 0 | 48.1 |
| Intensifying cold spot (%) | 13.4 | 22.2 | 0 | 83.0 |
| Persistent cold spot (%) | 7.3 | 15.3 | 0 | 80.8 |
| Consecutive cold spot (%) | 1.1 | 4.2 | 0 | 59.3 |
| Diminishing cold spot (%) | 0.1 | 0.8 | 0 | 10.8 |
| Sporadic cold spot (%) | 15.1 | 21.0 | 0 | 78.1 |
| Oscillating cold spot (%) | 0.4 | 2.0 | 0 | 27.6 |
| Historical cold spot (%) | 0.4 | 1.9 | 0 | 16.4 |

## 3.4 Results and discussion

### 3.4.1 Spatial shifts in catch rates (CPUE)

Spatial shifts in catch rates are noticeable when observing CPUE over time (Figure 3.2). The heatmaps represent the average CPUE by vessel for each of the 18 areas in 5-year increments. In 1990-1995, the highest catch rates are observed in the more southern regions of the Bay of Fundy and the western coast of Nova Scotia, while lower catch rates are observed in the northern region (Gulf of St. Lawrence) in these early years. Around 2005, we see the Gulf of St. Lawrence emerging as one of the most productive lobster fishing zones and this continues to be the case throughout the rest of the years analyzed. By 2015, this area had the highest catch rates, surpassing those in the Bay of Fundy. By 2018, catch rates are visibly less productive in the Bay of Fundy than those in the Gulf of St. Lawrence.

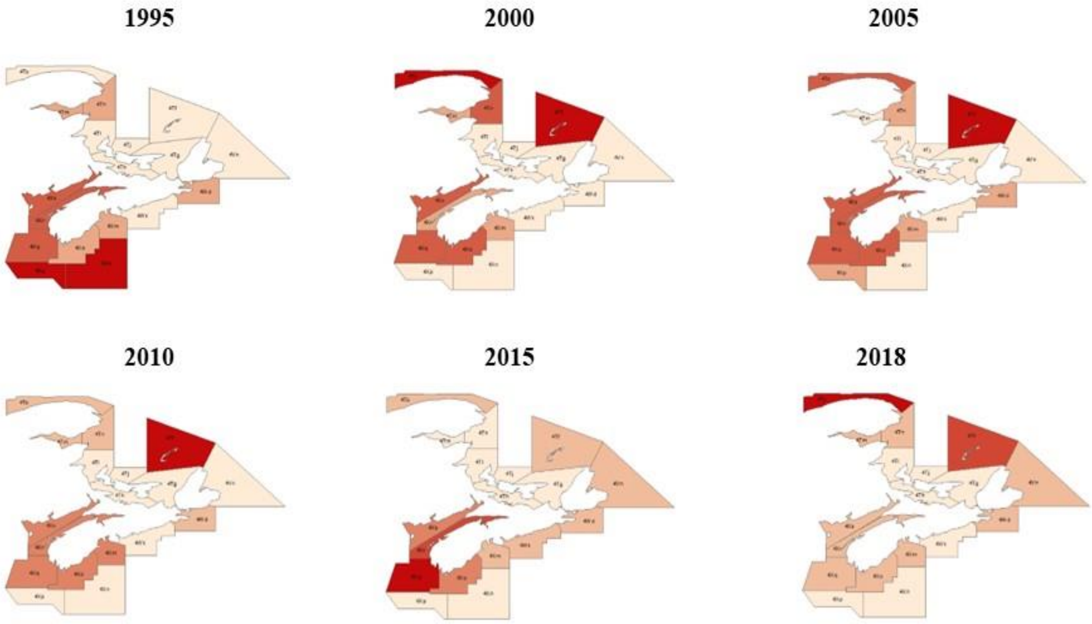


**Figure 3.2: Regime shifts in catch per unit effort (CPUE) in the lobster fishery over time**

### 3.4.2 Estimations from regression

The estimation results are presented in Table 3.4. The two vessel-related coefficients (length of vessel and gross tonnage) are both significant and have the expected sign. Logically, larger and more powerful vessels are associated with greater catch rates. Moreover, interesting findings emerge when we observe the significance, sign, and magnitude of the environmental coefficients.

**Table 3.4: Estimation results from generalized linear mixed model**

| **Variable** | **Coefficient** | **Std. err.** | **P-value** | **C.I. (lower)** | **C.I. (upper)** |
|---|---|---|---|---|---|
| Length of vessel (ft) | 6.193** | 2.445 | 0.011 | 1.401 | 10.984 |
| Tonnage (T) | 53.997* | 27.808 | 0.052 | -0.506 | 108.501 |
| Mean temperature anomaly (°C) | 26.021* | 13.604 | 0.056 | -0.641 | 52.684 |
| New hot spot (%) | 24.329 | 14.998 | 0.105 | -5.068 | 53.725 |
| Intensifying hot spot (%) | 34.513*** | 12.850 | 0.007 | 9.327 | 59.699 |
| Persistent hot spot (%) | 9.026*** | 2.408 | 0.000 | 4.306 | 13.746 |
| Consecutive hot spot (%) | -21.918 | 33.054 | 0.507 | -86.702 | 42.867 |
| Diminishing hot spot (%) | -0.266 | 2.519 | 0.916 | -5.203 | 4.671 |
| Sporadic hot spot (%) | -0.481 | 1.245 | 0.699 | -2.921 | 1.959 |
| Oscillating hot spot (%) | -2.826 | 10.466 | 0.787 | -23.340 | 17.688 |
| Historical hot spot (%) | -2.662 | 3.957 | 0.501 | -10.417 | 5.093 |
| New cold spot (%) | 15.102*** | 5.267 | 0.004 | 4.779 | 25.425 |
| Intensifying cold spot (%) | -0.428 | 0.483 | 0.375 | -1.374 | 0.517 |
| Persistent cold spot (%) | -1.704* | 0.975 | 0.081 | -3.615 | 0.207 |
| Consecutive cold spot (%) | -2.589** | 1.057 | 0.014 | -4.660 | -0.518 |
| Diminishing cold spot (%) | -29.795*** | 4.678 | 0.000 | -38.964 | -20.626 |
| Sporadic cold spot (%) | -0.914 | 0.593 | 0.123 | -2.075 | 0.248 |
| Oscillating cold spot (%) | 19.852*** | 4.120 | 0.000 | 11.778 | 27.927 |
| Historical cold spot (%) | -5.788*** | 1.864 | 0.002 | -9.442 | -2.134 |
| Constant | -86.255 | 139.488 | 0.536 | -359.646 | 187.135 |
| Vessel-level random effect ($\mu_i$) | 283.979 | 47.942 | 0.000 | 203.979 | 395.355 |
| Area-level random effect ($\mu_j$) | 379.183 | 89.517 | 0.000 | 238.725 | 602.281 |

*** p < 1%; ** p < 5%; * p < 10%

The coefficient for mean temperature anomaly is positive and significant, albeit only at the 10% level. This finding is in line with the trend that has been observed in the Canadian lobster fishery (Wright and Liu 2023). The colder waters in this region have likely meant that rising temperatures have resulted in increased biomass in the area. It should be noted that beyond a certain temperature threshold (e.g., 20°C) this would not be the case but for the most part, waters are yet to reach this critical tipping point.

The estimated coefficients for the hot and cold spot variables provide valuable insights into how catch rates are influenced by spatiotemporal trends in ocean temperature. This is particularly beneficial in a fisheries context as temperature-induced changes in biomass are more likely to be the result of longer term warming and cooling trends, rather than shorter term fluctuations. For example, a region that has experienced a period of warming for several years - even decades - might still see the odd year in which the temperature is colder than average. Relating catch rates to own-year temperature anomalies can pose a problem for this reason. Emerging hotspot analysis improves on this through a two step process: the first is to mine patterns in the data based on spatial clustering and temporal trends in warming and cooling effects, and assign each space-time bin a category (Table 3.1). The second step is to regress catch rates on the percentage of each fishing area that is spanned by each category.

Some notable patterns emerge in the sign, significance, and magnitude of the hotspot and coldspot coefficients. In general, the fishing areas with a greater proportion of hot spot patches are associated with higher catch rates and the areas with a greater proportion of cold spot patches are associated with lower catch rates, with some exceptions. The most prominent hot spot classification in terms of magnitude (and significant at the 1% level) is the "intensifying" hot spot, which is defined as a hot spot location that has been statistically significant for 90 percent of the time-step intervals including the final time step, and is experiencing an overall increasing trend. This is an important finding as not only does it reaffirm that warming effects are likely associated with higher catch rates[2], but that the increasing severity of these warming effects are found to have the most profound impact. When dealing with complex ecological systems it is difficult to relate changes in catch rates to acute changes in ocean temperature. This underscores the benefit of this method, as shorter term fluctuations would be contained in one of the other categories (e.g. "oscillating" or "sporadic"). The second most prominent hot spot is the "persistent" hot spot (a location that has been a statistically significant hot spot for 90 percent of the time-step intervals with no discernible increasing or decreasing trend). The commonality between these two is that they are deemed to be a significant hot spot for at least 90 percent of the time-

[2] This would only hold true for areas that are not yet at risk of hitting the stress threshold.

step intervals. The other hot spot categories (which happen to be those showing less of a clear trend) are found to be statistically insignificant. Although this aligns with what other studies have observed, it is nonetheless an important empirical result. It is clear that catch rates are tracking with the emergence and changing locations of these hotspots. A visualisation of how these hotspots are changing over time is shown below (Figure 3.3).

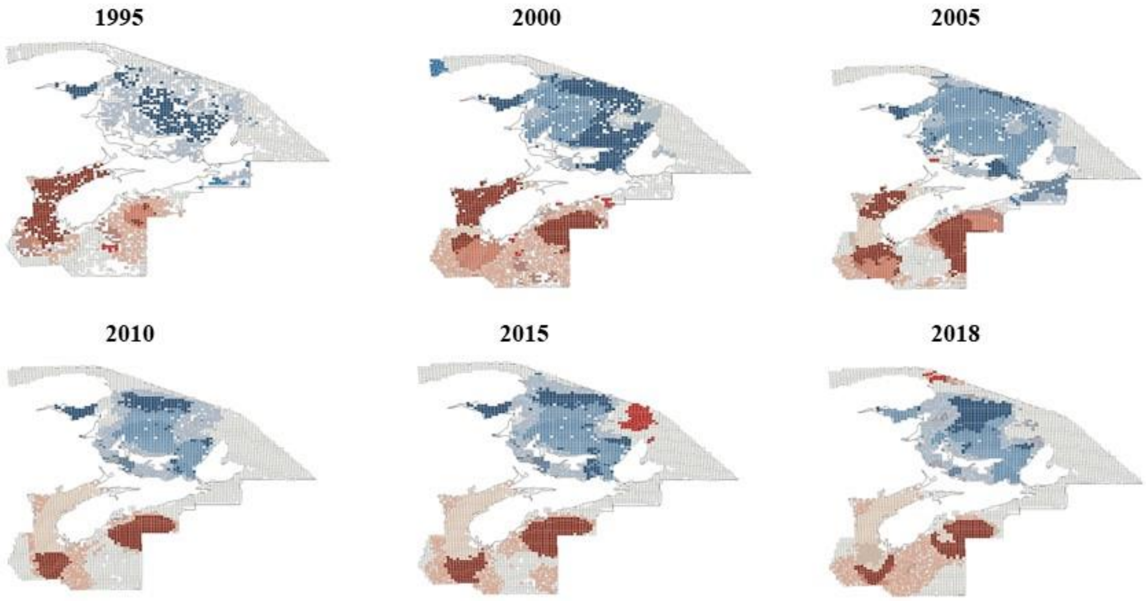


**Figure 3.3: Visualization of hot and cold spots over time**

The most dominant cold spot category is the "diminishing" cold spot, defined as a location that has been a statistically significant cold spot for 90 percent of the time-steps, with a decrease in the intensity of cold spot clustering over time. Interestingly, this is the reverse of the most dominant hot spot category - "intensifying". The cold spots which are "historical" (90% of years are cold but not the most recent), "consecutive" (two of the most recent time steps were cold), and "persistent" (90% of years are cold with no discernible trend in intensity) are also significant and negative, albeit with a smaller magnitude. Notably, two cold spot coefficients are positive: "oscillating" and "new" cold spots. The former is defined as one that is a cold spot for the final time step but has been a hot spot prior, and the latter is one that is a cold spot for the final time step but has not been a cold spot before. Given that both of these are ambiguous and not strictly cold spots, it is reasonable for these to be positive.

As shown in Figure 3.3, the spatiotemporal trends in ocean bottom temperature have changed over time. As each new year of data is added to the space-time cube, it is re-analyzed using emerging hotspot analysis. We see that new trends emerge: new hot and cold spots form or dissipate, and the intensity level for existing spots either intensify or fade. In 1995, the spatial coverage is patchy as there are not as many observations to extract trends, but we start to see clear trends forming. By 2000, we see that a significant portion of the Bay of Fundy and the southern portion of the Scotian Coast are hot spots, while the Gulf of St. Lawrence is mainly comprised of cold spots. As the years progress, the intensity of the hot spots in the Bay of Fundy lessens, and some parts transition into oscillating or historical hot spots. By 2015 and then by 2018, we start to see the cold spots in the Gulf of St. Lawrence shrinking relative to earlier years. Another interesting finding emerges, as we start to see small patches of hot spots emerge where previously there were none.

These findings are relevant and timely as the spatial structure of fisheries becomes increasingly important for policymakers. Spatial heterogeneity in both environmental conditions and fisher behaviour makes a one-size-fits-all approach to management problematic. As stocks move further north or offshore, fishers adapt and change their fishing grounds to the extent they can do so. The current management of the Canadian lobster fishery has rigid restrictions on fishing zones, seasonal timings, and number of licenses per area. Despite the changing dynamics of the fishery in the last several decades, very few corresponding changes have been made to regulations. New licenses are not being issued for the fisheries in this region, and the only way for a fisher to acess a new area is to buy an existing license at prohibitively high prices.

One exception and recent new initiative occurred in May of 2024 when the Government of Canada issued 25 exploratory fishing licences for Lobster Fishing Area (LFA) 18 on Quebec's North Shore (not included in our study area). From the official press release, "In the context of climate change and the resulting warming of the oceans, it is more important than ever for the Government of Canada to be agile, and explore every new economic opportunity for the benefit of coastal communities." This is the result of an influx of lobster abundance in this area in recent years. As data on the state of the stock remains limited, these new licenses were issued in an effort to collect data to determine if this increase in effort will be sustainable. Based on compliance as well as the results received, these new licenses could be eventually converted to commercial permits.

The issuance of these exploratory licenses is an encouraging step and shows that regulators are open to expanding fishing opportunities for areas that are seeing increased abundance as the result of warming waters. However, more lenience in other fishing areas might be beneficial as well. For example, fishers in Newfoundland are seeing the abundance of lobster as a bright light after the depletion of cod, scallop, and mackerel stocks that once dominated the industry. Despite stock assessments showing positive prospects for lobster in Newfoundland, fishers are still struggling to obtain these new licenses (CBC 2024). Despite the many detrimental impacts of climate change, certain regions are beneficiaries, presenting opportunities to expand economic opportunities in these areas. However, to prevent history from repeating itself, it is crucial to ensure that decisions are not made hastily, leading to over-exploitation. The temptation to expand fishing opportunities must be balanced with sound scientific advice. Issuing a small number of these exploratory licenses on the condition that appropriate data is collected, is a way to better inform management while also helping these struggling communities.

## 3.5 Conclusion

It is crucial to consider the spatial structure of fisheries, especially as we contend with climate impacts that disadvantage certain regions while benefiting others. Too often, fisheries are viewed through a static lens despite the overwhelming evidence that fisheries are constantly evolving. A lack of spatially detailed data and a temptation to maintain the status quo can lead to certain regions being overfished, while resources in other areas are untapped.

For the Canadian lobster fishery, it has been well known for many years that warming waters have a physiological effect on the species, and is causing distributional shifts. Despite this, few studies have attempted to uncover how fishers react to these changes. This paper uses a novel approach to examine how changes in catch rates track with warming trends in Atlantic Canada. We first use the emerging hotspot analysis tool in ArcGIS to identify areas that are experiencing hot or cold spots, and the type of trend associated with each. We then use this in a modelling exercise by regressing catch rates on the percentage of each fishing area that experienced these hot or cold spots. We find clear evidence that emerging hotspots are associated with higher catch rates but moreover, the intensification of these spots have a large positive association. This finding has profound implications for management, as rules have remain unchanged in several decades. Encouragingly, the Government of Canada has recently shown openness to exploring the issuance of new licenses in areas that have seen increased landings. However, more conversations and willingness to adapt is necessary in order to protect the fishing industry and ensure its healthy sustainablity for generations to come.

## 3.6 References

Aiken, D.E., Waddy, S.L. (1986) Environmental Influence on Recruitment of the American Lobster *Homarus americanus*: A Perspective. Canadian Journal of Fisheries and Aquatic Sciences, 43(11): 2258–2270.

Aminizadeh, M., Mohammadi, H., Karbasi, A. (2024) Determinants of fishing grounds footprint: Evidence from dynamic spatial Durbin model. Marine Pollution Bulletin 202: 116364.

Anselin, L. (1995) Local Indicators of Spatial Association—LISA. Geographical Analysis, 27(2): 93-115.

Belotti, F., Hughes, G., Mortari, A.P. (2017) Spatial panel-data models using Stata. The Stata Journal 17(1): 139-180.

CBC (2024) Now or never: Feeling forgotten, aging fishermen in northern Newfoundland are looking to lobster for economic salvation. CBC News, https://www.cbc.ca/newsinteractives/features/now-or-never.

Columbia Public Health (2024) Hot Spot Spatial Analysis, https://www.publichealth.columbia.edu/research/population-health-methods/hot-spot-spatial-analysis.

Crossin, G.T., Al-Ayoub, S.A., Jury, S.H., Howell, W.H., Watson, W.H. (1998) Behavioral Thermoregulation in the American Lobster *Homarus Americanus*. Journal of Experimental Biology, 201(3): 365-374.

DFO (2021a) Marine Environmental Data Section Archive, https://meds-sdmm.dfo-mpo.gc.ca, Ecosystem and Oceans Science, Fisheries and Oceans Canada. Data obtained on 2021/09/07

DFO (2021b) The Canadian Hydrographic Service CHS NONNA bathymetric data, https://www.charts.gc.ca/data-gestion/index-eng.html, Fisheries and Oceans Canada. Data obtained on 2021/10/03.

Esri (2024) How Emerging Hot Spot Analysis works, https://pro.arcgis.com/en/pro-app/latest/tool-reference/space-time-pattern-mining/learnmoreemerging.htm.

Everett, B.I., Fennessy, S.T., van den Heever, N. (2021) Using hotspot analysis to track changes in the crustacean fishery off KwaZulu-Natal, South Africa. Regional Studies in Marine Science, 41: 101553.

Feng, Y., Chen, X., Liu, Y. (2018) Examining spatiotemporal distribution and CPUE-environment relationships for the jumbo flying squid *Dosidicus gigas* offshore Peru based on spatial autoregressive model. Journal of Oceanology and Limnology 36: 942-955.

Getis, A., Ord, J.K. (1992) The Analysis of Spatial Association by Use of Distance Statistics. Geographical Analysis, 24: 189-206.

Greenan, B.J.W., Shackell, N.L., Ferguson, K., Greyson, P., Cogswell, A., Brickman, D., Wang, Z., Cook, A., Brennan, C.E., Saba, V.S. (2019) Climate Change Vulnerability of American Lobster Fishing Communities in Atlantic Canada. Frontiers in Marine Science, 6: 579.

Goode, A.G., Brady, D.C., Steneck, R.S., Wahle, R.A. (2019) The brighter side of climate change: How local oceanography amplified a lobster boom in the Gulf of Maine. Global Change Biology, 25(11): 3906-3917.

Grieve, B.D., Hare, J.A., Saba, V.S. (2017) Projecting the effects of climate change on *Calanus finmarchicus* distribution within the U.S. Northeast Continental Shelf. Nature Scientific Reports, 7: 6264.

Harrington, A.M., Tudor, M.S., Reese, H.R., Bouchard, D.A., Hamlin, H.J. (2019) Effects of temperature on larval American lobster (*Homarus americanus*): Is there a trade-off between growth rate and developmental stability? Ecological Indicators, 96(1): 404-411.

Harrington, A.M., Clark, K.F., Hamlin, H.J. (2020) Expected ocean warming conditions significantly alter the transcriptome of developing postlarval American lobsters (*Homarus americanus*): Implications for energetic trade-offs. Comparative Biochemistry and Physiology Part D: Genomics and Proteomics, 36: December 2020, 100716.

Hobday, A.J., Pecl, G.T. (2013) Identification of global marine hotspots: sentinels for change and vanguards for adaptation action. Reviews in Fish Biology and Fisheries, 24: 415-425.

Hughes, J.T., Sullivan, J.J., Schleser, R. (1972) Enhancement of Lobster Growth. Science, 177(4054): 1110-1111.

Kendall, M.G. (1975) Rank Correlation Methods. New York, NY: Oxford University Press.

Le Bris, A., Pershing, A.J., Gaudette, J., Pugh, T.L., Reardon, K.M. (2017) Multi-scale quantification of the effects of temperature on size at maturity in the American lobster (*Homarus americanus*). Fisheries Research, 186(1): 397-406.

Le Bris, A., Mills, K.E., Wahle, R.A., Chen, Y., Alexander, M.A., Allyn, A.J., Schuetz, J.G., Scott, J.D., Pershing, A.J. (2018) Climate vulnerability and resilience in the most valuable North American fishery. Proceedings of the National Academy of Sciences, 115(8): 1831-1836.

Mann, H.B. (1945) Nonparametric tests against trend. Econometrica, 13: 245–259.

Mason, E., Beaudreau, A.H., Arnold, S.N., Belknap, S., Scalisi, E.D. (2024) Adaptive capacity of the Maine lobster fishery: insights from the Maine Fishermen's Climate Roundtables. FACETS, 9: 21 August 2024.

Mazur, M.D., Friedland, K.D., McManus, M.C., Goode, A.G. (2020) Dynamic changes in American lobster suitable habitat distribution on the Northeast U.S. Shelf linked to oceanographic conditions. Fisheries Oceanography, 29(4): 349-365.

McClenachan, L., Grabowski, J.H., Marra, M., McKeon, C.S., Neal, B.P., Record, N.R., Scyphers, S.B. (2019) Shifting perceptions of rapid temperature changes' effects on marine fisheries, 1945–2017. Fish and Fisheries, 20(6): 1111-1123.

McLeese, D.W. (1956) Effects of Temperature, Salinity and Oxygen on the Survival of the American Lobster. Journal of the Fisheries Board of Canada, 13(2): 247–272.

McMahan, M.D., Cowan, D.F., Chen, Y., Sherwood, G.D., Grabowski, J.H. (2016) Growth of juvenile American lobster *Homarus americanus* in a changing environment. Marine Ecology Progress Series, 557: 177-187.

Oppenheim, N.G., Wahle, R.A., Brady, D.C., Goode, A.G., Pershing, A.J. (2019) The cresting wave: larval settlement and ocean temperatures predict change in the American lobster harvest. Ecological Applications, 29(8): e02006.

Pershing, A.J., Record, N.R., Franklin, B.S., Kennedy, B.T., McClenachan, L., Mills, K.E., Scott, J.D., Thomas, A.C., Wolff, N.H. (2019) Challenges to natural and human communities from surprising ocean temperatures. Proceedings of the National Academy of Sciences, 116(37): 18378-18383.

Pezzack, D.S., Denton, C., Ros, M.C., Tremblay, M.J. (2015) Assessment of the Canadian LFA 41 Offshore Lobster (*Homarus americanus*) Fishery (NAFO Divisions 4X 5Zc). Canadian Science Advisory Secretariat (CSAS), 2015/066.

Quinn, B.K., Rochette, R., Ouellet, P., Sainte-Marie, B. (2013) Effect of Temperature on Development Rate of Larvae from Cold-Water American Lobster (*Homarus Americanus*). Journal of Crustacean Biology, 33(4): 527–536.

Quinn, B.K. (2017) Threshold temperatures for performance and survival of American lobster larvae: A review of current knowledge and implications to modeling impacts of climate change. Fisheries Research, 186(1): 383-396.

Reygondeau, G., Beaugrand, G. (2010) Future climate-driven shifts in distribution of *Calanus finmarchicus.* Global Change Biology, 17(2): 756-766.

Saba, V.S., Griffies, S.M., Anderson, W.G., Winton, M., Alexander, M.A., Delworth, T.L., Hare, J.A., Harrison, M.J., Rosati, A., Vecchi, G.A., Zhang, R. (2016) Enhanced warming of the Northwest Atlantic Ocean under climate change. Journal of Geophysical Research: Oceans, 121(1): 118-132.

Sampson, G.S. (2018) Economic spillovers in spatial harvest behavior. Ecological Economics 145:57-74.

Tanaka, K.R., Chang, J., Xue, Y., Li, Z., Jacobson, L., Chen, Y. (2018) Mesoscale climatic impacts on the distribution of Homarus americanus in the US inshore Gulf of Maine. Canadian Journal of Fisheries and Aquatic Sciences, 76(4): 608-625.

Vlietstra, L.S., Thoenen, J.E. (2024) Poleward shifts in commercial fishing vessel distribution over the Bering Sea shelf, 2013–2022. Polar Biology, 47: 1121-1135.

Waller, J.D., Wahle, R.A., McVeigh, H., Fields, D.M. (2017) Linking rising pCO2 and temperature to the larval development and physiology of the American lobster (*Homarus americanus*). ICES Journal of Marine Science, 74: 1210–1219.

Wahle, R.A., Dellinger, L., Olszewski, S., Jekielek, P. (2015) American lobster nurseries of southern New England receding in the face of climate change. ICES Journal of Marine Science, 72: i69-i78.

Wang, Z., Lu, W., Greenan, B., Brickman, D., DeTracey, B. (2018) BNAM: An eddy-resolving North Atlantic Ocean model to support ocean monitoring. Fisheries and Oceans Canada, Canadian Technical Report of Hydrography and Ocean Sciences 327.

Watson, W.H., Gutzler, B.C., Goldstein, J.S., Jury, S.H. (2023) Impacts of Increasing Temperature on the Metabolism of Confined and Freely Moving American Lobsters (*Homarus americanus*). The Biological Bulletin, 245(2): October 2023.

Wright, D., Liu, Y. (2023) Assessing the impact of environmental variability on harvest in a heterogeneous fishery: a case study of the Canadian lobster fishery. Journal of Environmental Economics and Policy, 13(1): 55-69.

Young, T., Fuller, E.C., Provost, M.M., Coleman, K.E., St. Martin, K., McCay, B.J., Pinsky, M.L. (2019) Adaptation strategies of coastal fishing communities as species shift poleward. ICES Journal of Marine Science, 76(1): 93-103.

# 4 Paper 3: Assessing Production Risk Under Environmental Variability: A Case of the Canadian Lobster Fishery

*Submitted to Australian Journal of Agricultural and Resource Economics for review.*

## Abstract

Fisheries face various risks influenced by a range of factors, adding complexity and challenges to the industry. Identifying and understanding these risks is crucial for developing effective management strategies and ensuring the resilience and long-term viability of fisheries. This paper uses a Just-Pope production framework to analyze production risk in an input-controlled fishery subject to environmental variability. The Canadian lobster fishery is examined as a case study, with data pertaining to landings, effort, vessel characteristics, and weather conditions. A generalized linear model with two-way random effects is employed, and results suggest that extreme weather conditions have a detrimental effect on fishing operations. On a monthly basis, fluctuations in wind speed are negatively associated with expected harvest, while mean wind speed is found to have a variance-increasing effect on harvest. Wave height above a certain threshold significantly reduces expected monthly catch. The study underscores the importance of incorporating extreme weather conditions in fishing planning and decision-making, highlighting the need for adaptive management strategies. For instance, extending fishing seasons to counteract climate-induced delays, or shifting from effort controls to rights-based management could be beneficial.

**Keywords:** two-stage model, Just-Pope model, production risk, climate change, environmental variability, lobster fishery

**JEL code:** C33, C34, D22, D81, Q22, Q54

## 4.1 Introduction

Fishing is an occupation that is fraught with uncertainty, and fishers are subject to diverse risks emerging from economic instability, environmental conditions, regulatory measures, and occupational hazards. Their decision-making is challenged by limited information on species abundance, expected catch, and critical components of production which are influenced by intricate and complex ecological systems. While not a new concept, production risk is relatively novel in the context of capture fisheries. The pioneering work of Just and Pope (1978) developed a production function that enables us to model risk in the production process as a heteroskedastic variance function. To the extent that fishers control the intensity of inputs such as labour and capital, they might be able to control overall harvest levels while also mitigating production gluts. However, external factors that are beyond their control complicate this. Poor weather conditions pose a significant risk to fishing operations and might lead to fluctuations in yields. For fisheries subject to input controls, fisheries managers can directly influence production and its associated risk through restrictions on vessel size or power, season length, etc. Management strategies that fail to consider the changing environment can potentially lead to welfare loss for the industry.

Despite initiatives aimed at making fishing safer, fishing remains a dangerous occupation and poor weather conditions pose a significant risk. There are economic incentives driving fishers to outcompete others by fishing despite inclement weather, and coupled with a lack of property rights this exacerbates the inherent risks associated with commercial fishing (Pfeiffer and Gratz 2016). It is becoming increasingly evident that climate change is altering weather patterns, and some marine regions might experience more frequent occurrences of storms and strong winds (Fox-Kemper et al. 2021). These intensifying changes may pose a growing risk to fisheries. For fisheries that are regulated by effort controls such as limits on season length, fishers might take calculated risks to maximize their catch within the allotted time (Reid-Musson et al 2021).

The objective of this paper is to investigate production risk in an input-controlled fishery, emphasizing the influence of exogenous factors such as weather conditions on fishing operations. As an empirical case study, we examine the American lobster *(Homarus americanus)* fishery in Atlantic Canada, investigating how climate-related factors contribute to expected catch as well as variance of catch. A generalized linear model with mixed effects is employed along with commercial catch data and historical wind and waves reanalysis data. Sound evidence-based approaches are needed to aid in policy discussions, and empirical findings can help guide adaptive management strategies in the context of a changing climate.

### 4.1.1 Risk-taking behaviour in fisheries

Fishers' attitudes toward risk have been a common subject of inquiry amongst researchers, particularly in understanding risk preferences as they relate to economic incentives (Bockstael and Opaluch 1983, Dupont 1993, Mistiaen and Strand 2000, Eggert and Tveterås 2004, Holland 2008). It was previously assumed that fishers are risk-loving, but the bulk of the recent literature provides evidence to the contrary. Risk-seekers make decisions that might yield higher returns with a greater degree of uncertainty, but it seems more likely that fishers prefer stable revenues over high-risk and high-reward scenarios. While some fishers might decide to fish despite poor weather conditions (Pfeiffer and Gratz 2016), the frequency of extreme weather events coupled with increased regulations, initiatives, and knowledge of the dangers will likely lead the majority of boats to tie up when conditions are considered dangerous.

There is precedent for using weather variables such as wind speed or wave height to study the effects of inclement weather on fisheries. In the California sea urchin dive fishery, Smith (2002) used weather buoy data to assess divers' risk preferences and determine if safety risk is correlated with financial incentives. Stafford (2018) investigated how weather conditions influenced participation decisions in the Florida spiny lobster fishery, and found that fishers are significantly deterred by harsh weather at the site locations, and higher expected revenue increases the probability of participation. Sainsbury et al. (2021) explored how fishers manage the trade-off between risks posed by adverse weather conditions such as greater wind speed and wave height and the potential economic reward in terms of expected catch and prices.

The management approach of the fishery also plays a significant role in shaping these interactions. While effort-based controls may encourage excess competition and incentivize risk-taking (Emery et al 2014), rights-based instruments (e.g., quota systems) tend to lead to safer and less risk-taking behaviour (Leal 2005, Pfeiffer and Gratz 2016; Pfeiffer et al. 2022). For example, Pfeiffer and Gratz (2016) use the West Coast sablefish fishery in the United States as a case study to evaluate how the adoption of catch shares influences risk-taking behaviour. They found that the probability of fishing in high winds decreased by 82% under the catch share system, and that the average annual rate of fishing on high wind days decreased by 79%.

### 4.1.2 Modeling production risk

While there are various ways to measure risk in fisheries production, researchers find the stochastic production model of Just and Pope (1978 and 1979) convenient due to its flexibility. Central to the Just-Pope model is the idea that in addition to the usual deterministic production function, we can assess production risk through the variance of output. The total output therefore is specified to be the sum of a deterministic and stochastic function of inputs. The separation of mean and variance effects in production allows us to assess the effects of environmental variables on production risk. The Just-Pope production model has its roots in agricultural economics, and it was developed to assess crop yield for corn and oats as a result of varying levels of fertilizer. The framework was adopted by Kumbhakar (1993), who used the Just-Pope model to measure production risk and technical efficiency amongst dairy farmers in Sweden. Battese et al. (1997) similarly used the model to assess technical efficiency resulting from fertilizer use amongst Ethiopian farmers. Further, Isik and Devadoss (2006) utilized the modeling framework to quantify the impacts of climatic variables on the mean, variance, and covariance of crop yields. They found that the climate change has modest effects on mean crop yields, but significantly reduces the variance and covariance for most of the crops considered. These results have implications for allocations of agricultural land among crops and for crop production mix. Holst et al. (2013) adopted the Just-Pope function to analyze the climate impacts on grain production in China. The analysis indicates that the effects of temperature and precipitation differ between North and South China for both yield production and risk. Yu et al. (2024) examined the heterogenous impact of climate factors on rice yield during different rice growing periods using a Just-Pope model and quantile regression approach. The study results show that both accumulated temperature and precipitation have significant non-linear effects on rice yield, and accumulated heat has an inverted U-shaped effect on rice yield variability during the seedings period and maturing period.

Although the Just-Pope model had its origins in agricultural economics, it has gained popularity in fisheries and aquaculture economics. For example, Tveterås (1999) used the Just-Pope production model to assess risk in Norwegian salmon aquaculture. Salmon farming is subject to considerable risk due to disease, sea temperature change, inclement weather, and toxic algae. Although some of these factors cannot be controlled, it is thought that their effects can be mitigated or exacerbated by input choices. The findings suggest that fish feed and smolt input increase output risk, while labour decreases output risk. Kumbhakar and Tveterås (2003) similarly used Norwegian salmon farms as a case study and again found that fish feed and smolt input are risk-increasing, while labour and capital are risk-decreasing. Khan et al. (2018) applied the Just-Pope model to investigate the production risk of pangas farming in Bangladesh. The study revealed that production risk presents differently for small versus large farms. Do and Thuy (2022) applied the Just-Pope framework to examine the impact of mangrove forests on the productivity and volatility of shrimp aquaculture output. Their findings provide robust evidence that mangrove forests have a negative but risk-reducing effect on shrimp yield.

Most examples to date have focused on aquaculture, but a few have used it in the context of capture fisheries. For example, Eggert and Tveterås (2004) used the Just-Pope framework to investigate gear choice in the Swedish trawl fishery. More recently, Asche et al. (2020) estimated production and variance functions for vessel groups in the Norwegian fishing fleet and found that production risk varies between fleet groups and input factors. For example, capital has a risk-decreasing effect for the ocean fleet, but is risk-increasing for coastal fisheries. It might be considered unorthodox to use a Just-Pope production model for capture fisheries, as the production process is less controlled and available data on input use is often scarce. To the best of our knowledge, there is no existing literature that investigates production risk in relation to climate or environmental factors within the Just-Pope modeling framework for capture fisheries. However, with careful specification of a model we believe that this framework can still provide valuable insights. With respect to the current literature our contributions are threefold. The first is to identify the risk factors present in production for an effort-controlled fishery. To achieve this, we use an econometric model with Just-Pope production assumptions, which to date has been used infrequently for capture fisheries. Our second contribution is the inclusion of weather-related variables such as wind speed and wave height. These factors affect navigability and prevent fishing from occurring when conditions are poor. As climate change brings about more intense bouts of bad weather, it is a valuable exercise to explore how these phenomena affect fishing seasons. Our third contribution is an empirical application to the commercial lobster fishery in Atlantic Canada. The lobster fishery is the lifeblood of many coastal communities, and it is highly vulnerable to climate change. More targeted studies are needed to understand how this fishery might be impacted, and to develop management and fishing strategies to cope with these changes and their associated uncertainties.

### 4.1.3 Empirical application: the Canadian lobster fishery

The American lobster (*Homarus americanus*) is distributed along the Atlantic coast of North America from North Carolina to Newfoundland and Labrador, with the most abundant populations found in the Gulf of Maine, Nova Scotia, and the southern Gulf of St. Lawrence. The lobster fishery is one of the most lucrative fisheries in Canada, with annual landings close to CAD $2 billion (DFO 2024). The inshore lobster fisheries are managed through input controls with limited entry, gear restrictions, delimited seasons and zones, and protection of juvenile and ovigerous females. These regulations, including the opening dates, length of fishing seasons, and trap limits vary across lobster fishing areas (LFAs). Fishing effort is competitive within LFAs, and there is a particular rush to claim territory and set traps at the beginning of the season. As this management regime restricts fishing effort rather than harvest quota, fishers can strategically increase capacity which creates a race for fish and intensifies fishers' safety risks (Munro and Clark 2003, Reid-Musson et al. 2022).

Although the Canadian lobster fishery has seen record landings in recent years, the future of the fishery is uncertain due to risks posed by climate change. The fishery is frequently subject to delays in season starts due to dangerous weather conditions. It is commonly reported that when the wind speed on a particular day exceeds 26 knots it is considered too dangerous to fish. This applies especially to setting day (the first day of the season when fishers lay their traps at sea), when boats are heavier with the traps aboard. There is evidence that average wave heights in Atlantic Canada have increased since the mid $20^{th}$ century (Rhein et al. 2013, Bromirski and Cayan 2015), and that the frequency of extreme storms has increased (Wang et al. 2016). Therefore, it is timely to study the linkages between extreme weather events and harvest. Given the importance of this fishery and the unique management rules that dictate its operation, we believe that it is the ideal choice for our case study. However, the insights gained from this case study can be extrapolated to other fisheries sharing similar characteristics.

## 4.2 Methodology and data

### 4.2.1 Modeling framework

We estimate a hierarchical mixed-effects model accounting for vessel and fishing area random effects. The Just-Pope production function is flexible in that it allows us to investigate how inputs influence mean harvest separately from how they influence variance of harvest. This is made possible by the additive terms in the production function, which is given by,

$$y = f(x, \beta) + h(x, \xi)\eta \quad (1)$$

where $f$ and $h$ are the mean production function and the variance function, respectively, and production risk is estimated by the variance function $h$. $\eta$ is a stochastic error term with mean zero and variance of 1. $x_1$ and $x_2$ are vectors of variable inputs (e.g., number of trips), fixed/quasi-fixed inputs (e.g., vessel length and tonnage), and environmental factors (e.g., wave height and wind speed). We assume that both the mean production function and the variance function in the Just-Pope production model takes on a Cobb-Douglas form:

$$y_{it} = \beta_0 + \Sigma_j \beta_j x_{it} + \mu_i + \mu_k + u_{it} \qquad (2)$$

$$var(u_{it}) = \xi_0 + \Sigma_j \xi_j x_{it} + \gamma_i + \gamma_k \qquad (3)$$

where $y$ is catch in tonnes, $x$ are the chosen covariates, and $\beta$, $\xi$, $\mu$, and $\gamma$ are the parameters to be estimated. $\mu_i$ and $\gamma_i$ are vessel-level random effects on production and production risk, respectively. $\mu_k$ and $\gamma_k$ are fishing area-level random effects, and $u_{it}$ is the stochastic error term. After estimating the production model, we take the logarithm of the squared residuals and perform the second stage regression to estimate the production risk model. Coefficients are estimated using maximum likelihood estimation (MLE) and robust standard errors are calculated for both models.

### 4.2.2 Data

#### *4.2.2.1 Catch and vessel data*

Anonymized lobster fishing data for the years 1990 to 2018 at the vessel level are aggregated to the monthly level. The number of trips taken by each vessel per month is the main effort-related variable used in the analysis. Vessel length (m) and gross tonnage are used as measures of fishing capacity, and gross tonnage is a categorical variable that takes on values according to the criteria below (Table 4.1). The rationale behind the choice of variables is based on fishery production theory as well as knowledge of the intricacies of this particular fishery. Vessel length is commonly included in mean production as it is a measure of capacity for traps and other gear, as well as an indicator of the number of crew members on board.

**Table 4.1: Gross tonnage and associated factor variables**

| Value | Tonnage |
|---|---|
| 0 | 1-24.9 T |
| 1 | 25-49.9 T |
| 2 | 50-149.9 T |
| 3 | 150-499.9 T |
| 4 | 500-999.9 T |
| 5 | 1000-1999.9 T |

We use Northwest Atlantic Fisheries Organization (NAFO) subdivisions to delimit fishing areas as these areas have the finest spatial resolution that is available for the whole length of the time series. The Canadian lobster fishery is managed at the lobster fishing area (LFA) level, however the data at the

LFA-level has poorer coverage. Our study area encompasses 18 zones in the Bay of Fundy, the Scotian Shelf, and the Gulf of St. Lawrence (Figure 4.1). Smaller amounts are landed in Newfoundland and Northern Quebec but these only account for 0.3% of the landings over this time period.

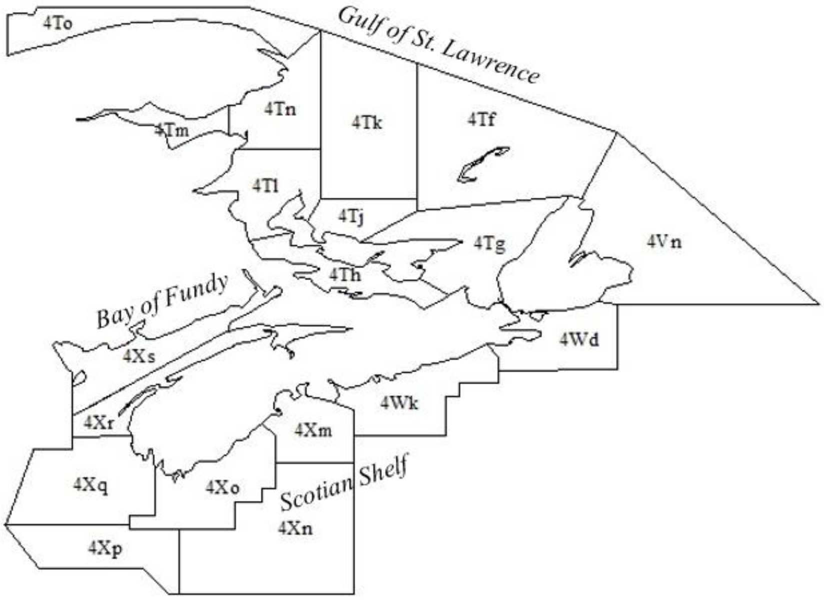


**Figure 4.1: NAFO subdivisions spanning the most productive lobster fishing zones**

#### *4.2.2.2 Wind and waves hindcast*

We use monthly wind speed and wave height data from the Meteorological Service of Canada (MSC) 50 North Atlantic Wave Hindcast. The MSC dataset contains statistics of wind and waves calculated from hourly reanalysis data of historical surface winds and waves for Atlantic Canada for the period 1954-2018. The original purpose of the data was to aid in the study of marine surface climate conditions, trends, and variability for Canadian waters. From this dataset the monthly variables we use in the two models are mean wind speed (km/h), standard deviation wind speed (km/h), mean wave height (m), and standard deviation wave height (m). We also use four variables that represent the number of hours per month that wind speed exceeded 39.6 km/h (11 m/s) and 61.2 km/h (17 m/s), and the number of hours per month that wave height exceeded 3 meters and 6 meters. These statistics are included in the dataset and are not calculated by us. We use nearest neighbours matching to select the grid point closest to the centroid of each fishing area. We observe a significant amount of heterogeneity in wind speed and wave height across the different fishing areas (Figure 4.2).

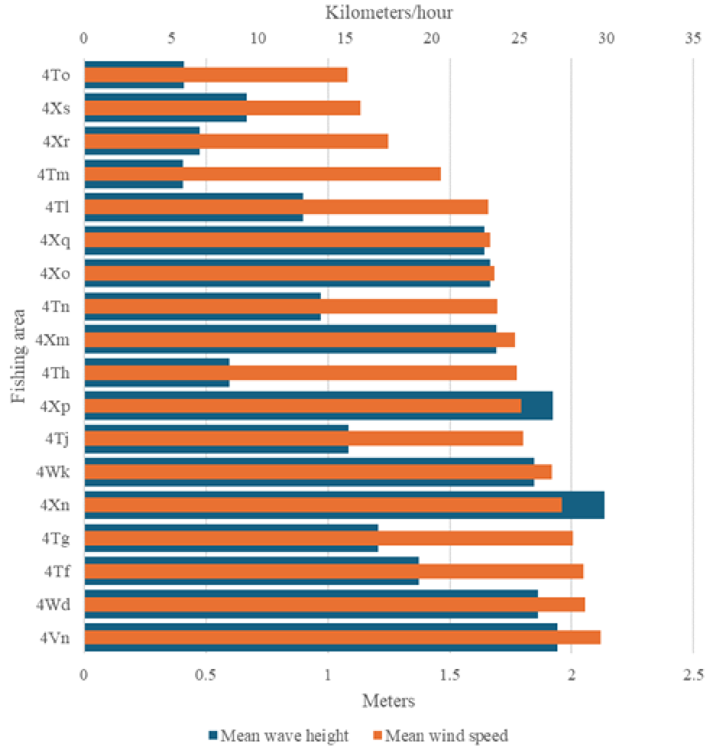


**Figure 4.2: Mean wind speed and wave height by NAFO subdivision**

We observe an overall upward trend in both wind speed and wave height over the 29-year time series (Figure 4.3). Fluctuations are expected as there are cyclical weather patterns that occur, as well as sporadic phenomena such as El Niño and La Niña. However, the upward trend observed over this time period is indicative of intensifying extreme weather events.

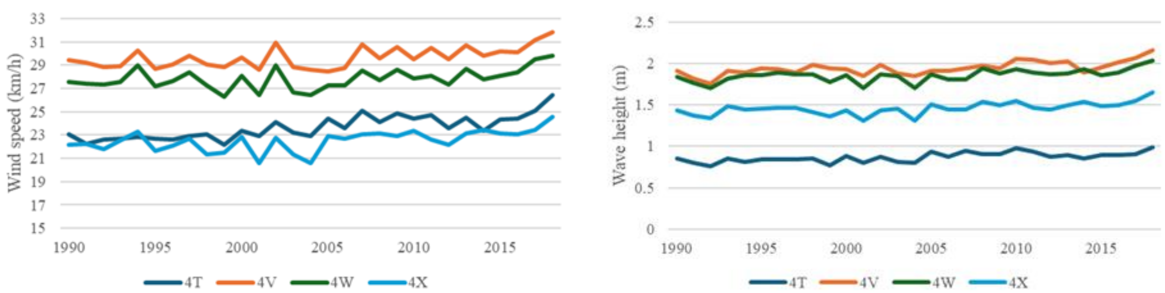


**Figure 4.3: Time series of wind speed (left) and wave height (right) by NAFO division**

We choose to include wind speed and wave height as these are monitored continuously in order to provide marine forecasts and weather warnings (Environment and Climate Change Canada 2017). Wind speed and direction are monitored closely, and wind warnings are issued when wind is expected to be above a certain threshold, e.g., strong wind, gale, storm, and hurricane force. Wave height forecasts are issued twice per day and covers the current day and the next day. This forecast describes the expected significant wave height, which is the average of the highest one-third of all waves.

## 4.3 Results and discussion

Table 4.2 presents the summary statistics of the variables used in the mean production and variance models. The minimum and maximum catch are censored so as to not disclose the catch weight for particular vessels. The average vessel length is 11.7 meters and most vessels that harvest lobster are under 15 meters. On average, vessels undertake 16.6 trips per month during the fishing season. The mean wind speed is 22.1 km/h, varying from a low of 9.2 km/h to a high of 47 km/h. On average there are 65.2 hours when wind speed exceeds 39.6 km/h, and 3.9 hours when it exceeds 61.2 km/h. Wave conditions indicate an average wave height of 1.2 meters, with a range from 0.1 to 4.4 meters. There are, on average, 34.8 hours when wave height exceeds 3 meters, and 0.8 hours when it exceeds 6 meters. The analysis is based on a total of 606.2 thousand datapoints.

**Table 4.2: Variables and associated summary statistics**

| **Variable** | **Mean** | **St. dev.** | **Min.** | **Max.** |
|---|---|---|---|---|
| Weight (tonnes) | 2.6 | 3.0 | | |
| Number of trips | 16.6 | 17.8 | 1 | 31 |
| Length of vessel (m) | 11.7 | 2.1 | 4 | 43 |
| Gross tonnage | 0.06 | 0.27 | 0 | 5 |
| Mean wind speed (km/h) | 22.1 | 5.8 | 9.2 | 47 |
| Std. dev. wind speed (km/h) | 10.4 | 2.3 | 3.6 | 20.1 |
| Hours wind speed>39.6 km/h | 65.2 | 73.5 | 0 | 498 |
| Hours wind speed>61.2 km/h | 3.9 | 9.5 | 0 | 153 |
| Mean wave height (m) | 1.2 | 0.6 | 0.1 | 4.4 |
| Std. dev. wave height (m) | 0.6 | 0.3 | 0.1 | 2.3 |
| Hours wave height>3m | 34.8 | 56.8 | 0 | 513 |
| Hours wave height>6m | 0.8 | 4.3 | 0 | 165 |

N=606,178

In Table 4.3 we present the estimation results of the mean production function. We find the expected result that number of trips is positively associated with expected harvest, as is vessel length and tonnage. For both wind speed and wave height, we analyze both mean and standard deviation as we are interested in not only the monthly average but also the variability of weather conditions over the month. We also look at the four threshold variables because we want to determine the risk to fishing operations that arise when wind speed and wave height exceed a level that is considered dangerous. We would expect the estimation results to yield negative coefficients for these variables, and especially so for the number of hours that wind speed exceeds 61.2 km/h and the number of hours that wave height exceeds 6 meters. We find that average wind speed does not have a statistically significant influence on mean harvest, while the standard deviation of wind speed is found to be negative and significant at the 10% level. In other words, higher variability of wind speed leads to a reduction in mean harvest. Intuitively, small increases in wind speed might not deter fishing operations significantly, while more volatile wind speeds during the month are more likely to affect catch amounts.

The average wind speed over all months that lobster fishing occurs is 22 km/h so looking solely at the average wind speed does little to suggest how dangerous conditions affect monthly harvest. Therefore, we also explicitly look at two threshold variables to see how increasingly dangerous conditions affect fishing operations. According to definitions by Environment and Climate Change Canada, strong wind is classified as being between 20-33 knots (~37-61 km/h). Thus, the first threshold we look at (number of hours that wind speed exceeds 39.6 km/h) surpasses the lower limit for a strong wind warning, but this is still lower than what is often reported as being too dangerous to fish which is 26 knots (~48 km/h). Because of this, it does not come as a surprise that the lower threshold variable yields a positive, albeit very small, coefficient. On the other hand, we would expect the higher threshold variable (number of hours that wind speed exceeds 61.2 km/h) to have a negative estimated coefficient as this verges on gale force wind. But surprisingly we find it is positive and almost three times larger than the coefficient of the lower threshold. It is evident that the less frequent occurrence of these strong winds means that increases in the number of hours during a given month do not deter fishing operations.

Ideally, we would choose different thresholds, but these were the ones chosen by the developers of the MSC reanalysis model.

**Table 4.3: Coefficient estimates from mean production function**

| Variable | Coeff. | Std. error | P-value |
|---|---|---|---|
| Number of trips | 0.0840*** | 0.0082 | 0.000 |
| Length of vessel (m) | 0.3055*** | 0.0336 | 0.000 |
| Gross tonnage | 0.2516** | 0.1111 | 0.024 |
| Mean wind speed (km/h) | 0.0504 | 0.0544 | 0.797 |
| Std. dev. wind speed (km/h) | -0.5266* | 0.0758 | 0.054 |
| Hours wind speed>39.6 km/h | 0.0046** | 0.0021 | 0.028 |
| Hours wind speed>61.2 km/h | 0.0145** | 0.0063 | 0.021 |
| Mean wave height (m) | -0.1099 | 0.8616 | 0.898 |
| Std. dev. wave height (m) | 1.0027* | 0.5893 | 0.089 |
| Hours wave height>3m | -0.0011 | 0.0039 | 0.778 |
| Hours wave height>6m | -0.0458*** | 0.0157 | 0.003 |
| Constant | -2.0964*** | 0.6770 | 0.002 |
| $\mu_i$ (vessel-level effect) | 1.4718*** | 0.0970 | 0.000 |
| $\mu_k$ (area-level effect) | 1.3223*** | 0.2172 | 0.000 |

*** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$

The estimation results show that the coefficient for mean wave height is negative but statistically insignificant, while standard deviation wave height is positive and significant at the 10% level. This is a somewhat unexpected result but there is not as much variation in wave height as in wind speed, so this effect might not truly be captured when using monthly data. The number of hours that wave height exceeds 3 meters is negative but insignificant, while the number of hours that wave height exceeds 6 meters is negative and significant at the 1% level. This suggests that moderately high waves might not deter fishing or lead to reduced catch necessarily, but at this higher threshold wave height the monthly catch is reduced. This is expected, but it is nonetheless an important empirical result given the increasing frequency of storms. We also find significant and positive coefficients for both random effects, indicating the presence of heterogeneity at both the vessel-level and area-level.

Table 4.4 reports the coefficient estimates for the production risk model. A positive coefficient indicates a risk-increasing input while a negative coefficient indicates a risk-decreasing input. Interestingly, while an increase in the number of trips, vessel size, or capacity leads to higher expected catch, we find that these inputs also have a variance-increasing effect. The larger coefficients on the two capacity-related variables are notable, and suggest that while larger vessels are able to catch more on average, catch levels are less consistent and more volatile. Many of the weather-related variables are either statistically insignificant or have a negligible effect, casting doubt on the usefulness of the Just-Pope framework when dealing with data of this nature. The limitations around available data (namely a lack of accurate effort data such as trap hauls, and a lack of data on stock biomass) mean that there is likely a significant amount of noise confounding estimates. We find a significant and positive coefficient for mean wind speed, indicating a risk-increasing effect. This is an interesting finding, as mean wind speed was not found to have a significant effect in the mean production model. On the other hand, the standard deviation of wind speed was found to have a negative association with expected harvest, while in the production risk model there was no significant effect.

**Table 4.4: Coefficient estimates from the production risk model**

| **Variable** | **Coeff.** | **Std. error** | **P-value** |
|---|---:|---:|---:|
| Number of trips | 0.0357*** | 0.0040 | 0.000 |
| Length of vessel (m) | 0.2482*** | 0.0360 | 0.000 |
| Gross tonnage | 0.2387** | 0.1163 | 0.040 |
| Mean wind speed (km/h) | 0.1110*** | 0.0197 | 0.000 |
| Std. dev. wind speed (km/h) | -0.0414 | 0.0519 | 0.426 |
| Hours wind speed>39.6 km/h | -0.0005 | 0.0014 | 0.709 |
| Hours wind speed>61.2 km/h | 0.0072 | 0.0046 | 0.121 |
| Mean wave height (m) | -1.5259*** | 0.3707 | 0.000 |
| Std. dev. wave height (m) | 0.2863 | 0.3176 | 0.367 |
| Hours wave height>3m | 0.0075*** | 0.0026 | 0.004 |
| Hours wave height>6m | -0.0268*** | 0.0080 | 0.001 |
| Constant | -5.1203*** | 0.6879 | 0.000 |
| $\mu_i$ (vessel-level effect) | 0.8477*** | 0.0444 | 0.000 |
| $\mu_k$ (area-level effect) | 1.5510*** | 0.2993 | 0.000 |

*** p < 1%; ** p < 5%; * p < 10%

Despite its limitations, our analyses suggest that weather-related variables exert an influence on both mean harvest and variance of harvest in the Canadian lobster fishery. Notably, we find that standard deviation wind speed has a significant negative influence on mean harvest, and that average wind speed has a significant risk-increasing effect on harvest. Although it seems like an anticipated finding that weather conditions, particularly extreme ones, influence fishing operations, it highlights that this is a significant challenge that warrants further attention and research. Poor weather conditions frequently scuttle fishing operations, but confirming this by using real historical data provides a quantitative basis for what has often been observed anecdotally. This empirical evidence is crucial for developing targeted policy measures to support the lobster fishery under varying weather conditions. Additionally, the estimated coefficients for the variables related to vessel capacity are notable, and the presence of heterogeneity as estimated by the random effects underscores the need for tailored management approaches. Management strategies should consider vessel capabilities and regional specificities to effectively mitigate the impacts of adverse weather on the lobster fishery.

Our findings are timely as climate change reshapes weather patterns, causing fishers to face more frequent or severe inclement weather conditions. Poor weather conditions are not only a significant contributor to occupational risk, but fishing activities are significantly impacted by them. Unfavorable weather affects the ability of fishing vessels to operate safely, leading to reduced fishing days and making it more challenging for fishers to plan and carry out their fishing activities efficiently. Unpredictable weather, coupled with an uncertain economic climate, could result in a concerning 'perfect storm' for the industry.

The Canadian lobster fishery is effort-controlled and not subject to rights-based fisheries management such as individual fishing quotas (IFQ). Effort-controlled fisheries, unlike quota fisheries, may experience increased production risk during adverse weather conditions as reduced fishing opportunities can lead to uncertain catch levels and economic returns (Pfeiffer and Gratz 2016). Consequently, this management regime incentivizes a race to fish the most productive areas, and this pressure can lead to fishing in dangerous conditions to minimize production shortages that might occur due to prolonged bad weather. To reduce production risk, more proactive support from fisheries authorities and managers might be required to help fishers adapt to changing climate and economic situations and build resilience for the fishing industry and coastal communities. Introducing some flexibility in regulations such as season extensions during years of particularly unfavourable weather conditions could help mitigate production risks and improve climate resilience.

In addition, economic instruments such as individual vessel/transferable quota, also called catch shares, may be introduced to minimize production risks if appropriately set (Pfeiffer and Gratz 2016). Catch shares provide security and flexibility to fish when they want or during times of the year when the value of their catch is higher, or costs are lower (Grafton 1996; Birkenbach et al. 2017; Hoshino et al. 2020). A 2017 meta-analysis tested 39 fisheries in the USA and found strong evidence that catch shares reduce race to fish competition and extend fishing seasons (Birkenbach et al. 2017). Another potential benefit of catch shares is improved fisher safety. Pfeiffer and Gratz (2016) found that after the implementation of catch shares in the United States West Coast sablefish fishery, a harvester's probability of taking a trip in high wind conditions decreased significantly, and that the average annual rate of fishing on high wind days decreased by 79%.

Although to our knowledge there are no current discussions on adopting catch shares in the lobster fishery, this strategy has been proven to be effective in other fisheries and this warrants further research and discussion. Given the immense uncertainty that fisheries face in the coming years, more effective and efficient solutions may be required to reduce production risk, protect fishers' livelihoods and well-being, while also protecting marine resources. While this case study focuses on the lobster fishery in Canada, the issues discussed in this paper are not unique to this fishery. We believe there are valuable insights that can be applied to fisheries with similar challenges such as inclement weather, management that includes timed openings, and effort-controlled management regime.

As previously noted, our study has some limitations. Ideally, measures of effort-related inputs such as number of traps used per trip, setting hours at sea, crew, and actual travel distance should be used in the model, but unfortunately these data are not publicly available. Stock biomass is an important part of fisheries production functions, but reliable biomass estimates are not available for the vast region covered in this study. Lastly, the reanalysis data from the MSC dataset is the best option available for weather trends as it has the best spatial and temporal coverage, but it might not be reflective of the exact conditions at each location and at each point in time.

## 4.4 Conclusion

In this study, we aimed to investigate production risk in the lobster fishery in Atlantic Canada. This fishery provides an insightful setting for an empirical case study as it is an input-controlled rather than quota-controlled fishery. This management approach lends to various challenges and might lead to greater variation in production, especially as many elements influential to production are beyond fishers' control. The fishery is one of the most commercially important fisheries in Canada, but it is known to be subject to frequent delays due to poor weather conditions, as well as volatile buyer and input markets.

To assess production risk, we first estimated a mean production model using a Cobb-Douglas functional form. We then used the residuals in a new regression on the covariates to obtain estimates of production risk. This approach helps identify factors that either increase harvest variance (risk-increasing) or reduce harvest variance (risk-decreasing). The Just-Pope production model facilitates this analysis by allowing separability between the mean harvest function and the variance function. We found significant effects for some inputs, and notably we found that wind speed is influential for both components of production. The analysis highlights the importance of region-specific management strategies that account for varying weather patterns and the capabilities of fishing vessels. We discuss some potential adaptive strategies, with a focus on the management of the fishery and propose the implementation of output controls such as catch shares as a potential management solution to mitigate production risk, and provide other benefits such as enhanced fishery safety, economic considerations, and biological health of the stock. Given the crucial role of the lobster fishery in many communities along the coast of Atlantic Canada, ongoing careful monitoring and informed, appropriate interventions are critical to ensure its sustainable future.

## 4.5 References

Asche, F., Cojocaru, A.L., Pincinato, R., Roll, K.H. (2020) Production Risk in the Norwegian Fisheries. Environmental and Resource Economics, 75: 137-149.

Battese, G.E., Rambaldi, A.N., Wan, G.H. (1997) A Stochastic Frontier Production Function with Flexible Risk Properties. Journal of Productivity Analysis, 8: 269-280.

Birkenbach, A.M., Kaczan, D.J., Smith, D.J. (2017) Catch shares slow the race to fish. Nature, 544(7649): 222-226.

Bockstael, N.E., Opaluch, J.J. (1983) Discrete modelling of supply response under uncertainty: The case of the fishery. Journal of Environmental Economics and Management, 10(2): 125-137.

Bromirski, P.D., Cayan, D.R. (2015) Wave power variability and trends across the North Atlantic influenced by decadal climate patterns: North Atlantic Decadal Wave Variability. Journal of Geophysical Research: Oceans, 120: 3419-3443.

Burke, D. (2016) Lobster season on Nova Scotia's southwest coast delayed by bad weather. from https://www.cbc.ca/news/canada/nova-scotia/lobster-fishing-dfo-delays-fishermen-safety-weather-1.3869898.

DFO (2022) Fisheries and Oceans Canada, Lobster Fishing Areas 27 – 38: Integrated Fisheries Management Plan https://www.dfo-mpo.gc.ca/fisheries-peches/ifmp-gmp/maritimes/2022/inshore-lobster-homard-cotiere-eng.html.

DFO (2024) Fisheries and Oceans Canada, Seafisheries landed value by province, 2022 https://www.dfo-mpo.gc.ca/stats/commercial/land-debarq/sea-maritimes/s2022pv-eng.htm.

Do, H.L., Thuy, T.D. (2022) Productivity response and production risk: A study of mangrove forest effects in aquaculture in the Mekong River Delta. Ecological Economics, 194: 107326.

Dupont, D.P. (1993) Price Uncertainty, Expectations Formation and Fishers' Location Choices. Marine Resource Economics, 8(3): 219-247.

Eggert, H., Tveterås, R. (2004) Stochastic Production and Heterogeneous Risk Preferences: Commercial Fishers' Gear Choices. American Journal of Agricultural Economics, 86(1): 199-212.

Emery, T.J., Hartmann, K., Green, B.S., Gardner, C., Tisdell, J. (2014) Fishing for revenue: how leasing quota can be hazardous to your health. ICES Journal of Marine Science, 71(7): 1854-1865.

Environment and Climate Change Canada (2017) Marine weather products and services: Atlantic coast https://www.canada.ca/en/environment-climate-change/services/general-marine-weather-information/understanding-forecasts/regional/products-services-atlantic-coast.html#p2.

Fox-Kemper, B., Hewitt, H.T., Xiao, C., Aðalgeirsdóttir, G., Drijfhout, S.S., Edwards, T.L., …, Yu, Y. 2021: Ocean, Cryosphere and Sea Level Change. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York: 1211–1362.

Holland, D.S. (2008) Are Fishermen Rational? A Fishing Expedition. Marine Resource Economics, 23(3): 325-344.

Grafton, R.Q. (1996) Individual transferable quotas: theory and practice. Reviews in Fish Biology and Fisheries, 6: 5–20.

Harvey, A.C. (1976) Estimating Regression Models with Multiplicative Heteroscedasticity. Econometrica, 44(4): 461-465.

Holst, R., Yu, X., Grün, C. (2013) Climate change, risk and grain yields in China. Journal of Integrative Agriculture, 12(7): 1279-1291.

Hoshino, E., Van Putten, I., Pascoe, S., Vieira, S. (2020) Individual transferable quotas in achieving multiple objectives of fisheries management. Marine Policy, 113: 103744.

Isik, M., Devadoss, S. (2006) An Analysis of the Impact of Climate Change on Crop Yields and Yield Variability. Applied Economics, 38(7): 835-844.

Just, R.E., Pope, R.D. (1978) Stochastic specification of production functions and economic implications. Journal of Econometrics, 7: 67-86.

Just, R.E., Pope, R.D. (1979) Production function estimation and related risk considerations. American Journal of Agricultural Economics, 61(2): 276-284.

Khan, A., Guttormsen, A., Roll, K.H. (2018) Production risk of pangas (*Pangasius hypophthalmus*) fish farming. Aquaculture Economics & Management, 22(2): 192-208.

Kumbhakar, S.C. (1993) Production risk, technical efficiency, and panel data. Economics Letters, 41(1): 11-16.

Kumbhakar, S.C., Tveterås, R. (2003) Risk preferences, production risk and firm heterogeneity. Scandinavian Journal of Economics, 105: 275-293.

Leal, D.R. (Ed) (2005) Evolving property rights in marine fisheries. Oxford, UK: Rowman and Littlefield Publishers Inc.

Mistiaen, J.A., Strand, I.E. (2000) Location Choice of Commercial Fishermen with Heterogeneous Risk Preferences. American Journal of Agricultural Economics, 82(5): 1184-1190.

Munro, G.R., Clark, C.W. (2003) Fishing Capacity and Resource Management Objectives, in S. Pascoe and D. Gréboval (Ed) Measuring capacity in fisheries, FAO Fisheries Technical Paper 445.

Pfeiffer, L., Gratz, T. (2016) The effect of rights-based fisheries management on risk taking and fishing safety. Proceedings of the National Academy of Sciences, 113(10): 2615-2620.

Pfeiffer, L., Petesch, T., Vasan, T. (2022) A safer catch? The role of fisheries management in fishing safety. Marine Resource Economics, 37(1): 1-33.

Reid, H., Finnis, J. (2019) Summarizing metocean operating conditions as a climatology of marine hazards. Theoretical and Applied Climatology, 135: 1387-1397.

Reid-Musson, E., Finnis, J., Neis, B. (2021) Bridging fragmented knowledge between forecasting and fishing communities: Co-managed decisions on weather delays in Nova Scotia's lobster season openings. Applied Geography, 133: 102478.

Reid-Musson, E., Neis, B., Finnis, J. (2022) Fishing safety and timed openings in Atlantic Canada's lobster fisheries: the mediating role of local management systems. Maritime Studies, 21: 223-234.

Rhein, M., Rintoul, S.R., Aoki, S., Campos, E., Chambers, D., Feely, R.A., …, Wang, F. (2013) Observations: Ocean. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York: 255-316.

Sainsbury, N.C., Schuhmann, P.W., Turner, R.A., Grilli, G., Pinnegar, J.K., Genner, M.J., Simpson, S.D. (2021) Trade-offs between physical risk and economic reward affect fishers' vulnerability to changing storminess. Global Environmental Change, 69: 102228.

Smith, M.D. (2002) Two Econometric Approaches for Predicting the Spatial Behavior of Renewable Resource Harvesters. Land Economics, 78(4): 522-538.

Smith, M.D., Wilen, J.E. (2005) Heterogeneous and Correlated Risk Preferences in Commercial Fishermen: The Perfect Storm Dilemma. The Journal of Risk and Uncertainty, 31(1): 53-71.

Stafford, T.M. (2018) Accounting for outside options in discrete choice models: An application to commercial fishing effort. Journal of Environmental Economics and Management, 88: 159-179.

Tveterås, R. (1999) Production Risk and Productivity Growth: Some Findings for Norwegian Salmon Aquaculture. Journal of Productivity Analysis, 12: 161-179.

Wang, X.L., Feng, Y., Chan, R., Isaac, V. (2016) Inter-comparison of extra-tropical cyclone activity in nine reanalysis datasets. Atmospheric Research, 181: 133-153.

Yu, Y., Tian, Q., Xing, X., Huang, J. (2024) Heterogenous response of rice yield to climate factors: a Just-Pope stochastic production function and quantile regression analysis. Theoretical and Applied Climatology, 155(3): 2297-2309.

# 5 Conclusion

As climate change continues to pose significant threats to global fisheries, the growing availability of extensive datasets offers a unique opportunity to conduct empirical studies that explore the intricate connections between fishery dynamics and the natural environment. These studies are essential for uncovering how shifting environmental conditions such as rising sea temperatures, increasingly frequent extreme weather events, and changing marine ecosystems affect fish populations, harvests, and the broader socio-economic systems that depend on them. By analyzing these relationships, research can generate evidence-based insights to inform the development, refinement, and implementation of adaptive management strategies in response to climate change. Such strategies are critical for safeguarding the livelihoods of communities that rely on fisheries, ensuring sustainable resource use, and enhancing resilience to climate-driven disruptions. To achieve these goals, these studies in this thesis employ advanced econometric and statistical methods, which enable the estimation of key parameters and the identification of trends, patterns, and causal relationships. The findings from these studies not only advance our understanding of fisheries economics but also contribute to the broader discourse on sustainable resource management in the face of a changing climate. Paper 1 investigates the relationship between ocean temperature change and catch using a production function that directly includes bottom temperature as an input. A generalized linear mixed model (GLMM) with random effects is employed to account for heterogeneity among fishing vessels and locations. Estimations reveal a statistically significant relationship between temperature and catch, and also finds that the mixed-effects model performs better in estimation than a standard pooled model.

Paper 2 utilizes Emerging Hotspot Analysis, a novel geostatistical approach to identify areas that are experiencing significant warming effects. It first identifies areas that are experiencing notable trends in ocean temperature changes, then a generalized linear model (GLM) is used to assess how catch per unit effort (CPUE) aligns with these warming effects. The findings provide solid evidence that emerging hotspots of warming waters are associated with higher catch rates, particularly in areas where warming effects are intensifying. This provides valuable insights into how localized climate changes influence fishery productivity.

Paper 3 frames climate change impacts on fisheries within the concept of production risk. The Just and Pope (1978 and 1979) production model is adopted as it enables production risk to be evaluated through the variation in harvest in addition to expected harvest. This dual capability allows us to assess not only how the intensity of inputs contributes to overall harvest, but also how they increase or decrease production risk. It identifies risk factors present in production resulting from effort, vessel-related, and environmental variables. In particular, it finds evidence that wind speed increases production risk.

Together, this thesis provides a comprehensive understanding of how climate change influences fishery production, offering empirical evidence and methodological innovations that contribute to the development of adaptive management strategies in response to changing climate. The findings emphasize the need to account for environmental variability, localized warming trends, and production risks to ensure the resilience and sustainability of fisheries in a changing climate.

# Appendix

*Attached: Wright, D., Liu, Y. (2023) Assessing the impact of environmental variability on harvest in a heterogeneous fishery: a case study of the Canadian lobster fishery. Journal of Environmental Economics and Policy, 13(1): 55-69. doi: 10.1080/21606544.2023.2207535*


Journal of Environmental Economics and Policy

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/teep20

# Assessing the impact of environmental variability on harvest in a heterogeneous fishery: a case study of the Canadian lobster fishery

Dana Wright & Yajie Liu

**To cite this article:** Dana Wright & Yajie Liu (2024) Assessing the impact of environmental variability on harvest in a heterogeneous fishery: a case study of the Canadian lobster fishery, Journal of Environmental Economics and Policy, 13:1, 55-69, DOI: 10.1080/21606544.2023.2207535

**To link to this article:** https://doi.org/10.1080/21606544.2023.2207535



Published online: 11 May 2023.

JOURNAL OF ENVIRONMENTAL ECONOMICS AND POLICY
2024, VOL. 13, NO. 1, 55–69
https://doi.org/10.1080/21606544.2023.2207535



# Assessing the impact of environmental variability on harvest in a heterogeneous fishery: a case study of the Canadian lobster fishery

Dana Wright and Yajie Liu

Norwegian College of Fishery Science, Faculty of Biosciences, Fisheries and Economics, The Arctic University of Norway, Tromsø, Norway

**ABSTRACT**

Global fisheries face significant challenges in the coming years due to climate change. Understanding and anticipating the impacts of climate change is a necessity for implementing appropriate fisheries management. This study uses a panel dataset of individual fishing vessels to examine how variation in ocean temperature affects fish harvest. Using the American lobster (*Homarus americanus*) fishery in the Maritimes region of Canada as a case study, this paper employs a generalised linear mixed model (GLMM) taking into account heterogeneity amongst fishers, gear, vessels, and fishing areas. The GLMM is found to have better performance and estimations when compared against alternative specifications. As expected, a significant and positive relationship was found, further contributing to the existing evidence of warming impacts on the lobster fishery. The implications of this study are twofold: first, it provides further evidence that environmental change does have a significant positive impact on harvest. This information should be considered by fishing industry and fisheries authorities when implementing appropriate adaptive management strategies and measures in their decision making. Second, it illustrates that allowing for mixed-effects using GLMMs is a valuable empirical tool when dealing with hierarchical data structures.

**ARTICLE HISTORY**
Received 17 October 2022
Accepted 18 April 2023

**KEYWORDS**
Generalised linear mixed model; mixed-effects; bioeconomics; climate change; environmental variable; heterogeneity

**JEL CODE**
C18; C33; Q21; D22; Q50; C52; Q54

## 1. Introduction

Global fisheries face significant challenges in the coming years, many of which are caused either directly or indirectly by climate change. According to the Intergovernmental Panel on Climate Change (IPCC)'s special report on the ocean and cryosphere, the world's oceans are becoming warmer and more acidic, impacting the productivity, abundance, and distribution of marine species (Bindoff et al., 2019). As waters warm beyond species' optimal range, species that once inhabited certain areas may begin to move their distribution northward and into deeper waters, while some may begin to die out entirely. A global study revealed that climate change extensively affects the distribution of global catch potential leading to changes in fisheries productivity, with increase in the polar regions and a loss in the tropics (Cheung et al. 2010). Harvesters and communities that are heavily reliant on fisheries revenue are the most vulnerable to these changes. This is especially true for the ones who cannot diversify the species they catch or obtain alternative

**CONTACT** Dana Wright dana.e.wright@uit.no

employment. Climate-induced changes in productivity and distribution pose challenges to fisheries management (Bryndum-Buchholz et al. 2020). Thus, anticipating the consequences of climate change on fishing operations and advancing our understanding of these impacts is crucial for developing appropriate mitigation and adaptation measures.

This paper seeks to empirically investigate the impacts of changing environmental conditions on a fishery resource using a panel dataset of harvest and fishing effort of commercial vessels. The inclusion of environmental variables in the harvest production function is a convenient way to estimate the relative effects on harvest by treating the environmental variable as an additional input in production. However, this is not without its limitations – there are several pitfalls that can arise when attempting this type of modelling exercise. For example, the model can suffer from omitted variables such as missing stock size data or unobserved characteristics between subjects. These latent variables may be correlated with the explanatory variables, violating the key assumption of independence that is required for ordinary linear regression. While traditional fisheries production models assume homogeneity among fishers, vessels, and fishing areas, more recent research confronts the issue of how to incorporate heterogeneity among these factors of production. This is a key issue that is explored in depth in this paper.

A generalised linear mixed model (GLMM) with both fixed and random effects is employed to account for heterogeneity among fishing vessels and fishing locations. It will attempt to isolate the effect of ocean bottom temperature on annual harvest from other production inputs; this effect is disentangled from the operational and effort-based measures such as number of fishing days, vessel size, and vessel power. Exploiting the hierarchical structure of the data, we are able to mitigate some of the common pitfalls that are often encountered, and to show that efficiency in estimation is improved. Compared against a model without mixed effects, we find that the mixed-effects model performs better in estimation. As a case study, we use the American lobster (*Homarus americanus*) fishery in Canada to explore how ocean bottom temperature affects harvest, but it is important to note that this method can also be applied to other fisheries and to other environmental variables. The main contribution of this paper is to provide a robust econometric framework for empirical estimation of environmental elasticities as an input in production of a natural resource.

## 2. Case study: the American lobster fishery in Atlantic Canada

The American lobster (*Homarus americanus*) is geographically distributed along the coast of the northwestern Atlantic, ranging from North Carolina to Newfoundland and Labrador (DFO 2020). The most abundant populations are found in the Gulf of Maine, the Nova Scotian shelf, and the southern Gulf of St. Lawrence. The lobster fishery is the most commercially important fishery in Atlantic Canada, with annual landed value exceeding CAD $1 billion (DFO 2021a).[1] The fishery in the Scotia-Fundy region alone provides employment for approximately 7,500 people and generates many other direct and indirect economic benefits (DFO 2020). It has become the backbone for the inshore commercial fisheries in the region. It is ecologically important to the biodiversity of the area, and it is an intrinsic part of the culture and identity of the East Coast of Canada (Greenan et al. 2019). Although the Canadian lobster fishery has seen record landings in recent years, the future of the fishery is uncertain due to risks posed by climate change. It is difficult to predict the net effects of climate change on lobster populations as stocks will be influenced by changes at both the regional level and larger scale changes in ocean conditions (DFO 2020).

Lobster fisheries in Canada are primarily located in inshore waters of the Maritimes region. This paper focuses on the lobster fisheries in the Scotia-Fundy region of Canada, which includes the eastern coast of Nova Scotia and the Bay of Fundy. These correspond to lobster fishing areas (LFAs) 27–34 and 35–38, respectively (Figure 1). This region encompasses the inshore waters from the northern tip of Cape Breton to the New Brunswick-Maine border and is one of the most productive regions for lobster fishing in Canada. This paper focuses only on the inshore lobster fishery, as the offshore lobster fishery (LFA 41) is managed separately and accounts for a small amount of annual landings.

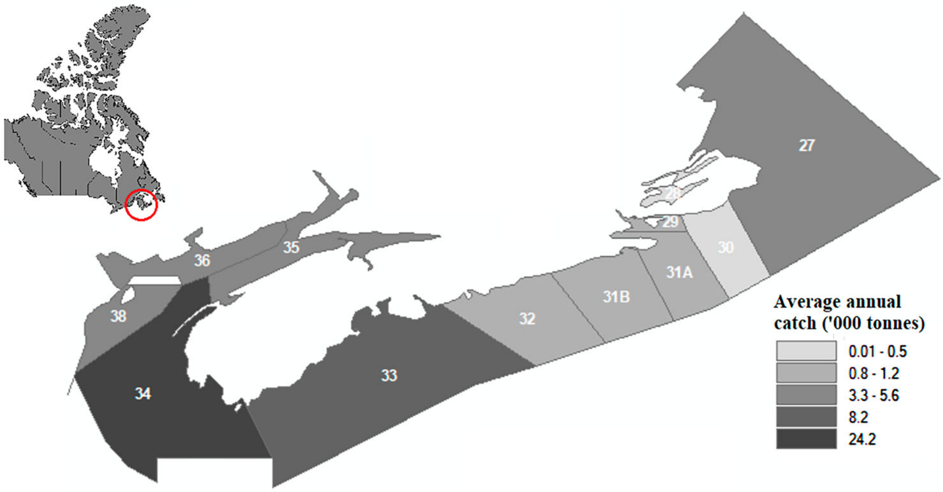


**Figure 1.** Inshore lobster fishing areas (LFAs) in the Scotia-Fundy region of Canada. The shaded regions depict average annual landings in thousand tonnes for the years 2014–2018.

The inshore lobster fisheries are managed through effort-based controls with limits on number of licences and traps, delimited seasons and zones, and protection of juvenile and ovigerous females. The fishing areas (LFAs) are the primary management tool to control fishing effort for each designated area, and the opening and length of fishing season vary across different LFAs (Reid-Musson and Neis 2022). There are also restrictions on number of traps per licence holder that also varies by licence type and LFA. Fishing effort is fully competitive, and this type of management may potentially create a 'race to fish' scenario and intensify harvesters' safety risks (Reid-Musson and Neis 2022).

In the North Atlantic, air temperatures are rising and ocean circulation patterns are changing, leading to higher temperatures both at the surface and in deeper waters of the ocean (DFO 2021b). It has been well-established that rising ocean temperature has an impact on lobsters' habitat preference, coincided with the species' range shifting further north (Le Bris et al. 2018; Greenan et al. 2019; Goode et al. 2019; Tanaka et al. 2020). As ocean temperatures are cooler in the Scotian Shelf and Gulf of Maine than in areas that have experienced stock depletion such as New England, warming ocean temperatures have increased lobster habitat suitability in these regions (ASMFC 2020). Higher temperatures also have an impact on lobsters' growth, size at maturity, and reproduction. It affects molting phenology making them more vulnerable to predators, and it increases susceptibility to epizootic shell disease (Groner et al. 2018). These climate-induced changes in habitat and biological functions present challenges for the management of lobster fisheries in the region.

## 3. Literature review

There are two broad categories of economic production models to analyse fisheries: optimal or simulated bioeconomic production models (e.g. the classical Gordon-Schaefer model) and empirical econometric modelling. The former combines biological/ecological and economic components in the optimal or simulation setting for homogenous fisheries, while the latter applies econometric techniques based on cross-sectional, time-series, and panel data on individual fishing vessels. A detailed review of fisheries production models can be found in Squires and Walden (2021).

It has long been acknowledged that ocean biophysical conditions such as water temperature, salinity, waves, wind, and storms have effects on fish stocks (Bindoff et al., 2019). Given the uncertainty and complexity of the linkages between environmental conditions and fish stocks, the incorporation of environmental variables in fisheries production models has been sporadic. Population dynamics are influenced by environmental characteristics in many complex, and often nonlinear ways. The limitations in methodologies and availability of data have impeded researchers' abilities to empirically assess the impacts of climate change on fishery resources and fishing sectors. The inherent complexity of ecological systems lends to interactions with the environment in bioeconomic modelling being simplistic. Despite this, there are some notable examples of economic models being applied to estimate production in the midst of a changing environment.

Environmental variables might be included as an input in production (Barbier 2000), but alternatively they might enter the biomass growth function, or alter consumers' utility functions. Lynne, Conroy, and Prochaska (1981) examined the Florida Gulf Coast blue crab fishery, which relies on the threatened mangrove forests as habitat. In this case, the extent of mangrove forest is the environmental input and the relationship between catch and mangrove area is modelled. Similarly, Barbier and Strand (1998) modelled catch against mangrove area in the shrimp fishery in the Bay of Campeche, Mexico. Kahn and Kemp (1985) estimate the economic losses from the destruction of submerged aquatic vegetation on the commercial striped bass fishery in Chesapeake Bay. They estimated industry supply and demand functions where environmental degradation enters the supply function, and the equations are solved to find the bioeconomic equilibrium catch under different levels of degradation. Foley, Van Rensburg, and Armstrong (2010a) and Foley, Kahui, Armstrong (2010b) examine the bioeconomic interplay between cold water coral as habitat for fish species and the impacts of habitat reduction on these species. Cheung et al. (2010) used a dynamic bioclimate envelope model to project the maximum exploitable catch of a species under climate change scenarios, and the findings suggest that the polar region is benefiting while the tropics are losing from climate change.

Several empirical studies have linked environmental variables to harvest in the lobster fisheries of Canada and the United States. Bell and Fullenbaum (1972) were one of the first to include a variable for environmental quality in the analysis of the inshore lobster fishery in the United States. In this case study, seawater temperature appeared directly in the production function. The results indicated that seawater temperature has a positive effect on the growth of the lobster stock, citing trends that suggest that declining seawater temperature is partially responsible for declining coastal lobster catches. Henderson and Tugwell (1979) estimated a production function for two lobster fishing areas in Nova Scotia that included both current and lagged bottom temperature. The assumption is that temperature affects the catchability of lobster, as lobsters tend to move around more and cover more territory when temperature rises. Several other studies found correlations between lobster harvest and ocean temperature, such as McCleese and Wilder (1958), Dow (1961), and Flowers and Saila (1972). Hudon (1994) and Drinkwater et al. (2006) similarly found correlations between harvest and temperature, and in addition found wind to be a significant determinant of catch amounts.

As with some of the existing studies, this current paper incorporates environmental values by having the environmental variable enter the model as an input directly in the harvest production function. With the increasing availability of panel data and more advanced econometric techniques, empirical vessel-level analysis in response to environmental issues has garnered more interest. Huang, Smith, and Craig (2010) used a differenced bioeconomic framework and individual fishing data combined with oxygen monitoring data to quantify the economic effects of hypoxia on the brown shrimp fishery in North Carolina. Later, Huang and Smith (2014) applied a restricted Cobb–Douglas production function to model harvest which is determined by both fishing inputs and other inputs such as season closure, wind, waves, and stock size. Autoregressive models combined with Seemingly Unrelated Regression (SUR) models were applied to estimate an output production function. Nguyen (2022) used a partial equilibrium analysis with combined production, demand, and aggregate supply functions to project welfare impacts of climate change on fisheries in Vietnam. In this study, the production function included sea surface temperature, precipitation, number of typhoons, maximum wind speeds of typhoons, and the Southern Oscillation Index. An autoregressive distributed lag model (ARDL) was used to predict fishery yields.

When the panel data are complex and nested, e.g. fishers operating within fishing areas, multilevel modelling (otherwise known as mixed-effects or hierarchical modelling) is a powerful tool that can accommodate various data structures and improve inference (Gelman 2006; Gelman and Hill 2006). Generalised linear models (GLMs) are a generalisation of linear regression that allow a linear model to be related to the response variable via a link function (Nelder and Wedderburn 1972). Generalised linear mixed models (GLMMs) are an extension of GLMs that allow for both fixed and random effects to be estimated when data has a hierarchical structure (Breslow and Clayton 1993). The fixed effect is the population-averaged effect, while the random effects are the subject-specific effects that manifest through variances that represent individual-specific heterogeneity. Mixed-effects modelling can be a useful tool in fisheries research because there are often many unobserved characteristics that confound estimation (Hyun, Cadrin, and Roman 2014; Thorson and Minto 2015), but this method has also been widely applied in disciplines such as ecology (Venables and Dichmont 2004; Bolker et al. 2009; Harrison et al. 2018), psychology (Moscatelli, Mezzetti, and Lacquaniti 2012; Meteyard and Davies 2020; Bono, Alarcón, and Blanca 2021), and medicine (Dean and Nielsen 2007; Casals, Girabent-Farrés, and Carrasco 2014).

## 4. Material and methods

### 4.1. Methodology

A Cobb–Douglas harvest production function is specified, the goal of which is estimate and assess the relative effects of an environmental variable (ocean temperature) as well as technical and effort-based variables (number of days fished, length of vessel, and vessel tonnage) on lobster harvest. The hope is that the model yields reliable coefficient estimates that can allow us to glean something about the relationship between environmental variability and harvest without undue complexity.

First, we consider the following basic model,

$$y_{ijt} = \beta_0 + \beta_1 d_{ijt} + \beta_2 l_{ijt} + \beta_3 g_{ijt} + \beta_4 t_{jt} + \varepsilon_{ijt} \tag{1}$$

where $y$ is harvest, $d$ is days fished, $l$ is length of vessel, g is gross tonnage, t is temperature anomaly, and $\varepsilon$ is the idiosyncratic error term. The subscript $i$ corresponds to each vessel, $j$ to LFA, and $t$ to year. Since the data have a hierarchical structure (vessels operating within fishing areas), we exploit this by using a generalised linear mixed model (GLMM) that allow for random effects to be specified. In matrix form, the specification is given by,

$$g\{E(y|X, u)\} = X\beta + Zu \tag{2}$$

where the dependent variable $y$ is an $n \times 1$ vector. $X$ is an $n \times k$ design matrix for the fixed effects $\beta$. This contains the explanatory variables and their associated coefficients. $Z$ is an $n \times m$ design matrix for the random effects $u$. $g$ is the invertible link function which can take on many different functional forms. In our case, the outcome variable is annual harvest of individual fishing vessels, which is a continuous and repeated variable and is heavily right-skewed, not normally distributed (Figure 2). Different distributions can be used to deal with this, but log-normal is chosen as we suspect this most closely approximates the data-generating process. Therefore, we choose a log link function and a Gaussian distributional family.

Taking the hierarchical structure of the data into consideration and allowing for random intercepts, we consider the following extended model,

$$y_{ijt} = \beta_0 + \beta_1 d_{ijt} + \beta_2 l_{ijt} + \beta_3 g_{ijt} + \beta_4 t_{jt} + u_{ij} + u_j + \varepsilon_{ijt} \tag{3}$$

where the first six terms represent the fixed component and are equivalent to Equation (1). This is the dependent variable, the explanatory variables, and their estimated coefficients. The last three

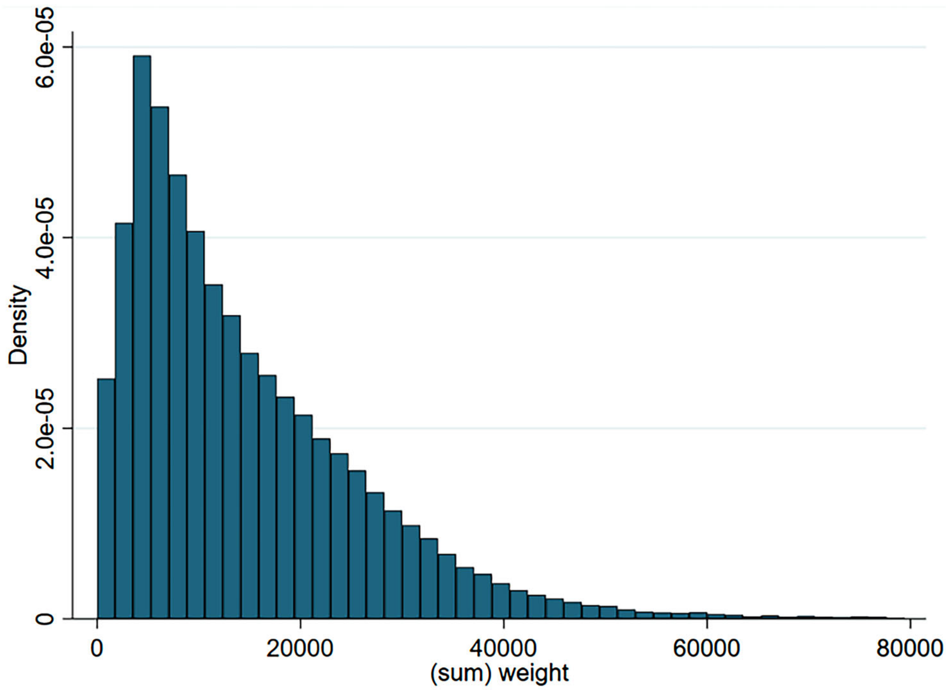


**Figure 2.** Histogram of harvest observations (kg).

terms represent the random component which are two additional random intercepts and the error term. To illustrate the intuition behind the three levels of effects, consider the following equations,

$$y_{ijt} = \gamma_{0j} + \gamma_{0ij} + \beta_1 d_{ijt} + \beta_2 l_{ijt} + \beta_3 g_{ijt} + \beta_4 t_{jt} + u_{ij} + u_j + \varepsilon_{ijt} \tag{4}$$

$$\gamma_{0j} = \beta_{00} + u_{oj} \tag{5}$$

$$\gamma_{0ij} = \beta_{000} + u_{oij} \tag{6}$$

The equation for the intercept $\gamma_{0j}$ consists of the LFA-level mean intercept $\beta_{00}$ and an LFA-specific random intercept $u_{oj}$. The equation for the intercept $\gamma_{0ij}$ consists of the overall mean intercept $\beta_{000}$ and a vessel-specific random intercept $u_{oij}$. Rearranging and collapsing to one intercept for the fixed portion of the model, we are left with Equation (2) where $u_j$ represents the LFA-level unobserved effects and $u_{ij}$ represents the vessel-within-LFA unobserved effects.

The reasoning behind this choice of model is that in addition to stochastic effects, there are unobserved effects that are particular to LFAs and vessels. At the vessel level, there may be technological inputs or crew skill that are not accounted for. At the LFA level, there are oceanographic, biological, and ecological influences that are difficult to observe or quantify. Accounting for multilevel structures in the data can improve statistical inferences. As opposed to ordinary linear regression which treats all explanatory variables as independent and calculates standard errors using only the residual variance, mixed-effects models allow subjects at each level to deviate by its own mean and calculates standard errors using both the residual variance and the variance between the higher levels of the hierarchy. By not accounting for the variances at the different levels when hierarchical structures exist, coefficient estimates are likely to be biased upward and can lead to a type I error, i.e. finding statistical significance when none exists.

This method enables us to obtain reliable estimates despite missing pertinent data. Perhaps most importantly, biomass data are not directly observed, and this creates difficulties for this type of modelling exercise. Biomass is a crucial component of the traditional harvest function, however, data on population size is often unavailable or spotty across space and time. Since all vessels operating in the same LFA share the same stock in each time period, the biomass can be treated as a random intercept. Although not a perfect solution, this method should still allow us to obtain coefficient estimates for the environmental variables, which is what we are interested in.

#### 4.1.1. Estimation procedure

To justify the application of a multilevel model, we analyse the variance components by calculating the intraclass correlation coefficient (ICC). Assuming that our model is correctly specified, conditional on the explanatory variables (the fixed part of the model), the ICC calculates the dispersion of harvest weight around a mean value for each level of the hierarchy (the random intercepts $u_i$ and $u_{ij}$). The intuition behind this is that the higher the correlation is within the clusters (the larger the ICC) the lower the variability is within the clusters and the higher the variability is between the clusters. Having a high degree of correlation within clusters can lead to biased estimates if regular pooled regression is used, as it violates the assumption of independence.

The ICC is calculated and the level-3 intraclass correlation, which is the correlation of observations between the same LFA, is estimated to be 0.21. The level-2 intraclass correlation, which is the correlation between yearly observations for each vessel, is estimated to be 0.68. Therefore, conditional on the covariates, we find that annual harvest is only weakly correlated within the same LFA, but strongly correlated across year classes for each vessel. A rule of thumb can be used to determine if the hierarchical structure should be taken into consideration. The literature defines the design effect of a sample statistic as the ratio of the actual variance of a sample to the variance of a simple random sample of the same number of elements (Kish 1965). In multilevel modelling, the design effect (DE) is estimated as a function of the ICC and the average size of the clusters (c) (Muthen and Satorra 1995):

$$DE = 1 + (c - 1)*ICC \tag{7}$$

The rule of thumb is that when the design effect is less than 2, the multilevel structure can be ignored. The average number of vessels in each LFA is calculated and it equals 598.9. This leads to a design effect of $\sim$127, and thus the multilevel structure of the data cannot be ignored. The coefficients for the mixed-effects model with random intercepts are estimated using maximum likelihood.

In addition to the mixed-effects model, two other versions of the model are employed for comparison (Table 2). The first column is the model with only the fixed component (Eq. 1). The second column is the mixed-effects model but with random effects only at the vessel level, and the last column is the mixed-effects model with random effects at both the vessel and the LFA level (Eq. 3).

### 4.2. Data collection

#### 4.2.1. Logbook data

The landings data used for this analysis are from commercial fisheries logbook data collected by Fisheries and Oceans Canada (DFO). The variables retrieved from the logbook data are catch in kilograms, date landed, lobster fishing area (LFA), vessel identifier, vessel length, and vessel tonnage. The data span the years 2006–2018. The logbook data is geographically delineated by NAFO division, subdivision, and LFA, but LFA was chosen as the fishery is managed at the LFA level. LFAs 28 and 29 were excluded as sampled temperature data points were sparse in this area, and LFA 37 is a small area shared by LFAs 36 and 38. All variables are continuous except for tonnage class which is a dummy variable that is coded 1 if the vessel is greater than 25 tons and 0 if the vessel is less than 25 tons. The reason for this is that it is a categorical variable in the logbook data. After compiling the logbook data, we are left with 10 fishing areas and 4,064 vessels operating over the 13 years analysed. The data have a hierarchical structure in that each LFA contains vessel observations, and each vessel contains repeated observations for each year. The panel is balanced in the spatial dimension in that there are observations for each year for each LFA, but highly unbalanced at the fleet level. Some vessels drop in and out, some are retired, and some are newly added. A total of 36,672 observations will be used for the analysis.

#### *4.2.2. Bottom temperature data*

Complete ocean temperature profiles at all depths were retrieved from DFO's Marine Environmental Data Section (MEDS) (DFO 2021c). To determine which profiles reached the seafloor, these data were cross-referenced with the Canadian Hydrographic Service Non-Navigational (NONNA) Bathymetric Data (DFO 2021d). Although there are a large number of observations that span the study area, the locations sampled are not consistent from year to year. Therefore, bottom temperature data are expressed in terms of anomalies from their long-term mean. Present climate data were retrieved from DFO's Bedford Institute of Oceanography North Atlantic model (BNAM) (Wang et al. 2018). Bottom temperature in the model are monthly averages for the years 1990–2015 on a spatial grid of 1/12 degrees. Each real temperature observation was matched with its nearest geodetic neighbour from the BNAM long-term averages, and the difference between these points were calculated by subtracting the long-term average observation from each real temperature observation. Shapefiles that delineate the LFAs' polygons were used to determine which observations fall into which LFA and the observations were grouped accordingly. The average temperature anomalies for each LFA for each year were then calculated, and these anomalies are proxies for temperature change. A negative observation represents a colder-than-average anomaly, and a positive anomaly represents a warmer-than-average anomaly. The minimum temperature anomaly is – 2.9 degrees Celsius and the maximum is 6. Since logarithms cannot be taken for negative values, the temperature anomalies are rescaled so that the minimum is zero and the maximum is 100. All of the variables used in the analysis and their associated summary statistics are given in Table 1.

## 5. Results and discussion

For all model specifications the coefficients are statistically significant at the 1% level, with the exception of vessel tonnage ≥25 tons (Table 2). The model that achieves the best fit according to the Akaike information criterion (AIC) is the mixed-effects model with random effects at both the vessel and LFA level. All variables except vessel tonnage are continuous, therefore the log-transformed variables are elasticities. Vessel tonnage ≥25 tons is a dummy variable, so the exponentiated coefficient is the ratio of the mean harvest weight for vessels ≥25 tons to the mean harvest weight for vessels <25 tons. Therefore, this would give an estimate of the expected percent increase in mean harvest weight that would result when going from vessels <25 tons to vessels ≥25 tons, holding other variables constant. However, the estimated coefficients are statistically insignificant for all

**Table 1.** Variables and associated summary statistics.

| | Mean | S.D. | Min | Max |
|---|---|---|---|---|
| Bottom temperature anomaly | | | | |
| Degrees Celsius | 1.62 | 1.61 | −2.88 | 6.03 |
| Rescaled | 50.56 | 18.02 | 0.28 | 99.997 |
| Vessel and effort variables | | | | |
| Weight landed (kg) | 14,796 | 12,564 | 6 | 170,994 |
| Number of days fished per vessel | 42 | 23 | 1 | 624* |
| Length of vessel (feet) | 38.08 | 6.08 | 0 | 64 |
| Vessel tonnage ≥25 tons (dummy) | 0.07 | 0.25 | 0 | 1 |

*Since number of logbook entries is used as a proxy for days fished, there are some instances where fishers record multiple entries per day. There are two instances in which the number of a vessel's logbook entries exceeds the number of calendar days: 624 in 2006, and 397 in 2013.

**Table 2.** Coefficients and standard errors from maximum likelihood estimation: the model with the fixed component only, the mixed-effects model with only vessel-level random effects, and the mixed-effects model with random effects at both the vessel and fishing area-level.

| Variable | Fixed component only (Eq. 1) Coeff. (St. error) | Mixed-effects model (random effects only at vessel level) Coeff. (St. error) | Mixed-effects model (random effects at both vessel and LFA, Eq. 3) Coeff. (St. error) |
|---|---|---|---|
| Intercept | −3.4821 (0.0807)*** | −2.0762 (0.1806)*** | 0.1789 (0.2228) |
| Days fished | 0.5354 (0.0045)*** | 0.5729 (0.0046)*** | 0.5726 (0.0047)*** |
| Vessel length | 2.8232 (0.0221)*** | 2.498 (0.0495)*** | 1.9138 (0.0526)*** |
| Vessel tonnage ≥25 tons | −0.0115 (0.0147) | 0.0261 (0.0334) | −0.0273 (0.0298) |
| Bottom temperature anomaly | 0.1564 (0.0072)*** | 0.0558 (0.0054)*** | 0.0476 (0.0054)*** |
| *Random effects* | | | |
| LFA | | | 0.1301 (0.0598)** |
| Vessel | | 0.3707 (0.0092)*** | 0.2994 (0.0075)*** |
| Overall variance | 0.4833 (0.0036) | 0.2105 (0.0017) | 0.2015 (0.0016) |
| AIC | 76388.45 | 57931.53 | 56197.42 |
| BIC | 76439.42 | 57991.00 | 56265.40 |
| Log-likelihood | −38188.22 | −28958.76 | −28090.71 |

*** $p < 1\%$; ** $p < 5\%$; * $p < 10\%$

four models. The negative coefficients for two of the three models suggest that an increase in tonnage would decrease output which is contrary to what would be expected. The statistical insignificance could be because harvest is inelastic to vessel tonnage, but it should be noted that the vast majority of vessels (93%) are < 25 tons.

Most coefficients have the expected signs, and reasonably plausible magnitudes. The results from the estimation of our chosen models using the historical data available suggest that a 1% increase in ocean bottom temperature anomaly results in a 4.8%–15.6% increase in harvest by weight, depending on model specification. The directional signal tracks with previous studies that found positive correlation between bottom temperature and harvest. However, it is important to note that the precision of the estimated coefficients rely heavily upon the transformation of the temperature data to anomalies. Although this was chosen as the least problematic method given inconsistencies in the sampling areas, this makes interpretation difficult and we would be better served by using raw temperature data if this was possible.

As expected, number of days fished and vessel length have a large and positive impact on harvest. Thus, controlling for technical efficiency of the fleet is crucial as changes in harvest can be attributed to changes in biomass or changes in the amount of fishing pressure that is applied. The increase in landings seen in recent years may be caused by an increase in abundance, which could be linked to climate-related factors, but could also be the result of increased fishing capacity. Although the number of licence holders has decreased and the number of traps allocated to each licence holder has stayed relatively constant, it is likely that effort capacity and fishing efficiency has effectively increased. According to the 2007 report by the Fisheries Resource Conservation Council (FRCC), there is general agreement that harvesters' ability to catch lobster has improved due to improved gear, vessels, and technology (Fisheries Resource Conservation Council 2007).

Results from the mixed-effects models are compared with results from the model with only the fixed component. Since the portion of the variance attributed to LFA is fairly small, a mixed-effects model with random effects only at the vessel level was also compared. It is useful to compare the fixed coefficients that are estimated under the different specifications as it provides insight into what exactly mixed-effects modelling does, how it is different, and why it is useful. The coefficient for number of days fished does not change significantly with the different specifications. Meanwhile, the coefficient for vessel length decreases from 2.8 with the fixed model to 1.9 with the mixed-effects model. This suggests that not accounting for the variance at the vessel level results in an over-estimation of the coefficient for vessel length.

The difference in the coefficients between the fixed model and the mixed-effects model can be attributed to the concept of partial pooling, otherwise known as shrinkage. When the data are pooled, each observation has an equal chance of success. With partial pooling, each unit (vessel in our case) has a different chance of success and this is informed by the vessel-specific characteristics. This allows vessels with less observations and more extreme values to borrow strength from vessels with more observations and less extreme values, and therefore 'shrinks' the estimated coefficient back to a more reasonable value. It acknowledges that each unit has characteristics in common, while also placing less importance on extreme values within each unit (Clark 2019).

A notable takeaway is that the estimated bottom temperature anomaly elasticities vary substantially across the models. It decreases from 15.6% in the fixed-only model to 5.6% in the model with random effects at the vessel level only to 4.8% in the model with random effects at both the vessel and area levels. It makes sense that the coefficient does not differ significantly between the latter two, as the variance at the LFA level is not very large. The difference between the coefficients from the fixed and mixed-effects models can again be attributed to the idea of partial pooling. The influence of bottom temperature on harvest may be higher when considering each unit separately, but when imposing a normal distribution on each vessel's observations this makes extreme values less probable, thus shrinking the coefficients back toward a more reasonable value.

This empirical exercise is useful for investigating the historical impact of bottom temperatures on harvest as well as illustrating the merits of mixed-effects models. However, it is important to note that this alone cannot be used to make predictions of future harvest. Lobsters' tolerance to temperature exhibits a bell-shaped curve. Although lobster abundance has increased steadily as temperatures have increased, it is still at the ascending part of the curve. Once temperatures reach a certain point, productivity will start to decline and distribution will be shifted offshore and into deeper water (Oppenheim et al. 2019). Additionally, there are many complex interactions at play that are not accounted for by this convenient production framework. Although there is a well-established link between landings and temperature, there are different pathways through which this is realised. For example, temperature can impact landings through changes in recruitment, likelihood to enter traps, availability of food sources, etc. Models that contain these interactions are complex and are beyond the scope of this paper. Making predictions based on future environmental scenarios would involve a much more complex model, and this would be interesting to explore as future research.

### *5.1. Model validation*

In addition to the coefficient estimates, best linear unbiased predictions (BLUPs) are retrieved for the random effects (Henderson 1950). Usually, random effects are only reported in terms of variance components, but BLUPs can also be estimated in addition to coefficients as another form of model selection. By inserting BLUPs into the estimation equation and solving, fitted values can be obtained. To assess goodness of fit, we plot the log-transformed harvest weight observations against the fitted values. We compare the fitted values of the model with the fixed component only with the mixed-effects model with random effects at both the vessel and area level (Figure 3). We also plot the residuals from these models against the fitted values (Figure 4).

Visualising the fitted values and the residual errors allows us to see how the model performs with and without the random effects. Figure 3 clearly shows that the GLMM results in a better goodness-of-fit than the model without mixed effects. Figure 4 shows that the residuals are more tightly centred around zero with the GLMM; they are dispersed fairly evenly above and below zero, although they tend more toward negative values. This implies that our model tends to over-estimate, but this is made much less severe with the GLMM.

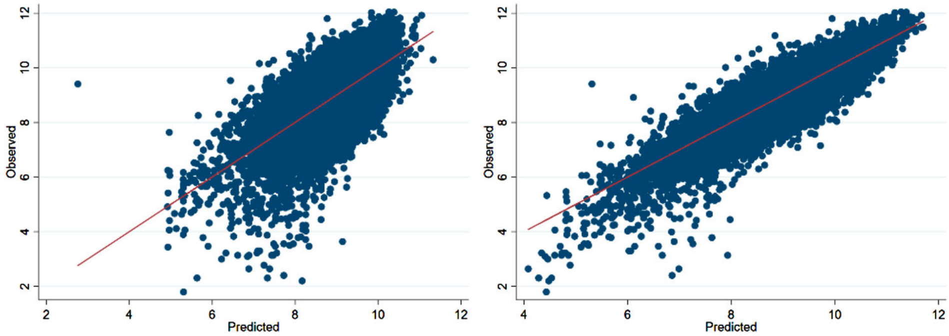


Figure 3. Observed log-transformed harvest versus fitted values from the model with the fixed component only (left) and the mixed-effects model (right).

## 5.2. Random effects estimates

It is also helpful to look at how the estimated random effects change over time. The median vessel-level random effects hover around zero but there is a significant amount of dispersion (Figure 5, left panel). The estimated unobserved effects at the vessel level also appear to be increasing over the time period analysed. This suggests that indeed there are unobservable effort-related factors at play such as more crew or more advanced technology, and that these are increasing over time. This is consistent with the FRCC report's suggestions that harvesters' ability to catch lobster is improving. This can muddy the waters for estimation because the traditional effort-based measures will be under-estimating the operational influences on harvest. Consequently, this makes incorporating environmental variables into the analysis difficult as the true effect will be harder to isolate from the noise. The random effects at the fishing area level remain relatively constant over the time period, suggesting that unobserved effects at these larger spatial scales are time-invariant and less problematic for estimation (Figure 5, right panel). Perhaps most importantly, how much of the increase in harvest is attributed to increasing stock size rather than increased fishing pressure or technological change remains a mystery for now. Catch per unit of effort (CPUE) in terms of catch per fishing trip in the logbook data displays an increasing trend, but with the available data it is not possible to say conclusively what is driving this. Further research that uses more detailed effort data such as number of trap hauls may be able to uncover this. Unfortunately, the number of trap hauls per fishing trip is not available in the data that were available to us.

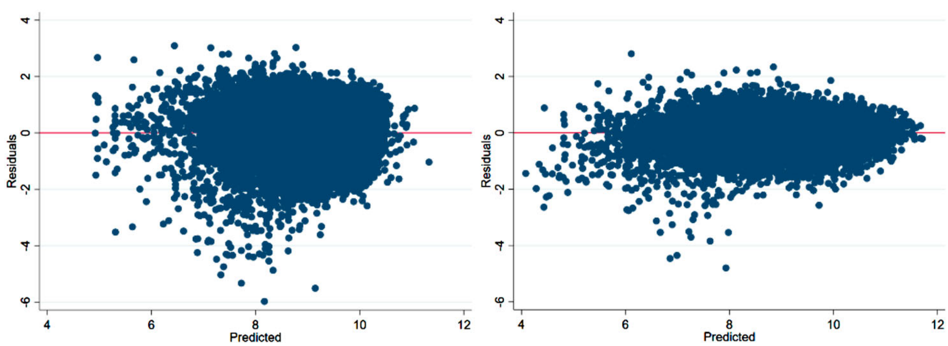


Figure 4. Residuals versus fitted values from the model with the fixed component only (left) and the mixed-effects model (right).

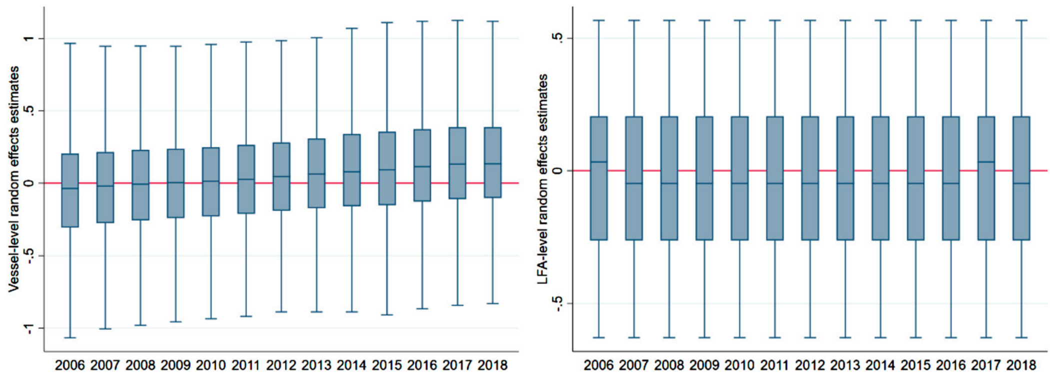


**Figure 5.** Box and whisker plots of vessel-level random effects estimates (left) and LFA-level random effects estimates (right).

## 6. Conclusions

The aim of this paper was to examine the economic consequences of ocean temperature increases on the lobster fishery in Atlantic Canada. This study pulled data from multiple sources and set up an empirical econometric framework that models annual lobster harvest as a function of environmental and operational variables. Coefficients were estimated using a maximum-likelihood mixed-effects estimator and these were compared with two other model specifications to see which model fits the best. The mixed-effects model was selected as the best fitting model according to the AIC, and goodness-of-fit plots visually substantiated this. All coefficients were statistically significant at the 5% level apart from vessel tonnage. The estimated coefficients suggest that a 1% increase in bottom temperature anomaly results in approximately a 5% increase in harvest weight with the chosen model specification, and this was the most conservative estimate of the three models. The estimated coefficients for the effort-related variables vessel size and number of fishing days are large and positive, as expected. Best linear unbiased predictions (BLUPs) were estimated for the random effects at the vessel level. The unobserved effects at the vessel level are significant and have increased over the years 2006–2018. This complicates matters when trying to isolate the relative effects of environmental variables, and suggests that finding a way to incorporate technological progress would improve estimation. There is a vast body of research that aims to measure technical efficiency in fisheries (i.e. stochastic frontier analysis) and incorporating this would be a boon to future research.

The implications of this study are twofold: first, it provides further evidence that environmental change does have a significant impact on harvest. Although this empirical framework does not capture all of the intricate ecological systems at play, it is highly likely that the significant and positive effect of temperature on harvest is reflective of real-world phenomena. As fisheries are confronted with considerable environmental uncertainty in the coming years, there is a fear that warming waters will exacerbate other issues such as excess fishing pressure and competition. This must be considered by policymakers when implementing management measures, as distributional changes may tempt increases in allowances or access. In the case of the Canadian lobster fishery, the current management measures include designated fishing areas, fishing seasons, and limits on the number of traps per licence holder. This management regime incentivizes a race to fish the most productive areas, and fishers have the incentive to outcompete others by increasing vessel power, size, speed, number of crew, or make other capital investments aimed at maximising catch (Pfeiffer and Gratz 2016). As lobsters' preferred habitat shifts, the existing management measures may not be adequate to mitigate excess capacity. In the colder parts of lobsters' range, increasing temperatures may lead to greater abundance, and these areas might become more attractive for fishing. In warmer areas that are approaching the upper limit of lobsters' thermal range, the negative impacts on the species' physiology will begin to manifest. The strong relationship between harvest and temperature underscores that conservation measures should be taken while temperatures are still at a manageable level. This analysis is more exploratory than prescriptive, and caution must be taken when making assumptions about the future of the fishery based on historical trends. However, it calls attention to something that must be delved into deeper.

The second implication of this analysis is one of a more technical nature: that mixed-effects modelling can be a useful part of the natural resource economist's toolbox when the data are hierarchically structured. Given that fisheries management is often area-based, mixed-effects models are surprisingly under-utilized in fisheries economics research. Models that combine both fixed and random effects provide a more flexible approach for analysing the data that are not normally distributed. In this case, we find that the model that most closely resembles reality is the model with random effects at the vessel level and the fishing area level. On the other hand, a pooled model with only fixed effects that ignores the hierarchical structure of the data resulted in a poorer model fit. This is a lesson in the importance of accounting for heterogeneity when these data structures exist.

## Note

1. Annual landed values in the last five years were consistently above $1 billion with the exception of 2020, which was valued at $761 million.

## Acknowledgements

We thank Barbara Best and Gisele Magnusson at Fisheries and Oceans Canada (DFO) for their gracious assistance in data collection and manuscript review. We also thank Luc Bujold at DFO's Marine Environmental Data Section for providing bottom temperature data, Zeliang Wang at DFO's Bedford Institute of Oceanography for providing BNAM model output, and Christine Irwin at DFO's Economic Analysis and Statistics group for providing shapefiles.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

## ORCID

*Dana Wright* http://orcid.org/0000-0003-3332-8259

## References

ASMFC. 2020. *American Lobster Benchmark Stock Assessment and Peer Review Report*. Woods Hole, MA: Atlantic States Marine Fisheries Commission.

Barbier, E. B. 2000. "Valuing the Environment as Input: Review of Applications to Mangrove-Fishery Linkages." *Ecological Economics* 35: 47–61. doi:10.1016/S0921-8009(00)00167-1

Barbier, E. B., and I. Strand. 1998. "Valuing Mangrove-Fishery Linkages – A Case Study of Campeche, Mexico." *Environmental and Resource Economics* 12: 151–166. doi:10.1023/A:1008248003520

Bell, F. W., and R. F. Fullenbaum. 1972. *Economic Impact of Alternative Management Strategies for the Northern Lobster Fishery*. United States National Marine Fisheries Service, Economic Research Division, number 233538.

Bindoff, N. L., W. W. L. Cheung, J. G. Kairo, J. Arístegui, V. A. Guinder, R. Hallberg, N. Hilmi, et al. 2019. "Changing Ocean, Marine Ecosystems, and Dependent Communities." In: *IPCC Special Report on the Ocean and Cryosphere in a Changing Climate,* edited by H.-O. Pörtner, D. C. Roberts, V. Masson-Delmotte, P. Zhai, M. Tignor, E. Poloczanska, K. Mintenbeck, A. Alegría, M. Nicolai, A. Okem, J. Petzold, B. Rama, and N. M. Weyer, 447–587. Cambridge: Cambridge University Press. doi:10.1017/9781009157964.007

Bolker, B. M., M. E. Brooks, C. J. Clark, S. W. Geange, J. R. Poulsen, M. H. Stevens, and J. S. White. 2009. "Generalized Linear Mixed Models: A Practical Guide for Ecology and Evolution." *Trends in Ecology & Evolution* 24: 127–135. doi:10.1016/j.tree.2008.10.008

Bono, R., R. Alarcón, and M. J. Blanca. 2021. "Report Quality of Generalized Linear Mixed Models in Psychology: A Systematic Review." *Frontiers in Psychology* 12: 666182. doi:10.3389/fpsyg.2021.666182

Breslow, N. E., and D. G. Clayton. 1993. "Approximate Inference in Generalized Linear Mixed Models." *Journal of the American Statistical Association* 88: 9–25. doi:10.2307/2290687

Bryndum-Buchholz, A., D. G. Boyce, D. P. Tittensor, V. Christensen, D. Bianchi, and H. K. Lotze. 2020. "Climate-change Impacts and Fisheries Management Challenges in the North Atlantic Ocean." *Marine Ecology Progress Series* 648: 1–17. doi:10.3354/meps13438

Casals, M., M. Girabent-Farrés, and J. L. Carrasco. 2014. "Methodological Quality and Reporting of Generalized Linear Mixed Models in Clinical Medicine (2000–2012): A Systematic Review." *PLOS ONE* 9: e112653. doi:10.1371/journal.pone.0112653

Cheung, W. W., V. W. Lam, J. L. Sarmiento, K. Kearney, R. E. G. Watson, D. Zeller, and D. Pauly. 2010. "Large-scale Redistribution of Maximum Fisheries Catch Potential in the Global Ocean Under Climate Change." *Global Change Biology* 16: 24–35. doi:10.1111/j.1365-2486.2009.01995.x

Clark, M. 2019. "Shrinkage in Mixed Effects Models." https://m-clark.github.io/posts/2019-05-14-shrinkage-in-mixed-models/.

Dean, C. B., and J. D. Nielsen. 2007. "Generalized Linear Mixed Models: A Review and Some Extensions." *Lifetime Data Analysis* 13: 497–512. doi:10.1007/s10985-007-9065-x

DFO. 2020. "Fisheries and Oceans Canada Lobster Fishing Areas 27–38 Integrated Fisheries Management Plan." https://www.dfo-mpo.gc.ca/fisheries-peches/ifmp-gmp/maritimes/2019/inshore-lobster-eng.html.

DFO. 2021a. *Fisheries and Oceans Canada Seafisheries Landed Value*. Ottawa: Zonal Interchange File.

DFO. 2021b. *Fisheries and Oceans Canada Oceanographic Conditions in the Atlantic Zone in 2020*. Canadian Science Advisory Secretariat, Science Advisory Report 2021/026.

DFO. 2021c. "Marine Environmental Data Section Archive." https://meds-sdmm.dfo-mpo.gc.ca, Ecosystem and Oceans Science, Fisheries and Oceans Canada. Data obtained on 2021/09/07.

DFO. 2021d. "The Canadian Hydrographic Service CHS NONNA bathymetric data, https://www.charts.gc.ca/data-gestion/index-eng.html, Fisheries and Oceans Canada. Data obtained on 2021/10/03.

Dow, R. L. 1961. "Some Factors Influencing Maine Lobster Landings." *Commercial Fisheries Review* 23: 1–11.

Drinkwater, K. F., M. J. Tremblay, and M. Comeau. 2006. "The Influence of Wind and Temperature on the Catch Rate of the American Lobster (*Homarus americanus*) During Spring Fisheries off Eastern Canada." *Fisheries Oceanography* 15: 150–165. doi:10.1111/j.1365-2419.2005.00349.x

Fisheries Resource Conservation Council. 2007. *Sustainability Framework for Atlantic Lobster 2007: Report to the Minister of Fisheries and Oceans*. Ottawa.: Fisheries and Oceans Canada.

Flowers, J. M., and S. B. Saila. 1972. "An Analysis of Temperature Effects on the Inshore Lobster Fishery." *Journal of the Fisheries Research Board of Canada* 29: 1221–1225. doi:10.1139/f72-182

Foley, N. S., V. Kahui, C. W. Armstrong, and T. M. Van Rensburg. 2010. "Estimating Linkages Between Redfish and Cold Water Coral on the Norwegian Coast." *Marine Resource Economics* 25: 105–120. doi:10.5950/0738-1360-25.1.105

Foley, N. S., T. M. Van Rensburg, and C. W. Armstrong. 2010. "The Ecological and Economic Value of Cold-Water Coral Ecosystems." *Ocean & Coastal Management* 53: 313–326. doi:10.1016/j.ocecoaman.2010.04.009

Gelman, A. 2006. "Multilevel (Hierarchical) Modeling: What It Can and Cannot Do." *Technometrics* 48: 432–435. doi:10.1198/004017005000000661

Gelman, A., and J. Hill. 2006. *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge University Press.

Goode, A. G., D. C. Brady, R. S. Steneck, and R. A. Wahle. 2019. "The Brighter Side of Climate Change: How Local Oceanography Amplified a Lobster Boom in the Gulf of Maine." *Global Change Biology* 25: 3906–3917. doi:10.1111/gcb.14778

Greenan, B. J. W., N. L. Shackell, K. Ferguson, P. Greyson, A. Cogswell, D. Brickman, Z. Wang, A. Cook, C. E. Brennan, and V. S. Saba. 2019. "Climate Change Vulnerability of American Lobster Fishing Communities in Atlantic Canada." *Frontiers in Marine Science* 6, Article 579. doi:10.3389/fmars.2019.00579

Groner, M. L., J. D. Shields, D. F. Landers, J. Swenarton, and J. M. Hoenig. 2018. "Rising Temperatures, Molting Phenology, and Epizootic Shell Disease in the American Lobster." *The American Naturalist* 192: E163–E177. doi:10.1086/699478

Harrison, X. A., L. Donaldson, M. E. Correa-Cano, J. Evans, D. N. Fisher, C. E. Goodwin, B. S. Robinson, D. J. Hodgson, and R. Inger. 2018. "A Brief Introduction to Mixed Effects Modelling and Multi-Model Inference in Ecology." *PeerJ* 6: e4794. doi:10.7717/peerj.4794

Henderson, C. R. 1950. "Estimation of Genetic Parameters." *Annals of Mathematical Statistics* 21: 309–310.

Henderson, J. V., and M. Tugwell. 1979. "Exploitation of the Lobster Fishery: Some Empirical Results." *Journal of Environmental Economics and Management* 6: 287–296. doi:10.1016/0095-0696(79)90009-3

Huang, L., and M. D. Smith. 2014. "The Dynamic Efficiency Costs of Common-Pool Resource Exploitation." *American Economic Review* 104: 4071–4103. doi:10.1257/aer.104.12.4071

Huang, L., M. D. Smith, and J. K. Craig. 2010. "Quantifying the Economic Effects of Hypoxia on a Fishery for Brown Shrimp *Farfantepenaeus aztecus*." *Marine and Coastal Fisheries* 2: 232–248. doi:10.1577/C09-048.1

Hudon, C. 1994. "Large-scale Analysis of Atlantic Nova Scotia American Lobster (*Homarus americanus*) Landings with Respect to Habitat, Temperature, and Wind Conditions." *Canadian Journal of Fisheries and Aquatic Sciences* 51: 1308–1321. doi:10.1139/f94-130

Hyun, S. Y., S. X. Cadrin, and S. Roman. 2014. “Fixed and Mixed Effect Models for Fishery Data on Depth Distribution of Georges Bank Yellowtail Flounder.” *Fisheries Research* 157: 180–186. doi:10.1016/j.fishres.2014.04.010

Kahn, J. R., and W. M. Kemp. 1985. “Economic Losses Associated with the Degradation of an Ecosystem: The Case of Submerged Aquatic Vegetation in Chesapeake Bay.” *Journal of Environmental Economics and Management* 12: 246–263. doi:10.1016/0095-0696(85)90033-6

Kish, L. 1965. *Survey Sampling*. New York, NY: John Wiley & Sons, Inc.

Le Bris, A., K. E. Mills, R. A. Wahle, Y. Chen, M. A. Alexander, A. J. Allyn, J. G. Schuetz, J. D. Scott, and A. J. Pershing. 2018. “Climate Vulnerability and Resilience in the Most Valuable North American Fishery.” *Proceedings of the National Academy of Sciences* 115: 1831–1836. doi:10.1073/pnas.1711122115

Lynne, G. D., P. Conroy, and F. J. Prochaska. 1981. “Economic Valuation of Marsh Areas for Marine Production Processes.” *Journal of Environmental Economics and Management* 8: 175–186. doi:10.1016/0095-0696(81)90006-1

McCleese, D. W., and D. G. Wilder. 1958. “The Activity and Catchability of the Lobster (*Homarus americanus*) in Relation to Temperature.” *Journal of the Fisheries Research Board of Canada* 15: 1345–1354. doi:10.1139/f58-073

Meteyard, L., and R. A. Davies. 2020. “Best Practice Guidance for Linear Mixed-Effects Models in Psychological Science.” *Journal of Memory and Language* 112: 104092. doi:10.1016/j.jml.2020.104092

Moscatelli, A., M. Mezzetti, and F. Lacquaniti. 2012. “Modeling Psychophysical Data at the Population-Level: The Generalized Linear Mixed Model.” *Journal of Vision* 12: 26–26. doi:10.1167/12.11.26

Muthen, B. O., and A. Satorra. 1995. “Complex Sample Data in Structural Equation Modeling.” *Sociological Methodology* 25: 267–316. doi:10.2307/271070

Nelder, J. A., and R. W. M. Wedderburn. 1972. “Generalized Linear Models.” *Journal of the Royal Statistical Society: Series A (General)* 135: 370–384. doi:10.2307/2344614

Nguyen, T. V. H. 2022. “Welfare Impact of Climate Change on Capture Fisheries in Vietnam.” *PLOS ONE* 17: e0264997. doi:10.1371/journal.pone.0264997

Oppenheim, N. G., R. A. Wahle, D. C. Brady, A. G. Goode, and A. J. Pershing. 2019. “The Cresting Wave: Larval Settlement and Ocean Temperatures Predict Change in the American Lobster Harvest.” *Ecological Applications* 29: e02006. doi:10.1002/eap.2006

Pfeiffer, L., and T. Gratz. 2016. “The Effect of Rights-Based Fisheries Management on Risk Taking and Fishing Safety.” *Proceedings of the National Academy of Sciences* 113: 2615–2620. doi:10.1073/pnas.1509456113

Reid-Musson, E. R., and B. Neis. 2022. “The Brexit Deal and UK Fisheries—has Reality Matched the Rhetoric?.” *Maritime Studies* 21: 1–17. doi:10.1007/s40152-022-00259-0

Squires, D., and J. Walden. 2021. “The Economics of Production in Marine Fisheries.” In *Handbook of Production Economics*, edited by S. C. Ray, R. G. Chambers, and S. C. Kumbhakar, 1–40. Singapore: Springer.

Tanaka, K. R., M. P. Torre, V. S. Saba, C. A. Stock, and Y. Chen. 2020. “An Ensemble High-Resolution Projection of Changes in the Future Habitat of American Lobster and sea Scallop in the Northeast US Continental Shelf.” *Diversity and Distributions* 26: 987–1001. doi:10.1111/ddi.13069

Thorson, J. T., and C. Minto. 2015. “Mixed Effects: A Unifying Framework for Statistical Modelling in Fisheries Biology.” *ICES Journal of Marine Science* 72: 1245–1256. doi:10.1093/icesjms/fsu213

Venables, W. N., and C. M. Dichmont. 2004. “GLMS, GAMs and GLMMs: An Overview of Theory for Applications in Fisheries Research.” *Fisheries Research* 70: 319–337. doi:10.1016/j.fishres.2004.08.011

Wang, Z., W. Lu, B. Greenan, D. Brickman, and B. DeTracey. 2018. *BNAM: An Eddy-Resolving North Atlantic Ocean Model to Support ocean Monitoring*. Fisheries and Oceans Canada, Canadian Technical Report of Hydrography and Ocean Sciences 327.