QUANTIFYING FISHER RESPONSES TO ENVIRONMENTAL AND REGULATORY DYNAMICS IN MARINE SYSTEMS

By

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Abstract

Commercial fisheries are part of an inherently complicated cycle. As fishers have adopted new technologies and larger vessels to compete for resources, fisheries managers have adapted regulatory structures to sustain stocks and to mitigate unintended impacts of fishing (e.g., bycatch). Meanwhile, the ecosystems that are targeted by fishers are affected by a changing climate, which in turn forces fishers to further adapt, and subsequently, will require regulations to be updated. From the management side, one of the great limitations for understanding how changes in fishery environments or regulations impact fishers has been a lack of sufficient data for resolving their behaviors. In some fisheries, observer programs have provided sufficient data for monitoring the dynamics of fishing fleets, but these programs are expensive and often do not cover every trip or vessel. In the last two decades however, vessel monitoring systems (VMS) have begun to provide vessel location data at regular intervals such that fishing effort and behavioral decisions can be resolved across time and space for many fisheries. I demonstrate the utility of such data by examining the responses of two disparate fishing fleets to environmental and regulatory changes. This study was one of "big data" and required the development of nuanced approaches to process and model millions of records from multiple datasets. I thus present the work in three components: (1) How can we extract the information that we need? I present a detailed characterization of the types of data and an algorithm used to derive relevant behavioral aspects of fishing, like the duration and distances traveled during fishing trips; (2) How do fishers' spatial behaviors in the Bering Sea pollock fishery change in response to environmental variability; and (3) How were fisher behaviors and economic performances affected by a series of regulatory changes in the Gulf of Mexico grouper-tilefish longline fishery? I found a high degree of heterogeneity among vessel behaviors within the pollock fishery, underscoring the role that markets and processor-level decisions play in facilitating fisher responses to environmental change. In the Gulf of Mexico, my VMS-based approach estimated unobserved fishing effort with a high degree of accuracy and confirmed that the regulatory shift (e.g., the longline endorsement program and catch share program) yielded the intended impacts of reducing effort

and improving both the economic performance and the overall harvest efficiency for the fleet. Overall, this work provides broadly applicable approaches for testing hypotheses regarding the dynamics of spatial behaviors in response to regulatory and environmental changes in a diversity of fisheries around the world.

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General Introduction

The aphorism about counting fish being like counting trees ("…Except that you can't see them and they move", credited to John Shepherd) is often used to exemplify the challenges of assessing fish stocks, but these challenges are equally true for other unobserved agents, including fishers. In fact, studying fishers, or more specifically, fisher behavior, may have more levels of complexity than studying the fish themselves. Studies of fisher behavior require the ability to understand how human predators pursue mobile prey species that cannot be easily seen or counted, and that respond both contemporaneously and via lagged relationships to their dynamic natural environments. Not only do fishers respond to prey and environmental dynamics, they must also respond to shifting regulatory structures that are implemented to ensure the sustainability of these prey, thus creating an inherently cyclic relationship. These broad drivers of fisher behavior (e.g., fish abundance and location, environmental conditions, regulations) create a universe of dynamics that I refer to as the fishery landscape. This fishery landscape extends beyond fish location and catch limits though; it also includes global dynamics of fuel prices, fish prices, market demand, processor-level operating differences, etc. Admittedly, there are more possible influences on fisher behavior than can be modeled. However, in the modern age of "big data" there are increasing opportunities to resolve at least some of the major components of the fishery landscape and how they may affect fisher behaviors.

One data source that has revolutionized our ability to characterize fisher behaviors and to subsequently link those behaviors to the fishery landscape is vessel monitoring systems (VMS). VMS transmit vessel locations at regular intervals, and are now required by dozens of national governments and regional fisheries management organizations, including more than 4,000 vessels in the United States alone. These systems provide the ability to monitor how speeds, turn angles, locations, and other aspects of vessel movements may indicate when vessels are fishing during a trip versus when they are transiting or searching for fish. Originally used for enforcement and compliance with spatial fisheries regulations (e.g., Enguehard et al. 2012), VMS now provide a suite of management applications across fisheries. Many early VMS studies used position records to calculate vessel speeds and subsequently, to estimate fishing effort by differentiating fishing speeds from transit speeds (e.g., Deng et al. 2005). However, with the evolution of computing power and the accessibility of more complex statistical tools, more advanced methods to estimate fishing effort have included hidden Markov models (Joo et al. 2013; Gloaguen et al. 2014), neural networks (Russo et al. 2011a), random forests (O'Farrell et al. 2017), and now, generalized additive models (see Chapter 3). Many studies have built upon effort estimates by mapping the spatial distributions of fishing effort and delineating fishing grounds (e.g., Witt and Godley 2007; Jennings and Lee 2012). Increasingly, analyses have included other aspects of interest to fishery managers and researchers: data quality control (e.g., Palmer and Wigley 2009; Bastardie et al. 2010), fishery interactions with non-target species (e.g., Kai et al. 2013), conservation / closure evaluation (e.g., Holmes et al. 2011), estimating gear type (Russo et al. 2011b) and identifying illegal fishing (Aanes et al. 2011) to name just a few.

In regions where VMS and other data sources (e.g., logbooks) have standard formats, software packages can now automate many of the above analyses, but in much of the world, a lack of standardization necessitates customized analytical approaches. VMStools (Hintzen et al. 2012) and VMSbase (Russo et al. 2014), for example, allow users of European VMS data to automate the process of breaking strings of vessel position records into discrete trips based on known port polygons. A suite of analytical tools within these programs also allows users to interpolate vessel tracks, allocate fishing effort to spatial grids, and identify fishing gear types, among other things. However, these systems are optimized for European fisheries data and ports, and many of the tools have less utility for fisheries elsewhere. Additionally, while the available tools have considerable utility for common management queries, they offer less flexibility for research questions that may require unique or custom manipulation of data. In such cases, existing software packages may offer tools for pre-processing of data, but may be generally limited for hypothesis-based inference.

In the United States, VMS data have been historically difficult to access and a lack of data standardization across fishery management regions has made applications like VMStools or VMSbase less accessible. Despite the recent global surge in use of VMS data, they have been applied in only a few cases in the U.S. (e.g., Murawski et al. 2005; Palmer and Wigley 2009; O'Farrell et al. 2017; Ducharme-Barth and Ahrens 2017) with this dissertation representing the only known published VMS studies from U.S. Pacific waters (Watson and Haynie 2016 [chapter 1]).

In the work that follows, I have sought to establish both the methodological basis for dealing with some of the challenges of using U.S. VMS data, and to illustrate the potential for deriving and analyzing the necessary metrics for contemporary and relevant fishery management questions. To date, few (if any) studies have taken the step of linking classic fisheries analyses using VMS (e.g., estimation of fishing effort) to social or behavioral aspects of fishing. In a sense, I seek to begin bridging that gap. This work is in no way a rigorous economic analysis of fishing behavior, but it provides a framework by which econometricians may view the potential of these datasets differently. Importantly, I have sought to describe fishing effort not only from the fish-centric periods when nets or hooks are in the water, but also in terms of entire trip durations, for which the scales of economic and opportunity costs are relevant to fishers.

Some coastlines of the world boast relatively simple topography, along which the identification of ports as the starting and ending points of fishing trips is quite straightforward; other coastlines offer greater ambiguity. Complex coastlines can offer difficulties in automating analyses with VMS data, as it can be challenging to determine when and where fishing trips begin and end, which is a critical component for determining changes in trip durations. In chapter 1, I present a detailed algorithmic approach that demonstrates how to deal with some of the challenges associated with identifying individual trips and how to differentiate which trips are fishing trips and which are not. While primarily a presentation of methods, this chapter establishes the foundation for developing a dataset of trip characteristics that can be used for subsequent inference about fishing behaviors. The approach used to resolve these characteristics has implications for understanding the types and quality of the behavioral metrics that are derived, and thus the degree of hypotheses that can subsequently be tested.

In chapter 2, I use the dataset derived in chapter 1 to quantify a time series of fishing location choices in the Bering Sea fishery for walleye pollock (*Gadus chalcogrammus*), one of the most valuable fisheries in the world (Fissel et al. 2015). I explore how the distances traveled by fishers varies as a function of the fishery landscape. This story becomes most interesting as the complexities of the fishery landscape expand to emphasize the dynamic interactions among fisher behaviors, the environment, markets, processors, and fish abundance. This story emphasizes the role that variability may play in how we think about managing individual vessels vs. entire fleets, and it reaffirms the work of Haynie and Pfeiffer (2012) that asserts, "Why economics matters for understanding the effects of climate change on fisheries."

Chapter 3 is geographically a departure from the stories of the first two chapters but the approaches are much the same. In this chapter, I analyze data from the bottom longline fishery for groupers and tilefishes in the Gulf of Mexico. This fishery underwent a protracted regulatory transition period in 2009 - 2010, so I use a suite of logbook, observer, and VMS data to examine whether the goals of these regulatory changes were met. For this work, I modify the methods of chapter 1 to fit an entirely different, yet still quite complicated, coastline, to identify individual fishing trips. I then develop a novel model for estimating fishing effort in a longline fishery and derive a suite of metrics to assess how changes in catch and earnings rates changed across the transition period.

In the chapters that follow, I quantify fisher responses to environmental and regulatory dynamics in two distinct marine ecosystems. By using disparate fishery systems, I not only test hypotheses about fisher behaviors, but I also establish a framework that is applicable to many fisheries globally. Many fisheries have VMS and mandatory logbook-reporting, which can quickly generate big data for even data-limited fisheries. These data sets are not without their problems, and they are certainly no replacement for the value of observer data or more comprehensive electronic monitoring, but in the absence of these more expensive protocols, VMS can provide extensive improvements to spatially-explicit questions relevant to fisheries management.

Chapter 1 Using vessel monitoring system data to identify and characterize trips made by fishing vessels in the United States North Pacific[1]

1.1 Abstract

Time spent fishing is the effort metric often studied in fisheries but it may under-represent the effort actually expended by fishers. Entire fishing trips, from the time vessels leave port until they return, may prove more useful for examining trends in fleet dynamics, fisher behavior, and fishing costs. However, such trip information is often difficult to resolve. We identified ~30,000 trips made by vessels that targeted walleye pollock (*Gadus chalcogrammus*) in the Eastern Bering Sea from 2008 – 2014 by using vessel monitoring system (VMS) and landings data. We compared estimated trip durations to observer data, which were available for approximately half of trips. Total days at sea were estimated with < 1.5% error and 96.4% of trip durations were either estimated with < 5% error or they were within expected measurement error. With 99% accuracy, we classified trips as fishing for pollock, for another target species, or not fishing. This accuracy lends strong support to the use of our method with unobserved trips across North Pacific fisheries. With individual trips resolved, we examined potential errors in datasets which are often viewed as "the truth." Despite having > 5 million VMS records (timestamps and vessel locations), this study was as much about understanding and managing data errors as it was about characterizing trips. Missing VMS records were pervasive and they strongly influenced our approach. To understand implications of missing data on inference, we simulated removal of VMS records from trips. Removal of records straightened (i.e., shortened) vessel trajectories, and travel distances were underestimated, on average, by 1.5 – 13.4 % per trip. Despite this bias, VMS proved robust for trip characterization and for improved quality control of human-recorded data. Our scrutiny of human-reported and VMS data advanced our understanding of the potential utility and challenges facing VMS users globally.

1.2 Introduction

Fisheries researchers often use catch per unit effort (CPUE) as a means by which to assess the dynamics and health of fish stocks. In such cases, effort is typically defined as the time during which fishing gear is actively deployed, and thus CPUE becomes a standard metric for resolving the costs of fishing on commercial stocks. Resolving the costs of fishing to humans, however, relies not only upon how long gear was deployed, but also upon how long a vessel remained at sea; and how far and where it traveled (Haynie and Layton 2010). Such fundamental aspects of fishing trips (e.g., duration, distance

[1] Watson J.T., Haynie A.C. 2016. Using Vessel Monitoring System Data to Identify and Characterize Trips Made by Fishing Vessels in the United States North Pacific. PLoS ONE 11(10):e0165173.

traveled, location) become increasingly critical as we consider the impacts on fishers' from a changing climate (e.g., Haynie and Pfeiffer 2013), shifting fish populations (e.g., Joo et al. 2014) and variable fuel costs (e.g., Abernethy et al 2010). These factors may affect the profitability of trips, so as fishers strive to minimize cost, the ability to assess changes in trip characteristics may be fundamental for understanding fleet dynamics over time. Despite the importance of resolving trip behaviors, the details of fishing trips often remain poorly characterized, or insufficient data may be available to examine their trends.

A "fishing trip" is one of the simpler concepts in fisheries research but in practice, both the data and even the definition can be rather complex. There are many definitions of a fishing trip that may affect the interpretation of vessel behavior. In the United States, regulations define trips based on management programs and vessel classifications, so a statutory "trip" can have different meanings (50 CFR 679.2). For example, regulations specify that a trip begins for catcher vessels targeting groundfish when the harvesting of fish commences; the trip ends when the last of the catch is offloaded. This definition may drastically underestimate the time that a vessel spends at-sea and it may provide no guidance for determining, for example, whether fishers now travel farther to catch their fish than in previous years. The North Pacific Groundfish Observer Program (NPGOP) starts a trip when a vessel unties from a dock or floating processor and ends a trip when the vessel ties up at either a dock or a floating processor, or if an observer exits the vessel (NOAA 2016a). Observers in the NPGOP have been present on many of the trips in the Bering Sea and Aleutian Islands (BSAI) and the Gulf of Alaska (GOA) for more than a quarter century. However, detailed trip information has not always been maintained and the levels of coverage have varied across fleets and years. Thus, while the trip definition used by the NPGOP is largely conducive to examining trip behaviors over time, the sampling extent may leave trip patterns incomplete for both fishing and non-fishing trips in the region. In such cases, vessel monitoring systems (VMS) have the potential to resolve substantial uncertainty in vessel trips, from the time a vessel leaves a port / processor to the time it returns to a port / processor. Thus, it is this definition of a fishing trip (from port / processor to port / processor) that we use throughout our study.

VMS are increasingly required for fishing fleets worldwide. Largely implemented to enforce fishery closures or other spatial management regulations, VMS transmit a vessel's location (latitude and longitude) at regionally-mandated time intervals, typically from 30 - 120 min. Supplemental to their utility for law enforcement, VMS data have been used to estimate fishing effort (e.g., Lee et al. 2010; Chang and Yuan 2014), validate logbook data (e.g., Palmer and Wigley 2009; Bastardie et al. 2010), and delineate habitats impacted by fishing (e.g., Mills et al. 2007; Stelzenmüller et al. 2008; Jennings and Lee 2012). Such applications of VMS data can be applied to cases when vessels are either observed or unobserved, and they can also be used to resolve gaps in data resulting from sparse observer coverage. Several software packages (VMStools [Hintzen et al. 2012]; VMSbase [Russo et al. 2014]) even provide automated analyses of some of the above functions with VMS data, but they are refined primarily for European fleets and ports, leaving limited functionality for U.S. and other non-European fisheries. This is not surprising, however, as VMS data from U.S. fishing vessels, for example, have only been sparsely used in research (Murawski et al. 2005; Palmer and Wigley 2009) despite the U.S. having more vessels with VMS (> 4,000) than any other nation (www.nmfs.noaa.gov/ole/about/our_programs/vessel_monitoring.html). With tens of millions of VMS records for some U.S. fisheries, these data represent a major source of information for fisheries management that has been largely under-utilized. As such, the limitations of these data have also been scarcely addressed in the United States. In theory, VMS records should make trips easy to identify. Trips begin when a vessel leaves a port / processor and they end when the vessel returns to a port / processor. However, inconsistencies in the transmission of VMS data, variable port geography and fishing behaviors, vessels delivering to multiple ports / processors, and other possible factors complicate trip identification.

We present an example using a VMS dataset that has not previously appeared in the literature. Thus, we provide a framework for VMS data whose utility and limitations were previously unknown, a situation that is applicable to many VMS programs worldwide. The fishery for walleye pollock (*Gadus chalcogrammus*; hereafter "pollock") in the eastern Bering Sea is the largest commercial fishery in the United States. The fishery was rationalized (i.e., moved to catch shares) by the American Fisheries Act (AFA) in 1998 (www.npfmc.org/american -fisheries-act-afa-pollock-cooperatives/), and it has an annual harvest valued at more than $1 billion (Fissel et al. 2015). The pollock quota is divided roughly in half between at-sea catcher-processors and catcher-vessels (CVs) that deliver to both shoreside processors and "mothership" vessels. Our study examines CVs in particular, whose pollock trips are usually 1 – 4 days long but whose non-pollock trips span the North Pacific and may last up to several weeks. While these vessels are the only catcher boats permitted to fish for pollock in the Bering Sea, many of these vessels also participate in other fisheries (including non-trawl fisheries) from the Bering Sea to the west coast of the United States (a range of ~ 4,000 km). It is because of their participation in the pollock fishery that they have been required to transmit VMS data since 2002. However, because of their broad spatial extent and participation in many fisheries, these vessels also offer a good proxy for understanding vessel movements into and out of more than 50 fishing ports in the North Pacific, as many of them spend extended periods on non-pollock trips as well as pollock trips.

Our objectives were to develop a VMS-based modeling approach to (1) identify individual BSAI and GOA trips made by CVs from the Bering Sea pollock fleet; (2) quantify trip distances and durations traveled and ground-truth them against observer data; (3) characterize trips as "fishing for pollock," "fishing for other target species," or "non-fishing"; (4) identify ways that autonomously-collected data like VMS data may be used to corroborate, and to quality-check human-collected sources like observer and fish ticket (fishery landings reports) data. We present our method, refined for the North Pacific, as a demonstration of how these data may be approached, but the generalities of our methodology and the data issues identified are applicable to many global fisheries with VMS.

1.3 Methods

We first present an overview of the data, followed by a description of the algorithm used to identify individual trips (including calculation of fields, algorithmic rules, and integration of data sources). We then describe the calculation of trip metrics (distance and duration) and we use trip duration to compare VMS-based trips with observed trips. Next, we use a set of decision rules and regressions to characterize trips as fishing versus non-fishing and to identify the type of fishing when it occurs. Detailed appendices for methodological specifics are provided to assist researchers using VMS that face similar data challenges. However, the core of this section is written more generally to accommodate users of different VMS datasets. All analyses were performed using R Statistical Software Version 3.2.1 (R Core Team 2015), with specific packages as noted in the text.

1.3.1 Data overview and preliminary processing

All available data from each of three sources were extracted from their respective databases (VMS (Spalding 2016); Observer (NOAA 2016b); Fish ticket (ADFG 2015)) for any CV that was permitted to fish in the AFA pollock fishery from 2008 – 2014 (Table 1.1). Each of these datasets are confidential and their access requires written authorization from their respective entities within National Oceanic and Atmospheric Administration's National Marine Fisheries Service (NOAA Fisheries) and the State of Alaska.

VMS have been mandated to transmit the location of vessels fishing for pollock in the BSAI at 30 min intervals since 2002. However, as this paper relies on a comparison with observer data to validate our approach, we present only those years with the requisite trip information (e.g., start and stop times) from observers (2008 – 2014). VMS data are required to be transmitted continuously, including when vessels are in port, though exceptions occasionally occur during extended port or anchorage periods. Preliminary processing of VMS data were required before project objectives could be addressed. Duplicate VMS records were removed and several data fields were generated: distance between sequential VMS records for a given vessel, distance from port, vessel speed, and the State and federal management areas for each VMS record (see Appendix 1.7.1 for descriptions of field calculations). VMS records were occasionally reported for which a vessel position was egregiously distant from its nearest neighbors, resulting in nonsensical vessel speeds or locations (e.g., on-land). Maximum vessel speeds were typically ~ 12 knots

(22.2 kph) so we removed all VMS records with apparent speeds > 14 knots (a conservative upper bound) to remove erroneous records. VMS data were linked to available observer data such that a VMS record was part of an observed trip if its time-stamp fell within the observer-recorded start and stop time for a trip.

Throughout the study period, CVs with VMS have been monitored by government-trained observers through the NPGOP (part of NOAA Fisheries, Alaska Fisheries Science Center). Observer coverage of CVs was divided into two components: vessels with 100% coverage of pollock fishing days at sea (≥125 ft. in length) and vessels with historically only 30% coverage (< 125 ft. in length). Prior to 2007, no trip data (haul-level data only) were collected for the fleet and, for our purposes, a trip was unobserved if it lacks trip information (e.g., start and stop times). From late 2007 through 2010, trip records were maintained for all observed trips. Beginning in 2011, 100% of federally managed fishing days at sea for the entire pollock fleet became observed, creating a complete record of trips for all pollock fishing activity in the Bering Sea since that time. However, even for 100% observed vessels, some trips remained unobserved or may lack detailed trip information because they were not part of a federally regulated fishery that required observer coverage. For example, vessels may be chartered for research, participate in state-waters fisheries, transport salmon catch between smaller vessels and processors ("tendering"), or undergo long transits to ports outside of Alaska. Furthermore, as observer data do not indicate a vessel's target species, those data alone may be insufficient to indicate whether a vessel was fishing for pollock (some CVs also target crab or other groundfish).

A potential data source for identifying target species and characterizing the type of fishing trip is fish ticket data. Seafood processors issue fish tickets when CVs land their catches and they record the date during which catches by species are landed. Additionally, fishers report the gear type (e.g., pelagic or bottom trawl, longline, pot), a code that identifies the management / permit program under which fishing occurs, and the management areas in which vessels report fishing. The data available from these landings data have evolved over time and some fields may not be present in all years.

1.3.2 Trip identification algorithm

To address our first objective, we developed an algorithm that partitioned strings of consecutive VMS records for each vessel into individual trips. The foundation of the trip algorithm was to identify when vessels transitioned from being *at-sea* to being *in-port* and when they transitioned to being *at-sea* once again. For the majority of trips (88 %), this simple approach (similar to that of Hintzen et al. [2012] and Russo et al. [2014]) was sufficient. However, due to missing VMS records, the identification of vessels' transitions into and out of ports sometimes required a number of nuanced steps.

Initial assignment of *in-port* designations was made for all VMS records within 10 nautical miles (nmi) (18.5 km) of the nearest port. Dutch Harbor and Akutan - the primary ports for the AFA pollock fishery - sit within large protected bays where relatively little fishing occurs; an examination of VMS data confirmed that few vessels traveled within 10 nmi of either port unless the port was their destination (or origin). In contrast to Dutch Harbor and Akutan, many of the smaller, more exposed ports were located < 10 nmi from fishing grounds or vessel transit corridors so their *in-port* definitions were individually constrained to port-specific distances < 10 nmi. Due to gaps in VMS coverage, simple port polygons (like those used by Hintzen et al. (2012)) were not always sufficient for identifying when a vessel was returning to port. Combinations of distance from port, vessel speed and the amount of time between VMS records were often necessary to resolve whether vessels were leaving/ entering port, fishing or simply passing a port (Appendix 1.7.2).

1.3.3 Fish ticket matching

Fish processors issue fish tickets to vessels when they deliver their catch. Fish tickets, observer, and VMS data all share a vessel identification number which bolsters the ability to join the datasets. The utility of matching VMS-based trips to fish tickets was threefold: identification of missing port information, distinguishing between fishing and non-fishing trips, and determining if fishing trips were AFA pollock trips.

Long gaps between VMS records could obscure a trip's *in-port* periods, and thus the port of embarkation or disembarkation may be unknown. However, when a fish ticket could be matched to the VMS trip, it identified the port in which the trip ended. In some cases, the fish ticket match could also elucidate missing ports of embarkation, though these matches were less obvious as embarkation port was not recorded on the fish ticket.

Fish tickets included fields for the date that fishing started within each management area and the date on which those fish were landed. The procedure to match fish tickets to VMS relied on whether a trip included at least one VMS record that fell within a reported state statistical management area (www.adfg.alaska.gov/index.cfm?adfg=fishingCommercialByFishery.statmaps) from the fishing start through fish landed dates. A series of additional conditions were required to account for nuances associated with short trips, multiple trips ending on the same day, gaps in VMS transmissions, and trips that offloaded to multiple processors or over multiple days.

1.3.4 Calculating trip characteristics and ground-truthing the trip algorithm

To address our second objective, we first calculated the distances traveled and the durations of trips. The majority of trips (88%) had an *in-port* record at both their start and their end, but in most cases, that *in-port* record had a distance from port > 0 nmi (because vessels dock in any number of places within a port). For consistency, if the port was neither Dutch Harbor nor Akutan (which are described below) we linearly extrapolated the vessel's trajectory to the point at which distance from port was 0 nmi. If an end port was missing however, we had to first resolve missing port information. If a trip was matched to a fish ticket and the trip's end port was missing due to a gap in the VMS data, the missing port was assigned from the fish ticket port. To ensure the quality of such port assignments, we examined the locations and times of VMS records on either side of the VMS gap and we calculated the speed that would have been necessary for the vessel to have reached the newly assigned port and each of the VMS records on either side of the gap. If that speed was > 14 knots, we instead assigned the final port to be the closest port to the final VMS record prior to the vessel's entry to port.

The large spatial buffer zones (10 nmi) around Dutch Harbor and Akutan required a different approach to calculating trip durations and distances traveled. Vessels in these ports may have spent substantial amounts of time in transit while still *in-port* and their distances traveled may have been greater than estimated by the 10 nmi port threshold alone. A full analysis of *in-port* behaviors (e.g., ferrying, fueling, delivering) was beyond the scope of our study, but ignoring *in-port* behaviors altogether left the potential for under estimating trip durations and biasing comparison with observer estimates of trip durations, which start at the dock. By analyzing those trips for which contiguous VMS data (≤ 30 min between records) were present between the dock and the 10 nmi threshold, we estimated mean durations and distances traveled by vessels within both Dutch Harbor and Akutan. Vessels were estimated to travel 13 nmi (in 101 min) and 12 nmi (in 92 min) within Akutan at the beginning and end of each trip, respectively. In Dutch Harbor, vessels traveled on average 10 nmi (in 80 min) at both the start and ends of trips. These constants were added to the duration and distances traveled by vessels, starting at the point at which they crossed the 10 nm threshold (see Appendix 1.7.3 for details).

On rare occasions, (< 0.1% of observed trips) a vessel repeatedly crossed the 10 nmi threshold near Dutch Harbor during a short time window, perhaps due to fishing, shuttle runs or gear testing. These would result in inexplicable, repeated trips of very short duration (typically < 4 VMS records, or ~ 120 min). All trips of four or less VMS records total were removed.

Trip distances were calculated by summing the distances between each VMS record plus any of the *in-port* constants or extrapolations to port that were described above. Trip durations were calculated between the first and last VMS record plus any *in-port* constants or extrapolations to port.
Observed and VMS trips were matched for comparison if at least one VMS record fell within the observed trip period and the observed trip duration was > 200 min (73.1% of observed trip records; 0.07% of observed fishing trips). Most of these short observed trips (< 200 min) did not have a matching VMS trip because by our definition they never left port (e.g., a refueling trip within port, moving from the

processor to a different dock), and VMS records were often sparse during such periods. Trips of such short duration with VMS data could have measurement errors > 50% and were deemed outside of the precision of our approach. For the remainder of trips, we expected that the VMS-based trip duration may systematically over or under estimate the observer-based trip duration (which we assumed to be the true duration) so we fit a series of regression models to estimate and then, if present, to correct any bias (Appendix 1.7.4).

1.3.5 Characterizing fishing versus non-fishing trips

To address our third objective, we used a multi-tiered approach to characterize fishing and non-fishing trips. Our goal was to parse AFA pollock fishing trips from non-fishing trips (e.g., transits between Dutch Harbor and Akutan or working as a tender) and from fishing trips for non-AFA target species or fisheries (e.g., crab or other groundfish). The first step of trip characterization was based on a set of decision rules (Appendices 1.8.6 and 1.8.7) that examined fish ticket matches, ports, gear types, vessel speeds, trip location and date. The second step relied on regression to predict those trips that still remained uncharacterized after the decision rules. In the final step, we used a set of spatial and behavioral filters to differentiate AFA and non-AFA fishing trips (e.g., if a vessel had no fish tickets for AFA trips within a given month, any unmatched VMS trips during that month were classified as non-AFA trips).

Not all trips could be classified using the decision rules so we fit a regression model to predict fishing versus non-fishing for the remaining, unassigned trips (N=1,782). We used the already classified trips to fit the model, and among these, we used only those trips that were likely to be representative of the remaining uncharacterized trips (e.g., all trips that were part of scientific surveys or that occurred in certain regions had already been characterized as non-fishing). We also omitted trips for which a single trip overlapped with multiple observed trips, or vice versa, to avoid ambiguous model inputs. Finally, we excluded long (> 15,000 min) and short (<200 min) trips from the training data as they were unrepresentative of the remaining uncharacterized trips.

Binomial generalized linear and additive models (GAMs; R package mgcv version 1.8-4 [Wood 2006]) were fit to 22,260 already characterized fishing and non-fishing trips to predict the probability that a given trip was a fishing trip. Candidate models were evaluated based on predictive accuracy using training and test datasets of 75% (N = 16,695 trips) and 25% (N = 5,565) of the data, respectively. A suite of trip and vessel characteristics were explored as potential predictors (Table 1.2), with models iteratively fit via removal of covariates. Smoothing was examined with default selection and with univariate smoothers constrained to 4 estimated degrees of freedom. The final logistic GAM formulation was

$$\mathrm{logit}(\mathrm{p(fishing)}) = \mathrm{s}_1(\ln(duration), avesp) + \mathrm{s}_2(sddif) + \mathrm{s}_3(sdsp) + season_j + start_k + end_l, \quad (1)$$

where $s_i(.)$ represents the individual smoothing functions. We used an isotropic bivariate smoother (Wood 2006) for *avesp* and *duration* because longer trips are likely to have more transits and thus, higher average speeds. Univariate smoothing functions (default thin plate regression splines) were fit for the remainder of predictors and the final model used default smoothing.

1.3.6 Bias estimation from simulation of VMS gaps

The primary complication with the use of VMS data was inconsistent transmission intervals. In addition to complicating the trip algorithm, gaps in VMS transmissions may have also affected the estimated distances traveled. The calculated distance traveled will depend on the trajectory of the vessel between VMS records. Inevitably, data that are sampled as infrequently as VMS data (as opposed to AIS data, which are collected constantly) will under-estimate distances traveled (and subsequently, vessel speeds), because we calculate only straight-line distances between VMS records. The role of temporal sampling resolution on inference is the subject of entire papers (e.g., Deng et al. 2005; Palmer 2008; Postlethwaite 2013) and thus a full assessment of errors in the estimated distance traveled was beyond the scope of this study. However, previous studies primarily focused on mandated transmission frequencies (e.g., all VMS records being transmitted at 30 min vs. 60 min intervals). These studies did not address the role of missing data or gaps so we conducted a basic simulation to demonstrate how a single or several missed VMS records may affect the travel distance for a given trip.

We simulated gaps in VMS transmission > 30 min by removing VMS records from trips with complete data sets. We removed a single record from a trip such that the VMS data would have a single gap of 60 min instead of 30 min. Removal of a second VMS record (adjacent to the first) would yield a gap of 90 min, and so on, for additional removals. To simulate the effect of such gaps, we identified trips whose VMS records were transmitted at regular intervals (25 – 35 min) and we removed 1 – 4 consecutive VMS records from each trip to simulate gaps of 60, 90, 120, and 150 min. We randomly sampled 5,000 trips, with replacement. Distances traveled between consecutive records varied with vessel behavior throughout the course of a trip, so the position of the removed VMS record within the trip sequence was also randomly chosen (thus, sampling with replacement was not a concern). The subsequent removals occurred at the positions one, two, or three VMS records prior to the first removal.

1.4 Results

Our first objective was to use VMS data to identify individual trips made by CVs in the BSAI and GOA. We expected this objective to be a straightforward "vessels leave port and then return to port" analysis but as many VMS records (8.9%) were transmitted at 35 – 60 min intervals (instead of the expected 30 min) and another fraction (2.1%) were transmitted less frequently, our method evolved into the more intricate presentation described above. This development however underscores the value of understanding the data at hand and emphasizes that even though software packages exist for processing VMS data, it is still valuable to understand how the particular dataset may affect inference. By scrutinizing the data, we developed an algorithm to accommodate variable transmission rates and we identified 29,969 trips from 2008 – 2014, of which 15,418 were matched for comparison with observed trips.

1.4.1 Calculating trip characteristics and ground-truthing the trip algorithm

Our second objective was to quantify the distances and durations of each trip and to ground-truth the estimated trip durations with observed trip durations. VMS and observed trips were matched when at least one VMS record fell within the observed trip period. A VMS trip that started and ended at exactly the same time as an observed trip would have no difference in the estimated versus observed duration. However, even cases where the trip algorithm perfectly captured the dynamics of a trip still have a range of expected error. For example, if VMS records were transmitted at 12:00 and 12:30, and an observer reported a trip to start at 12:01, the algorithm would start the trip at 12:30 and a 29 min difference would exist between the VMS and observed trips. Similarly, if the observer ended a trip at 12:01 but the next VMS record did not appear until 12:30, a 29 min difference in trip endings could exist. Thus, even with VMS records transmitted at regular 30 min intervals, the difference could be as large as 58 min (29 min at the start and 29 min at the end of a trip). This measurement error would increase as the time between VMS records increased, such that the error would be two times the VMS transmission rate minus two minutes. The duration of a trip impacts the significance of this measurement error. For example, for trips longer than 1,160 min (19.3 hrs), the 58 min measurement error represents < 5% of the total trip. Among observed trips (Figure 1.1), 86.4% of durations were estimated within their measurement error, 76% of estimates were ≤ 5% of the observed duration, and 96.5% of durations were estimated either within their measurement error or within 5% of the observed duration. Estimated and observed trip durations had a Spearman $\rho = 0.98$.

The distribution of trip durations was bimodal (Figure 1.1a), with predominantly non-fishing trips < 700 min and fishing trips ≥ 700 min. As the 1:1 line (Figure 1.1b) illustrates, trips ≥ 700 min were both under and over estimated while trips < 700 min appeared to be biased toward over-estimation for the shortest trips (more points above the 1:1 line) and under-estimation as trips got longer (more points below the 1:1 line). The aggregate duration (sum of all durations) of VMS trips was 1.4% less than the aggregate duration of observed trips and trip-level durations had a mean absolute error of 5.78%. Regressions to correct for bias in estimated trip duration yielded mixed results, with aggregate durations slightly improved by models and trip-level durations slightly worsened (see Appendix 1.7.4 for regression details; this approach may be quite effective in other fisheries or regions). These findings underscore that multiple types of behaviors may exist within a given fishing fleet. While a regression-based approach to correct biases in our study did not have a large effect, it may have more traction in different fisheries and is a valuable tool to have at the analyst's disposal.

Only a small fraction of trips (~0.1%) had absolute errors greater than 100%. All of these were the result of over-estimated trip durations, occurring because the algorithm was unable to detect the transition from one trip to the next. The majority of these resulted from gaps in VMS data greater than 4 hours while the remainder were a combination of cases where the trip algorithm simply missed a trip transition (e.g., the speed conditions around a particular port did not trigger a new trip), a floating processor was too far from the GPS coordinate we used to define it as a "port," or the observer-reported time did not align with the vessel's return/ departure from port. The small error rate suggests that the trip algorithm approach worked well and that regardless of how well the algorithm is tuned, there will inevitably be data issues that will result in at least small amounts of error.

1.4.2 Classification of trips

Decision rules classified 19,877 trips as either fishing or non-fishing. Among those classified trips with matching observer data, 99.9% (N=11,678) and 98.8% (N=2,777) of observed fishing and non-fishing trips, respectively, were correctly assigned.

The GAM explained 91.1% of the model deviance and demonstrated a 99.0% accuracy predicting out-of-sample (N = 1,210 non-fishing trips, 4,355 fishing trips). The model predicted whether fishing occurred during the remaining 1,768 unclassified trips. Among these trips, 386 and 1,382 were designated as non-fishing and fishing, respectively.

The combination of decision rules and regressions classified 29,794 trips (99.4%) as fishing or non-fishing, and as either an AFA pollock trip or a non-AFA fishing trip (Table 1.3). The final distribution of non-fishing, non-AFA fishing trips and AFA fishing trips by year (0.6% of trips remained unclassified and are omitted here) is shown in Table 3 (see Appendix 1.7.7) for more detailed descriptions of trip type compositions).

As demonstrated by the above percentages, our combination of decision rules and regressions yielded highly successful classifications of trips, when compared with observer data, supporting our objective of classifying trips as non-fishing, fishing for pollock, or fishing for species other than pollock, based on trip-level characteristics like gear type, port, and average speeds. Furthermore, by laying out the rationale behind the chosen model covariates (Table 1.2) we believe that adjusting this approach for other fisheries and with other data should be relatively straightforward, even if different decision rules and different final models are ultimately necessary.

1.4.3 Bias estimation from simulation of VMS gaps

Understanding how variability in the transmission of data may affect inference is critical for evaluating the utility of data and any approach that uses those data. While other studies have examined the roles of sampling frequencies, we have simulated the role that data quality (in the form of discontinuities in the data) may affect conclusions. Simulations that removed one, two, three, and four consecutive VMS records from a trip (Figure 1.2) reduced estimated trip distances (compared to the same trips without gaps) by a mean (± 1 mean absolute deviation [MAD]) of 1.5% (± 1.1%), 4.1% (± 2.6%), 8.1% (± 5.0%), and 13.4% (± 8.3%), respectively. While only a relatively small portion of trips had appreciable gaps in VMS data, these gaps are capable of substantially reducing trip distances. However, given the high degree of accuracy seen when estimated trip durations were compared with observed trip durations, we believe that the effects on trip distances were insufficient to invalidate our methods. They may however provide guidance on estimating error rates when extending such analyses to fuel consumption calculations or other trip-level metrics.

1.5 Discussion

Many studies have used VMS to examine facets of fishing behavior, often analyzing copious amounts of information with little discussion of the nuances of data processing and management or how necessary assumptions may affect interpretations. We have examined such subtleties through providing a complicated answer to the trivial questions, "When does a fishing trip start and end?" and "What type of fishing trip was it?" As we demonstrated, nuanced approaches were required to account for region-specific aspects of the data (e.g., geography of fishing ports and targeting behavior) and discrepancies between different data sources (e.g., inconsistent VMS transmissions and imprecise dates/ times in human-recorded data). The challenges that we have addressed here – while specific in their geography and peculiarities – represent several of the key challenges facing users of VMS data globally. These challenges represent some of the critical road blocks that researchers and managers face when using VMS data to resolve metrics like trip-level effort, trends in fleet behavior, responses of the fleet to climatic or regulatory changes, and dynamic costs to fishers. While much of the subsequent discussion describes the important challenges to using these "big data," we emphasize that highly accurate results were still obtainable by taking extra steps to understand and account for data issues.

1.5.1 VMS Data

Spatial data are increasingly available to track the movements of marine vessels worldwide. Fishery researchers have recently found two such sources of data to help resolve unobserved fishing behaviors globally. Automatic identification systems (AIS) and VMS rely on historically different technologies and purposes. Designed to improve maritime safety, AIS transmit high resolution location data (typically < 1 second intervals) from vessels in real-time and they inform neighboring vessels of their movements. Traditionally, AIS was based on VHF transmissions and required line-of-sight to another vessel or a shore-based receiver in order to transmit data. However, more recently, satellite AIS systems have enabled tracking of vessel movements across the globe. Given the virtually continuous streaming of AIS data, this technology offers promise for improving prediction of vessel behaviors (e.g., Last et al. 2014) and correcting some of the biases introduced by the relatively longer sampling frequencies of VMS data. However, proximity to shore-based receivers and poor satellite reception can affect data quality (e.g., in the North Pacific) (Renner and Kuletz 2015), and exemptions have historically existed for some fishing vessels, allowing them to deactivate their AIS units to protect the confidentiality of fishing grounds. At present, AIS data access can also be difficult (we tried to obtain AIS data for this study) so while improving technology offers an alternative or a complement to VMS data, some challenges still remain. Meanwhile, VMS data offered much potential, despite having challenges of their own.

The irregular and sometimes long gaps in VMS transmissions were responsible for the majority of the challenges encountered in this study. Gaps may occur when vessels receive permission to deactivate their VMS units, have equipment failures or poor satellite reception, or are a result of illicit behavior / tampering. Gaps in coverage are scarcely mentioned in the VMS literature (though see Joo et al. (2013); Chang and Yuan (2014)), but preliminary exploration of VMS data from a different region of the United States also found gaps, suggesting that they may be pervasive and thus, critical to how VMS data are analyzed. Without such gaps, our approach would have been dramatically simplified; transitions into and out of ports would have been more readily captured and a simple point-in-polygon approach like that of existing software (VMStools (Hintzen et al. 2012) and VMSbase (Russo et al. 2014)) would have likely been sufficient. Instead, > 10% of trips were missing an *in-port* VMS record at the beginning or the end of the trip, thereby precluding an easily identifiable trip start and end. Meanwhile, some trip transitions were missed altogether because gaps spanned the entire *in-port* period. These missing port periods required a more substantial approach to trip identification, but after careful accounting, comparison with observed trip durations (average errors < 1.5%) suggested that some of the data complications were well-accounted for.

Even when gaps in VMS transmissions did not affect trip identification, the missing information associated with the gaps was still important. Simulated gaps yielded mean underestimation of trip distances (± 1 MAD) of 1.5 (1.1) % to 13.4 (8.3) %. These results were particularly poignant given that ~ 34% of actual trips had at least one gap > 60 min and ~15% of trips had at least one gap > 150 min (Fig 3). While the implications of this are straightforward – gaps in VMS data often lead to underestimation of trip distance – the range of the errors (Fig 1.2) is also important. In each of the gap scenarios, the lower end of the range was zero percent difference. This highlights the importance of the vessel behavior when a gap occurs. If a vessel is transiting in a straight line for the duration of the gap, little or no error may occur in the estimation of distance. However, as the sinuosity of a vessel's path increases, especially at higher speeds, the error in travel distance will increase. A substantial body of literature has examined the role that different VMS transmission frequencies may play on the estimation of effort (Deng et al. 2005; Mills et al. 2007; Palmer 2008) and several studies (Hintzen et al. 2010; Russo et al. 2011) have presented interpolation techniques for resolving coarse temporal sampling in vessel tracks. However, while such studies provide valuable discussions of broader errors associated with periodically sampled data, they focus on systemic biases instead of the smaller yet still substantial errors that may be introduced and easily overlooked by a single or only a few missing VMS records. We hope that despite the simplicity of the simulations presented here, users of VMS data will recognize the dramatic impact that even small gaps in VMS transmissions have on inference.

1.5.2 Human-recorded data ("the truth")

We used observer data from more than 15,000 trips as the empirical information with which we performed validation. However, in some cases, inscription errors may exist in the observer data themselves, resulting in failed matches with VMS trips, or more frequently, leading to under or over estimation of duration as compared to the VMS data. Two typical cases emerged upon manual inspection of many matched trips. Observed trips are defined as starting when a vessel unties from the dock and ending when it ties up at the dock again. However, it was not uncommon for the observed start of a trip to occur while the vessel remained at the dock (or vice versa, at the end of the trip), sometimes for extended periods. While these at-the-dock periods led to erroneously long trips, other situations occurred where the vessel was several miles and/ or hours outside of port when the observed trip began or ended, leading to observed trip durations that were shorter than the apparent trip duration based on VMS. Notes in observer logs may explain such exceptions, but notes may be infeasible to incorporate with datasets of this size. Nonetheless, cases like these are responsible for discrepancies between the observed and VMS trip durations that are unrepresentative of the true errors of our approach.

Fish tickets were the other human-recorded data source upon which we relied. They were used for identifying missing port information, as well as identifying fishing and non-fishing trips and parsing AFA from non-AFA fishing trips. Several aspects of the fish ticket data complicated this matching procedure.

However, the matching of fish tickets relied on the dates that were manually recorded, so incorrect or imprecise dates could lead to errors in the matching or an inability to match trips altogether. For example, VMS could identify that a vessel that reported landing its catch in Dutch Harbor on January 20th did not come within 30 nmi of Dutch Harbor until January 21st. Alternatively, a vessel may have delivered their catch on January 20th but the fish ticket reports January 21st, when the vessel is already 30 nmi from port. In our case, many fish tickets were omitted from matching because the dates were clearly incorrect but the correct date was unclear.

While recording, rounding, transcription, or other time-keeping differences may have led to errors in matching VMS trips with observer data or fish tickets, or may have led to errors in their comparisons, manual inspection of many matched trips suggested that these human-reported errors were relatively rare in the NPGOP data. This was not surprising given the scale of the NPGOP and the several decades of development they have had for quality control protocols. However, our approach was able to identify errors and it may offer observer and fish ticket programs globally an additional method by which to assure the quality of their datasets. For example, we could modify this algorithm so that the observer program could examine cases where the VMS trip duration was misaligned with that of the observed trip duration and in plotting the vessel speeds and distances from port, they could easily identify – within 30 min – when the vessel actually left or returned to/ from port. Similarly, one example of an error in fish ticket data occurred when a fish ticket reported having a fishing start date of 01/03 and an end date of 02/01. However, there were three other fish tickets for this vessel occurring on 1/20-1/22, 1/23-1/24, and 01/25-01/27. In such a case, it is was clear that either the start or the end date of the fish ticket was wrong, but without knowing where the vessel was during either of those dates, it would be impossible to rectify the error. By mapping the VMS trips that occurred during that period, it was trivial to rectify which of the two dates was the incorrect one. Similarly, by identifying all of the fish tickets matched to a single VMS trip, errors in reporting might be identified or fish tickets might be more effectively grouped for other analyses. Finally, data fields in fish tickets were occasionally blank or port locations were recorded incorrectly, and these could be rectified via VMS-based vessel location.

1.5.3 The trip algorithm

Our algorithmic approach performed well, matching observed trips and estimating their durations with differences typically < 1.5%. Some of the discrepancies that did occur between observed and estimated trips were the result of different trip definitions between the algorithm and observers. For example, if a vessel anchored in port instead of tying up at the dock, the algorithm ended the trip (such differences were indistinguishable by VMS) but the observer did not. Similarly, some stops at floating processors were identified as new trips by the algorithm but not by the observer. Other rare discrepancies occurred when the algorithm missed the transition between observed trips; even with regular VMS transmissions, brief stops that occurred between VMS records occasionally remained undetected. An additional point of discrepancy could occur if a vessel spent longer than average within the port boundary for Dutch Harbor or Akutan. For example, a lineup at the fuel dock or a long wait to deliver to a processor could result in greater than expected durations from observed trips such that the *in-port* constant added to trip durations was low. In other rare cases, floating processors were in unexpected locations and were not among the list of port coordinates in the algorithm so trip transitions were missed altogether. Finally, a transiting vessel may have passed close enough to a port while also satisfying the algorithm's speed conditions for that port, such that a new trip was incorrectly triggered by the algorithm. Our algorithm was finely tuned to account for as many of the above contingencies as possible while recognizing that without over-fitting, higher accuracy was unlikely. Nonetheless, some vessel movements and transitions were simply unable to be captured or anticipated. However, the majority of the errors that did occur were more likely the result of data issues than model fits.

1.5.4 Applications and future directions

Despite numerous data challenges, VMS provide a method by which trip characteristics are estimated to a high degree of accuracy. We further identify types of vessel and targeting behaviors, making this study the first, to our knowledge, to use VMS to identify métiers (specific fisheries by gear, region, target species) (Marchal 2008) in U.S. fisheries. In the Bering Sea, all trips targeting pollock are now observed but our approach enables us to characterize unobserved trips elsewhere throughout the North Pacific and retrospectively for years prior to full observer coverage. Our continuing steps include applying our approach (developed with 91 trawl vessels) to more than 500 longline and trawl vessels with VMS in the BSAI and GOA. Meanwhile our approach has been adapted for vessels in the Gulf of Mexico (using longlines, troll gear, trawl, hand lines, pots, traps, and divers) indicating the extent of the generalizability. Our approach may help other VMS users in the future to quickly identify the role that gaps may play in their dataset, as well as how geography of their particular ports may affect inference.

Contemporary fisheries literature is rife with projections of climate-induced shifts in fish populations and the subsequent implications for global fisheries (e.g., Hollowed et al (2013) and references therein). Range expansion of fish populations (Drinkwater 2005; Nye et al. 2009; Kotwicki and Lauth 2013) may be accommodated by longer transits to fishing grounds or by increased search time between fishing activities. However, even if catch per unit effort, as typically defined based on active fishing time, can be maintained under longer transit scenarios, costs to fishers may increase (Haynie and Layton 2010), and ultimately, the profitability (and thus, sustainability) of fisheries may be compromised. Precise estimates of travel distances, trip durations, and the diversification of fishing strategies (e.g., change in métiers per vessel over time) (Kasperski and Holland 2013) may thus become a critical component to understanding and characterizing the resilience of certain fisheries. For example, a shift in pollock populations away from port would impact the smaller vessels in the fleet more than the larger vessels which have greater hold capacity and a greater ability to buffer against increased fuel costs (Criddle and Strong 2013). Linking trip characteristics with extrinsic factors like fuel price allows analyses to estimate the breaking points at which vessels change their fishing behavior and ultimately alter their impacts to the coastal economies that are supported by them.

This study presents a methodology for assessing trip characteristics when pre-packaged software (e.g., VMStools, VMSbase) are incompatible (e.g., due to missing port information or port geography outside of the programmed regions) with a particular dataset or level of precision. Additionally, as we discovered, even a dataset with coverage of the entire fleet for more than a decade is likely to require greater than expected scrutiny. That scrutiny may increase as additional datasets (e.g., observer, fish ticket or logbook data) are brought into the mix, while also presenting new avenues for quality control across data programs.

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Table 1.1: Description of data coverage and sources. Data coverage has varied over time. Since 2011, pollock vessels have been fully observed; previously, vessels < 125 feet long were only observed for 30% of pollock fishing days at sea while longer vessels were fully observed.

Data	Coverage requirement	Years	Vessels	N	Source
VMS	100% of trips	2008 – 2014	91	~3.5 million VMS records*	Spalding 2016
Observer	30% of pollock fishing days at sea	2008 - 2010	65	2,366 trips†	NOAA 2016a
Observer	100% of pollock fishing days at sea	2008 - 2010	26	1,897 trips†	NOAA 2016a
Observer	100% of pollock fishing days at sea	2011 - 2014	91	14,482 trips†	NOAA 2016a
Fish ticket	100% of fishing trips	2008 - 2014	91	27,503 trips	ADFG 2015

* Individual VMS records

† Trips with observed durations > 200 min.

Table 1.2: Candidate predictor variables for predicting whether a trip is a fishing or non-fishing trip. Trip-level predictors are based on the characteristics of all VMS records per trip that meet the given descriptions.

Candidate predictors	Description	Expectation
avesp	Average speed for all VMS records per trip > 10 nmi from port and traveling > 0 knots	Trips with lower average speeds are more likely to be fishing trips.
duration	Trip duration (min)	Fishing trips are typically 1 – 4 days
sddif	Standard deviation (per trip) of the difference between speeds of consecutive VMS records when traveling between 0 – 5 knots (fishing speeds)	Trips with more variability among their slower VMS records are less likely to be engaged in fishing (trawling speeds tend to be fairly constant).
avedif	Average (per trip) of the difference between speeds of consecutive VMS records when traveling between 0 – 5 knots (fishing speeds)	Trips with very slow (< ~ 1 knots) average speeds among their slower VMS records are less likely to be engaged in fishing.
sdsp	Standard deviation of speed for VMS records per trip > 10 nmi from port and traveling > 0 knots	Trips with a higher variability of speed are more likely to be fishing.
avgspstat	Average speed for VMS records per trip occurring in statistical management areas known as "fishing areas"	The average speed at fishing grounds is likely to be slower if fishing occurs.
$start_k$	Port from which the trip began, grouped into one of four regions: Gulf of Alaska, Bering Sea, Aleutian Islands, or Other (see S6 Text for breakdowns by port)	Fishing trips are less likely to occur if started from certain ports.
end_l	Port in which the trip ended, grouped into same regions as in $start_k$	Fishing trips are less likely to return to certain ports.
$season_j$	Pollock fishing is divided into a winter "A" season and a summer "B" season, with "N" representing non-pollock season trips.	Vessel often target different locations during the different seasons, which would affect statistical moments calculated for speed.
size	Vessel length	Smaller vessels may transit and fish differently than larger vessels.

Table 1.3: Distribution of fishing and non-fishing trips. Distribution of fishing and non-fishing trips. Total numbers of trips and vessels, plus the percent of the total trips for AFA fishing, non-AFA fishing, and non-fishing trips. Annual tallies are provided by season (Winter "A" season, Summer "B" season, and "N" non-AFA season).

Season	Year	Total trips	AFA trips	Non-AFA trips	Non-fishing trips	Vessels with AFA trips	Vessels with non-AFA trips
A	2008	1459	40.7	42.2	17.1	75	61
A	2009	811	45.4	35.6	19	66	37
A	2010	1394	39.1	37.4	23.5	76	51
A	2011	1873	43.4	34.2	22.4	80	52
A	2012	1904	41.7	36.6	21.7	80	55
A	2013	1765	42.6	36	21.4	73	52
A	2014	1710	43	40	17	68	53
B	2008	2069	51.9	14.5	33.6	74	40
B	2009	1668	44.9	13.2	41.9	69	31
B	2010	2140	39.8	12.1	48.2	69	27
B	2011	2896	45.1	10.5	44.4	74	33
B	2012	2538	49.9	11.3	38.8	76	34
B	2013	2788	43.1	11.3	45.6	72	38
B	2014	2297	50.9	8	41.1	73	31
N	2008	467	0	50.7	49.3	0	57
N	2009	649	0	59.8	40.2	0	77
N	2010	326	0	28.5	71.5	0	27
N	2011	137	0	19.7	80.3	0	13
N	2012	165	0	19.4	80.6	0	12
N	2013	290	0	34.1	65.9	0	28
N	2014	515	0	56.1	43.9	0	40

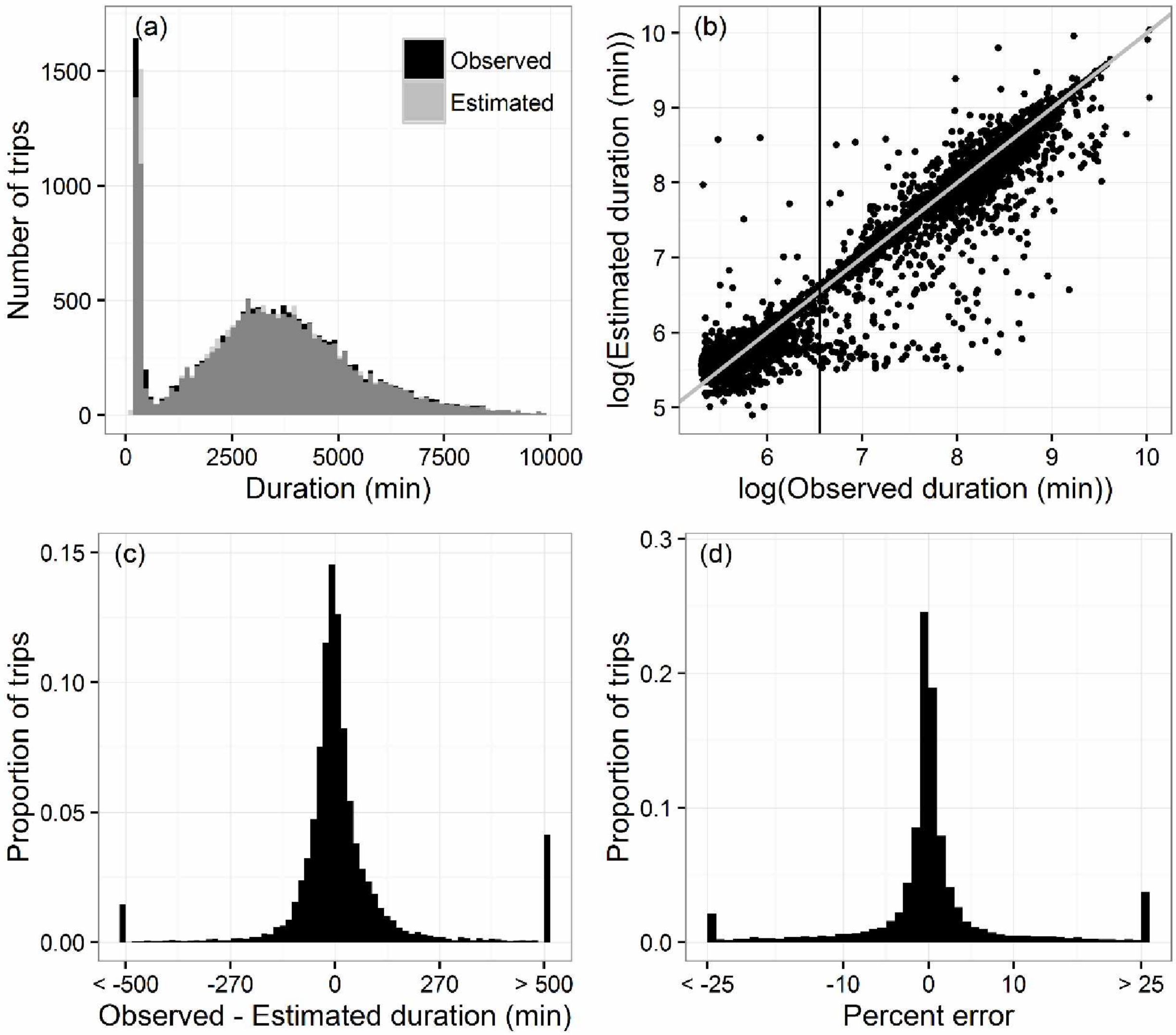

Figure 1.1: Distributions of observed and VMS-estimated trip durations. (a) Overlain histograms of durations for observed and VMS-estimated trips. Dark grey areas show overlap. For illustration purposes, figures are scaled to a maximum of 10,000 min which omits < 1% of trips with longer durations. (b) Observed versus VMS-estimated duration for each trip. Data are log-transformed to better illustrate the clusters of data greater than and less than ~ 700 min. The vertical line shows the log-transformation of 700 min (6.55), the cutoff for exploring different models to estimate bias in estimated duration. The grey line represents the 1:1 line. (c) Difference between observed and estimated trip durations. For illustration purposes, values < -500 and values > 500 are binned as "< -500" and ">500," respectively. (d) Percent error (positive errors indicate over-estimation) of observed versus estimated trip durations. For illustration purposes, values less than < -25% and greater than 25% are binned as "< -25" and "> 25."

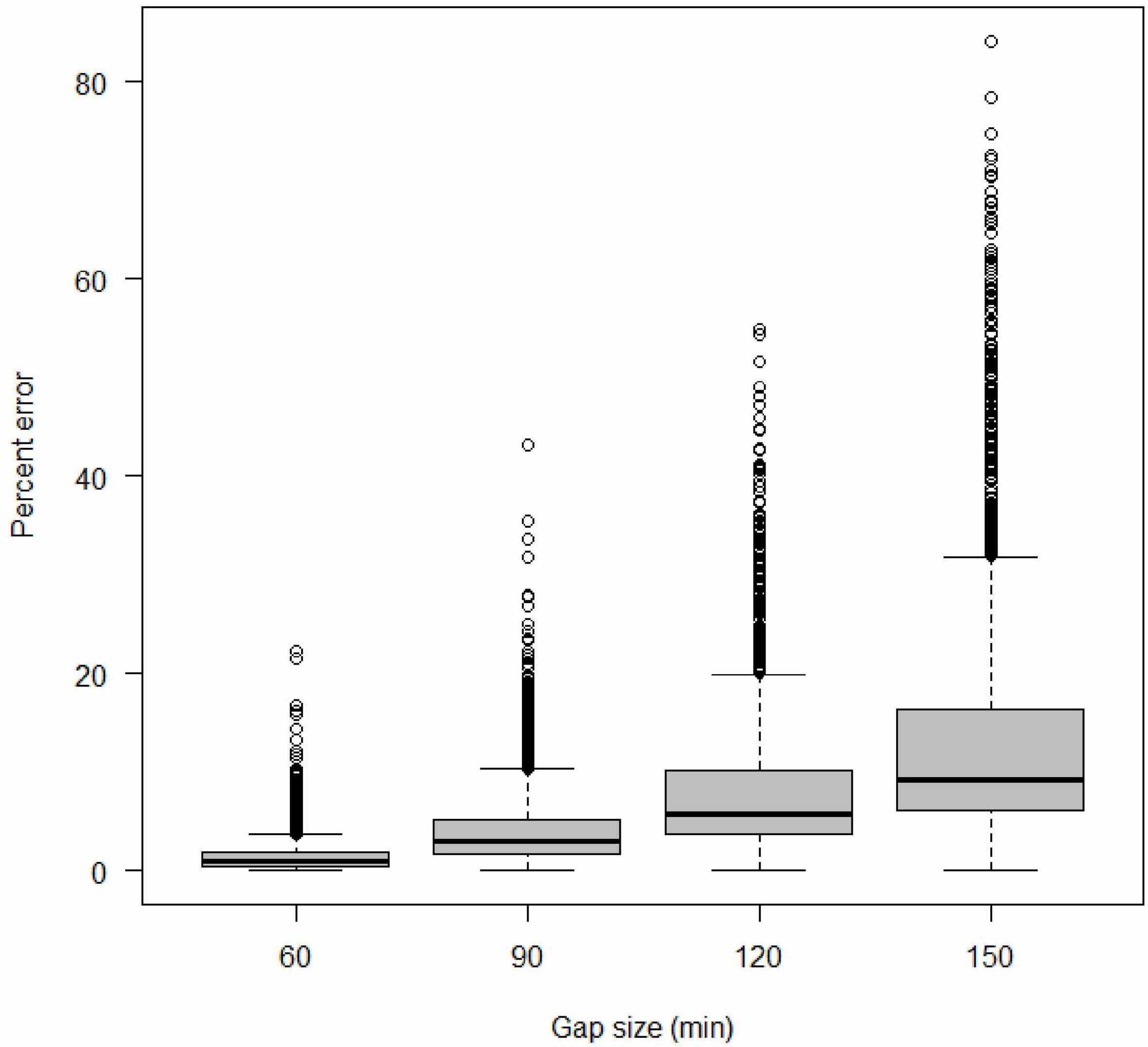

Figure 1.2: Percent errors in the estimated trip duration as a function of time gaps in VMS transmissions. Gaps in the regular transmission frequency greater than the expected 30 min intervals were simulated by removing 1 – 4 VMS observations from a random location within a trip's sequence of VMS records. Removals yielded gaps in the VMS sequence of 60, 90, 120, and 150 min. Points outside of the whiskers represent outliers (> 1.5 times the upper quartile), whiskers represent the range (excluding outliers) and the boxes represent upper and lower quartiles with the median depicted by horizontal lines.

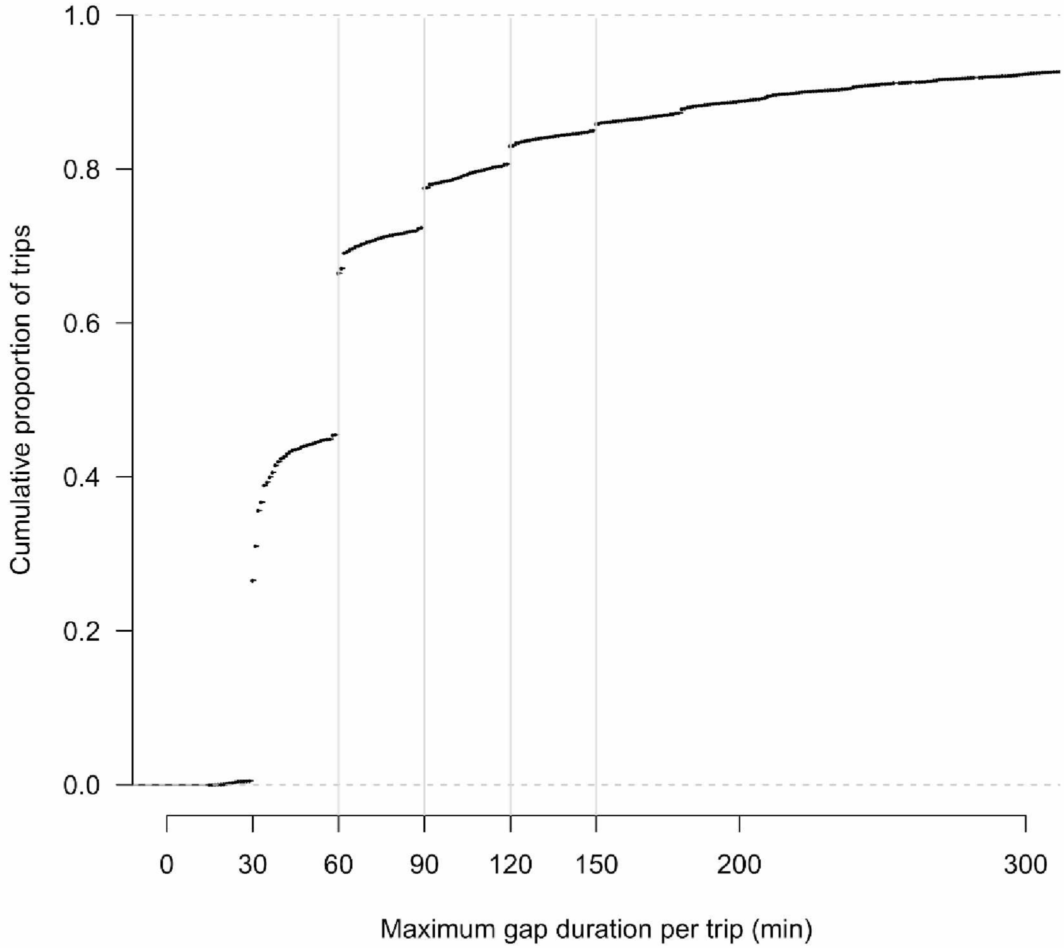

Figure 1.3: Cumulative distribution of the maximum time gap between VMS records for each trip. For illustration purposes, the 10% of trips with maximum gaps > 300 min are not shown here. Vertical grey lines are shown at each of the gap durations for which we simulated removals of VMS records.

1.7 Appendices

1.7.1 Calculation/ description of fields from VMS data

Distance from port - The distance of each VMS record from port was calculated using the Haversine formula by iteratively identifying the closest port from among all potential northeast Pacific commercial fishing ports.

Vessel speed - Some VMS instruments transmit a vessel's instantaneous speed but this field was inconsistent in the data for different VMS instruments and during different years so vessel speeds were instead calculated from the time difference and the distance traveled between VMS records (using the Haversine formula for calculating great-circle distances). In most literature studies with tagging or movement data, speeds are either calculated between the current and previous or the current and subsequent records. However, with the relatively long duration between VMS records, we also calculated and utilized the mean of the forward- and backward-calculated speeds. Unless otherwise stated, any reference to vessel speed refers to this average speed term.

Notably, any distance or speed calculation (which is a function of distance) from data that are not sampled continuously are prone to under-estimation because calculations are based on the straight line distances between sampling points. The more tortuous a vessel's path between sampling, the greater the degree to which distances will be under-estimated. While this is a critical aspect of using these data, a full characterization of this concept was beyond the scope of this paper. This concept has been pointedly addressed in numerous studies however, and we encourage analysts to explore how the movements of their individual fishery may vary. In our case, trips are typically characterized by relatively long transits and relatively short fishing periods. Errors are expected to be near zero during transits, and based on the gap simulations we present later in the paper, on the order of 20% during fishing periods (though vessels travel slower while fishing and thus the overall magnitude of the errors during the periods will be much less).

ADF&G and NMFS management areas - VMS locations were linked to a polygon shapefile (via PBSmapping version 2.67.60 in R Statistical Software Version 3.1.1) consisting of 1807 Alaska Department of Fish and Game statistical areas nested within 26 NMFS management areas that define fishery boundaries in the BSAI and GOA. It is not unusual for VMS instruments to transmit locations that are clearly erroneous and occur on-land; such records are referenced in other VMS studies (e.g., Hintzen et al., 2012; Russo et al. 2014) and are typically removed indiscriminately. However, in contrast to other studies, VMS records near port were critical to our objectives and some of the seemingly erroneous records were only barely on-land and appeared to be legitimate *in-port* records. These apparent errors may have been the result of different geodetic datums, VMS measurement error, shapefile resolution, extreme tides or another unforeseen factor. The coastline defines the boundary for each of the NMFS management areas and thus, on-land points were not automatically assigned to a NMFS area. Instead of haphazardly removing these points we first determined the distance of each unmatched point to the nearest management area (using the gDistance function in rgeos Version 0.3-8 for R) and if an area was within 5 km (km were used instead of nm because it was the native output from gDistance), the point was matched to that area.

1.7.2 Approach for determination of *in-port* status for VMS records.

Port-specific distance, speed and time thresholds were determined based on manual inspection of trips around each port (Table S1.1. The initial steps of the trip algorithm assigned any VMS record as *in-port* if it was within 10 nmi of a port. Conditions were then used to identify which of those records should not be treated as *in-port*.

"Dist" refers to distance from port in nautical miles.
"Speed" refers to the average of the forward- and backward-calculated vessel speeds.
All records were designated as *in-port* if:

- Speed < 0.1 knots & Dist < 60 nmi of NPT
- Speed < 0.1 knots & Dist < 50 nmi & Port is within southeast Alaska, Washington, Oregon, or PWS

All records were designated *at-sea* if:

- PORT = (IFP, LRB, LZB, PTB, OLD, FSP, KCO, ALI, CDB, EMM, GRM, HOM, KAS, KEN, MOL, NIN, NUN, SAV, SEL, UNA) & (Dist > 2 nmi)
- PORT = CHG & (Dist > 2 nmi) & (Speed > 2 kts)
- PORT = (KCO, IFP, SPT, ATK) & (Speed ≥ 1 kts) & (Gaps ≤ 60 min)
- PORT = (KCO, ATK) & (Speed ≥ 9 kts) & (Gaps ≤ 200 min)
- PORT = FSP & (Speed ≥ 0.5 kts) & (Gaps ≤ 200 min)
- PORT = PTL & (Speed ≥ 0.5 kts) & (Dist > 2 nmi)
- PORT = SDB & ((Speed ≥ 0.5 kts & Dist > 1) or (Speed ≥ 3 kts))
- PORT = STP & ((Dist >2 nmi)) or ((Dist <2 nmi) & (Gaps < 120 min) & (Speed > 0.2 kts)))
- PORT = KOD & ((Dist > 5 nmi) or ((Dist > 1 nmi) & (Gaps < 60 min) & (Speed > 2 kts)))
- PORT = TOG & (Speed > 2 kts)
- PORT = TOG2 & (Speed > 2 kts) & (Dist > 10 nmi)
- PORT = SNK & ((Speed > 0.5 & Dist > 1.5 nmi) or (Speed > 5))
- PORT = AKU & (((Speed ≥ 9 kts) & (Gaps < 35 min)) or ((Speed ≥ 5 kts) & (Gaps < 60 min)))
- PORT = ATK & (Gaps < 30 min) & (Speed > 0.5 kts)

- PORT = (ADA, ADA2, YAN) & (Speed ≥ 0.1 kts) & (Dist > 2 nmi)
- PORT = SPT & (Dist > 7 nmi) & (Speed > 0.1 kts))
- PORT = (FSP, DUT, KOD, AKU) & the total duration of an *in-port* period is < 120 min
- Gaps > 3000 min

Several contingencies were necessary to account for cases during which large gaps in VMS transmissions occurred between the last *at-sea* record and the first *in-port* record. If more than 120 min passed between these two VMS records, then the two were decoupled (i.e., the first *in-port* record was not considered to be part of the trip that was ending). The same methodology was applied to the last *in-port* record of a cluster and the start of the subsequent trip. If only one *in-port* record existed in a cluster and the time difference between that record and one of the *at-sea* clusters on either side was > 120 min, then the *in-port* record was assigned to the trip < 120 min away. If both trips were > 120 min then neither trip was coupled to the *in-port* record. If both trips were < 120 min from the *in-port* record, the prior of the two trips was (arbitrarily) coupled to the *in-port* record.

Using VMS from observed trips, we examined the distribution of long gaps in VMS transmissions that occurred while a vessel was *at-sea*. Long gaps were relatively rare during trips (as opposed to while a vessel was in / near port) and we qualitatively determined 3,000 min (i.e., 50 hours) to be the maximum allowable gap threshold during a trip. Any gap between VMS records > 3,000 min automatically triggered the start of a new trip.

1.7.3 Calculation of distances traveled and durations spent in transit while a vessel was *in-port*

We standardized *in-port* durations and distances traveled for Dutch Harbor and Akutan by examining trip starts where the VMS data had gaps ≤ 30 min from the time the vessel left the dock and the time the vessel reached the 10 nmi threshold (and vice versa for the end of trips). We considered a vessel to have just left the dock if the speed between the current and previous VMS record was < 0.25 knots and the speed between the current and subsequent record was > 0.25 knots. Records at the beginning of a trip that met these criteria (Dutch Harbor N=35 trips; Akutan, N=1,081 trips) were then compared with the first VMS record at-sea. If the first at-sea record was exactly 10 nm from port, the duration and distances traveled between that point and the first record away from the dock were calculated. In most cases, the first *at-sea* record occurred > 10 nmi from port. Using the speed calculated between the two VMS records straddling the 10 nmi boundary, the point at which the boundary was crossed was linearly interpolated. The time and distance traveled between the dock and the interpolated point were subsequently determined. The reverse process was performed at the end of trips, identifying instead the last record *at-sea* and calculating the distance and duration traveled until the last record when the previous speed was > 0.25 knots and the subsequent speed was < 0.25 knots (Dutch Harbor N=13 trips; Akutan N=1,200 trips).

Trips in Dutch Harbor spent an average of 80 min and traveled 10 nm while *in-port* with the same amount of time (t-test, P > 0.1) and distances (t-test, P > 0.1) spent at both the beginning and the end of the trip. Akutan trips differed between the start and ends of trips for both duration (t-test, P < 0.01) and distance traveled (t-test, P < 0.01). Akutan trips began with an average of 101 min and 13 nm of transit and ended with 92 min and 12 nmi of transit.

In order to apply the constant *in-port* duration and distances consistently across all Dutch Harbor and Akutan trips, we also had to standardize the points to which the constant start and end values were appended. If the first *at-sea* record occurred at exactly 10 nmi from port, the constant could simply be added to the time and distance of that VMS record. More often however, the last *in-port* and first *at-sea* records straddled the 10 nmi threshold (e.g., records were 8 nmi and then 12 nmi from port). In such cases, we linearly interpolated the point at which the vessel would have crossed the 10 nmi threshold based on the calculated speed between the two records on either side of the threshold. The *in-port* constants were then added to that interpolated point.

In some cases (~12% of trips), no *in-port* records existed for a trip and the first (or last) VMS record was outside the 10 nmi threshold. In such instances, the first record could occur anywhere between 10 nmi and several hundred nautical miles from port. Vessel trajectories were extrapolated between the first (or last) VMS record back to port using a transit speed of 8.5 knots.

1.7.4 Regression to correct estimated trip duration

We examined a series of linear, generalized linear and generalized additive modeling approaches to best fit observed trip duration with covariates including vessel, VMS-based trip duration, season (the pollock season is divided into a winter / spring season and a summer/ fall season), year, the distances from port of the first and last VMS records of a trip, and the size of gaps in VMS transmissions. Model selection was based on predictive ability, so models were compared by fitting a randomly selected subset of 75% of trips and comparing prediction accuracies from the remaining 25%. This model comparison was based on their ability to predict with the lowest percent error ([observed – predicted]/observed) for several different metrics. *Aggregate* (aggregate error), the error of the sums of all trip durations where positive errors indicate under-estimation. *Trip* (trip-level error), where the mean / median was calculated for the percent errors of all trips. This metric assesses whether there is a bias in the predicted duration (e.g., a positive value would indicate that, on average, the model under-predicted duration). *Abs* (mean/median absolute trip-level error), similar to the trip-level error but assesses the magnitude of the errors instead of the bias.

A suite of GAM and linear models were tested with covariates including: estimated trip duration, pollock fishing season, vessel size, the distances from port of the first (*startDIST)* and last (*endDIST*) VMS records per trip, number of VMS records per trip, the mean VMS transmission interval, and year. GAMs had consistently lower prediction errors for all three error metrics than did linear models. A back-fitting process was used for model selection but instead of comparing AIC from successive removals of predictors, we compared the change in the prediction accuracy. If a predictor was removed without decreasing the prediction accuracy, the predictor was dropped from the model. This process was repeated with both default smoothing of the predicted duration term and with the estimated degrees of freedom constrained to 4 (to determine if over-fitting was a factor in the prediction accuracy).

Exploratory plots revealed a clear break in trip durations (Figure 1.1b) greater than or less than 700 min. Because vessel behaviors may vary between short and long trips, we explored model selection for models that included all data, data for trips < 700 min, and data for trips ≥ 700 min. While fit with different coefficients, the latter two models were combined into our so-called piecewise model.

Model selection using three different error metrics was straightforward for most models but a final set of models had either similar accuracy or their performances varied across metrics, making a decision more difficult. Thus we present three final models (Table S1.2), each fit to the full dataset and to the two piecewise datasets. For comparison, we also provide the errors from the raw data (i.e., observed vs. VMS-estimated trip duration).

A final set of best models was iteratively fit to 100 randomly sampled training datasets consisting of 60% of the total data (additional models with different training-test data splits were also examined – results not shown) and tested on the remainder of data for each dataset and iteration. Training and test dataset sizes were varied to examine how results may fluctuate for fisheries with different levels of observer coverage.

We present results for a GAM that included only the estimated duration as a predictor, and a GAM that included several predictors:

$$\ln(\text{Duration}_{\text{observed}}) = \alpha + s_1(\ln(\text{Duration}_{\text{estimated}})) + s_2(\text{startDIST}) + s_3(\text{endDIST}) + \varepsilon, \qquad (1)$$

where *s(·)* are smooth functions of the VMS-estimated trip duration ($\text{Duration}_{\text{estimated}}$), and the distances from port of the first (*startDIST)* and last (*endDIST*) VMS records per trip. Smooth functions were estimated via thin plate regression splines. Table S1.2 includes errors from the above GAM with automatic smoothing selection (GAM1), a GAM with restricted smoothing on estimated duration (edf=4; GAM2), and a GAM with only $\ln(\text{Duration}_{\text{estimated}})$ as a covariate (GAM3).

Regression efforts to standardize estimated trip duration yielded mixed results, depending on whether we were more interested in aggregate trip durations or trip-level durations. For the former, GAMs reduced the aggregate percent error by more than half in some cases (e.g., GAM1 and GAM2, or GAM3 with the single regression). However, in most cases the trip-level errors were lower without using the regression. For those models that were successfully fit, prediction accuracies were similar across the range of test dataset sizes.

1.7.5 Characterizing fishing and non-fishing trips

Fish tickets only exist for fishing trips and thus, all trips that were matched with a fish ticket were classified as fishing trips. Fishing trips were designated as non-AFA trips if fish ticket codes identified management other than "AFA", gear other than pelagic trawl (the only gear allowed by the AFA), fishing outside of the Bering Sea (NMFS areas 500 – 530; https://alaskafisheries.noaa.gov/sites/default/files/reporting-areas.pdf), or delivery to a non-AFA processor. Fishing trips were also designated as non-AFA if their entirety occurred outside of the Bering Sea or outside of the AFA pollock fishing seasons (https://alaskafisheries.noaa.gov/sustainablefisheries/plckseas.pdf), or if the trip landed at St. Paul Island (which has no AFA processor) without a fish ticket from an AFA floating processor. Trips with observer data from the west coast fishery for Pacific hake (*Merluccius productus*) were also listed as non-AFA. Much of the geographic range of the AFA CV fleet can be generally designated as consisting of non-fishing trips. Vessel activities each summer may involve tendering for salmon fisheries in Bristol Bay, southeast Alaska or Prince William Sound (PWS). Additionally, many vessels' homeports and maintenance yards are in Washington State or Oregon and trips may include long transits between Alaska and the Pacific Northwest. We designated any trip (without a fish ticket) that originated or terminated in one of these regions (Bristol Bay, southeast Alaska, PWS, Pacific Northwest) (Table S1.3), as well as trips that occurred while a vessel was under charter, as non-fishing trips. Some vessels may participate in a state-managed PWS groundfish fishery between January and March, so PWS trips during this time which landed in either Kodiak or Seward were designated as non-AFA fishing trips; all other PWS trips were designated as non-fishing.

Within the Bering Sea, there were two vessel transit "corridors" that typically included short, non-fishing trips between Dutch Harbor and Akutan (~ 45 nmi travel distance) or between Dutch Harbor and a floating processor in nearby Beaver Inlet (~ 33 nmi travel distance). Any trip for which all VMS records were contained within one of these corridors was designated as non-fishing.
Trawl gear used by North Pacific groundfish fisheries was typically fished at speeds between ~ 1 - 5 knots so trips without at least one VMS records < 5 knots while the vessel was *at-sea* were unlikely to be

fishing. To be conservative, any trip (without a fish ticket) whose minimum *at-sea* speed was > 6 knots were designated as a non-fishing trip.

An additional filter identified all state management areas in which fishing was observed. We examined the minimum vessel speed within any of these management areas for the duration of a trip. If the minimum speed in one of these areas never fell between 0.5 - 5 knots, it was deemed a non-fishing trip. If the speed only fell within this threshold for management areas that were outside of the Bering Sea region, that trip was identified as a non-AFA fishing trip.

Non-AFA fishing grounds were defined as those state statistical areas in which at least 50 VMS records occurred during observed fishing. We calculated the mean vessel speed across all of these areas. If a trip included at least one of these areas and the mean vessel speed within that area was 0.5 - 5 knots, the trip was designated as a fishing trip. Many mean speeds within fishing areas were > 5 knots because a vessel may transit through one fishing area while traveling to another. However, it is notable how many mean speeds are < 5 knots for fishing trips and equally notable how few mean speeds for non-fishing trips were < 5 knots. Several non-fishing trips did have mean speeds < 0.5 knots and manual inspection of these trips usually indicated that a vessel was anchored overnight. Only 2.6% of the 980 non-fishing trips fell within this speed range; 99.6% of the known fishing and non-fishing trips in these areas (N=5,573) were correctly characterized based on this speed filter. All of the areas examined here were outside of the AFA fishery boundaries so all of these trips designated as fishing were also determined to be non-AFA fishing trips.

Finally, all fishing trips should have a fish ticket. So while any remaining fishing trips were unmatched to a fish ticket (likely because of incorrect date-reporting on the fish ticket or VMS gaps), an analysis of the fish ticket data alone should reveal whether or not a vessel's trips were AFA or non-AFA. For a given month-year combination, if a vessel only had fish tickets from AFA deliveries, then any fishing trip during that vessel's month-year combination was considered to be an AFA trip (or vice versa for non-AFA deliveries).

The GAM used to predict fishing versus non-fishing relied on regional groupings for both start and end port (Table S1.3). The groupings from Table S1.3 were further consolidated such that only 4 regions were included in the model for start and end port (Table S1.4). Model selection was primarily based on predictive ability but model output is provided in Table S1.5.

1.7.6 Non-fishing corridor between Dutch Harbor and Akutan or Beaver Inlet

The majority of personnel and supplies for the port of Akutan are transported from Dutch Harbor via fishing vessels and thus many trips occur between these two ports (~ 43 nmi) (Figure S1.1). Often, vessels will leave Dutch Harbor and stop in Akutan before then heading to the fishing grounds. Similarly, vessels may deliver their catch in Akutan before then returning to Dutch Harbor prior to their next fishing trip. Arguably, many of the transits between Dutch Harbor and Akutan are thus part of a fishing trip but for consistency, we define these trips as non-fishing trips.

To define the corridor, we plotted VMS tracks from observed non-fishing transits between Dutch Harbor and Akutan and manually created a polygon shapefile that encompassed the VMS records from these trips (*rgdal* Version 0.9-1 and *sp* Version 1.0-16 packages in R Statistical Software Version 3.1.1). This polygon subsequently served as an *ad hoc* transit corridor; any trip for which all VMS records fell within this polygon were determined to be transiting between Dutch Harbor and Akutan and were thus designated as *non-fishing*.

A similar transit situation exists between a floating processor located in Beaver Inlet (Figure S1.1), an approximately 33 nm transit from Dutch Harbor. Most transits occur after a vessel has delivered their catch to the floating processor and then returns to Dutch Harbor. Because the Observer Program considers floating processors to be "ports," observers end a trip when a vessel ties up at a floating processor, and thus so does our approach. Subsequently, the transit from the floating processor back to Dutch Harbor is a standalone, non-fishing trip. The same approach was followed for creating a polygon shapefile that encompasses entire trips transiting between Dutch Harbor and this stationary floating processor.

1.7.7 Distribution of fishing and non-fishing trip types and ports

As a complement to Table 1.3 (main body of manuscript), the distribution of trip types and ports are presented. There were 19,302 fishing trips (12,280 AFA and 7,022 non-AFA) and 10,494 non-fishing trips. Among the non-fishing trips, 296 were surveys, 1,515 remained within in the corridor between Dutch Harbor and Beaver Inlet, 2,106 remained within the corridor between Dutch Harbor and Akutan, and 5,422 occurred within Bristol Bay, Prince William Sound, Southeast Alaska, or the Pacific Northwest. The remainder were scattered throughout the BSAI and GOA.

Among the non-AFA fishing trips, 10.7% landed their catches in the Aleutian Islands, 32.2% landed in the Bering Sea (Dutch Harbor, Akutan and a few trips at St. Paul Island), 49.6% landed their catches in Kodiak, with the remaining 7.5% of trips landing elsewhere in the GOA. AFA fishing trips were primarily split between Akutan (39.2%) and Dutch Harbor (45.3%), with the remainder going to the Beaver Inlet floating processor (10.5%), King Cove (4.0%) and a few other processors and motherships.

1.7.8 References

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Table S1.1: Port names and abbreviations for in-port determination.

Port	Code	Port	Code	Port	Code
Adak	ADA	Udagak Bay IFP	IFP	Port Lions (IFP)	PTL
Adak2 (IFP)	ADA2	Juneau†	JNU	Port Protection†	PTP
Akutan	AKU	Kake†	KAK	Savoonga	SAV
Alitak Bay	ALI	Kasilof	KAS	Seattle‡	SEA
Angoon†	ANG	King Cove	KCO	Seldovia	SEL
Astoria‡	AST	Kenai	KEN	Seward	SEW
Atka	ATK	Klawock†	KLA	Sitka†	SIT
ColdBay	CDB	King Salmon	KNG	South Naknek	SNN
Chignik	CHG	Kodiak	KOD	Soldotna	SOL
Cordova#	COR	Kodiak2	KOD2	Sanak Island (IFP)	SNK
Clarks Point	CPT	Ketchikan	KTN	Sand Point	SPT
Craig†	CRG	Larsen Bay	LRB	Saint Paul	STP
Dillingham	DIL	Lazy Bay	LZB	Tacoma‡	TAC
Dutch Harbor	DUT	Metlakatla†	MET	Tenakee Springs†	TEN
Egegik	EGE	Port Moller	MOL	Togiak	TOG
Ekuk	EKU	Naknek	NAK	Togiak2	TOG2
Elfin Cove†	ELF	Ninilchik	NIN	Unalakleet	UNA
Emmonak	EMM	Nome	NOM	Valdez#	VAL
False Pass	FSP	Newport‡	NPT	Whittier#	WHT
Port Graham	GRM	Nunivak Island	NUN	Wrangell†	WRN
Gustavus†	GUS	Old Harbor	OLD	Excursion Inlet†	XIP
Hoonah†	HNH	Port Alexander†	PAL	Yakutat	YAK
Haines†	HNS	Petersburg†	PBG	Yantarni Bay (IFP)	YAN
Homer	HOM	Pelican†	PEL		
Hydaburg†	HYD	Port Bailey	PTB		

(IFP) designates the locations of inshore fish processors, which are mobile vessels but returned to the same coordinates often enough to be treated as ports.
† Ports located in southeast Alaska
‡ Ports located in Washington or Oregon (i.e., outside of Alaska)
# Ports located in Prince William Sound
"Gaps" = refers to the time difference between the current and previous VMS record and the current and subsequent record.

Table S1.2: Percent errors (±1 SD) from model adjusted and unadjusted trip durations. Models were run on both a single set of duration data and via a piecewise regression that modeled trips ≥ or < 700 minutes separately and combined their predictions. *Aggregate* is the percent error between the sum of observed trip durations and the sum of predicted trip durations (positive values represent under-prediction). *Trip* is either the mean or median of all the percent differences between the VMS-estimated and the observed duration for each trip (positive values represent under-prediction). *Abs* takes the absolute value of the percent differences in *Trip* prior to summarizing with the mean or median (all values are positive).

			Single regression	**Piecewise regression**	**Single regression**	**Piecewise regression**	**Single regression**	**Piecewise regression**
		No model	GAM1	GAM1	GAM2	GAM2	GAM3	GAM3
Training Data - 60%	Aggregate	1.40(0.1)	0.58(0.2)	0.48(0.2)	0.59(0.2)	0.5(0.2)	0.57(0.2)	1.44(0.2)
	TripMean	0.34(0.3)	-1.27(0.4)	-0.77(0.2)	-1.24(0.4)	-0.75(0.2)	-1.31(0.4)	-1.19(0.3)
	TripMedian	-0.03(0.0)	-0.88(0.1)	-0.65(0.1)	-0.92(0.1)	-0.64(0.1)	-0.93(0.1)	-1.04(0.2)
	AbsMean	5.78(0.2)	6.78(0.2)	5.71(0.1)	6.79(0.2)	5.55(0.1)	6.35(0.3)	7.93(0.2)
	AbsMedian	1.27(0.0)	2.63(0.1)	2.17(0.1)	2.72(0.1)	1.94(0.1)	1.73(0.1)	4.33(0.2)

Table S1.3: Ports within each region. Port names are listed by the North Pacific region into which they are grouped for use with the algorithm. All trips that start or end in BB, PNW, PWS, or SEAK are designated as non-fishing trips. All KOD ports may represent non-fishing trips or non-AFA fishing trips.

Bristol Bay (BB)	Kodiak (KOD)	PNW	PWS	SEAK
Clark’s Point	Alitak Bay	Anacortes, WA	Cordova	Craig
Dillingham	Larson Bay	Astoria, OR	Valdez	Elfin Cove
Egegik	Lazy Bay	Bellingham, WA	Whittier	Gustavus
Ekuk	Nelson Bay	Blaine, WA		Hoonah
South Naknek	Old Harbor	Newport, OR		Juneau
Ugashik	Port Bailey	Seattle, WA		Ketchikan
		Tacoma, WA		Pelican
		Vancouver, BC		Petersburg
				Pt. Alexander
				Sitka
				Tenakee
				Wrangell
				Excursion Inlet
				Yakutat

Table S1.4: Ports within each region for identifying fishing trips.

Gulf of Alaska	Bering Sea	Aleutian Islands	Other*
Cold Bay	Akutan	Adak	Southeast Alaska
Chignik	Dutch Harbor	Atka	Bristol Bay
False Pass	Floating Processor	Adak2 (floating processor)	Prince William Sound
Homer			Pacific Northwest
King Cove			
Ninilchik			
Seward			
Sand Point			
Yantarni Bay			

Table S1.5: Model output for GAM used to predict whether fishing occurred on a trip.

Parametric coefficients	Estimate	Std. Error	Z value	Pr(>|z|)
(Intercept)	3.76	0.27	13.94	<<0.01
SEASON-B	-0.19	0.17	-1.14	0.256
SEASON-N	-0.77	0.29	-2.66	0.008
START.Bering	0.03	0.25	0.11	0.912
START.Aleutian	-2.49	0.56	-4.46	<<0.01
START.Other	-0.54	0.90	-0.60	0.55
END.Bering	0.69	0.25	2.81	0.005
END.Aleutian	2.48	0.53	4.69	<<0.01
END.Other	3.87	0.78	4.98	<<0.01
Smooth terms	edf	Ref.df	Chi.sq	p-value
s(lDuration,avspstat)	20.9	24.9	696.4	<<0.01
s(sddif)	4.5	5.4	77.0	<<0.01
s(sdsp)	6.2	7.3	200.2	<<0.01
R^2 (adj)	0.9			
Deviance explained	91.10%			

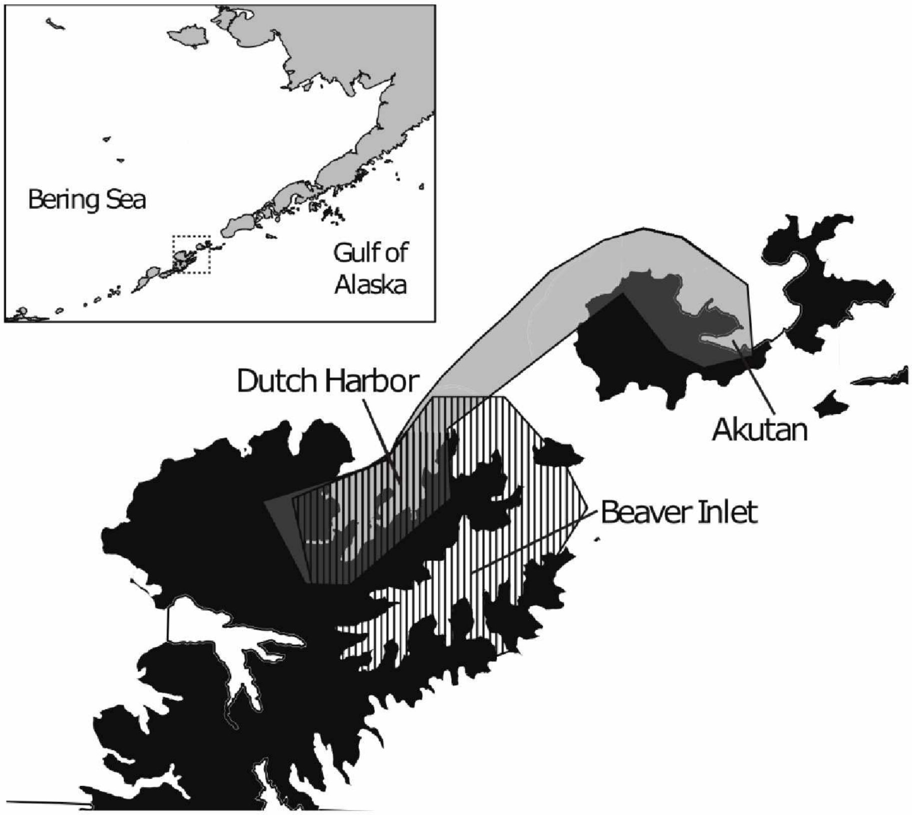

Figure S1.1. Transit corridors near Dutch Harbor. Illustration of the corridors of non-fishing transit trips between Dutch Harbor and Akutan (shaded grey) and Dutch Harbor and Beaver Inlet (hatched vertical lines).

Chapter 2 Paths to resilience: Alaska pollock fleet uses multiple fishing strategies to buffer against environmental change in the Bering Sea[2]

2.1 Abstract

Fishermen seek to maximize profits so when choosing where to fish, they must consider interactions among the environment, markets, costs, and fish prices. We examined catcher vessels in the U.S. Bering Sea fishery for walleye pollock (2003- 2015) to characterize fisher responses to environmental change (e.g., abundance and water temperature). When pollock were abundant and water warm, the fleet fished in similar locations. When temperatures were cooler or pollock abundance declined, two fishing strategies emerged, depending on the processor where a vessel delivered. One vessel group, whose catches were more likely to become fillets, often made shorter trips, requiring less fuel and time at-sea. A second vessel group, whose catches were more likely to become surimi, traveled farther offshore, to regions with higher catch rates but generally smaller fish. By fishing in different locations to satisfy different markets, the fleet sustained revenues and buffered against environmental change. They also demonstrated how spatially-explicit regulations could impact vessels disparately within fleets and across years, especially if they are operating at their boundaries for adaptation.

2.2 Introduction

Climate change impacts global fisheries both directly and indirectly. Warming waters are driving redistributions of target species with an expected northern shift of fisheries (e.g., Pinsky and Fogarty 2012) while management strategies (Ianelli et al. 2011) and stock assessments (Holsman et al. 2016) are adapting to and projecting future responses to such shifts among target species and systems. Climate change is not however, the first challenge to which fishers have had to adapt. Just as marine fishes demonstrate a portfolio of responses to environmental variability (e.g., Mueter et al. 2002; Schindler et al. 2010; Hollowed and Sundby 2014), fishers and fishing communities have demonstrated a portfolio approach to dealing with some of the uncertainties of a life dependent upon dynamic marine resources (Kasperski and Holland 2013; Sethi et al 2014). Understanding the margins of flexibility through which fishers respond to environmental change enables management to be crafted in a manner that allows the most cost-effective adaptation possible. To understand how fishers may adapt to changes in the fishery landscape - a term we use to represent the climate as well as management structure, markets, and other

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driving forces - it is critical to examine fishers' fine-scale behaviors, such as fishing location (van Putten et al. 2012; Joo et al. 2014; Joo et al. 2015) and trip length.

Economists have long used discrete choice models to examine fisher decisions about where to fish (e.g., Eales and Wilen 1986; Holland and Sutinen 2000; Haynie and Layton 2010). By assigning an expected net return to individual fishing locations, researchers can estimate the economic impacts of regulatory changes, such as marine protected areas or fishery closures (e.g., Zhang and Smith 2011), that reallocate fishing vessels spatially. Similarly, such approaches can be used to examine how other dynamics like climate change, fuel price, fish price, or shifting fish populations may impact fisher behaviors.

One fishery that has received considerable attention by fisheries scientists and economists is the Bering Sea fishery for walleye pollock or Alaska pollock (*Gadus chalcogrammus*; hereafter, simply "pollock"), one of the most valuable fisheries in the world; its Bering Sea landings accounted for an ex-vessel value of $474 million in 2014, 8% of the value of U.S. domestic landings that year (Fissel et al. 2015). A catch share management system was implemented in the fishery by passage of the American Fisheries Act (AFA) in 1998 (Felthoven 2002); the quota (and fleet) were divided among three sectors – catcher processors, catcher vessels, and motherships; the latter rely on other vessels to fish. The onboard processing capability of the large (> 62m) catcher processors enables them to stay at sea for weeks, thereby providing flexibility over where they fish (see Pfeiffer and Haynie (2012) or Haynie and Pfeiffer (2013) for discussions of fishing behavior in this fishery). While approximately 1/6 of pollock catcher vessel harvest is delivered to at-sea "mothership" processors, here we focus on catcher vessels that deliver to shoreside processors and account for nearly half of the total pollock catch (mention of trips or vessels hereafter refers to these shoreside trips and associated vessels).

Catcher vessels, 22 – 62 m in length, typically make 2- to 4-day trips and deliver to one of 7 processing plants, with vessels typically delivering all of their catch to the same processor. Since the AFA, the process by which fishing and deliveries is prosecuted has become increasingly efficient with greater harvest utilization (Fissel et al. 2015). Delivery times are scheduled by processors, enabling consistent production of product by well-timed deliveries. If a vessel is late, the price paid may plummet.

Vessel captains must decide when to begin a fishing trip by working backwards from their assigned delivery time. This requires an expectation of fish location, transit time, and fishing time required to fill their holds. This creates a high value of communication among the approximately 70 vessels that fish within a season, though their strategies often differ. Processors may specialize in different products (e.g., roe, fillets, surimi, "head and gut") across time. This variability alters constraints on fish size or fish freshness that a processor requires. This operational structure of the fishery establishes a range of potential responses to trade-offs that fishers consider when determining where to fish, and those responses may vary more when the fishery landscape changes.

Changing ocean conditions have both lagged and concurrent effects on pollock abundance (hereafter, abundance) and spatial distributions. A significant warm stanza in the Bering Sea (2001 – 2005) was associated with decreased ice cover and a resulting shift in zooplankton communities which left juvenile pollock with insufficient energy reserves for their first winter and led to poor warm-year cohorts (Coyle et al. 2011). As the weak cohorts recruited to the fishery, adult pollock (age-3+) abundance and total allowable catch (TAC) declined, illustrating the lagged effects of temperature on recruitment (Mueter et al. 2011). These lagged effects also occurred for a successive cold stanza (2007-2010) with increased ice cover, shifts in zooplankton communities, and larger cold-year cohorts of pollock that led to subsequent rebounds in both adult abundance and TAC (Sigler et al. 2016). Warming and cooling also have more immediate effects on the spatial distribution of adult pollock. The eastern Bering Sea is characterized by a broad continental shelf with a shallow water column where temperatures vary inter-annually with sea ice cover (Stabeno et al. 2012). Years with more ice have a larger cold pool, or region of cold bottom water, and adult pollock avoid the coldest waters of this pool (Wyllie-Echeverria and Wooster 1998). During the winter A-season, the fishery catches its fish relatively far south in the Bering Sea, where pollock spawn (Bacheler et al. 2012). The cold pool extent has not had large impacts on winter A-season fishing because the cold pool typically does not reach these southern areas (Pfeiffer and Haynie 2012). However, in the summer B-season, post-spawning pollock spread out, and cold pool avoidance is a more important factor in determining fish and fishing locations.

Here we hypothesize that dynamic fishery landscapes prompt changes in the spatial behaviors of pollock catcher vessels. Fishers travel to different locations to buffer against changes in their economic outcomes. If buffering is successful, we would expect relatively weak relationships between changes in their spatial behaviors and their net earnings. In our analysis, given the stability of catches that result from vessels usually filling their holds, we focus on the distances fishers travel to fish as the primary measure of the economic trade-offs associated with their decisions. These location choices then translate into potential differences in fishing outcomes (e.g., catch rates, earnings, costs, and ultimately, profit). Our objectives were to: (1) characterize trip-level spatial behaviors across the pollock fleet; (2) determine how spatial behaviors relate to the fishery landscape (e.g., do fishers move north in warm years?); and (3) examine fishing performance and economic outcomes (e.g., catch rates and net earnings) across years, vessels, and fishery landscapes. Together, these objectives help us to understand some of the factors driving fishing location, and how different spatial strategies may subsequently affect fishing fleet economics.

2.3 Data

We incorporated several datasets from the Bering Sea pollock catcher vessel fleet (91 vessels) from 2003 to 2015. Vessel monitoring system (VMS) data were obtained from the NOAA VMS database (Spalding 2016); observer data from the North Pacific Groundfish Observer Program (NOAA 2016); fish tickets (landings data) from the Alaska Fisheries Information Network (AKFIN) (ADFG 2015); vessel fuel consumption rates from the Amendment 91 Chinook Salmon Economic Data Report (www.psmfc.org/chinookedr/); fuel price survey data from the Fisheries Economic Data Program (http://www.psmfc.org/efin/data/fuel_ak.txt); and processor production data from AKFIN. Price and revenue data were adjusted to a base year of 2009 using an annual (seasonally adjusted) implicit price deflator for United States gross domestic product (https://research.stlouisfed.org/fred2/series/GDPDEF#). Analyses were performed using R version 3.3.0 (R Core Team 2016). See Supplementary Information for more details.

Vessel owners or leaseholders of permitted pollock vessels have been required to fill out (confidential) fuel consumption surveys since 2013 as a condition for evaluating bycatch mitigation measures. These surveys include average fuel consumption estimates (gallons per hour) for vessels while fishing and transiting.

We examined net earnings and other fishing performance and economic outcomes (hereafter, fishing outcomes; Table 2.1) that underlie net earnings. The trade-offs associated with some of these outcomes help explain net earnings and expected fishing profits. Our measure for net earnings per trip is *Price * Catch – Cost*, where *Price* (ex-vessel price per pound) is a function of many components not explicitly parameterized here. For example, supply (as dictated by TAC and fish location), fish size, product type, and freshness are determinants of price. Available price data were aggregated annually so were approximate. At the trip-level, *Catch* depends on fishing location and vessel size (i.e., capacity); at the season-level, *Catch* will also be driven by TAC (and individual vessel quotas). The *Costs* of individual trips are dominated by fuel and fuel usage is greatly impacted by fishing behavior and distance traveled. Vessels may use up to 3 times more fuel while fishing than while transiting. Thus, the proportion of a trip spent fishing versus transiting impacts costs; a longer trip with less fishing time may actually use less fuel than a shorter trip with longer hauls. Additionally, while fuel cost is obviously important, we also include the ratio of fuel cost to gross earnings, a unit-less measure.

Our study was focused on fisher behaviors and thus, the prices paid to fishers were expected to be primary motivations. However, processors apply different constraints on fishers based on their production strategies. Typically, fish must be fresher and larger for fillets than surimi, thereby constraining vessels to shorter trips. Thus, production data were important for explaining fishery behavior. These data included the end-products produced (though not at the trip-level) and the first wholesale values of those products.

First wholesale values represent the value after products have been processed (as opposed to ex-vessel prices which are paid to vessels for fish). These data were available annually so real-time or seasonal differences in production value were not assessed. Because of the aggregation of production data, we do not include these data as one of our metrics, though the data provided production trends for processors and a linkage of these trends with each vessel and behavior.

2.4 Analyses

Our analyses relied on the hypothesis that changes in the fishery landscape lead to changes in fishers' spatial behaviors, and that these changes would improve fishing outcomes given the constraints. To address this hypothesis, we present our analyses in three sections, where we: (1) characterized spatial behaviors (i.e., trip distances) in the fishery; (2) modeled the relationship between spatial behaviors and the fishery landscape; and (3) examined correlations between fishing outcomes and both the fishery landscape and trip distances.

2.4.1 Characterizing spatial behaviors in the fishery

We characterized spatial behaviors as trip distances traveled by the fleet and subgroups of vessels. Annual median trip distances were examined for vessels delivering to each processor; vessels fell into one of two groups (containing 3 and 4 processors, respectively) based on distinct trip distances in years with longer trips. We refer to these vessel groups as "nearshore" and "offshore" based on their typical travel distances. Confidentiality rules prohibit discussion of individual processors but vessels fell cleanly into the two groups so results would not have differed meaningfully from analyzing individual processors or vessel co-operatives.

2.4.2 Spatial behaviors as a function of the fishery landscape

To examine the relationship between the fishery landscape and fisher spatial behaviors, we fit models of median trip distance to four fishery landscape variables: average summer bottom temperature (hereafter, temperature), fuel price, TAC, and abundance. Starting with the full linear model:

$$\text{Trip distance} \sim \text{temperature} + \text{fuel price} + \text{TAC} + \text{abundance} + \varepsilon \qquad (1)$$

where ε represents Gaussian errors. We performed step-wise regression using F-tests to eliminate covariates that did not significantly ($P < 0.05$) improve model fits. Models were fit to the entire fleet and to the groups of vessels (nearshore and offshore) separately. Pairwise interactions were examined once main effects were included. Multicollinearity was tested and pairs of covariates were excluded if the square root of the variance inflation factor (*car* package for R [Fox and Weisberg 2011]) was greater than 2 (Fox and Monette 1992). Model residuals were inspected to ensure compliance with standard regression assumptions. Sensitivity analyses explored marginal effects by perturbing covariates independently and simultaneously by a fixed amount. Because our candidate models were simple first-order regressions, we also explored effect sizes using partial η^2 (Richardson 2011).

2.4.3 Fishing outcomes across vessel groups and years

An important aspect of changes in fishing behavior is whether they lead to different or more variable fishing outcomes (Table 2.1). We did not try to fit a predictive model between fishery landscape variables and fishery outcomes however, because we did not expect a structural relationship between them. Rather, we expected fisher behaviors to buffer against changes in fishing outcomes, leading to weak correlations between fishing outcomes and both the fishery landscape and trip distances.

We examined average fishing outcomes and the variability (coefficient of variation [CV]) of fishing outcomes for the two groups. The CV is an effective metric because it is scaled to provide a unit-less comparison across agents with different long-term means. It has also been used as a measure of economic risk exposure for fishers (e.g., Sethi et al. 2014), providing a valuable complement to average catches and revenues. To determine whether changes in fishing location helped to improve or sustain fishing outcomes, we measured the Pearson correlations between the average annual fishing outcomes (Table 2.1) and each of the four fishery landscape variables listed in the previous section. To determine whether there was an increased risk (i.e., more variability) associated with changes in the fishing landscape or trip distances, we also measured correlations between the variability (CV) of fishing outcomes with the fishery landscape and trip distances. Finally, to observe whether the vessel groups covaried in their outcomes, we measured the Pearson correlations between annual average outcomes. We tested for differences in variability (CV) of annual outcomes between vessel groups using Mann-Whitney tests.

2.5 Results

2.5.1 Characterizing spatial behaviors in the fishery

Trip distances were similar during winter A-seasons across years, whereas during summer B-seasons, distributions were unimodal in some years and bimodal in others. Trips made during winter A-seasons commonly target valuable roe-bearing pollock on relatively stable spawning grounds; we saw little heterogeneity among winter A-season trip distances (Figure 2.1). In contrast, summer B-season trip distances exhibited unimodal and bimodal distributions depending on the year (Figure 2.1), with much greater variability among summer B-season trips than among winter A-season trips; mean absolute deviation of trip distances was more than doubled during summer B-season (108 nmi vs. 223 nmi). Figure 2.1 illustrates the homogeneous winter A-season distributions of trip distances and the heterogeneous summer B-season distributions during 2003 and 2008. The CV of trip distances for summer B-season trips was nearly double that of winter A-season trips (0.38 vs. 0.67, respectively) so we focus the remainder of our analyses only on summer B-season trips.

Visual inspection of trip distances for each co-operative showed stark behavioral differences that were sufficient to clearly identify two groups of vessels – a “nearshore” and an “offshore” group. Confidentiality rules prohibit presenting individual co-operatives’ data but aggregated data demonstrate the clear separation of trip distances among the groups in several years. There were more vessels in the nearshore group than in the offshore group, and the nearshore vessels were typically smaller, made more trips (though not a statistically significant difference), and caught larger fish (Table 2.2).

In each year, trip distances and durations were less for the nearshore vessels. Not only were the distances traveled different between the two groups, there was little correlation (Pearson $\rho = 0.05$) between variability (CV) of distances traveled. The CVs of trip distances varied significantly across years, (Supplementary Table S2.1).

Some of the differences in fishing behaviors between the groups within a year were associated with differences in production by the associated processors. More than 50% of average annual first wholesale product value for the nearshore group was from fillet production while only about 20% was from surimi. Meanwhile, the processors associated with offshore vessels earned only about 30% from fillets and nearly 50% from surimi.

2.5.2 Spatial behaviors as a function of the fishery landscape

The Bering Sea experienced warmer than average water temperatures at the beginning and end of our time series (Figure 2.2) and cooler temperatures in the middle. Abundance and TAC declined steadily from 2003 to 2008, after which they rebounded and stabilized. Fuel prices generally increased until 2012, with one large spike in 2008, before decreasing somewhat.

Linear model fits revealed strong relationships between trip distances and both Bering Sea bottom temperature and abundance. Fuel price and TAC were not significant predictors on their own or when added to models with temperature or abundance. Significant relationships ($P<0.05$) and relatively high r^2 values were observed with covariates in linear models when the response data included median trip distances by all vessels, nearshore vessels, or offshore vessels (Figure 2.3; see Supplementary Table S2.2 for model coefficients and diagnostics). In the cases of all modeled groups (nearshore, offshore, all vessels), the lowest AIC values were obtained for models with both temperature and abundance. While temperature and abundance were relatively highly correlated with each other ($\rho = 0.72$), models with both terms met our variance inflation factor criterion so the bivariate models were retained. Despite the lower AIC for the model containing both abundance and temperature, we still include (Figure 2.3, Table S2.2) the temperature-only and pollock-only models for the sake of subsequent discussion about the individual effects.

At times, temperature and pollock trends diverged from each other, corresponding to years when the temperature-only or pollock-only models performed worse (Figure 2.3). For example, all three groups (all vessels, nearshore, offshore) were poorly fit by the pollock-only and the temperature-only models in 2012, when abundance had recovered from its previous decline and temperature was lowest (i.e., due to the lagged temperature-recruitment dynamics described above). Meanwhile, temperatures were cold and abundance was low in 2010, when even the nearshore vessels took longer trips. Distances during this year were not unusual for the offshore group of vessels, however, as all models performed comparably for this group. In contrast, in 2006, temperatures and abundance declined (despite high TAC), and the offshore group took much longer trips, leading to underestimated distances. When the offshore group was poorly fit (2006), the nearshore group fit better while the opposite occurred in 2010. This helps explain the improved performance (high r^2 values) of models for the all-vessel group, which benefit from smoothing.

Marginal effects of temperature and abundance on trip duration suggest that offshore vessels were more sensitive to changes, in particular to changes in abundance (Supplementary Figure S2.1). Because the final models only included linear, first-order combinations of covariates, effects are also readily interpretable by coefficient values (Table S2.2), though we present sensitivity analyses for better interpretation and visualization (Figure S2.1) of results. Given first order linearity, we present results for only a single perturbation, that of a (arbitrarily chosen) 20% increase per variable; results scale linearly such that a 10% increase would yield half the impact on fitted values as a 20% increase, or a 40% increase would yield double the impact. The bivariate models did not have a significant interaction term between temperature and abundance and because the models were first-order linear, the sum of the effects on median trip distance from perturbations of temperature and abundance were equivalent to a single model in which both covariates were increased. The three most notable observations regarding the marginal effects were that: (1) the univariate pollock model showed greater impacts, especially for offshore vessels; (2) nearshore vessels and 'all vessels' responded similarly to perturbations while the offshore vessels were always more sensitive to change (i.e., had a greater change in median trip distance); and (3) for offshore vessels, changes in abundance had a substantially greater effect than changes in temperature.

Effect size calculations for the bivariate model explained a greater proportion of variance (partial η^2) with temperature than abundance for the nearshore (0.64 vs. 0.38), offshore (0.62 vs. 0.48), and for all vessels groups (0.74 vs. 0.47).

2.5.3 Fishing outcomes across vessel groups and years

There were generally weak relationships between fishing outcomes and the fishery landscape (including trip distances). Thus, our expectation that changes in fishing behavior would buffer against environmental changes was largely met. Most notably, despite highly variable temperatures and abundance, average catch-per-trip for each group was relatively constant across years (Figure 2.4) with relatively weak correlations to the environment or trip distance (Table 2.4). More importantly, average annual net revenues-per-trip showed remarkably weak correlations with the environment and trip distances. These relationships demonstrate that all groups adapted fishing strategies to changing environments to sustain catches and revenues across time. A suite of factors, like vessels' sizes and the processors, appeared to affect how vessels traded-off catch rates with TAC, prices, and fish sizes, as described in the following paragraphs.

Vessels in the pollock fishery vary in size, and in most years, larger vessels traveled significantly farther, partially accounting for the within-group variability in trip distances (Figure 2.1). Despite the offshore group always taking longer trips (in distance and duration), there was a range of variability in trip distances and duration across years (Supplementary Table S2.1). Greater variability was seen for the nearshore group in many years and for many of the fishing outcome metrics, but there were a third more vessels in the nearshore group on average, and it had more variation in vessel length.

Measures of fishing outcomes at the trip-level were more variable than at the annual-level, where performance was more highly related to TAC (Figure 2.4; Table 2.4). Not surprisingly, average catch-per-year (B-season only) was strongly related to TAC for both vessel groups ($\rho>0.8$), but like catch per trip, it was only weakly related to the remainder of the fishery landscape variables. The discrepancy between the trip and yearly catch relationships with TAC make sense; TAC determines the level of annual catch by regulating the number of trips a vessel will take, but fishers seek to fill their holds during each trip, largely independent of the TAC. The strong relationship between catch per year and TAC for both vessel groups led to high covariation between the two groups ($\rho=0.84$). Average catch-per-trip for both vessel groups varied across time but without a clear relationship to trip length, or to other fishery landscape variables (Table 2.4).

The relationships between catch rates (CPUE) and trip distance were different for the two vessel groups and across time. Average catch rates (CPUE) were more variable than catch per trip across years (Figure 2.4) for the offshore group than for the nearshore group, which had a relatively strong relationship among CPUE, abundance, temperature, and trip distance (Table 2.4). However, not surprisingly, the relationships between CPUE and the fishery landscape were very different within than across years. The average annual CPUE for nearshore vessels was lowest during the years with the greatest average travel distances but within these years, CPUE across trips was increased by traveling farther (Figure S2.2). So during the coldest years with lowest abundance (2007-2010), nearshore vessels increased their CPUE by traveling farther whereas during warm years or years with greater than average abundance, there was a negative relationship between CPUE and trip distance, which was likely driven by some vessels visiting distant areas in low-CPUE times of the season. Offshore vessels showed a similar positive relationship between distance and CPUE but for more years (2005 – 2013). Despite variability in the inter-annual average CPUE (Figure 2.4c), the intra-annual variability of CPUE across vessels within each group was not statistically different in most years, suggesting some consistency in CPUE among vessels within a group.

Average catches per trip were relatively stable over time (Figure 2.4a) but average net earnings varied more (Figure 2.5a). The strongest relationship between a fishery landscape variable and net earnings-per-trip was with TAC, likely reflecting some inverse relationship between TAC (i.e., supply) and ex-vessel price. Prices (shown for each group in Figure 2.5d) were strongly related to TAC (Table 2.4) and net earnings per trip, in turn, were strongly related to ex-vessel price (ρ = 0.76, 0.81, for nearshore and offshore, respectively), which, by extension, links net earnings per trip to TAC. The covariance between vessel groups for net earnings per trip was relatively high, indicating that while vessel fishing strategies were different, they were similarly impacted by ex-vessel prices and they were similarly adaptive.

The annual-level (summer B-season only) average net earnings were not strongly related to any of the fishing outcomes. Average annual net earnings were much more variable across years for the offshore group (Figure 2.5c), with a relatively low degree of covariance between the two groups, and no clear pattern based on average travel distances. However, the CV of net revenues across years was only weakly correlated with the fishery landscape (Table S2.3), suggesting that adaptations in fishing strategies reduced revenue variability. When net earnings were standardized by the trip duration (i.e., net earnings per trip day; Figure 2.5b), the covariance between groups was strikingly high (ρ = 0.94), and the relationships with temperature, average trip distance, and (to a lesser degree) abundance were strong (Table 2.4). While the offshore group yielded approximately double the net earnings per trip in some years (Figure 2.5a), the greater travel times associated with those increased earnings led to similar net earnings rates (net earnings-per-trip-day) between the two vessel groups.

Vessels in the offshore group were typically larger (median = 38.8 m) than in the nearshore group (median = 34.4 m) and had higher fuel costs but also higher gross earnings so their fuel-to-earnings ratios were not different in most years (Supplementary Table S2.1). There were several years (2006, 2012-13, 2015) during which the nearshore group spent proportionally more on fuel due in part to their disproportionately lower CPUE (Figure 2.4). While other years (2009 – 2010) also exhibited greater disparities in CPUE between the groups, those years were also characterized by longer trip distances by the offshore group. The years with the greater differences in CPUE between the two groups were also the years during which the variability of the fuel-to-earnings ratios were greater among the nearshore group (Supplementary Table S2.1).

Fish size varied by fishing location, impacting ex-vessel price and the products that can be made. We omitted fish size from Table 2.4 because the complicated lagged relationships between fish size and fish abundance confound correlations across years. However, regressions of pollock size versus trip distance within each year illustrate their negative relationship (Figure S2.3). Nearshore vessels which primarily targeted fish for fillet production caught larger fish, a 240g average in mean annual fish weight, with the largest fish typically caught nearer to port. When vessels traveled farther, they had higher catch rates, but smaller fish. The offshore group also demonstrated more variable fish sizes than the nearshore group (Supplementary Table S2.1). Because price data were not of fine enough resolution to identify trip-level relationships between fish price and fish size, we cannot resolve size-dependent effects of fishing location on ex-vessel prices.

2.6 Discussion

When pollock were abundant and water was warm, vessels across the fleet behaved similarly. In contrast, when abundance declined or temperature cooled, the fleet fractured into two groups of vessels exhibiting distinct spatial behaviors in order to best sustain their catches; one group made shorter trips while the other made longer trips. Vessels with generally lower capacity were still able to fill their holds by fishing close to port and the majority of their catches were destined for fillets. Meanwhile, larger vessels had to travel farther to find adequate catch rates to fill their holds based on delivery windows, but often had more flexible delivery windows associated with a majority of catches becoming surimi. These different responses of vessels to the changing fishery landscape helped vessels to buffer against lower and more variable annual net revenues.

The implications of vessels' resiliency to change are particularly pertinent given that projections of warming in the Bering Sea are associated with recruitment failures of pollock (Mueter et al. 2011) that may motivate changes in management (Ianelli et al. 2011). We did not observe the climate-associated northward shift of fishers observed elsewhere (e.g., Pinsky and Fogarty 2012). Rather, pollock vessels traveled farther north during colder years, illustrating complex interactions between markets, the unique environment of the Bering Sea, and the opportunity for heterogeneous adaptive responses within the fleet. The variable responses of vessels included a partitioning of the fleet into two groups with behaviors based on the processors to which vessels delivered fish.

Processor-level distinctions in fisher behavior result from a combination of vessel size and product focus. Processors more focused on surimi were associated with the offshore vessel group. This group consisted of larger vessels that more often made longer trips. Larger vessels can carry more fish which allows them to be profitable on longer trips despite increased fuel costs. The focus on surimi production for these vessels is also associated with smaller fish and longer delivery windows, which provides greater flexibility to search for pollock. The ability to target more productive fishing grounds with higher catch rates also reduce costs for these large vessels because much more fuel is consumed during fishing than transiting (i.e., shorter tows farther away may actually use less fuel). Meanwhile, the nearshore group has maintained relatively stable annual earnings by targeting larger fish closer to port.

Our findings have strong implications for how vessels may respond to future trends in the fishery landscape, and how changes may more dramatically affect some vessels. We discuss the economic and performance aspects of a single fishery but much of our context and approach provides an approach for how to resolve the dynamics of other fisheries amidst a changing fishery landscape.

2.6.1 Fishing location and the fishery landscape

We observed a strong contemporaneous relationship between fishing location and the fishery landscape; during warmer years, fishing effort was concentrated closer to port whereas during colder years, much of the fishing effort moved farther from port. This relationship was better informed by the joint dynamics of temperature and abundance (Figure 2.6). In general, we observed longer trip distances during years of low abundance than years with higher abundance, but with the exception of 2010 (which had average temperature), years with below average abundance all occurred during years with below average temperatures (lower left quadrant of Figure 2.6). Meanwhile, the 5 years with the shortest trip distances were associated with warmer than average temperatures and above average abundances (upper right quadrant of Figure 2.6). In 2012, the Bering Sea saw its coldest waters of the time series but abundance was above average and trip distances very long (Figure 2.1). In 2013, abundance was similar to 2012 but waters were substantially warmer and trip distances were substantially shorter. These two observations (2012-2013) support the better fits of our temperature-only model versus the pollock-only model but they also underscore the role that specific years can play in driving behavioral results.

If the modeled time series had ended in 2011 instead of 2015, our interpretation of the roles of temperature and abundance would be different. From 2003 to 2011, temperature and abundance were substantially more correlated (Pearson ρ=0.94) than during the full time series (Pearson ρ=0.73). This high degree of correlation in the shorter time series leads to strong collinearity for models that include both temperature and abundance and would invalidate a bivariate model. However, univariate models during the shorter time series (results not shown) fit slightly better for abundance than for temperature. This is caused by 2005, where trip distances and temperature were less aligned (as also illustrated by model fits for the full time series in Figure 2.3). The divergence of the distance ~ abundance relationship for the full time series thus occurs during the 2012 – 2015 period, when average distances declined but abundance was relatively stable. During these years, the continued decline in trip distance was mirrored by increases in temperature (Figures 2.1, 2.2). The shifting dominance of temperature in the full time series to abundance in the shorter time series suggests two major conclusions: (1) there may be a threshold abundance above which fishers are more driven by the temperature-mediated movements of fish; (2) temperature and abundance are tightly coupled drivers of fisher behavior that are difficult to disentangle.

The interaction between temperature and abundance is complicated because while current conditions clearly affect fishing locations, present conditions result from temperature-mediated recruitment dynamics. The warm temperatures from 2003 – 2005 have been associated with very low juvenile pollock survival. These low-survival years subsequently led to failed cohorts during the cold years that followed (Coyle et al. 2011; Mueter et al. 2011). While our models examine only contemporaneous relationships, these relationships are the product of complex lagged recruitment and ecosystem processes that affect the age, size structure, and spatial distribution of pollock. For example, in 2007 – 2009, average size was largest, owing to the lack of young age classes from 2003 – 2005 recruiting to the fishery. In this case, the poor recruitment events only lasted a few years, so there were still previous cohorts for fishers to target, although biomass fell significantly. However, if warming leads to fewer large cohorts, there may be fewer large pollock, which could have the most significant impacts on nearshore vessels. With time, fewer large pollock may also affect recruitment, impacting the entire fleet.

Temperature and abundance did not always produce the same effects. In the upper right quadrant of Figure 2.6, we see large differences in median trip distances across warm high-abundance years. These differences may further reflect the influence of lags, even for climatically similar years. For example, a large (cold-year) cohort from 2012 recruited to the fishery in 2015. So despite similar anomalies of temperature and abundance, median trip distances in 2004, 2005, and 2014 were 1.3, 1.5, and 1.7 times greater than that of 2015 with a standard deviation of median trip distance of 59 nmi during those 4 years. Meanwhile, the 5 consecutive years in the lower left quadrant had a standard deviation of 27 nmi, less than half that during the warm, high abundance period. As noted, there may be an abundance threshold or another factor that leads to non-linearities in the interaction between abundance and temperature that are not captured here. Extreme and lagged fluctuations in water temperatures and pollock year classes are indicative of the broad environmental variability of the Bering Sea, and thus it should not be surprising that the fleet did not behave in a wholly predictable or consistent fashion during each year.

Under the Bering Sea conditions observed to date, both vessel groups have appeared capable of adapting but we have not observed warm years with low abundance (Figure 2.6, bottom right quadrant). The fishery has not yet experienced both a cohort failure and a simultaneous warm year, so our models have limited power to predict how the fleet may react to such conditions. In the past, low abundance and cold waters have both been associated with longer travel distances so it is unclear if, during a warm year with low abundance, behaviors would be more impacted by abundance or by temperature. In the most recent warm stanza (2014 – 2016), juvenile pollock survival was moderate, contrary to the low survival in the 2003 – 2005 warm stanza that led to the low abundances and TACs in subsequent years. It thus remains unclear if recent warming trends will lead to a new observation in the lower right quadrant of Figure 2.6, or if conditions may continue to fill other quadrants.

2.6.2 Fishing outcomes across vessel groups and years

Despite both vessel groups maintaining relatively stable catches-per-trip (Figure 2.4), the offshore group had higher average annual earnings with much higher variability while the nearshore group had lower but more stable average earnings. Trip distance was not the only aspect of the Bering Sea pollock fishery that changed from 2003 – 2015, with the ultimate economic outcome of interest being the net earnings per year (summer B-season only, in our case) (Figure 2.5c). While there was little covariation between the two groups during this period, net earnings of both groups varied substantially, with average variation in vessel-level annual earnings of 50% and 33% for the offshore and nearshore vessels, respectively.

Annual net earnings were not strongly correlated to any single component of the fishery landscape or average trip distances (Table 2.4). Given that expected net earnings are a function of *(Price*Catch) - Cost*, the relationships of each component of this equation with the fishery landscape drives both net earnings and their variability (Table 2.4, Supplementary Table S2.3). For example, annual catches were strongly related to TAC, prices were related to abundance and TAC, and the fuel-to-earnings ratio was related to trip distances (Table 2.4). Trip distances meanwhile were strongly related to both abundance and temperature. It was not our intent to describe what made vessels more or less profitable in a year. Instead, we sought to characterize some of the relationships with fishery performance and economics and to identify heterogeneities in these factors across the fleet and the complexities of these interactions.

Discrete choice models for fishing location have revealed how fishers target locations that maximize expected profit, which is estimated through examining how vessels trade off expected earnings and distances from different locations (Eales and Wilen 1986; Haynie and Layton 2010). However, applying such models across a fleet without recognizing and accounting for important forms of processor and vessel heterogeneity may yield dubious conclusions about fleet behavior. Similar vessels may make very different decisions about spatial tradeoffs of fish value and travel costs based on the vessel's processor (or other constraints in different fisheries). For example, if a processor will only purchase fish that were caught within 30 hours of delivery, this eliminates many choices. This suggests increased complexity in how expected catch rates interact with processor and vessel characteristics to drive fisher responses to landscape variability. This is relevant not only for understanding how climatically-driven changes in distribution could affect certain vessels, but it also highlights a complexity of managing fleets with spatially-explicit regulations. While beyond the scope of this study and the available price data, future work could benefit from a comparison that includes discrete choice models with and without vessel, product, and environmentally-driven heterogeneities as we have described here.

Fishers with different vessels and delivering to different processors adjusted their behavior to compensate for environmental changes to sustain their revenues. Though vessel size was not a significant predictor of trip distance, smaller vessels within each group tended to stay closer to port. These vessels could not travel as far to seek higher catch rates but they needed fewer fish to fill their holds and typically targeted smaller aggregations of larger and more valuable pollock. Meanwhile, larger vessels could make longer trips to better fishing grounds more worthwhile by carrying more fish. Future work could benefit from more precise, trip-level price data that could better explain the factors involved in setting prices. Nonetheless, with our aggregate price data, fishing behaviors were observed to buffer revenues within the range of environmental dynamics observed to date.

2.6.3 Implications

Multiple strategies were prosecuted simultaneously within the pollock fishery, demonstrating the importance of factoring intra-fleet and inter-annual heterogeneity into analyses of fleet behavior. For example, if management strategy evaluations projected the impacts of changing fish abundance and/or climate change on a fishery based on a "typical" vessel's behavior, they would misrepresent the fleet and bias covariate selection in models. Similarly, if the impacts of spatial closures were simulated based on an average vessel or year, closures or regulations would have disproportionate economic impacts on certain vessels or companies. Heterogeneous fleet behaviors may also affect exploitation on different populations or age classes of target stocks. Such exploitation differences may have implications for spatially-explicit quota allocation and bycatch avoidance measures or for stock assessments that rely upon fishery-dependent catch and effort data.

Understanding fleet strategies is important for current management challenges such as salmon bycatch in the pollock fishery. The pollock fleet is constrained by vessel-level hard-caps of Chinook salmon (*Oncorhynchus tshawytscha*) bycatch and there are rolling hotspot closures for Chinook and chum (*O. keta*) salmon bycatch (Ianelli and Stram 2015; Stram and Ianelli 2015). If pollock and salmon populations overlap spatially more during warm years when the pollock fleet was more concentrated, we may expect greater impacts on both salmon stocks and on the entire pollock fleet than if more overlap between salmon and pollock populations occurred in colder years, when the nearshore and offshore pollock vessels were targeting different locations. Furthermore, as salmon migration timing varies by stock, understanding multiple and shifting distributions of the pollock fleet may enable better resolution of the impacts to certain salmon stocks (e.g., Yukon River Chinook salmon) whose populations are of particular conservation concern (Ianelli and Stram 2015).

Fishery responses to climate warming will include the emergence of new fisheries or changing targeting behaviors (Pinsky and Mantua 2014). However, for fisheries with a high degree of specialization and automated processing, adaptation may in some cases actually be more challenging than for some less industrial fisheries (McIlgorm et al. 2010). Fishers are often constrained by their vessel and gear, permit and management restrictions, the environment where they fish, and markets. On average, the pollock fishery lands more than 1.2 million metric tons of fish per year, and the processing is mechanized for particular fish sizes and specialized production of fillets, surimi, and other products. In addition to management rigidities, it is challenging for processors to rapidly adapt their systems for different products or species and we more commonly observe the fishing fleet adapting to changes in the fishery landscape by changing their behaviors. Pollock vessels can lease quota and pursue alternative economic opportunities (e.g., participate in other fisheries) when conditions change, but even during years when abundances were low, nearly three quarters of vessels fished. Prices in the low-abundance years were some of the highest ever, and projections suggest that future declines in abundance may be partially offset through increased prices (Seung and Ianelli 2016). However, the degree to which such price changes will affect vessels throughout fleets may depend upon the heterogeneities of vessel behaviors and the local and global markets for a species.

By utilizing vessel movement information, patterns in vessel and fleet dynamics can be linked to the fishery landscape to improve our understanding of how fishers fit into ecosystem-based management. By using movement information we observed that pollock catcher vessels fished farther south during warm years and that some vessels fished farther north during cold years. This was contrary to expectations from the climate change literature that expect a "northward march" (e.g., Cheung et al. 2010) but consistent with some work (e.g., Haynie and Pfeiffer 2013; Haynie and Huntington 2016) that incorporates the complexities and heterogeneities associated with economic and social factors. It is also a good reminder that behaviors of fishing fleets will never be driven wholly by contemporaneous climatic conditions – management, markets, and lagged processes all impact fisheries datasets. We emphasize the role of human behaviors in the fishery ecosystem, and the importance of revisiting these relationships as the range of environmental conditions expands and fishers adapt in new ways.

2.7 References

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Table 2.1: Fishing and economic indicators calculated for each trip and their source or derivation. Some derivations include definitions provided in previous rows of the table.

Outcome	Derivation / Source
Catch per trip	Fish ticket reported pounds of pollock landed per trip
Fishing effort per trip	If trip was observed: observer reported effort (hours) If trip was not observed: number of VMS records determined to be fishing * median (VMS transmission interval per trip) (see Supplementary Information for further details)
Catch per unit effort (CPUE)	Catch per trip / Fishing effort
Catch per trip day	Catch per trip / Trip duration (days)
Gross earnings per trip	Fish ticket reported value of trip
Gross earnings per trip day	Gross earnings per trip / Trip duration
Fuel cost per trip	(Fuel price * fuel consumption while transiting * time spent transiting) + (fuel price * fuel consumption while fishing * time spent fishing)
Net earnings per trip	Gross earnings – Fuel cost
Net earnings per trip day	Net earnings per trip / Trip duration
Ex-vessel price*	Gross earnings per trip / Pounds landed per trip

* Annual average price across summer A- and winter B-seasons that does not account for trip-level differences in product size, quality, or type of processing, but that accounts for larger trends in price over time.

Table 2.2: Comparison of average (standard deviations) annual trip characteristics by vessel group. Groups were significantly different (Mann-Whitney test; $P < 0.05$) for all metrics except number of trips.

	Nearshore group	Offshore group
Number of vessels	40.3 (4)	30 (2)
Vessel length (m)	34.5 (7.7)	41.0 (9.0)
Number of trips	17.6 (9.9)	16.9 (6.5)
Earnings per trip ($1000)	52.8 (23.9)	100.5 (53.3)
Catch per trip (tonnes)	176 (73)	323 (160)
Fish weight (kg)	0.96 (0.15)	0.72 (0.10)

Table 2.3: Relationships between fishing outcomes and both the fishery landscape and trip distances. Values are Pearson correlation coefficients (ρ) with darkest shaded boxes highlighting correlations with an absolute magnitude > 0.7 and light shading between 0.3 and 0.7.

Fishery outcome	Vessel group	Pollock abundance	TAC	Fuel price	Temperature	Average trip distance
Catch / trip (tonnes)	Nearshore	0.52	0.19	0.4	0.47	-0.59
	Offshore	0.21	-0.06	0.05	0.1	-0.11
Catch / year (tonnes)	Nearshore	0.33	0.81	0.04	0.33	-0.16
	Offshore	0.55	0.93	-0.31	0.56	-0.42
CPUE (tonnes / hour fishing)	Nearshore	0.74	0.41	-0.45	0.8	-0.88
	Offshore	0.44	-0.04	-0.25	0.27	-0.33
Net earnings / trip ($1000)	Nearshore	-0.42	-0.82	0.32	-0.36	0.21
	Offshore	-0.24	-0.55	0.22	-0.21	0.21
Net earnings / trip day ($1000)	Nearshore	0.64	0.3	-0.33	0.81	-0.91
	Offshore	0.67	0.25	-0.16	0.75	-0.79
Net earnings / year ($1000)	Nearshore	-0.24	0.27	0.27	-0.17	0.3
	Offshore	0.43	0.58	-0.15	0.47	-0.33
Price / pound ($)	Nearshore	-0.74	-0.83	0.35	-0.77	0.69
	Offshore	-0.54	-0.65	0.46	-0.56	0.53
Trips / vessel	Nearshore	0.16	0.85	-0.28	0.28	-0.06
	Offshore	0.55	0.97	-0.37	0.61	-0.47
Fuel : earnings	Nearshore	-0.41	0.17	0.08	-0.53	0.56
	Offshore	-0.58	-0.19	0.55	-0.7	0.72

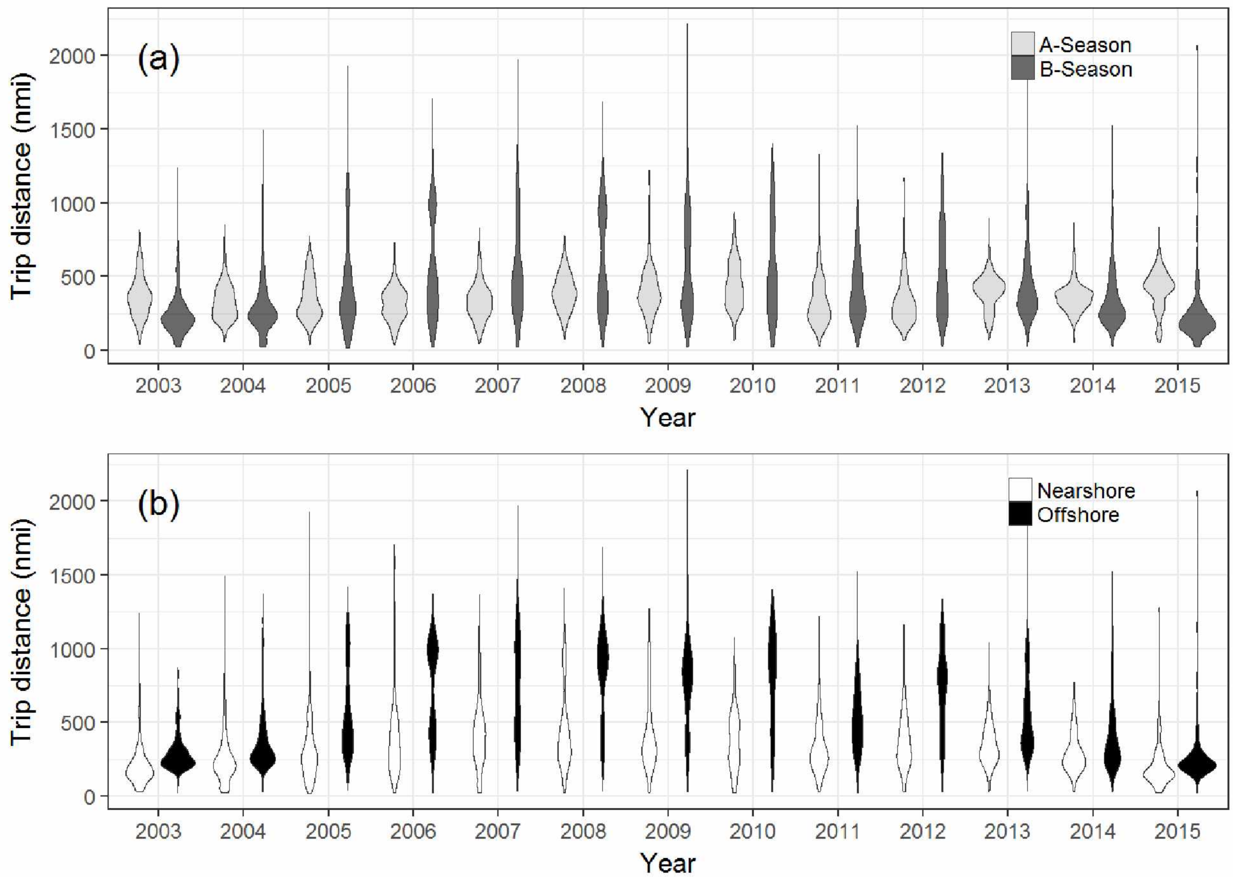

Figure 2.1: Trip distances by season and vessel groups. (a) Violin plots of trip distances during summer A-season (light grey) and winter B-season (dark grey) for all vessels. (b) Violin plots of B-season trip distances for vessels in the nearshore (white) and offshore (black) vessel groups.

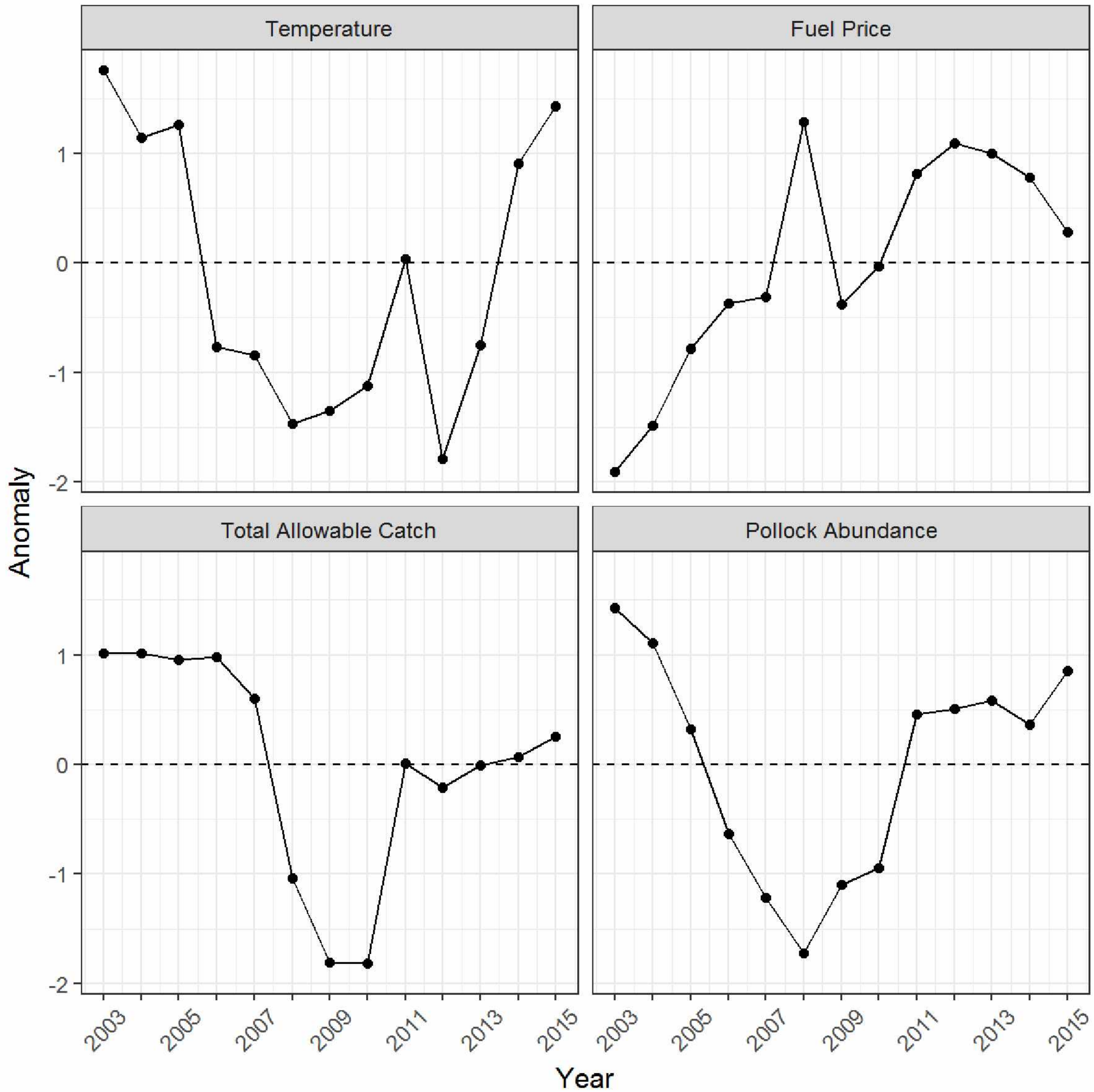

Figure 2.2: Several key characteristics of the fishery landscape and their anomalies from 2003 - 2015.

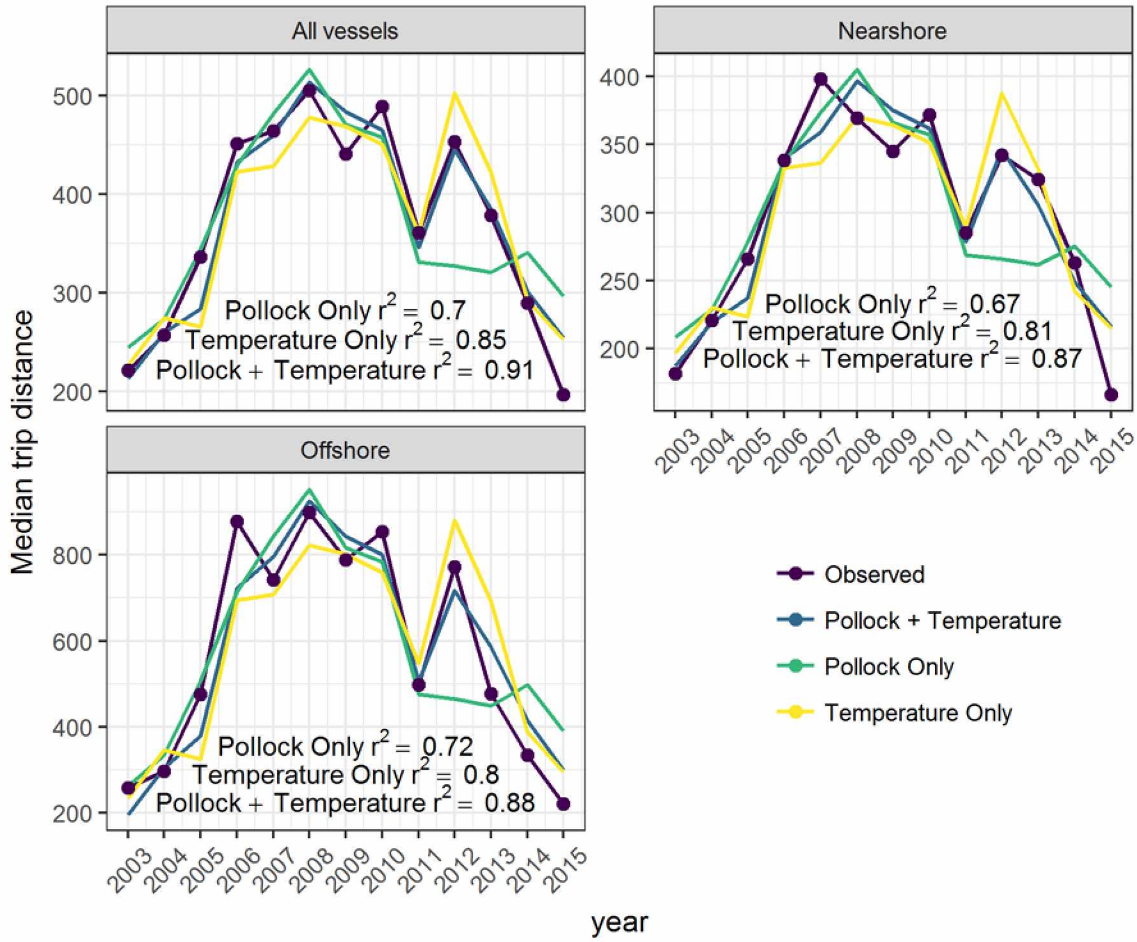

Figure 2.3: Model fits to annual median summer B-season trip distances. Models fit to all vessels (top left), the nearshore vessel group (top right), and the offshore vessel group (bottom left). Text values in each plot are the r^2 values from each linear model.

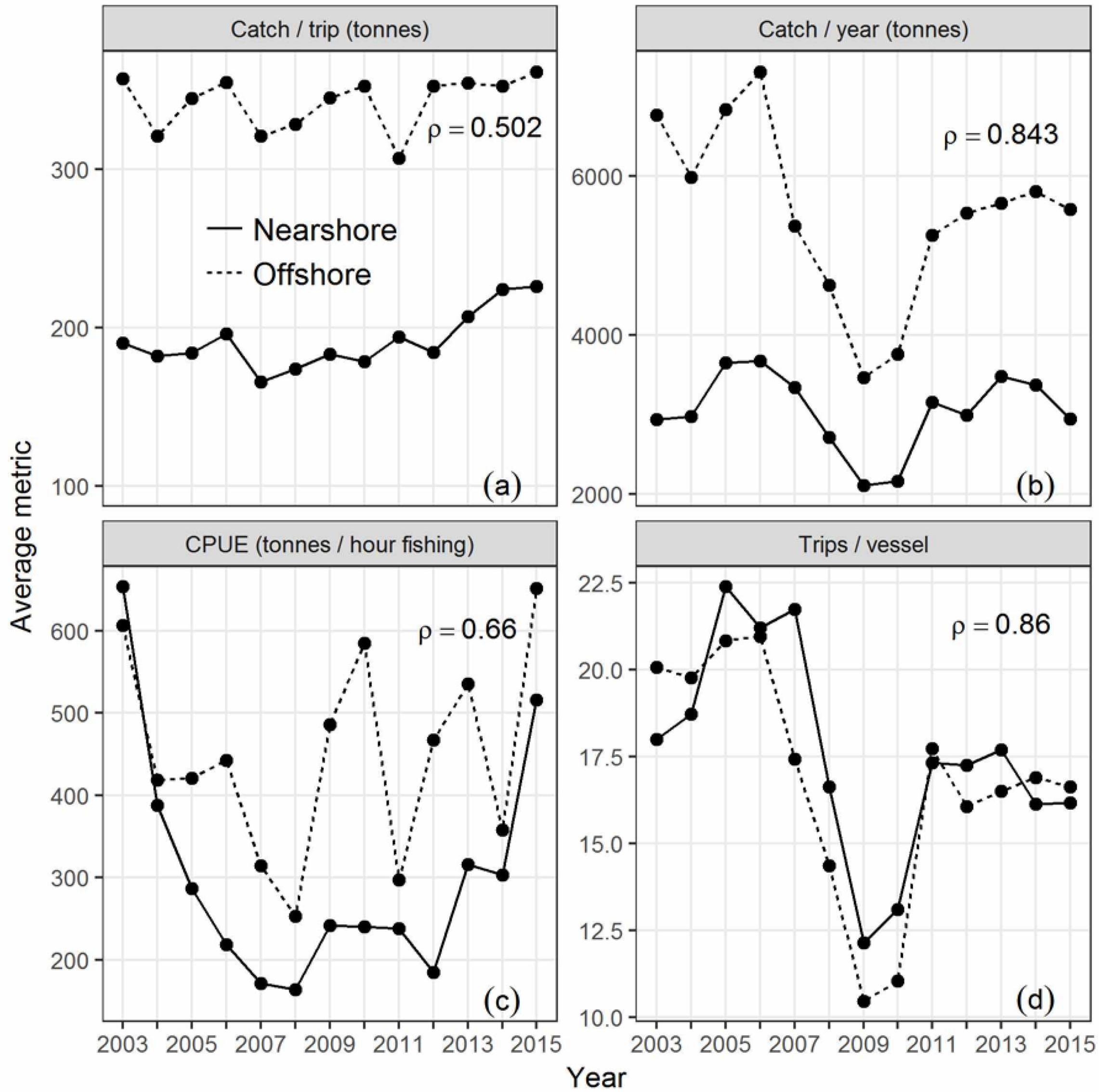

Figure 2.4: Average fishing performance and behavior by year (summer B-season only). Trends shown for the nearshore (solid lines) and offshore (dashed lines) vessel groups. Rho (ρ) values indicate Pearson correlations between the two groups.

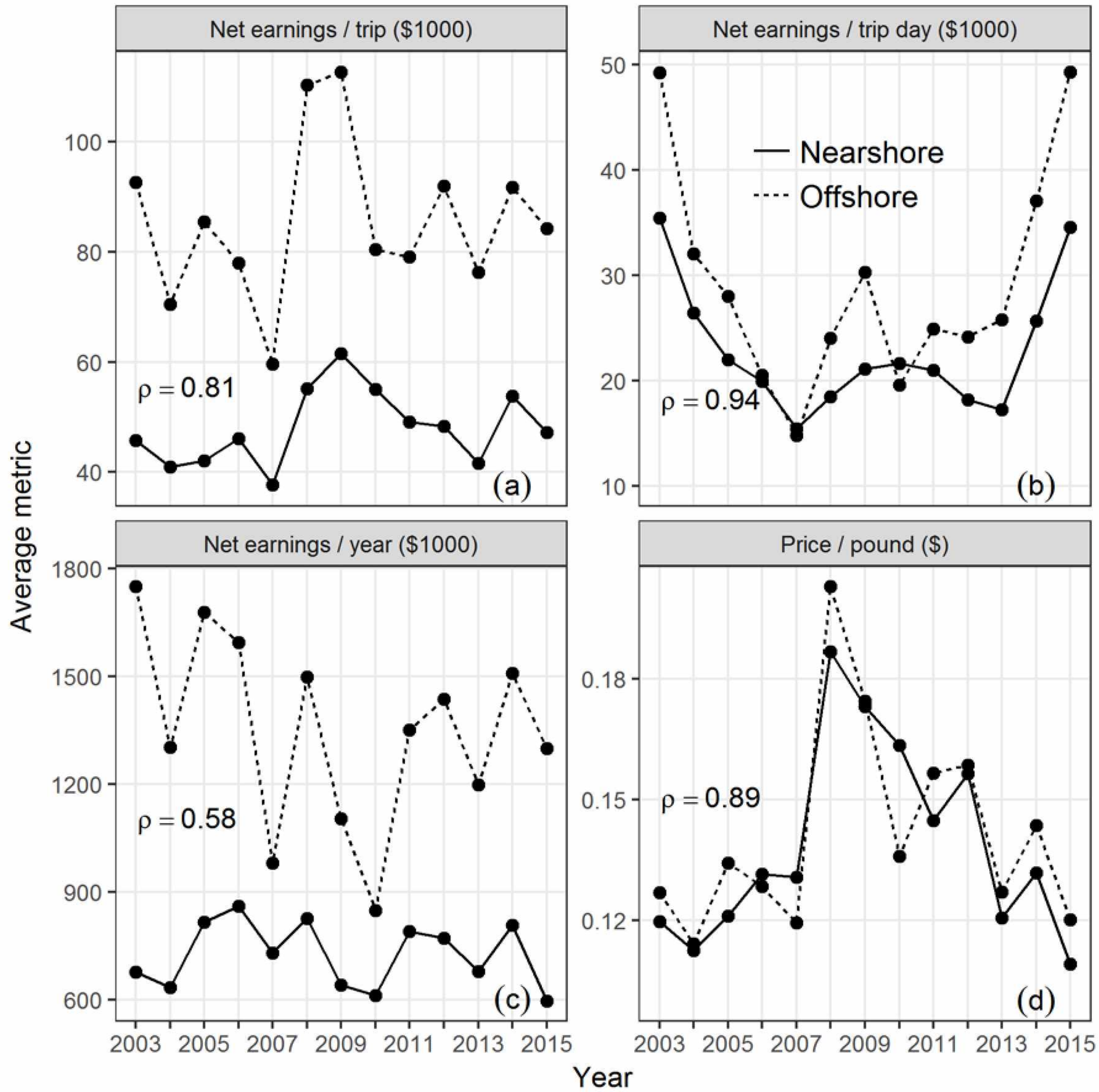

Figure 2.5: Average annual (summer B-season only) economic performance. Values shown for the nearshore (solid lines) and offshore (dashed lines) vessel groups. Rho values indicate Pearson correlations between the two groups.

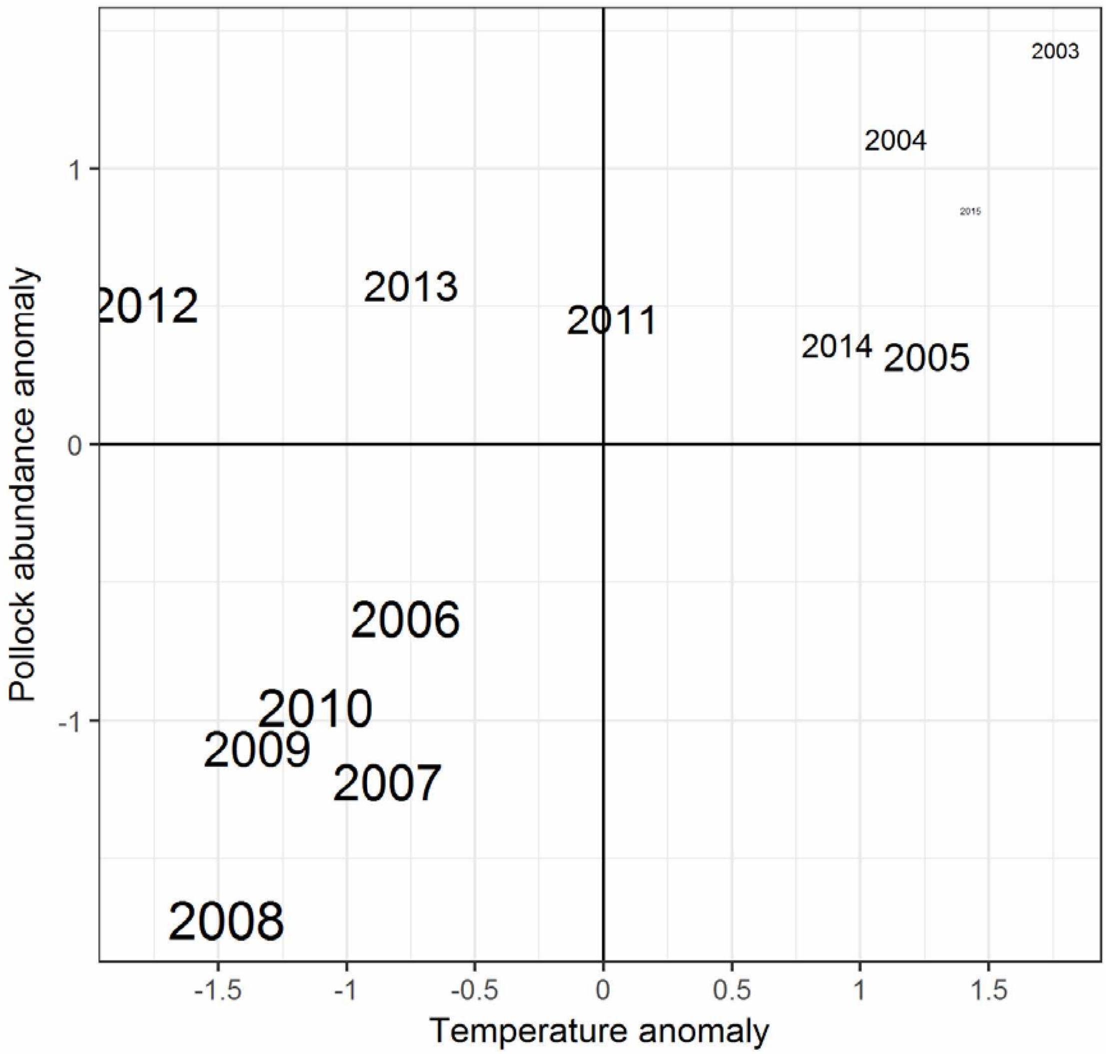

Figure 2.6: Relationship between temperature and pollock abundance anomalies. Label sizes are proportional to the median trip distance in each year, with larger labels representing longer median travel distances. Separate figures for the two vessel groups showed similar results.

2.8 Appendices

2.8.1 Data

Vessel monitoring system (VMS) data from the Bering Sea pollock fleet were obtained for the 91 catcher vessels that participated in the American Fisheries Act (AFA) pollock fishery at any time from 2003 – 2015 and delivered to inshore processors. Travel distances were calculated for trips made by the fleet from VMS data following Watson and Haynie (2016). We obtained effort data from fishery observer records from the North Pacific Groundfish Observer Program (NOAA 2016). Since 2011, all vessels in the AFA pollock fleet are observed for 100% of their pollock fishing days at sea. Prior to 2011, observers were present on 30% of the fishing days at sea for vessels <125 ft, (37.8 m) and 100% of days for vessels ≥ 125 ft (see Watson and Haynie [2016] for more details).

During years with partial observer coverage, or in cases where observer records lacked effort data, we used a speed filter applied to VMS data to determine whether a vessel was fishing (e.g., Deng et al. 2005). If a vessel's speed was between 0.9 and 4.1 knots (which we found to be the most accurate speed filter), a VMS record was considered to be fishing. Fishing duration was calculated for each unobserved trip by tallying the number of VMS records per trip that were fishing and multiplying that by the median time interval between VMS records for that trip (VMS are mandated to transmit at 30-min intervals; See Watson and Haynie [2016] for more details).

Fish tickets were issued when catches were delivered (ADFG 2015). These data included details regarding fishing trips, including the weight (pounds) and revenue (dollars) for each species landed. By combining fish tickets with information from VMS data (Watson and Haynie 2016), we derived net earnings and earnings per trip day. However, we could not derive a precise estimate of price-per-pound for a specific trip because earnings data are revised at the end of the year to incorporate bonuses and other adjustments. The result is a trip-level earnings value that incorporates a degree of annual averaging, valid for trends but not spatial differentiation of prices.

The fleet has reported their fuel consumption rates while fishing and transiting since 2012. After quality control, average fuel consumption rates during fishing and transiting from 2012 – 2014 were obtained for the 87 of the 91 vessels active in the study period. Fuel consumption rates were applied to the durations of each trip that was spent transiting and fishing to calculate trip-level estimates of the fuel consumed.

2.8.2 References

(NOAA) Alaska Fisheries Science Center. North Pacific (NORPAC) Groundfish and Halibut Observer Data Dictionary December 2007 –Present. 2016. Metadata and access details available at: https://inport.nmfs.noaa.gov/inport/item/7290.

(ADFG) Alaska Department of Fish and Game, and Alaska Commercial Fisheries Entry Commission. 2015. Alaska fish ticket data. Data compiled by Alaska Fisheries Information Network in COMPREHENSIVE_FT. Metadata: www.akfin.org/data/documentation/

Deng, R., Dichmont, C., Milton, D., Haywood, M., Vance, D., Hall, N., and Die, D. 2005. Can vessel monitoring system data also be used to study trawling intensity and population depletion? The example of Australia's northern prawn fishery. Can. J. Fish. Aquat. Sci. **62**(3): 611–622.

Watson, J. T., and Haynie, A. C. 2016. Using Vessel Monitoring System Data to Identify and Characterize Trips Made by Fishing Vessels in the United States North Pacific. Plos One. **11**(10): e0165173.

Table S2.1: Variability of fishery outcomes. Variability (coefficient of variation, CV) of fishery outcomes is indicative of risk associated with fishing so we compare differences in the CV across groups and years. Annual (B-season) CVs were calculated by vessel and the distribution of vessel-level CVs was compared between the nearshore and offshore vessel groups. The table shows results with the nearshore group as the base so that, for example, in 2003, the CV for trip distances was greater for the nearshore group than for the offshore group. If neither “<” (light grey) nor “>” (dark grey) appears in a cell, there was no difference. Colors and symbols represent the same relationship.

Year	Trip distance	Trip Duration	Avg. pollock weight	Catch	Effort	Catch / unit effort	Gross earnings	Gross earnings / day	Net earnings	Net earnings / day	Fuel-to-earnings ratio
2003	>	>		>		>	>	>	>	>	
2004											
2005		>	<	>			>		>		
2006	>	>	<	>	<		>	>	>	>	>
2007			<	>			>	>	<	>	>
2008	>	>	<	>		>	>	>	>	>	>
2009	>	>	<	>			>	>	>	>	>
2010	>	>		>		>	>	>	>	>	>
2011			<								
2012	>	>	<	>	<		>	>	>	>	>
2013				>			>	>	>	>	>
2014	<	<	<								
2015	>	>		>			>	>	>	>	>

Table S2.2: Linear model fits of trip distance vs. the fishery landscape. Linear model coefficients with their standard errors (SE) and P-values for fitting the relationships between median trip distance and two predictors. ΔAIC values compare only the three models within each vessel group.

Vessel group	Model	ΔAIC	Term	Estimate	SE	P-value
All Vessels	Pollock Only	15.7	Pollock Abundance	-89.3	16.7	<0.01
All Vessels	Temperature Only	6.3	Temperature	-99.5	11.8	<0.01
All Vessels	Temperature + Pollock	0	Pollock Abundance	-38.6	13	0.01
			Temperature	-70.9	13.2	<0.01
Nearshore	Pollock Only	11.1	Pollock Abundance	-62.2	12.2	<0.01
Nearshore	Temperature Only	4.2	Temperature	-68.7	9.5	<0.01
Nearshore	Temperature + Pollock	0	Pollock Abundance	-27.8	11.3	0.03
			Temperature	-48.1	11.5	<0.01
Offshore	Pollock Only	10.6	Pollock Abundance	-219.1	38.9	<0.01
Offshore	Temperature Only	6.5	Temperature	-233.4	33.7	<0.01
Offshore	Temperature + Pollock	0	Pollock Abundance	-110.9	36.6	0.01
			Temperature	-151.2	37.3	<0.01

Table S2.3: Correlations between annual variability of fishing outcomes and the fishery landscape. Correlations are Pearson's ρ from 2003 - 2015.

Fishery outcome	Vessel group	Pollock abundance	TAC	Fuel price	Temperature	Average trip distance
Catch / trip	Nearshore	-0.16	-0.35	-0.46	0.12	-0.07
	Offshore	-0.22	0.15	-0.25	-0.18	0.24
Catch / year	Nearshore	0.22	0.43	-0.66	0.26	-0.24
	Offshore	-0.06	0.24	-0.52	0.21	-0.09
CPUE	Nearshore	0.06	0.11	-0.64	0.14	-0.13
	Offshore	0.15	0.1	-0.48	0	-0.06
Fish weight	Nearshore	-0.31	-0.48	-0.34	-0.37	0.29
	Offshore	-0.56	-0.78	0.31	-0.81	0.75
Fuel:Earnings	Nearshore	0.5	0.44	-0.72	0.49	-0.55
	Offshore	0.27	0.42	-0.49	0.24	-0.22
Net earnings / trip	Nearshore	-0.57	-0.41	-0.05	-0.25	0.39
	Offshore	-0.16	0.36	-0.31	0.07	0.03
Net earnings / trip day	Nearshore	-0.58	-0.19	-0.04	-0.18	0.31
	Offshore	-0.29	0.06	-0.44	0.03	0.07
Net earnings / year	Nearshore	-0.02	0.4	-0.65	0.18	-0.06
	Offshore	-0.03	0.35	-0.53	0.31	-0.17
Price / pound	Nearshore	0.06	0.11	-0.49	0.28	-0.19
	Offshore	0	-0.01	-0.25	0.02	-0.05
Trips / vessel	Nearshore	-0.21	0.03	-0.37	-0.24	0.28
	Offshore	0.01	0.12	-0.43	0.1	-0.04

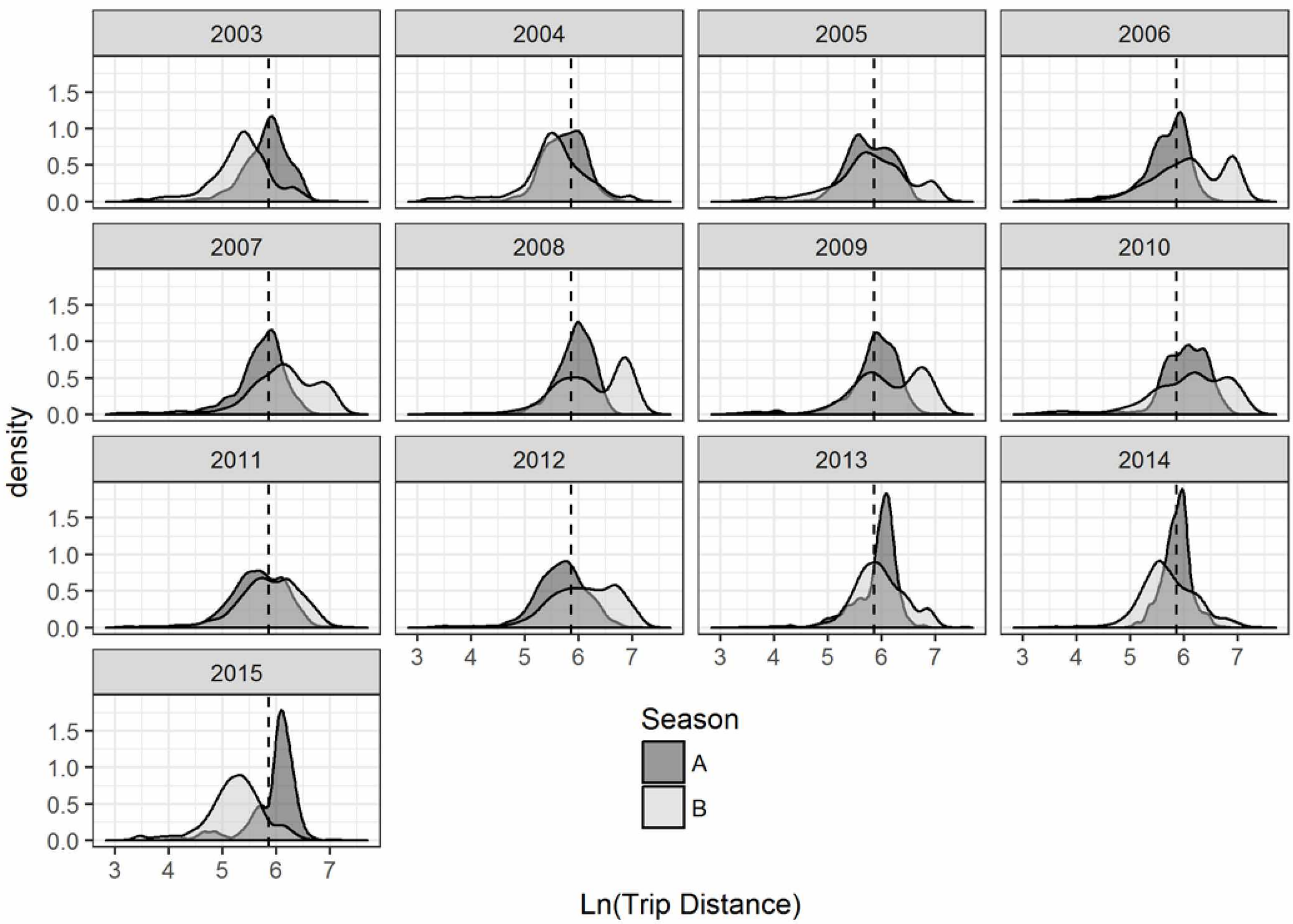

Figure S2.1: Seasonal trip distances. Distribution of the natural logarithm trip distances (nautical miles) during the winter A-season and the summer B-season. The vertical reference line at 5.8 (equivalent to natural log of 350 nautical miles) equals the median A-season trip distance for all vessels from 2003 to 2015.

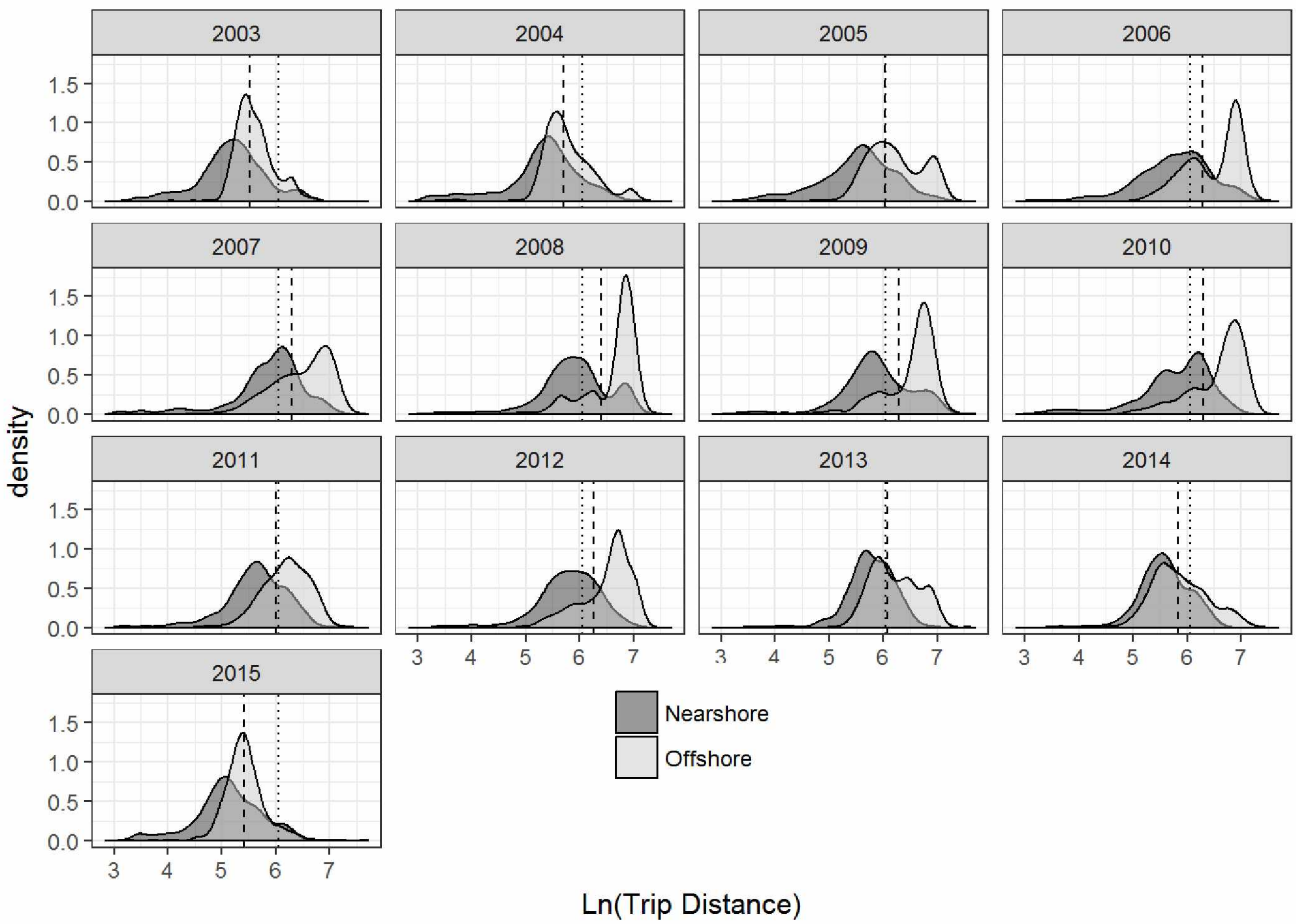

Figure S2.2: B-season trip distances by vessel group. Natural logarithm of distances traveled (nautical miles) for each trip by the nearshore (dark grey) and offshore (light grey) vessel groups in each year. The annual average distance and the average distance across all years for the entire fleet are shown by vertical dashed and dotted lines, respectively.

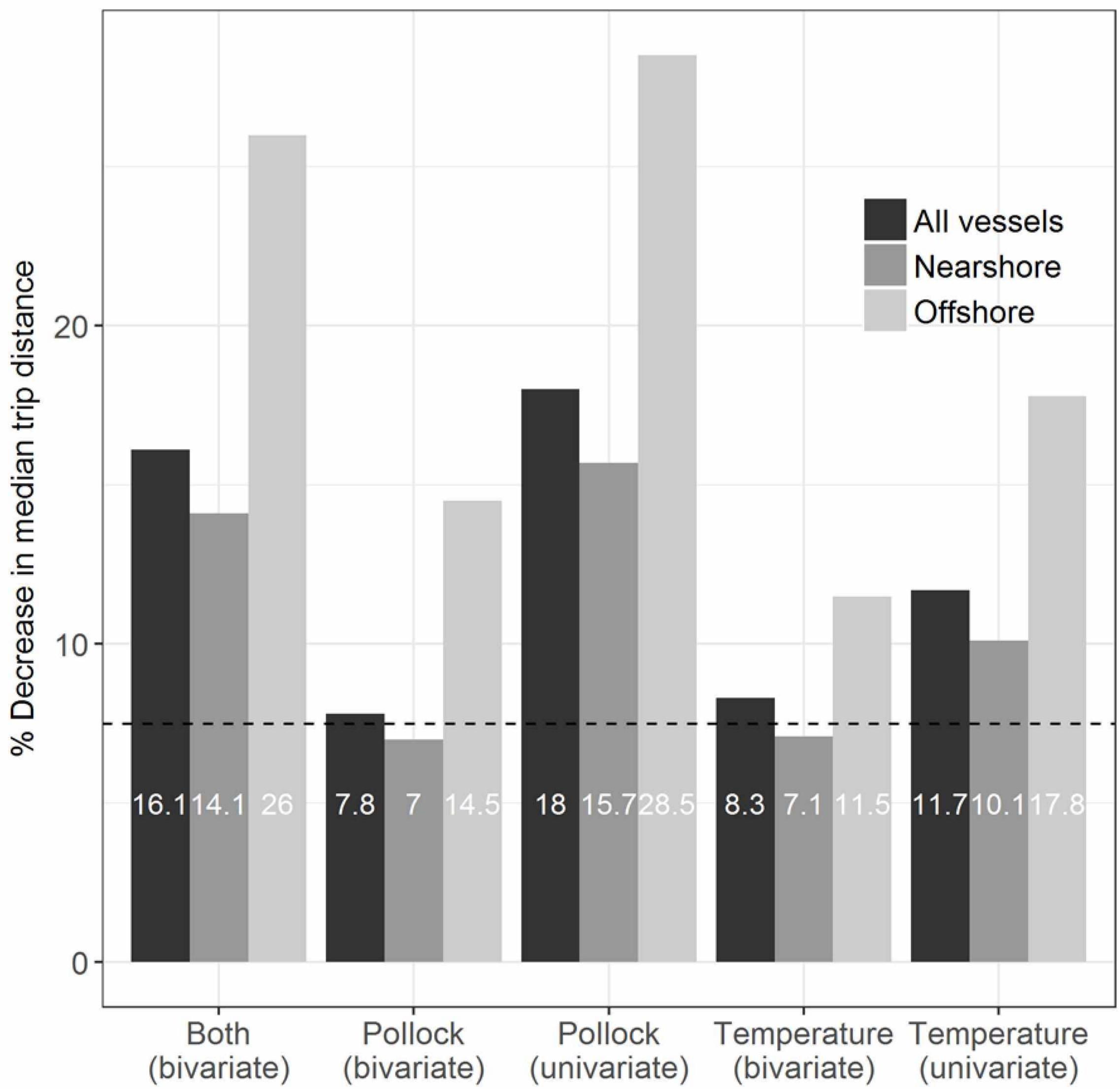

Figure S2.3: Sensitivity analyses for models of median trip distance. Bivariate models included temperature and pollock abundance and univariate models include either temperature or pollock abundance. Y-axis values are the percent median trip distance was estimated to decrease with a 20% increase in abundance or temperature. In the bivariate model, temperature or abundance was increased while the other was held constant except for “Both,” for which both variables were increased.

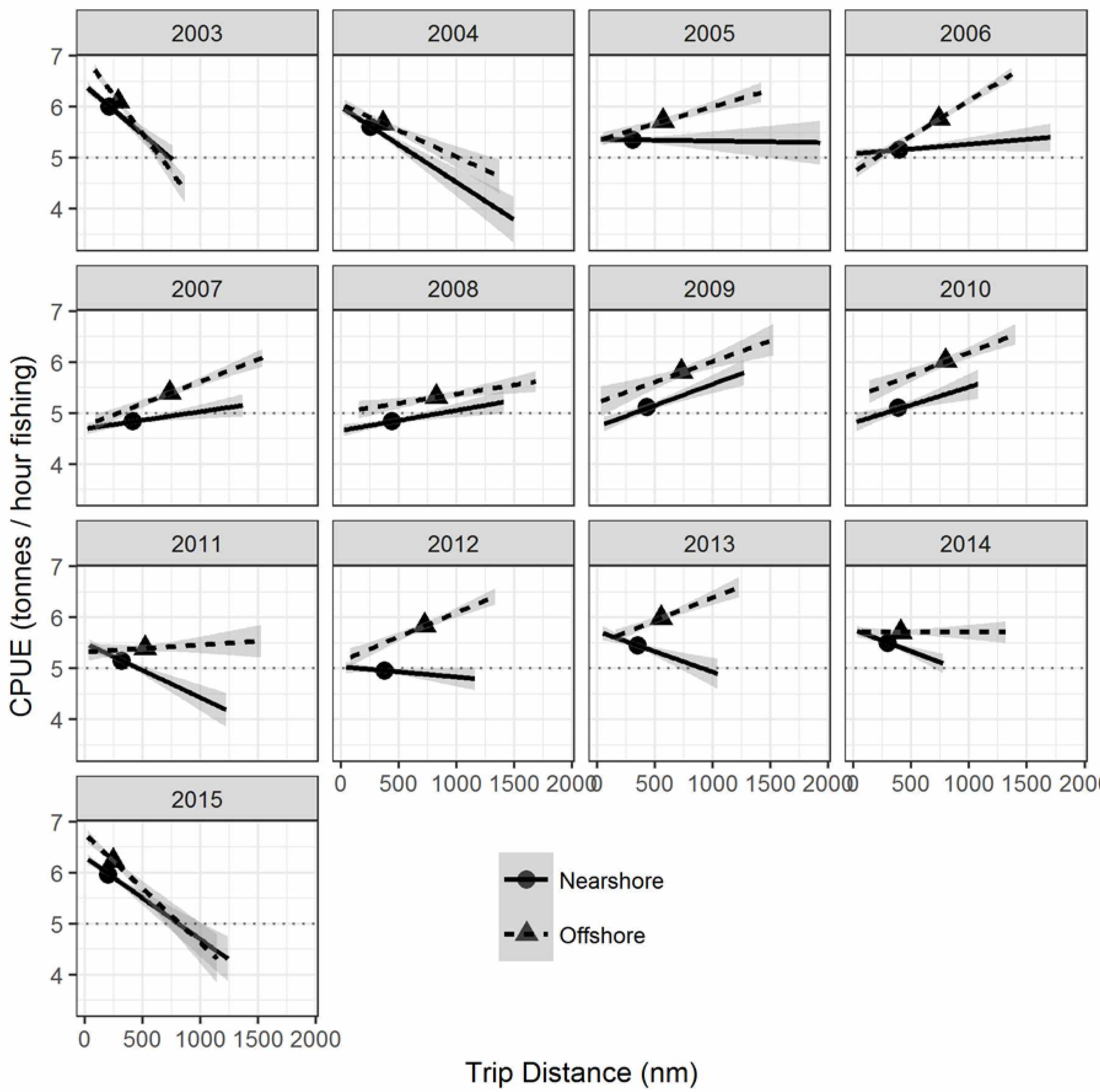

Figure S2.4: Regression of CPUE versus trip distance for each vessel group in each year. Lines show model fits and points illustrate the average trip distances and average CPUE for each vessel group in each year. Individual points are omitted for confidentiality.

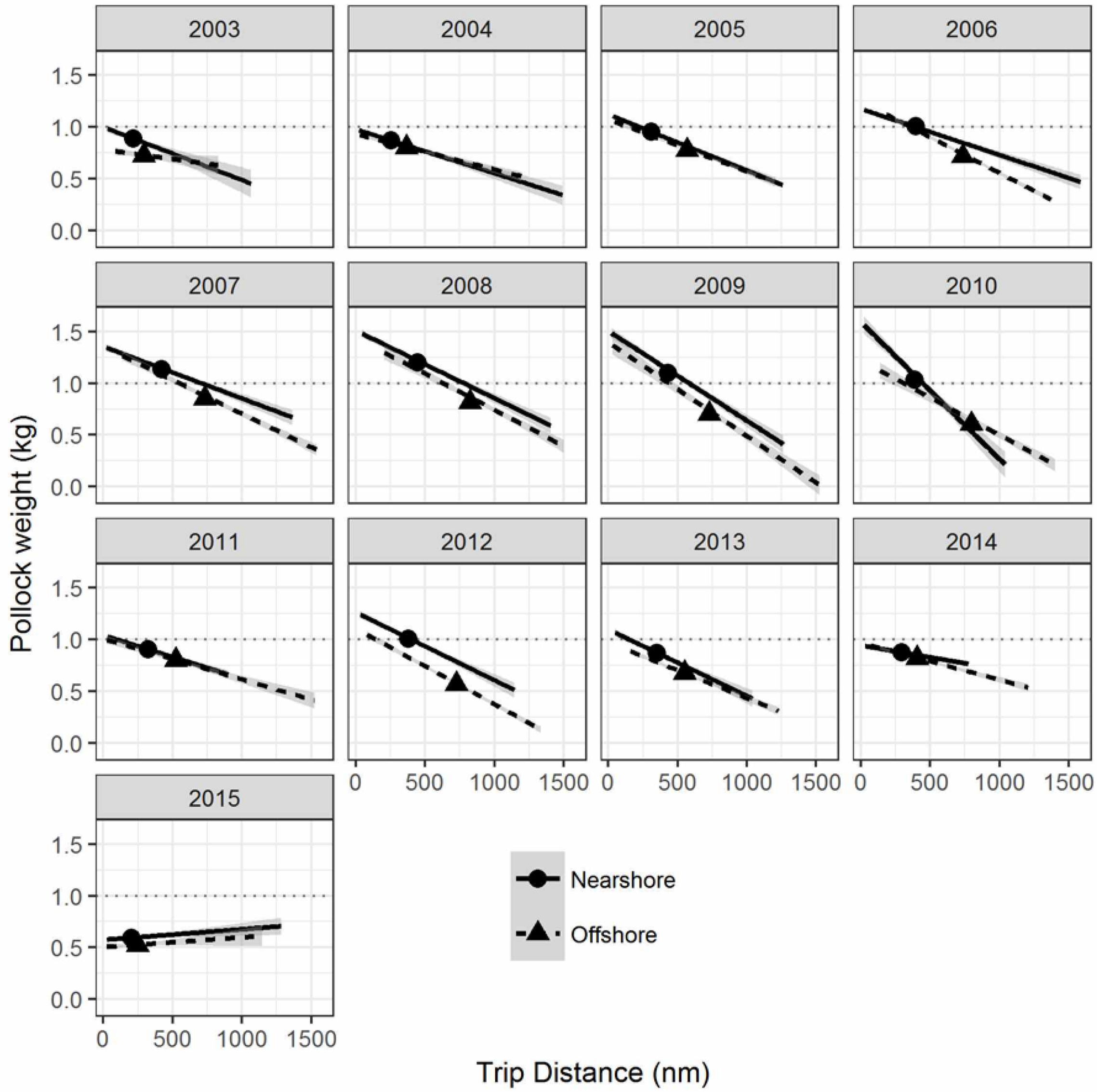

Figure S2.5: Regression of pollock weight versus trip distance for each vessel group in each year. Lines show model fits and points illustrate the average trip distances and average pollock weights for each vessel group in each year. Individual points are omitted for confidentiality.

Chapter 3 Vessel monitoring systems (VMS) reveal increased fishing efficiency following regulatory change in a bottom longline fishery[3]

3.1 Abstract

John Shepherd's aphorism about counting fish being like counting trees (except that you can't see them and they move) is often used to exemplify the challenges of assessing fish stocks, but these challenges are equally true for other unobserved agents, including fishers. However, with the global expansion of vessel monitoring systems (VMS), fishers' locations are increasingly observable. But, there is often a disconnect between the data and their use to evaluate impacts of fishing on target and non-target fish stocks or to assess the ramifications of fisheries management strategies on fishers. To resolve this, we demonstrate how VMS data can provide a suite of metrics for improvement of stock assessments, delineation of fishing habitats, and evaluation of climatic or regulatory impacts on fisher performance. Using VMS data from the Gulf of Mexico grouper-tilefish bottom longline fishery, we first developed a generalized additive modeling approach that predicts fishing effort with ~85% accuracy. We combined model outputs with logbook data to derive a suite of metrics that demonstrated fisher responses to regulatory changes, including implementation of a catch share program. A comparison of the fishery before and after regulatory changes revealed a large-scale reduction in capacity, accompanied by reduced fishing effort, shorter trips, lower expenses, higher catch rates, and more earnings for those vessels that remained in the fishery. This approach could be further developed for management strategy evaluations, parameterizing economic models of fisher behavior, improving fishery-dependent stock assessment indices, or deriving socioeconomic indicators in fisheries worldwide.

3.2 Introduction

Many factors drive the dynamics of commercial fisheries and substantial effort is focused on understanding and predicting how fisheries respond to such drivers. As fishing fleets respond to the dynamics of their environments, markets, and governance (i.e., management structure and regulations), the ability to quantify their behaviors becomes increasingly critical for understanding not only the dynamics of exploited stocks but the economic sustainability of the fisheries themselves (van Putten et al., 2012; Fulton et al., 2011).

Over the last few decades vessel monitoring systems (VMS) have led to a dramatic improvement in our ability to monitor fishing vessel movements, and subsequently, to derive a suite of metrics by which to evaluate fishing fleet behaviors and economic performance. VMS transmit vessel locations at

[3] Watson, J.T., Haynie, A.C., Sullivan, P.J., Perruso, L., O'Farrell, S., Sanchirico, J.N., and Mueter, F.J. Using vessel monitoring systems (VMS) to quantify fisher responses to regulatory change. For submission to Fisheries Research

regular intervals, and are now required by dozens of national governments and regional fisheries management organizations, for example for more than 4,000 vessels in the United States alone. These systems enable us to monitor how speeds, turn angles, locations, and other aspects of vessel movements may indicate when vessels are fishing versus when they are transiting or searching for fish.

Numerous studies have utilized VMS or similar data to estimate fishing effort (e.g., Mills et al., 2007; Peel and Good, 2011; Joo et al., 2013), to validate fisher-reported logbooks (e.g., Palmer, 2008; Palmer and Wigley, 2009; Bastardie et al., 2010), and to delineate fishing grounds (e.g., Stelzenmüller et al., 2008). Several useful software packages can simplify and automate some of these analyses with VMS data from European fisheries where data formats are standardized (e.g., Russo et al., 2014, or Hintzen et al., 2012). However, as analyses diversify, customized modeling approaches may be required. For example, Ducharme-Barth and Ahrens (2017) incorporated uncertainty into spatial estimates of fishing effort associated with the Deepwater Horizon Oil Spill. O'Farrell et al. (2017) examined VMS-based solutions to estimate effort when fishing events occurred for durations less than the VMS sampling frequency. Thus, while software may automate some tasks, we must also derive approaches and metrics that allow us to answer questions that are unique to fisheries and datasets. For example, once software approaches have helped to delineate fishing grounds, understanding how fishing grounds or fleets shift spatially in response to a suite of environmental drivers (e.g., Pinsky and Fogarty 2012; Joo et al., 2014; Joo et al., 2015) may require more customized tools. Similarly, as fishery management institutions adapt to climate change and increasing global pressures on fish stocks, the ability to measure success under different governance becomes increasingly critical (Melnychuk et al., 2012; Clay et al., 2014). Catch shares are one important management structure for which managers may want to quantify the effects of implementation..

Catch share systems seek to reduce the inefficiencies from too many fishers competing for a limited resource (Grafton, 1996), and VMS data provide a means by which to address many hypotheses associated with these management changes. In catch share systems, individual fishers are allocated shares of the total catch which enables fishers to catch (and process) fish in the most efficient and profitable manner (e.g., Birkenbach et al., 2017). For example, after implementation of catch shares in the Bering Sea fishery for walleye pollock, at-sea processors reported a 20% increase in yield because production rates were no longer constrained by a race for fish (General Accounting Office 2000). In an Alaska longline fishery for sablefish, catch share implementation increased fishery catch rate and decreased harvest of immature fish (Sigler and Lunsford, 2001). Fishers under catch shares can also take the time to evaluate their expected profits from catching fish in different locations (Haynie and Layton, 2010). In this sense, much of the context around quantifying value in a catch share system includes a spatially-explicit component, and thus, underscores the value that can be added from the spatial provisions of VMS data at the trip-, set-, or haul-level. VMS data provide the opportunity for a more refined measure of effort (at the temporal scale of VMS transmissions) that is otherwise typically not available for unobserved fishing. Through these VMS-derived estimates of effort, changes in the efficiency of fishing (e.g., catch or revenue per unit effort) can be quantified across time and regulatory transitions. Such refined effort estimates are particularly valuable in many cases where fishery-dependent data (e.g., estimates of longline soak time) are sparse or non-existent prior to regulatory changes, and thus preclude pre/ post comparisons.

The bottom longline reef fish fishery in the Gulf of Mexico is one fishery with VMS data that has undergone a dramatic regulatory transition, providing an opportunity for quantifying the associated changes in fisher response and economic performance. This fishery primarily targets gag grouper (Mycteroperca microlepis) and red grouper (Epinephelus morio) as well as tilefishes (Caulolatilus spp.) and a complex of other deep and shallow water groupers (Farmer et al., 2016; Appendix Table S3.1), with 2015 ex-vessel revenue of $28 million (NMFS, 2016). In 2010, an individual fishing quota (IFQ) was implemented in the grouper-tilefish fishery to revise a system that would otherwise "continue to be characterized by higher than necessary levels of capital investment, increased operating costs, increased likelihood of shortened-seasons, reduced safety at-sea, wide fluctuations in grouper supply, and depressed ex-vessel prices; leading to deteriorating working conditions and lower profitability for participants." (Amendment 29; Gulf of Mexico Fishery Management Council, 2008). The changes associated with the catch share transition came after a year of turtle bycatch regulations. These regulations consisted of time-varying, area-specific depth restrictions and a reduction in the maximum number of hooks. The fleet was further impacted by a longline endorsement program which restricted fishing to vessels that had sustained average annual catches greater than 40 000 pounds during 1999 - 2007 (Amendment 31; Gulf of Mexico Fishery Management Council, 2010). Despite mandatory logbooks in the reef fish fishery prior to these changes, reporting longline soak times has been optional since 2008. Thus, estimates of effort were limited to the number of days and hooks fished per trip. It is conceivable that hooks or hooks*trip days would provide a reasonable effort comparison (though without any intra-trip spatial component), but the bycatch mitigation program drastically reduced the number of hooks per trip, confounding comparisons.

The dataset from the Gulf of Mexico bottom longline reef fish fishery enables us to quantify trip-level and aggregate indicators of fishing effort, and use VMS data to test hypotheses. This level of behavioral and spatial detail in fishing activity enables us to explore performance indicators at a more detailed scale than some previous studies (e.g., Brinson and Thunberg, 2016). In this case, we demonstrate an application for testing hypotheses related to changes in fishing associated with regulatory changes. However, we could also apply this approach to develop indicators and compare fishing responses to climatic regime shifts, catastrophic events (e.g., oil spills), or fishery collapses, for example.

The objectives of our analyses were to (1) use VMS data to identify individual fishing trips and build a probabilistic model for estimating unobserved fishing effort and (2) derive and use relevant fishing performance metrics to test the hypothesis that regulatory changes increased the efficiency of the grouper-tilefish bottom longline fishery in the Gulf of Mexico.

3.3 Data and Methods

We integrated three data sources into our modeling approach. Observer data were used to train and validate models of VMS data for estimating fishing effort. VMS data were then merged with logbook data to derive and evaluate a suite of behavioral, performance, and economic metrics to understand the impacts of regulatory changes. All analyses were performed using R Statistical Software Version 3.3.2 (R Core Team, 2016).

3.3.1 Data

A mandatory observer program was established in 2006 for all vessels federally-permitted to target reef fish using bottom longlines in the Gulf of Mexico (Scott-Denton et al., 2011). The number of vessels in this program changed dramatically during our study period, as we address later. Trips in this fishery average about 10 days and on-board observers are randomly assigned to vessels in the fleet to record operational and catch information (e.g., information on gear, set, catch and trip characteristics). In our case, 183 bottom longline trips (~ 4% of trips) were observed on 62 vessels from 2007 - 2012 for which we also had VMS and logbook data.

Since 1993, commercial vessels that were federally permitted in the Gulf of Mexico also had logbook reporting requirements. Logbook requirements have evolved since then and for many years, longline soak times or other metrics of fishing duration were not consistently collected. Thus, no estimates of fishing effort were available from logbooks for the pre/ post regulatory transition.

VMS programs have required the transmission of hourly vessel location information since 2007 (Amendment 18A; Gulf of Mexico Fishery Management Council, 2005). We used VMS-based vessel locations and time-stamps to calculate the distance between VMS records (using the Haversine formula [Sinnot, 1984; Charles et al., 2014]), vessel speed, and distance from port.

Speed calculations were based on the average time and distance between records at time t and time t-1 and records at time t and time t+1. Records with either of these speeds exceeding 20 knots were considered erroneous and were excluded.

3.3.2 Identifying individual trips and merging with logbook data

Onboard VMS transmit continuous strings of data without identifying the starts or ends of trips, so the first step was to break the data into discrete trips. Individual trips were needed to merge VMS data with logbook landings so that trip-level catch, revenue and effort data could be merged. In the simplest case, a fishing trip could be identified from VMS data when a vessel exited and later returned to a clearly defined port (e.g., Russo et al., 2014, or Hintzen et al., 2012), and then stopped moving for an extended period of time. However, in the Gulf of Mexico, few ports were easily defined.

The shoreline of the Gulf of Mexico is complex and characterized by a continuum of marinas, rivers, islands and networks of docks so vessels often started or ended trips in locations that were not easily identified by spatial coordinates alone. Defining some port polygons was an ambiguous process and many shoreline shapefiles were poorly resolved for our purposes. Instead of individual port polygons or coordinates, we used the transition between state and federal waters to identify the start and end of trips. This was a reasonable approach because we were interested in a federal waters only fishery (i.e., no fishing activity could occur within state waters) so when vessels returned to state waters fishing had to have been legally finished. We used U.S. county polygons (Geographic Products Branch, 2013) where the seaward edge of each polygon extended 3 nautical miles (nmi) (5.6 km) (9 nmi for Florida and Texas) offshore to the boundary between state and federal waters. When vessels were within state waters they were considered to be in port. The distance of each VMS record from the closest edge of a Gulf of Mexico county served as a proxy for distance to port and was estimated between each VMS record and the polygon for each county (gDistance function in the rgeos package [Bivand et al., 2017]). Additionally, if a vessel was within 5 nmi of a county polygon and its average speed for at least 5 consecutive VMS records was < 1 knot, it was considered to be in port and a trip was ended. Trips were subsequently delimited based on a return to or exit from port. An additional benefit of classifying trip ends when they entered state waters was to eliminate changes in vessel speeds and other behaviors near port that increase classification errors. Furthermore, since vessels could not legally fish in state waters, none of the state waters VMS transmissions would be classified as fishing. If we had included such VMS records in our effort estimation model, we would have artificially increased the number of VMS records for each trip, which would have reduced the apparent prediction errors regardless of model accuracy because we would have automatically labeled them correctly as non-fishing.

Individual VMS-based trip data were merged with fisher-reported logbook data by date. If the midpoint date (the date between the reported start and end dates) of the logbook-reported trip fell between the start and end dates of the VMS trip, the trips were said to match (Bastardie et al., 2010). In addition to catch, cost, number of hooks, bait cost, fuel usage, and earnings data, logbook data also identified the primary gear type for each trip, which facilitated identification of longline trips.

3.3.3 Model-estimation of fishing effort from VMS data

When observer data were present (~ 4% of trips during our study period), observers reported the start and end times for each longline set, which allowed us to build a model that predicted fishing based on VMS data. Observers reported an average of 27 (±13.1) sets per trip with average durations of 4.2 hours, so the average set had 4 – 5 VMS records, depending on when VMS pings occurred relative to observed start and stop times of fishing (see O'Farrell et al., 2017 for a thorough discussion of VMS transmissions vs. the timing of observed fishing). If a VMS record occurred between observer-reported set start and end times, we considered the VMS record to be fishing. We then fit logistic generalized additive models (GAMs; Wood, 2006) with a logit link to all observed VMS records to estimate the probabilities that fishing occurred (p(fishing)) based on a suite of covariates (Table 3.1) that described fishing activities:

$$\text{logit}(p(\text{fishing})) = s_1(\text{Covariate}_1) + s_2(\text{Covariate}_2,\text{Covariate}_3) + \ldots + s_j(\text{Covariate}_k) \quad (1)$$

where si(•) represents an individual smoothing function for each covariate, fit using thin plate regression splines (tensor splines were also examined for bivariate terms but did not improve fits, likely due to isotropy of covariates). All candidate models included univariate predictors, as illustrated by s1(Covariate1), and some candidate models included bivariate terms allowing for interactions, as illustrated by s2(Covariate2,Covariate3). For strictly additive models with only univariate terms, j=k, we visually examined model outputs for spatial autocorrelation by mapping residuals. All covariates were continuous except for month and year, which were treated as factors. We examined a suite of models with both univariate and bivariate predictors describing vessel behaviors (Table 3.1). Computational demands prevented examination of all possible covariate combinations but several dozen models were explored based on hypothesized relationships between fishing behaviors and vessel movements (see Appendix Table S3.2 for examples of 12 candidate models). Model selection is discussed below. We minimized problems associated with multicollinearity by avoiding covariate combinations (e.g., speedt-1 and speedavg or speedt+1 and speedavg [described in Table 3.1]) that led to variance inflation factors > 5 (Zuur et al., 2010; R function corvif included in supplementary material of reference). Standard regression assumptions were checked via model diagnostic and residual plots.

Our primary interest with the GAM was to develop the most accurate measure of fishing effort for unobserved trips so model selection proceeded by seeking the model that minimized prediction errors. We compared predictive ability for each of the models using leave-one-out cross validation (LOOCV) with the 183 observed fishing trips whereby models were fit to all but one trip and predictive accuracy was tested on the remaining, holdout trip. This process was repeated for each of the 183 fishing trips, using parallel processing to reduce computation times (Knaus et al., 2009). We assessed prediction accuracy at the trip-level instead of set-level because our application of this model was more broadly focused on trip-level changes in fishing behaviors before and after the regulatory transition. To quantify prediction error at the trip-level we summed the predicted probabilities (p[fishing]) for all VMS records within each trip and compared this to the number of VMS records that were observed to be fishing. To ensure that our best model was not over-predicting fishing (which would provide a low relative error rate for fishing and a high relative error rate for non-fishing), we similarly compared the predictions for non-fishing trips by comparing the sum of (1 – p(fishing)) to the number of VMS records that were observed while not fishing. A simple percent error calculation ([observed-predicted]/observed) was performed for the comparisons. See Appendix for a discussion of predicted probabilities vs. an approach that assigns a probability threshold to determine whether individual VMS records were fishing or not fishing.

Once the final model was selected, we used the GAM to predict which VMS pings occurred while vessels were fishing during the remaining unobserved trips for which we had both VMS and logbook data (N=2 423 trips, 62 vessels). Effort was estimated for each trip by multiplying the sum of the predicted probability for a trip by the 60 min VMS transmission interval. Gaps in VMS transmissions greater than expected did occur (6.5 % of VMS records were transmitted at > 65 min intervals), but the median and mode of transmission frequencies were 60 min. We discuss the role of transmission gaps below.

3.3.4 Comparison of fishing behavior and performance before and after a regulatory transition

The catch share program successfully reduced fleet capacity as the fishery went from 129 and 120 vessels in 2007 and 2008, respectively, to 65 and 68 vessels in 2011 and 2012, respectively. Vessels that remained in the fishery after catch share implementation were allocated initial shares based on their historic catches for four of the five years from 1999 – 2004. During the pre-regulatory period (2007-2008), logbook data showed that vessels throughout the fleet had the same average length (~14 m) regardless of whether they remained in the fishery after the regulatory transition (i.e., size composition of the fleet did not change). However, while vessel sizes were similar during the pre-regulatory period, the vessels that ultimately left the fishery on average had landed only 76% as much fish per trip during the pre-regulatory period as those that remained. Additionally, they earned only 71% as much gross revenue per trip during the pre-regulatory period. At the annual level, those vessels that left the fishery landed on average only 56% as many pounds of fish per year as the vessels that remained in the fishery, and they earned only 52% as much gross revenue during the pre-regulatory period. Thus, many of the vessels that did not remain in the fishery following the management transition likely left the fishery because they did not meet the requirements of the longline endorsement and/ or they did not receive enough quota to make fishing worthwhile. To see how regulations affected those vessels that remained in the fishery, all comparisons of pre- and post-regulation use only those vessels that were present both before and after the transition.

To test the hypothesis that efficiency increased in the grouper-tilefish bottom longline fishery following a suite of regulatory changes, we compared fishing performance and behavior before (2007-2008) and after (2011-2012) a regulatory transition. In addition to the January 1, 2010 switch to a catch share program, a series of depth restrictions, gear modifications, time-area closures, and the Deepwater Horizon Oil Spill (which yielded its own series of short-term time-area closures) all occurred during these transition years (2009 - 2010), leading to a protracted changeover from pre- to post-regulation behaviors. Thus, we excluded the transition years and focused only on the before and after period.

We used linear mixed effects models to quantify the change in several fishery metrics, or response variables (Table 3.2) before and after the transition period. Several of these metrics are redundant (e.g., revenue) with those explored by Brinson and Thunberg (2016) to evaluate changes in fishing performance but most provide more detail to answer behavioral questions. One of the major regulatory changes included limitations on fishing depths during certain months, so we divided the year into seasons A (Jan-Mar), B (Apr-Jun), C (July-Sep), and D (Oct-Dec) to allow for intra-annual variability in responses. We fit individual models for each season (R package nlme [Pinheiro et al., 2017]). We explored the use of vessel and port as random effects. Random effects were explored with the full model (2) via restricted maximum likelihood (Zuur et al., 2009), yielding a random vessel intercept in all cases. Minimizing AIC via maximum likelihood, we then selected fixed effects (equation 2 vs. equation 3) for each response variable to yield one of the two formulas:

$$Y_{t,v} = (\beta_0 + b_{0v}) + (\beta_1)*Regulation_{t,v} + \beta_2 * \textit{Vessel Length}_v + \varepsilon_{t,v} \qquad (2)$$

$$Y_{t,v} = (\beta_0 + b_{0v}) + \beta_1*Regulation_{t,v} + \varepsilon_{t,v} \qquad (3)$$

$$b_{0v} \sim \text{Normal}(0, \sigma_v^2)$$
$$\varepsilon_{t,v} \sim \text{Normal}(0, \sigma^2)$$

The difference between (2) and (3) was the continuous covariate for vessel length (*Vessel Length*). The subscripts *t*, and *v* represented trip and vessel, respectively. *Regulation* was a dummy variable indicating whether a trip occurred during the pre- (0) or post-regulatory period (1). *Vessel Length* was treated as time-invariant so we omitted the trip-level subscript trip from this term in (2). The random intercept (b_{0v}) was assumed to follow a joint normal distribution with mean of zero and variances σ_v^2. The error ($\varepsilon_{t,v}$) was assumed to be normal with mean zero and residual variance σ^2.

The term of primary interest was the fixed coefficient on the *Regulation* dummy variable. For log-transformed response variables (denoted by an asterisk in Table 3.2), the coefficient was used to measure percent change. For untransformed response variables, the coefficient was divided by the model intercept to obtain percent change.

3.4 Results

3.4.1 Model-estimation of fishing effort from VMS data

For the VMS portion of our study, we first analyzed > 1 million VMS records to identify 4 371 longline trips made by 150 vessels in the Gulf of Mexico from 2007 – 2013. Among these trips, 183 (4 %) had observed fishing and were thus suitable for model training. We present model estimation and comparison with the observer data, but logbooks typically did not include soak times so no comparison with logbook estimates was possible.

The final model (see Appendix and Table S3.2 for candidate models and more selection discussion) selected by LOOCV was:

$$p(\text{fishing}) = s(\mathit{distance}) + s(\mathit{speed}_{t-1}, \text{speed}_{t+1}) + s(\mathit{\Delta distance}_s, \mathit{\Delta distance}_p) + s(\mathit{hour}) + s(\mathit{depth}) + \mathit{month} \qquad (4)$$

where all covariates were continuous covariates (see Appendix Figure S3.1 for partial dependence plots) except for *month*, which was a factor. Both the *distance* and *depth* covariates were expected components of the model as they identify minimum and maximum depths and distances from shore at which fishing would occur. The multiple *speed* formulations enabled the model to capture vessels speeding up and slowing down as they transitioned to different phases of gear setting and retrieval, consistent with other VMS-based estimates of fishing effort (e.g., Vermard, et al., 2010; Joo et al., 2013; Gloaguen et al., 2015) for which speed was important. The change in distance from port ($\Delta distance_s$, $\Delta distance_p$) terms allowed the model to capture the orientation of vessel movements along isobaths and, like the speed transitions, captured changes in vessel behaviors. For example, if a vessel was speeding up and slowing down while maintaining little change in the distance from shore (i.e., *Δdistance* was small), the vessel was likely following an isobaths, which often run parallel to the coast, and more likely to be fishing. Finally, most fishing occurred during daytime or early evening, with very little fishing between midnight and early morning, explaining the role of the *hour* covariate in the model. The *month* term was useful for estimating intra-annual differences in targeting behaviors, which may be associated with different distances from shore or depths. Model residuals did not visually demonstrate an obvious spatial pattern and the chosen model predicted better than models including a spatial term, suggesting an absence of spatial autocorrelation.

The best model selected via LOOCV had an average trip-level prediction error ([observed – predicted] / observed) of -4.0% (standard deviation 24.1%) (Appendix Table S3.2), with the negative sign indicating a propensity to predict more fishing than was observed. The average of the absolute percent error, was 15.1% and 8.6% for predicting fishing and non-fishing, respectively. It may seem counter-intuitive for models that tend to over-predict fishing to have a greater percent error at predicting fishing than non-fishing but fishing VMS records accounted for only two-thirds as many VMS records as non-fishing records. Thus, despite the slight over-prediction of fishing, it does not occur at such a rate that overwhelms the greater number of the non-fishing events. See Appendix and Figure S3.2 for a broader discussion of predicted probabilities and errors for trips and individual VMS records.

In order to maintain adequate sample sizes for building our predictive model, we included trips that occurred during the 2009-2010 regulatory transition period (and early 2013) and by vessels that did not remain in the fishery following the regulatory transition. Among the 183 observed trips, 88.5% were made by vessels that remained in the fishery throughout the study period and numbers of trips by year are included in Figure 3.1. The percent errors of predictions across years were not significantly different (ANOVA $P>0.05$), supporting the use of all observed trips during this period to model fisher behavior. It is not surprising that the behavioral aspects of fishing sets themselves (e.g., the speed at which setting and hauling occurs or the times of day during which fishing occurs) did not change throughout time, even if other aspects of fishing trips did (see the following section on before and after regulatory change). Additionally, we explored year as a model covariate to account for any other inter-annual differences in the responses that were not related to regulatory changes between the early and late period, but it did not significantly affect fits.

Not surprisingly, the greatest errors in model predictions occurred during trips with fewer numbers of observed fishing records (Figure 3.1), where smaller numbers of predictions could lead to larger percent errors, and outliers were generally indicative of over-predictions of fishing. Examination of the individual VMS records associated with such trips (e.g., those with percent errors < -50%) suggested that the behaviors on those trips were atypical compared to other observed trips. For example, in the most extreme case (-187.2% error), the model predicted a high probability of fishing when it was expected to do so; the vessel arrived at the fishing grounds, slowed to typical fishing speeds, and exhibited tortuous movement patterns consistent with other fishing sets, all at the time of day during which fishing generally occurred. However, the vessel was on the fishing grounds for more than 24 hours before the observer data indicated that fishing occurred. In a second extreme case, a trip was observed to be nearly 20 days long but fishing was only reported during the first half of this period. However, the vessel behaviors and the model continued to suggest fishing activity was occurring, despite a lack of reported fishing. Such rare and extreme behaviors were difficult to account for with models but overall, models fit well; trips with ≤

10% absolute prediction errors accounted for 43% of trips, while 68.7% of trips had absolute prediction errors less than the standard deviation of prediction errors (19.2%). An additional source of the errors associated with over-prediction of fishing often occurred for the VMS records that were adjacent to those observed to be fishing, suggesting that the transition to behaviors consistent with fishing often began before gear was set or continued slightly after gear was retrieved (Appendix Figure S3.2). Prediction errors are further examined in the discussion.

3.4.2 Comparison of fishing behavior and performance before and after regulatory transition

Vessels that remained in the bottom longline fishery throughout the regulatory transition period demonstrated an increase in fishing efficiency, as determined by a series of fishing behavior and performance metrics (see Appendix Tables S3.3 and S3.4 for coefficients and standard deviation of random intercepts). We analyzed 2 423 trips for which we could link VMS-derived metrics and logbook data, with comparable numbers of trips in the before (N=1 250) and after (N=1 173) periods. At the trip-level, the catch per unit effort (CPUE) nearly doubled while catch, earnings per unit effort, and revenue also increased substantially and across all four seasons while fishing effort decreased (Figure 3.2). Much of the ~ 50% decrease in effort (hooks * hours) was attributable to the 2009 implementation of a maximum number of hooks per set, which reduced hook usage by ~60% per trip. Nonetheless, this effort reduction coupled with increased catches of ~ 50% accounted for the doubling of CPUE. A notable difference occurred in several cases during C-season, during which fishing was restricted to waters beyond the 35-fathom isobath (for bycatch mitigation). During this period, the mean depth of fishing increased and there was a less marked decrease in effort than during other seasons, but catches shifted to valuable deep water species complexes that facilitated an increase in revenues. The C-season depth restrictions also led vessels to travel farther offshore, leading to no change in trip distances or durations during that period. During other seasons however, slight decreases in trip distances were observed. There was movement of fishing effort (Figure 3.3) closer to shore during A-season (consistent with reduced trip distances and distance from shore, as well as shallower fishing; Figure 3.2) and slightly more offshore effort (i.e., outside the 35-fathom isobaths) during C-season, but changes in the B and D-season distributions were unremarkable.

In addition to examining fishing performance and economic metrics at the trip level, we also modeled aggregate levels, where response values were summed for each vessel (that remained in the fishery throughout the study period) and year over all trips per season during the before (2007-2008) and the after (2011-2012) regulatory periods (Figure 3.4). The average number of trips per vessel per year decreased slightly (by an average of 0.5 trips per year) after the regulatory change but the decrease was not significant (Wilcoxon rank sum, P=0.5). Across all seasons, decreased bait costs, increased gross earnings, and decreased total effort were significant. Despite seasonal depth restrictions and the offshore movement of trips, a significant decrease in the number of trips ultimately led to significant reductions in annual distances and durations traveled per vessel during C-season. Maps suggested less notable movement in fishing locations during B and D-season (Figure 3.3) so the increases in revenue and overall performance (though not in revenue variability) were likely more associated with the reduced fleet capacity than with shifts in behavior. Meanwhile, A-season effort moved slightly shoreward which was associated with a minor reduction in average travel distances. Less fuel was used each season (though not significantly in C-season) perhaps related not only to travel distances but to reductions in actual fishing time (vessels often use more fuel while engaged in fishing than transiting)

3.5 Discussion

By combining the spatial aspects of VMS data with fisher-reported logbook information on catch, costs, and earnings, we quantified an increase in fishing efficiency following a regulatory transition in the Gulf of Mexico bottom longline fishery. This work required development of an accurate approach for estimating effort in a longline fishery that had no prior reporting of trip-level fishing durations and for which many of the more ‘typical’ VMS-based approaches for estimating effort (e.g., Deng et al., 2005) yielded too great of errors (not shown). This study also filled a gap in efforts to evaluate the performance of regulatory changes (e.g., catch shares [Clay et al., 2014; Brinson and Thunberg, 2016]), or other perturbations, by demonstrating how the relevant indicators of fishing performance could be derived, especially when valuable information like effort was not available.

The objectives of the grouper-tilefish IFQ program were: “reducing overcapacity, increasing harvest efficiency, and mitigating derby-fishing conditions” (NMFS, 2016). While only logbook and permit data are necessary to evaluate the reduction of fleet capacity (depending on the definition of ‘capacity’) and certain aspects of derby conditions, our VMS-based approach provides a means by which to evaluate changes in harvest efficiency. We demonstrated catch rates that nearly doubled and drastic reductions in fishing effort at both the trip- (Figure 3.2) and aggregate-levels (Figure 3.4), but fishing effort is a combination of both time spent fishing and the number of hooks fished. Because bycatch regulations reduced maximum hook numbers by ~ 60% per trip, much of the effort reduction was driven by hook numbers instead of reduced fishing times. For example, the greatest average trip-level reduction in effort was 48.7% (B-season) while the reduction in time spent fishing during that season was only 9.3%. This shortened fishing time is consistent with the overall decrease in B-season trip durations of 7.4%. This suggests that in terms of effort reductions as commonly defined for longline fisheries, bycatch mitigation played a greater role than the IFQ.

The effects of different regulations become confounded when describing fishery changes in terms of harvest efficiency. A longline endorsement program initiated a reduction in fleet capacity that further expanded under the shift to IFQ. The vessels that left the fishery during this protracted transition had only earned, on average, about half the annual revenue as vessels that remained, yet the reduction of fleet size still led to reduced competition that allowed fewer vessels with fewer hooks to catch more fish. So while trip durations remained either similar or slightly shorter after the regulatory transition, there was an overall increase in harvest efficiency, though attributing it to a single regulation is difficult. Meanwhile, bycatch regulations during C-season restricted the fleet to deeper waters farther offshore where increased catch rates enabled them to meet their quotas for deeper water species faster, reducing the number of offshore trips and subsequently, the overall days at sea during that period (Figure 3.4).

We identified shifts in performance and spatial fishing behavior in two seasons, and these observations highlight the difference in results that emerged from our method vs. one without VMS data. While C-season fishing effort moved offshore, there was an A-season shift to fishing nearshore, and both of these spatial redistributions were associated with higher catch rates, revenues, and earnings per unit effort, and lower revenue variability. To calculate how earnings per unit effort changed (Figures 3.2, 3.4), we divided the revenue by our estimates of fishing effort. Clay et al. (2014), for example, proposed revenue-per-unit-effort as an indicator for evaluating social and economic performance of catch share programs but doing so using logbook data alone could have been misleading in the Gulf of Mexico bottom longline fishery. If we had not used our VMS-derived effort metric but instead had used logbook-reported trip length, the only temporal proxy for effort available from logbooks, the estimated mean changes per season would have been approximately doubled, and thus would have dramatically over-estimated the effects of regulatory transition. Meanwhile, Brinson and Thunberg (2016) evaluate catch share implementation for 16 U.S. fisheries. In such a comprehensive synthesis, it is impossible to account for all nuances, and thus a focused case study provides an opportunity to better understand some of the relevant fishery-specific indicators and to better resolve details in the baseline period to which catch shares are compared. In Brinson and Thunberg (2016), a portion of their baseline period included gear and depth restrictions, and the implementation of catch shares was concurrent with a longline endorsement program that limited participation. We have thus offered an in-depth study that complements that broader synthesis.

3.5.1 Model-estimation of fishing effort from VMS data

While many studies have used VMS data to resolve spatial dynamics and effort of fishing fleets, relatively few have done so for longlines (e.g., Chang and Yuan, 2014). This is likely due to the more complicated speed characteristics of vessels during the multiple phases of setting, retrieving, and repositioning often associated with longline gears, as opposed to the relatively constant speeds of trawling. In fact, speed alone is often sufficient to achieve highly accurate estimates of effort from VMS data in trawl fisheries (e.g., Deng et al., 2005). In contrast, our longline model included a combination of factors that served as proxies for not only what the vessel was doing (e.g., speeding up or slowing down) but also the time of day and vessel location (e.g., depth, and orientation to shore).

Our modeled prediction of fishing was remarkably accurate, with an average absolute error of only 15.1%, though with a substantial standard deviation (19.2%). While our model inevitably failed to capture relevant vessel characteristics on some trips, a greater source of error may arise from aspects of the data themselves; trips with fewer numbers of VMS records that were fishing had greater prediction errors. There is a general impact from smaller numbers - a small amount of error during a short trip equates to a greater percent than the same amount of error during a longer trip. A second source of error may be explained by the VMS data (Figure 3.1). Observers report longline soak times for each set, so as longline soak times increase, we would expect a greater number of VMS records to be assigned as fishing. However, this relationship was not as strong as expected (Pearson, $\rho = 0.73$), likely because of longer-than-expected intervals between VMS transmissions. Despite mandated transmission frequencies of 60-min, more than half of observed trips had at least one gap in VMS intervals greater than 60-min, and more than 10% of trips had more than 6 such gaps. These gaps were indicative of less VMS sampling than expected for each trip. An 8-hour longline set, for example, should have approximately 8 associated VMS records. However, if there was an unexpected gap in VMS data, it would lead to fewer VMS records and skew the estimated effort. Additionally, as the time between VMS records increases, the accuracy of several of the covariates decreases. Vessel speeds and changes in distance from port were calculated between consecutive VMS records, so as the time between records increased, the accuracy of derived fields decreased, as did the strength of their relationships with the modeled response (see Watson and Haynie, 2016; Palmer, 2008). In other words, occasional gaps in VMS transmissions led to fewer behavioral observations and reduced the utility of some data points.

Among the models explored, several had similar prediction errors, suggesting that while slight variations in model structure made a difference, certain aspects of vessel behaviors were more important than the nuances of how they were modeled. For example, including two speed formulations as univariate vs. bivariate (i.e., an interaction) terms yielded little difference in predictive success. Similarly, in one case, a model that included latitude and longitude reduced the AIC by more than 100 AIC units, but the same model without the spatial component had a similar (slightly though not significantly better) mean absolute percent error. Thus, of the several dozen models that were explored many with only slight variations yielded negligible differences in predictive ability (thus our presentation of only 12 models in

Appendix Table S3.2). The best predictive models included at least a single formulation for speed, distance from shore, time of day, depth, and change in distance from shore.

While we describe our model selection and predictive ability in detail above, many candidate models greatly improved upon previous efforts to estimate effort in a longline fishery (e.g., as compared with Chang and Yuan, 2014). For our application of deriving socioeconomic indicators and evaluating a regulatory transition, several of our better models would have yielded negligible differences in effort and estimates of efficiency changes following regulation would have been similar. Thus, our top models would have been functionally interchangeable. However, for stock assessment or other management applications, we acknowledge that slight improvements may be relevant.

3.5.2 Implications for stock assessment

Our VMS-based approach is poised to improve both spatial and temporal aspects of fishing effort for the purposes of stock assessment. In the Gulf of Mexico bottom longline fishery, assessment scientists have used only number-of-hooks to calculate catch rates for groupers, snappers, and tilefishes because there was no reliable estimate for time actively fishing. Assessment of these stocks has been further complicated by the coarse spatial resolution of the logbook data; the entire fishery is divided into just a few statistical management grids, with single reporting areas stretching from the coastline to several hundred kilometers offshore and encompassing a depth range of more 200 m. When trips include landings of both deep and shallow-water stocks from a single management grid, there is no accounting for the proportions of effort that were allocated towards targeting deep species versus shallow species. Because the location of each VMS record can be rectified with bottom depth, the spatial distribution of effort can be resolved to account for targeting of species complexes associated with distinct habitats (like deep versus shallow waters) and can better resolve catch rates. This finer resolution is particularly important for species like groupers, whose biology includes aggregating behavior that can lead to hyper stable catch rates and subsequently, bias in stock abundance indices (Carruthers et al., 2015).

Since developing our modeling approach, biologists in the fishery have already begun to examine our modeled effort distributions to ensure that the locations of fishery surveys overlap with areas that are targeted by the fishery. Additionally, the ability to associate spatially-explicit fishing effort with habitats was identified as a major priority by stock assessment scientists in the Gulf of Mexico and is also an important advantage to assessment scientists in other regions and fisheries.

3.5.3 Broader implications and conclusions

While our study focused particularly on quantifying impacts from regulatory change, our approach also has broad applicability to understanding the spatial responses of fleets to climatic change.

A contemporary paradigm is that as waters warm, movement of fish to higher latitudes will be accompanied by similar shifts of fishing fleets (Pinsky and Fogarty, 2012). However, in cases like the Bering Sea pollock fishery, fisher responses to climate dynamics have not been straightforward due to physical (e.g., Pfeiffer and Haynie, 2012), economic (Haynie and Pfeiffer, 2013), or other factors. In the Bering Sea case, 100% observer coverage facilitated an understanding of the spatial behaviors of the fleet, but in most fisheries, such observer coverage is unavailable, and VMS data offer a cost-effective alternative. Regardless of whether fleets respond in an expected or unexpected fashion, the ability to resolve their spatiotemporal behaviors and to understand how those behaviors relate to their economic performance will be critical for adaptive management (Joo et al., 2015).

We have provided an example in which spatially-explicit fishery metrics were compared by examining the model coefficients of a binary dummy variable representing a regulatory change. However, this approach could be readily modified to examine continuous environmental covariates like water temperature, or to account for events like an oil spill or implementation of a marine reserve. Similarly, intra-fleet dynamics could be compared using vessel groups that: deliver to different processors, fish in different areas, target different species complexes, or are associated with different levels of bycatch or discards. The need for adaptive fisheries management has long been recognized (Walters, 1986), and with technological advances, we are now able to more accurately measure how fleets respond to such changes.

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Table 3.1: Model covariates explored for predicting fishing. Values were included from original data or derived for each VMS record of each trip.

Variable	Description	Expected relationship to fishing activity
Distance	Distance from nearest county line (proxy for distance from shore/ port)	A proxy for fishing location; certain distances are more likely to be associated with fishing.
Depth	Depth (m) calculated using NOAA NGDC bathymetry data.	Depth restrictions and depth-specific fish habitat will affect chances of fishing.
Month	Month of VMS record (categorical)	Different regulations occur during certain months.
Year	Year of VMS record (categorical)	Accounts for changes in the fishery that may reflect regulatory dynamics.
Hour	Hour of the day, modeled using cyclic penalized regression splines (Wood, 2006)	Little fishing occurs in the middle of the night.
$Speed_{t-1}$	Vessel speed calculated between the current and the previous VMS record	Indicative of what vessel speed was – certain speeds are not conducive to fishing.
$Speed_{t+1}$	Vessel speed calculated between the current and subsequent VMS record	Indicative of new speeds, associated with transitions into or out of fishing operations.
$Speed_{avg}$	Average of the forward and backward calculated speeds	When combined with above speed formulations, indicates slowing or speeding of vessel associated with fishing operations.
$Speed_{t5}$	Average of $Speed_{avg}$ over a 5 record moving window	Same as $Speed_{avg}$ but with a larger window
Δdistance	The change in the distance variable between the current and previous VMS record	Indicative of vessel direction to/from port versus along bathymetry lines
$\Delta distance_p$	Mean of the previous 5 values of Δdistance	Indicative of vessel direction during previous several hours
$\Delta distance_s$	Mean of the subsequent 5 values of Δdistance	Indicative of vessel direction during next few hours
$\Delta distance_{avg}$	Mean of deldist and the 2 previous and subsequent values of Δdistance	Similar to above with a different time window for transitions between directions
Latitude	Latitude	Identifies potential fishing grounds
Longitude	Longitude	Identifies potential fishing grounds

Table 3.2: Response variables examined for effects of regulatory change on the fishery.

Metric	Description	Expectation
Trip distance*	Cumulative distance between all VMS records per trip	A proxy for fishing location; distance provides a simple indicator of changes in spatial behaviors.
Trip duration*	VMS-derived time between start and end of trip	Similar to trip distance but enables accounting for nearer to port trips (i.e., less time) that changed in duration. An increase in efficiency would generally lead to expected decreases in trip durations.
Fishing duration†	(GAM-derived probability of fishing per trip) * (median VMS transmission interval per trip [typically 60-min])	Intermediate calculation for effort metric (below)
Proportion of trip spent fishing	Fishing duration / Trip duration	Serves as a complementary indicator to fishing and trip durations to illustrate changes in fishing strategy.
Effort	(Logbook-reported number of hooks per trip) * (Fishing duration)	Intermediate value for catch per effort metric (below)
Catch*	Logbook-reported pounds per trip	Intermediate value for catch per effort metric (below)
Catch / Effort*	Catch / Effort	An increase in this metric suggests that the same amount of effort yielded greater catches following the transition, and thus an increase in fishing efficiency.
Earnings*	Logbook-reported gross earnings per trip (US dollars)	Intermediate value necessary for earnings / effort
Earnings / Effort*	Earnings / Effort	An increase in this metric suggests that the same amount of effort yielded greater revenue following the transition, and thus an increase in fishing efficiency.
Mean depth fished*	Average depth for each VMS record where p(fishing) > 0.5	Allows for characterization of targeting behavior (shallow vs. deep water species complexes).
Mean distance from shore*	Average distance from county line closest to each VMS record	Similar to depth, this may be an indicator of different targeting behavior or habitat use.
Bait expense*	Logbook-reported cost of bait per trip	Indicator of fishing costs; a decrease suggests an increase in efficiency.
Fuel*	Logbook-reported quantity of fuel per trip	Indicator of fishing costs; a decrease suggests an increase in efficiency.

Some descriptions refer to metrics defined in previous rows of the table.
* Terms that were log-transformed for model fitting.
† Terms that were used to derive other metrics but that are not included here as model response variables

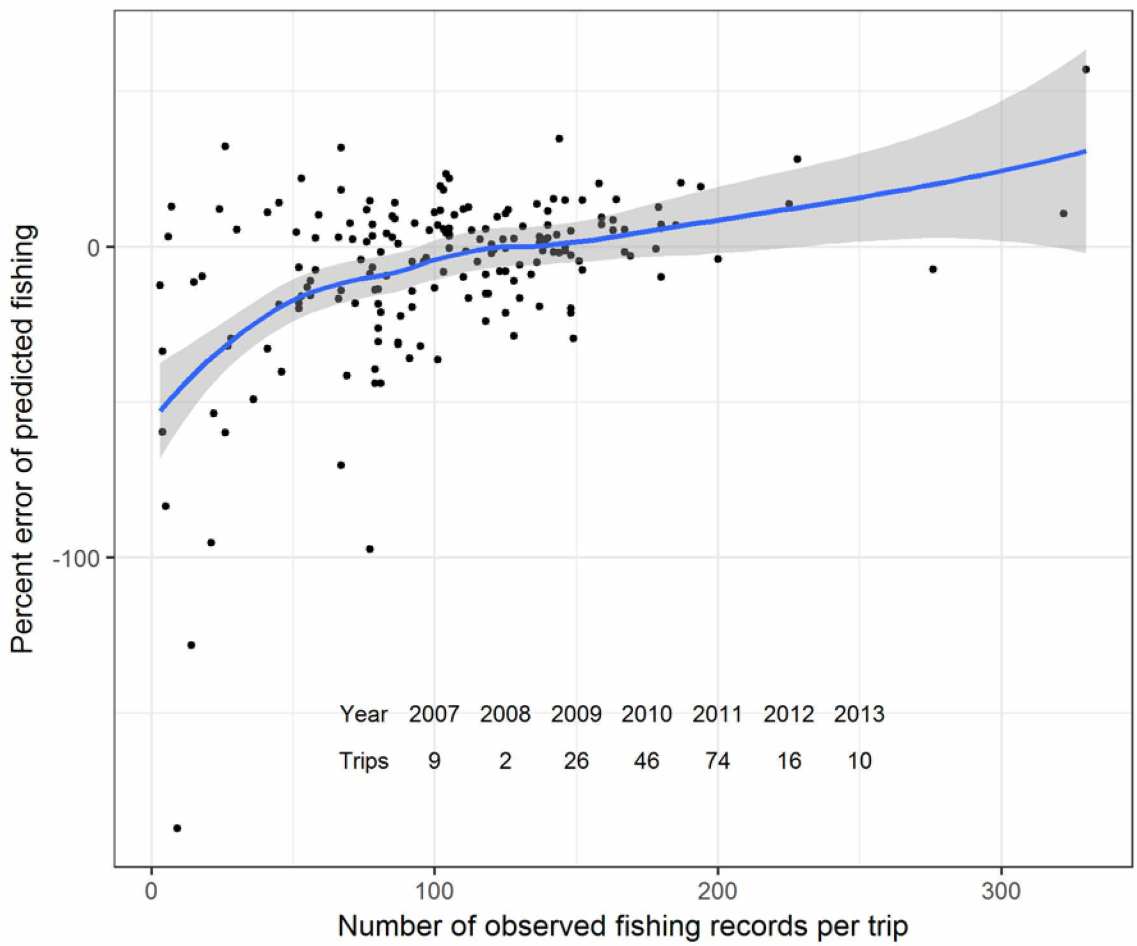


Figure 3.1: Observed fishing records vs. percent error. Number of observed fishing records for a trip versus the percent error ([observed – predicted] / observed) of predicting fishing for that trip, based on leave-one-out-cross validation. A smoother is added for reference though no statistical relationship is proposed here. The table of numbers indicate the number of trips per year that were modeled.

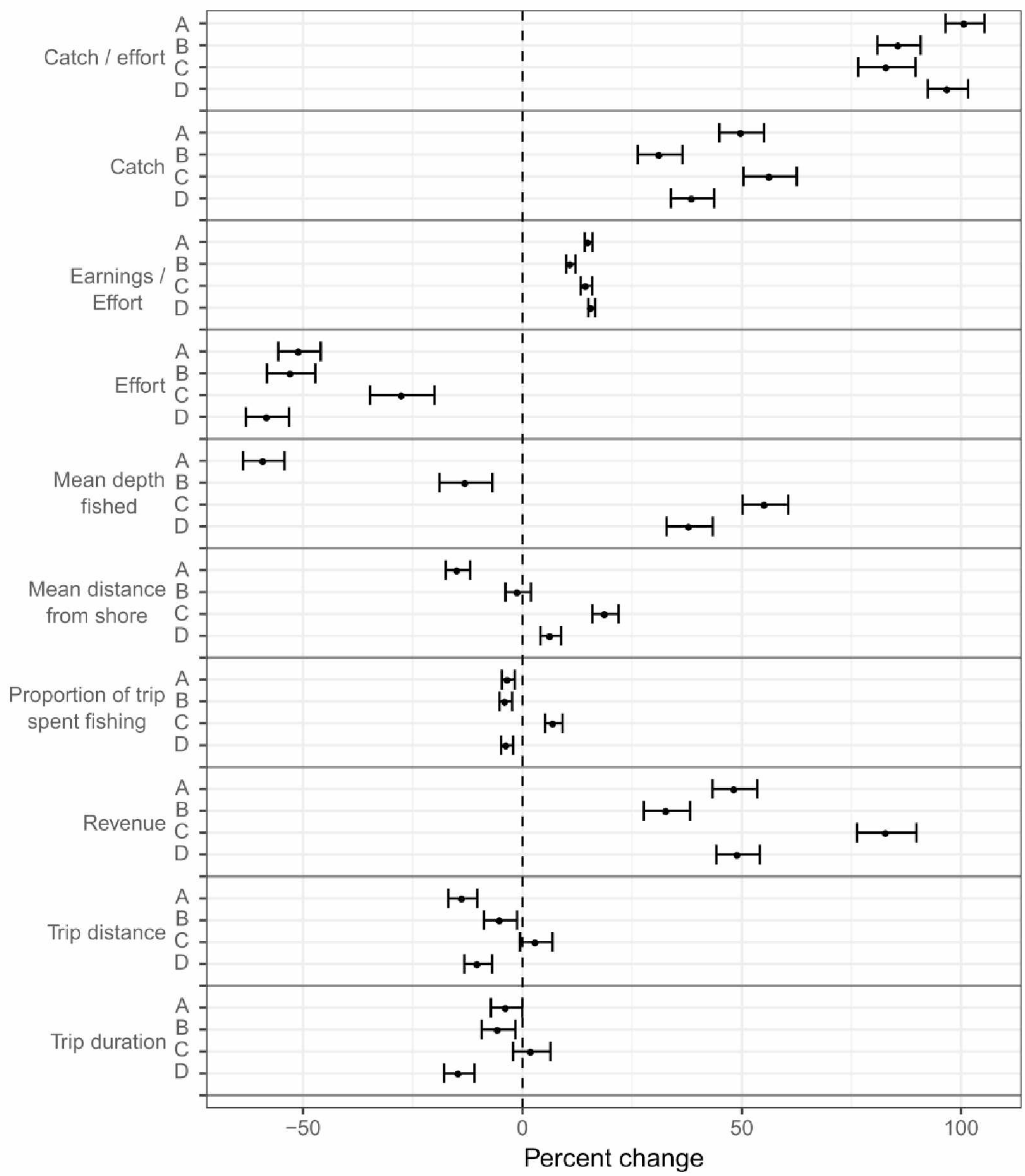


Figure 3.2: Estimated percent change (A-D seasons) in response variables after regulatory changes.

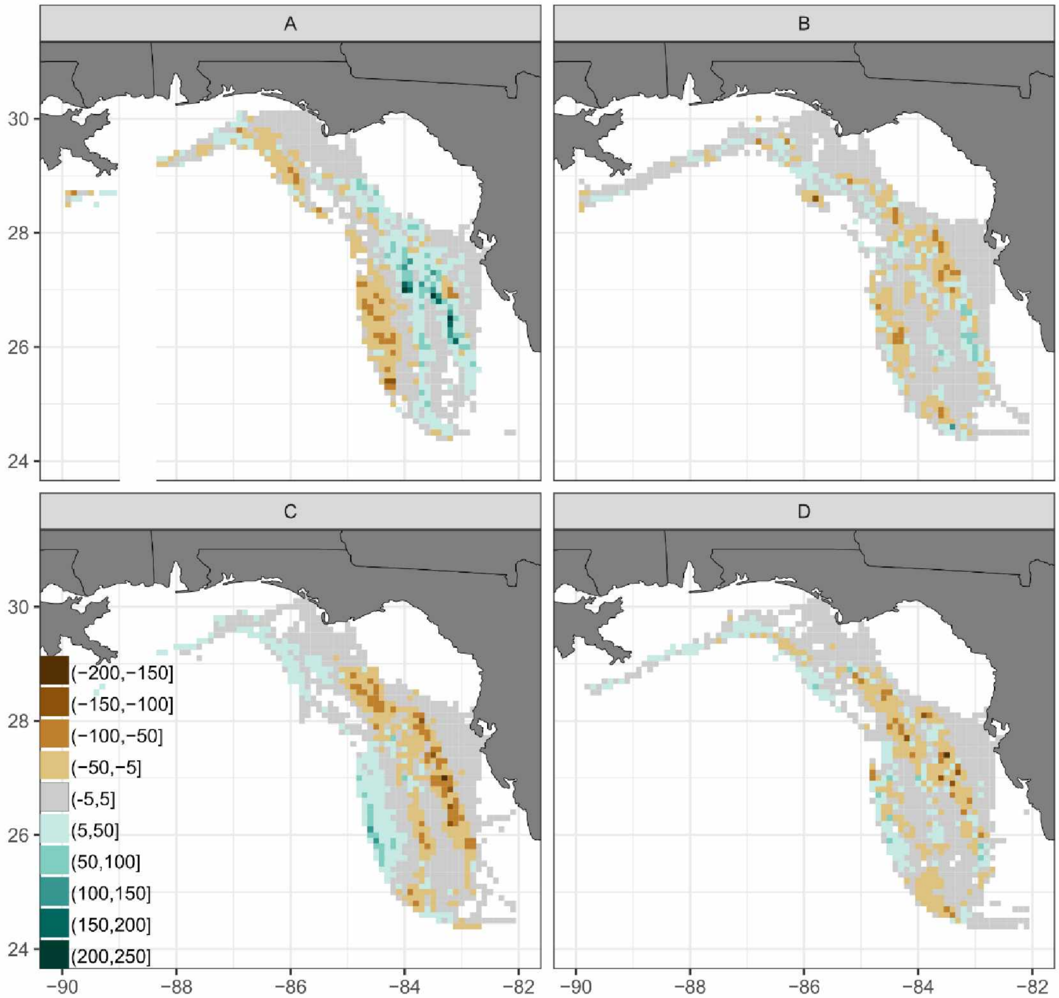


Figure 3.3: Difference in seasonal (A-D) fishing effort before vs. after regulatory transition. Values are the difference between the sum of the probabilities of fishing after the regulatory period minus the sum of the probabilities before the regulatory transition, so positive numbers (blue-green colors) indicate more fishing after (2011-2012) and negative numbers (brown colors) indicate more fishing before (2007-2008). Grey pixels represent areas with the least difference in pre/ post effort.

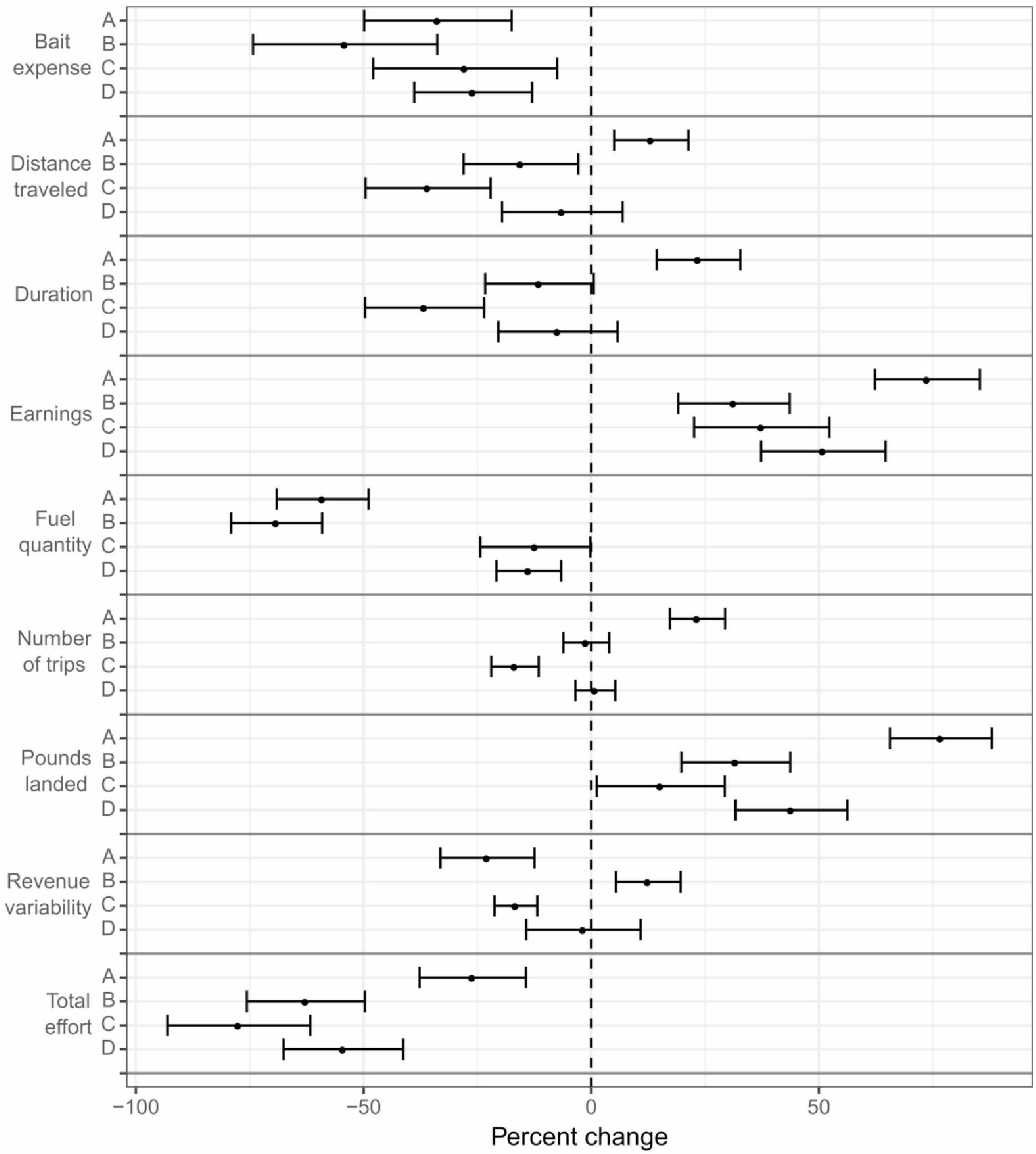


Figure 3.4: Estimated percent change (A-D seasons) in average annual vessel metrics.

3.7 Appendix

3.7.1 Model selection

We explored dozens of candidate models and have presented a representative sample in Table S3.2. Instead of choosing the model that minimized AIC, we instead chose the model that minimized the mean absolute percent error from the leave-one-out-cross-validation (LOOCV). An ANOVA F-test indicated no statistically significant difference when we compared the trip-level absolute percent error of each of the above models, suggesting similar prediction accuracies. However, given the lower mean absolute percent error for predicting both fishing (15.1%) and non-fishing (8.6%) by our chosen model, we believed that the model with the lowest AIC may be more likely to be over-fit. Table S3.2 does not include all of the models that we explored, as slightly different formulations (e.g., bivariate versus univariate combinations of the same covariates) often led to virtually identical results in terms of prediction accuracy. We present a range of different models that are illustrative of the role that different covariates played in the prediction process.

3.7.2 Predicting fishing

Summing probabilities across trips to estimate fishing effort is associated with the challenge that this method does not directly evaluate the accuracy of model predictions for individual VMS records. We present the sum of probabilities in the main body of this paper. However, in theory, this approach could lead to incorrect predictions of individual observations that yield low apparent aggregate errors. For example, a string of 5 non-fishing records could each be predicted to have a probability of 0.2 while a single fishing record predicted a probability of zero. The sum of probabilities would sum to 1 and the effort would have been predicted accurately, despite the obvious errors. However, on average, this method better captures the uncertainty of the observations.

To evaluate predictions for individual records, one could assign a probability threshold (e.g., $p(\text{fishing}) \geq 0.5$) above which values were determined to be fishing and below which they were not fishing. However, a threshold-based approach relies on selection of the threshold. In Figure S3.2, we present the predicted probabilities for observed fishing and non-fishing VMS records, with the non-fishing records broken into several different categories ('Preceding,' 'Proceeding,' and 'Between') based on their proximity to fishing records. If we had assigned a probability threshold of 0.5 (above which, fishing occurred), 87.0% of all fishing records would have been accurately predicted and 86.1% of all non-fishing records would have been accurately predicted. Overlain errors in the figure illustrate how the non-fishing records were predicted more accurately (93.0% correct) if they occurred more than one VMS record away from the nearest fishing record and least accurately (6.4% correct) if they occurred between two fishing records.

With this threshold approach, fishing records were predicted on average (1 sd) with 87.4% (10.6%) accuracy per trip and non-fishing records were predicted on average (1 sd) with 86.4% (6.4%) accuracy per trip. These errors are similar to the mean absolute errors presented (Table S3.2) for fishing and greater than the mean absolute errors presented for non-fishing (8.6% [7.8%]) as determined for the primary modeling approach that sums probabilities.

Prediction errors were the highest for non-fishing VMS records that occurred adjacent to fishing records. This is not surprising for several reasons. First, directly preceding and proceeding fishing, vessel behaviors can exhibit speeds and other behaviors that are consistent with fishing and vessels are often already (or still) on the fishing grounds. Additionally, while the time stamps associated with each VMS record are automated, and thus, precisely recorded, the times reported by observers may be rounded or may not necessarily equate exactly to the time at which fishing behaviors were exhibited by vessels, causing observed fishing times and VMS times to not match exactly. Such imprecise matching may explain a portion of high probabilities for non-fishing VMS records directly preceding or proceeding fishing records.

Table S3.1: Description of IFQ species groups, common names and species names.

IFQ share category	Species	Species
Deep-water grouper	Snowy grouper	*Epinephelus niveatus*
	Speckled hind	*Epinephelus drummondhayi*
	Warsaw grouper	*Epinephelus nigritus*
	Yellowedge grouper	*Epinephelus flavolimbatus*
	Misty grouper	*Epinephelus mystacinus*
Gag	Gag	*Mycteroperca microlepis*
Other shallow-water grouper	Black Grouper	*Mycteroperca bonaci*
	Scamp	*Mycteroperca phenax*
	Yellowfin grouper	*Mycteroperca venenosa*
	Yellowmouth grouper	*Mycteroperca interstitialis*
	Red hind	*Epinephelus guttatus*
	Rock hind	*Epinephelus adscensionis*
Red grouper	Red grouper	*Epinephelus morio*
Red snapper	Red snapper	*Lutjanus campechanus*
Tilefish	Blueline (grey) tilefish	*Caulolatilus microps*
	Golden tilefish	*Lopholatilus chamaeleonticeps*
	Goldface tilefish	*Caulolatilus chrysops*
	Anchor tilefish	*Caulolatilus intermedius*
	Blackline tilefish	*Caulolatilus cyanops*

Table S3.2. Representative list of candidate models and performance. Twelve of the generalized additive model formulations explored to estimate prediction of fishing effort. Models are sorted based on the lowest average absolute percent error ([predicted – observed] / observed) for predicting fishing, with standard deviations of percent error in parenthesis.

Mean absolute % error		Mean % error			
Fishing	Non-Fishing	Fishing	Non-Fishing	ΔAIC	Model
15.1 (19.2)	8.6 (7.8)	-4 (24.1)	-1.1 (11.6)	117	s(distance)+s(speed$_{t-1}$, speed$_{t+1}$)+s(Δdistance$_{s}$, Δdistance$_{p}$)+s(hour)+s(depth)+ month
15.6 (19.5)	9.1 (8.5)	-3.9 (24.7)	-1.4 (12.4)	0	s(distance)+s(speed$_{t-1}$,new.dist.lag)+s(Δdistance$_{s}$, Δdistance$_{p}$)+s(hour)+s(longitude,latitude)+s(depth)+month
16.2 (22.8)	8.8 (7.9)	-5.1 (27.5)	-1.1 (11.8)	465	s(distance)+s(speed$_{t-1}$, speed$_{t+1}$)+s(Δdistance$_{s}$)+s(hour)+s(depth)+ month
16.4 (22.9)	8.9 (7.8)	-5.2 (27.7)	-1.2 (11.7)	1002	s(distance)+s(speed$_{t-1}$)+s(speed$_{t+1}$)+s(Δdistance$_{s}$)+s(hour)+s(depth)
18.2 (25.8)	9.7 (8.6)	-6.4 (30.9)	-1.3 (13)	909	s(distance)+s(speed$_{t-1}$, speed$_{t+1}$)+s(Δdistance)+s(hour)+s(longitude,latitude)+s(depth)+ month
18.3 (27.6)	9.4 (8.1)	-7.4 (32.3)	-0.9 (12.4)	1780	s(distance)+s(speed$_{t-1}$)+s(speed$_{t+1}$)+s(hour)+s(depth)
18.9 (26.9)	10 (8.5)	-7.3 (32.1)	-1 (13.1)	2227	s(speed$_{t-1}$)+s(speed$_{t+1}$)+s(hour)+s(depth)
19.0 (23.5)	10.7 (9.7)	-5.6 (29.8)	-2.2 (14.3)	6704	s(Δdistance$_{s}$)+s(hour)+s(depth)
22.7 (36.5)	11.5 (10)	-9.4 (42)	-1.7 (15.1)	9189	s(Δdistance$_{s}$)+s(hour)
24.9 (40.4)	12.2 (11.3)	-11.3 (46.1)	-1.3 (16.7)	29949	s(distance)
25.2 (50.2)	11.6 (9.4)	-12.2 (54.8)	0.6 (14.9)	15260	s(speed$_{t-1}$)+s(speed$_{t+1}$)
29.5 (60.1)	12.4 (10.9)	-16.8 (64.9)	-0.7 (16.5)	13828	s(hour)

Table S3.3: Trip-level models. Coefficient values (β0, β1, β2) and the standard deviation of the random effect ($b0_v$) from equations (2-3) for trip-level models. If no β2 value is present, vessel length did not improve model fits and equation (3) was used.

Response	Season	β0	β1	β2	sd($b0_v$)
Catch*	A	7.51	0.5	0.02	0.33
	B	7.58	0.31	0.01	0.37
	C	6.59	0.56	0.03	0.25
	D	7.52	0.39	0.02	0.26
Catch/ effort*	A	-3.3	1.01	-	0.38
	B	-3.4	0.86	-	0.47
	C	-3.4	0.84	-	0.54
	D	-3.4	0.97	-	0.41
Earnings / effort*	A	0.13	0.15	-	0.07
	B	0.12	0.11	-	0.05
	C	0.1	0.15	-	0.05
	D	0.11	0.16	-	0.06
Effort*	A	11.6	-0.58	-	0.38
	B	11.5	-0.48	-	0.79
	C	10.9	-0.14	-	1.97
	D	11.6	-0.66	-	0.56
Trip distance*	A	5.49	-0.14	0.01	0.25
	B	5.24	-0.05	0.02	0.3
	C	4.99	0.03	0.02	0.25
	D	5.09	-0.1	0.02	0.26
Trip duration*	A	5.45	-0.04	-	0.22
	B	5.43	-0.05	-	0.33
	C	5.32	0.02	-	0.23
	D	5.48	-0.14	-	0.27
Prop trip fishing	A	0.44	-0.01	-	0.03
	B	0.47	-0.02	-	0.04
	C	0.41	0.03	-	0.05
	D	0.44	-0.01	-	0.03

Table S3.4: Aggregate-level models. Coefficient values (β0, β1, β2) and the standard deviation of the random effect ($b0_v$) from equations (2-3) for aggregate (pre- / post- regulation) models. If no β2 value is present, vessel length did not improve model fits and equation (3) was used.

Response	Season	β0	β1	β2	sd($b0_v$)
Distance	A	7.62	0.13	-	0.32
	B	7.73	-0.16	-	0.33
	C	7.84	-0.36	-	0.14
	D	7.66	-0.06	-	0.13
Duration	A	6.93	0.24	-	0.23
	B	7.03	-0.1	-	0.32
	C	7.14	-0.37	-	0.06
	D	7.05	-0.07	-	0.12
Earnings	A	10.9	0.74	-	0.27
	B	11	0.31	-	0.46
	C	10.8	0.38	-	0.34
	D	10.9	0.51	-	0.25
Bait expense*	A	6.77	-0.35	-	0.51
	B	6.72	-0.35	-	0.65
	C	6.62	-0.07	-	0.36
	D	6.74	-0.27	-	0.47
Fuel quantity*	A	6.39	-0.59	-	0.49
	B	6.41	-0.69	-	0.53
	C	6.02	-0.08	-	0.37
	D	6.13	-0.11	-	0.5
Number of trips	A	6.39	1.49	-0.04	0.83
	B	8.72	-0.09	-0.07	1.08
	C	10.1	-1.69	-0.08	0.16
	D	9.8	0.09	-0.09	1.42
Pounds landed	A	9.82	0.77	-	0.24
	B	9.87	0.31	-	0.42
	C	9.86	0.16	-	0.16
	D	9.86	0.44	-	0.21
Revenue variability	A	-1.4	-0.24	-	0.47
	B	-1.3	0.11	-	0.37
	C	-0.9	-0.41	-	0.33
	D	-1.2	-0.1	-	0.41

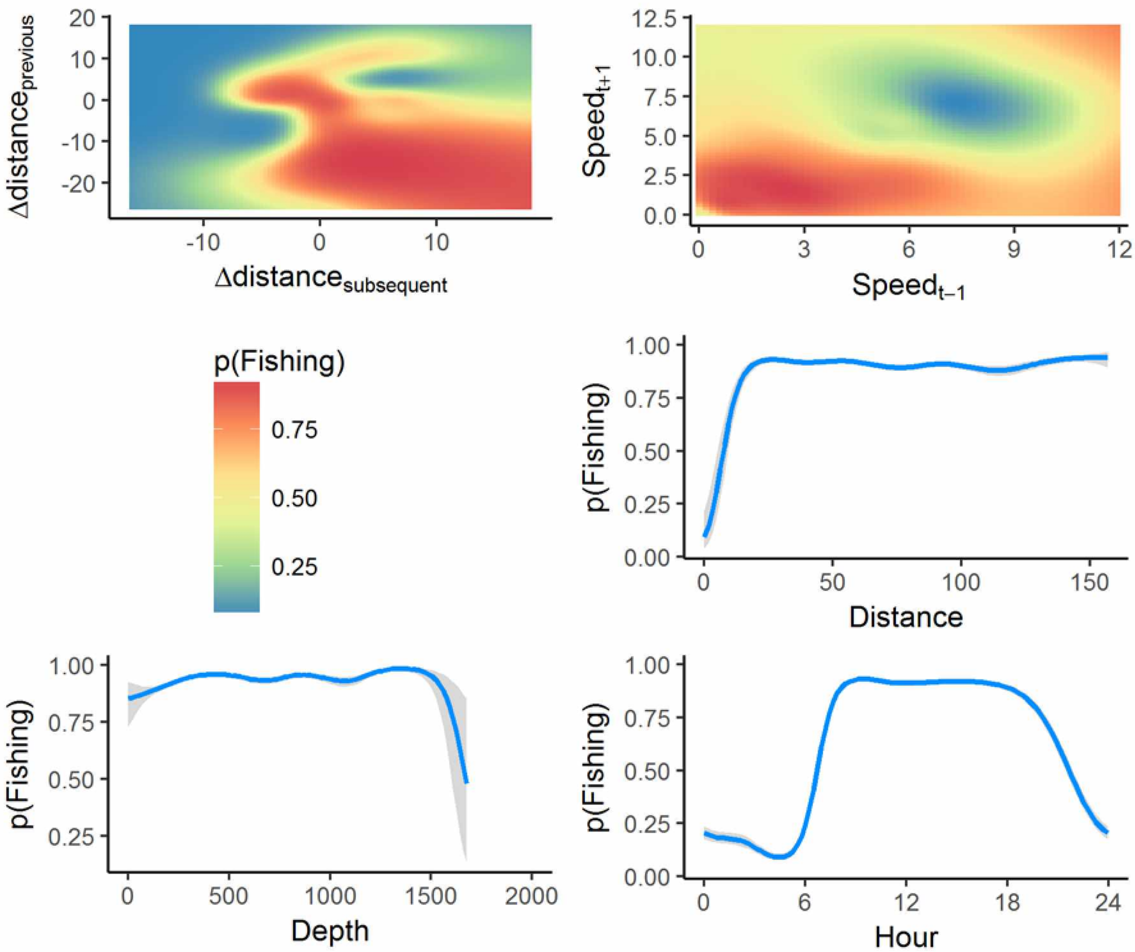
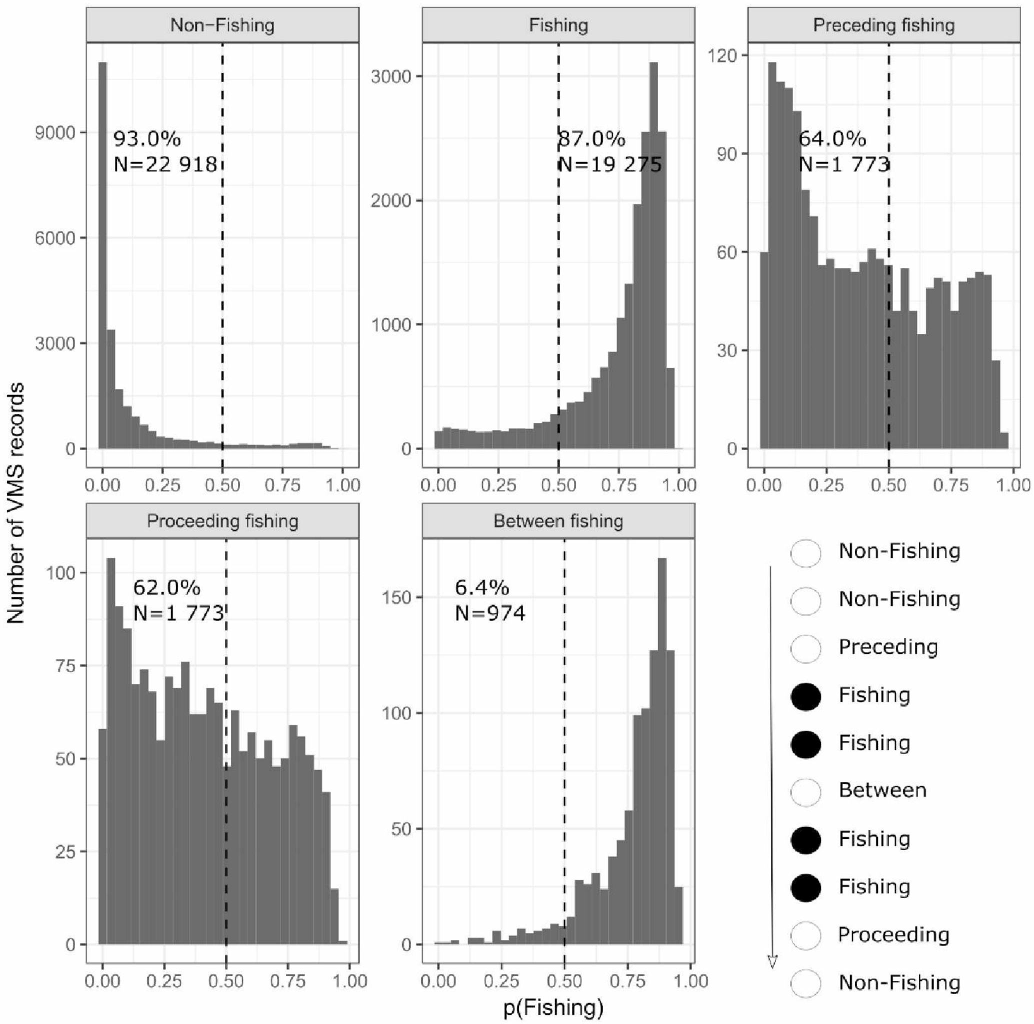


Figure S3.1: Partial dependence plots for continuous covariates of generalized additive model.



Figures S3.2: Distributions of predicted fishing probabilities (p(Fishing)) for observed VMS records. The bottom right illustrates an example top-to-bottom sequence of VMS records where filled circles represent observed fishing and empty circles are observed non-fishing. Labels relate to each panel of histograms. 'Preceding' and 'Proceeding' are non-fishing records occurring directly prior to or following a 'Fishing' record, respectively. 'Between' are non-fishing VMS records with fishing records occurring both before and after. The 'Non-fishing' panel includes the remaining non-fishing VMS records. Sample sizes (N) show the total number of VMS records for each panel and percentages indicate the number of those records that would have been correctly predicted if p(Fishing) $\geq$ 0.5 indicated fishing.

General Conclusions

This work represents a novel synthesis of multiple large datasets, algorithms, and statistical methodologies that help us to better understand the movements of fishers, the trade-offs with which fishers are faced, and the interactions among fishers, the environment, markets, and management structures. Combining tens of millions of data records from VMS, logbooks, fish tickets, and observers, I have provided a technical and conceptual framework by which fisher behaviors can be quantified and examined in the context of their responses to changes in their fishery landscape, a term that I use to encompass the broad universe of dynamics that fishers must face.

In chapter 1, I presented a detailed algorithmic approach by which massive swaths of vessel movement data could be integrated with fisher- and observer-reported information to identify individual trips and to classify those trips as fishing or non-fishing trips in one of the largest fisheries in the world, the Bering Sea fishery for walleye pollock. This fishery is renowned not only for its scale but also for its extensive observer coverage. However, that observer coverage has varied over time, provided only a partial time series of trip-level information over the last two decades, a time period characterized by large swings in environmental conditions. In this chapter, I established a step-by-step approach for dealing with idiosyncrasies of the complicated geography of ports and vessel movements along the Alaska coastline, demonstrating how VMS users globally could move beyond the constraints of the black box trip identification tools provided by some VMS analysis software. Furthermore, I provided the first (to my knowledge) published discussion of irregularities in VMS transmissions and the challenges and biases that they may introduce.

Chapter 2 made use of the rich trip-level dataset for the Bering Sea walleye pollock fishery (from chapter 1) to demonstrate the role that pollock markets and products play in how fishers respond to fluctuations in pollock abundance and temperature from year-to-year. This chapter was originally envisioned as a straightforward analysis of trip distances and durations but it took an unexpected turn as a result of the insightful experience of nearly a dozen pollock boat captains, crew members, and other industry professionals. While at sea with these professionals in the Bering Sea, I was introduced to many of the nuances of the fishery that had not been apparent from my original approach. Incorporating industry feedback, I revised my analyses of trip distances by season and year to allow for processor-level dynamics. When pollock were abundant and water was warm, vessels across the fleet behaved similarly. In contrast, when pollock abundance declined or temperature cooled, the fleet fractured into two groups of vessels exhibiting distinct spatial behaviors in order to best sustain their catches; one group made shorter trips while the other made longer trips. Vessels with generally lower capacity were still able to fill their holds by fishing close to port and the majority of their catches were destined for fillets. Meanwhile, vessels with larger capacities had to travel farther to fill their holds, but often had more flexible delivery windows associated with a majority of catches being processed as surimi. These different responses of vessels to the changing fishery landscape helped vessels to buffer against lower and more variable annual net revenues.

In chapter 3, I switched gears and analyzed VMS data from a longline fishery in the Gulf of Mexico. This chapter was notable for two reasons. First, despite dozens of studies in the literature that use VMS to estimate fishing effort, few have endeavored to do so for longlines because vessel behaviors are so complex during longline (as opposed to trawling). Chang and Yuan (2014) used a recursive partitioning approach to estimate effort in a Taiwanese longline fishery but their relatively high accuracies at predicting fishing were complemented by substantial over-prediction, thus reducing the utility of their approach for some applications. The method I present in chapter 3 however, uses a generalized additive modeling approach that balances the prediction of fishing and non-fishing (i.e., minimizes over-prediction). Once the effort estimation model was complete, I performed the first (to my knowledge) use of VMS data to evaluate a catch share management program (combined with several other regulatory constraints). In fact, while several studies have used VMS to evaluate fishery closures (e.g., Murawski et al. 2005; Holmes et al. 2011, Needle and Catarino 2011), few other attempts have been made to quantify responses of fishers to a regulatory change using VMS and no (known) studies have attempted to link revenue data to such behavioral responses. One of the stated goals of the regulatory transitions in the Gulf of Mexico bottom longline fishery had been to reduce capacity and increase fishing efficiency throughout the fleet. As defined by higher catches and earnings per unit effort, our VMS-derived effort metrics facilitated the determination that fleet efficiency did increase after a regulatory transition period.

These chapters provided individual case studies in which I tested hypotheses about changes in vessel behavior but they also demonstrated several important aspects of thinking about vessel and fleet behaviors. First was the value of not necessary treating all fleets or even vessels within a fleet the same. The distinct spatial fishing strategies of different vessels within the pollock fishery in response to environmental change suggests that management (e.g., bycatch quotas, spatially-explicit assessments or quotas, fishery closures) based on an “average” vessel could lead to inequitable impacts on fishers across the fleet. Alternatively, by allowing analysis of the Gulf of Mexico bottom longline fishery to vary intra-annually, we were able to observe how responses of vessels to regulations varied through the year, even though distinct seasons do not exist within the fishery.

In synthesizing concluded thoughts about this dissertation, it seems important to recognize not only the specific and technical lessons that were learned during this process but also how the conversation about fisher behavior has evolved during this process. For most of the history of commercial fisheries, it was impossible to directly observe the movements and locations of fishers without fishery observers or without trusting the information reported in logbooks (which fishers told me to take with a grain of salt), when they were available. However, as my understanding of vessel behavior and our tools available to study it have grown, so too has my understanding of the demand for tools and studies like the ones here. As fishers scramble to respond to increasing demand, shifting fish populations, evolving regulatory structures, and modern technology, there is an increasing need for understanding how the movements of fishers will change so that fishery managers can scramble along with them. The chapters presented here are examples of the direction that future studies will increasingly need to take; understanding how vessels move, where they move, how complex interactions with markets and space and time drive these movements will become necessary components of fisheries research amidst dynamic fishery landscapes.

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