NRC Research Press

ARTICLE

Paths to resilience: the walleye pollock fleet uses multiple fishing strategies to buffer against environmental change in the Bering Sea

Jordan T. Watson and Alan C. Haynie

Abstract: Fishers seek to maximize profits, so when choosing where to fish, they must consider interactions among the environment, costs, and fish prices. We examined catcher vessels in the US Bering Sea fishery for walleye pollock (*Gadus chalcogrammus*) (2003–2015) to characterize fisher responses to environmental change (e.g., abundance and water temperature). When pollock were abundant and the 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 from port 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. We identify a suite of socioeconomic indicators of the impacts of ecosystem change and illustrate that a one-vessel-fits-all approach may be insufficient for assessing the resilience of fleets.

Résumé : Comme les pêcheurs cherchent à maximiser les profits, ils doivent tenir compte, au moment de décider où pêcher, des interactions du milieu ambiant, des coûts et des prix du poisson. Nous avons examiné les unités de pêche dans la pêche américaine au goberge de l'Alaska (*Gadus chalcogrammus*) (2003–2015) dans la mer de Behring pour caractériser les réactions des pêcheurs aux changements ambiants (p. ex. abondance et température de l'eau). Quand les goberges étaient abondantes et l'eau était chaude, toute la flotte pêchait dans des lieux semblables. Quand les températures étaient plus fraîches et que l'abondance des goberges diminuait, deux stratégies de pêche émergeaient, selon l'usine de transformation où les navires livraient leurs prises. Un groupe de navires, dont les prises étaient plus susceptibles d'être transformées en filets, faisait souvent des sorties plus courtes, nécessitant moins de carburant et de temps passé en mer. Un second groupe de navires, dont les prises étaient plus susceptibles d'être transformées en surimi, s'éloignaient plus du port, vers des régions caractérisées par des taux de prise plus élevés, mais de plus petits poissons en général. En pêchant dans des lieux différents pour satisfaire différents marchés, la flotte maintenait le niveau de recettes et se protégeait contre les changements environnementaux. Nous établissons une série d'indicateurs socioéconomiques des impacts de changements écosystémiques et illustrons comment une approche basée sur un seul type de navire ne suffit peut-être pas pour évaluer la résilience de flottes. [Traduit par la Rédaction]

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; Anderson et al. 2017). 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 driving forces — it is critical to examine fishers' fine-scale behaviors, such as fishing location (van Putten et al. 2012; Joo et al. 2014, 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

Received 31 July 2017. Accepted 22 March 2018.

J.T. Watson. NOAA Fisheries, Alaska Fisheries Science Center, Auke Bay Laboratories, 17109 Pt. Lena Loop Rd., Juneau, AK 99801, USA; University of Alaska Fairbanks, College of Fisheries and Ocean Sciences, 17101 Pt. Lena Loop Rd., Juneau, AK 99801, USA.
A.C. Haynie. NOAA Fisheries, Alaska Fisheries Science Center, Resource Ecology and Fisheries Management Division, 7600 Sand Point Way NE, Building 4, Seattle, WA 98115, USA.

Corresponding author: Jordan T. Watson (email: Jordan.watson@noaa.gov).

"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 US 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; Strong and Criddle 2013). The AFA ended the race-to-fish by allocating fractions of the total allowable catch (TAC) across three sectors: catcher processors, catcher vessels, and motherships, the latter of which rely on other vessels to catch fish. The catch was further suballocated within each sector and co-operatives were established (Criddle and Macinko 2000; Matulich et al. 2001; Strong and Criddle 2013). Importantly, catch shares can be traded within each sector but they cannot be traded between sectors (Criddle and Strong 2013). The onboard processing capability of the large (>62 m) catcher processors enables these vessels to stay at sea for weeks, thereby providing flexibility over where they fish and thus a greater ability to seek fish that meet their desired processing goals (Pfeiffer and Haynie 2012; Criddle and Strong 2013; Haynie and Pfeiffer 2013). Approximately one fifth of pollock catcher vessel harvest is delivered to at-sea "mothership" processors, while nearly half of the total pollock catch is delivered to shoreside processors.

When the AFA was established, the notable structure that resulted included a co-operative in which catcher vessels and shoreside processors organized and in many cases established long-term contracts. The seven processing plants that account for shoreside production of AFA pollock products were each organized into one of seven co-operatives, which are owned by one of four firms (Strong and Criddle 2013). Some vessels in the fishery have maintained individual ownership, while many others are owned either directly or indirectly by the relatively few processors or companies (Strong and Criddle 2013). Contractual agreements and vessel ownership consolidation have led to a vertical coordination that allows markets and production to dictate much of the structure of the fishery.

With the end of the race-to-fish, processors increased capital investments in technology and specialization, subsequently boosting fish value (Strong and Criddle 2014; Fissel et al. 2015) but also introducing new constraints. Flexibility of processing can be limited by long-term contracts, the difficulty of switching between products (e.g., fillet and surimi), the need to keep machinery running, and minimum fish sizes and quality standards for certain products (see Strong and Criddle (2014) for a thorough discussion of drivers, constraints, and market considerations surrounding pollock production). The pollock fishery is divided into two seasons. During the winter A-season (January–May), the primary products are fillets, surimi, and roe. During the summer B-season (June–October), the primary products are fillets and surimi. If pollock are too small or they have been aboard a vessel for too long, they may be inadequate for fillet production and must instead be processed as surimi or lower value fish meal. Similarly, if fish are too large, they may not make quality surimi (Strong and Criddle 2014).

The constraints that seafood processors face with respect to pollock size and freshness influence (either directly or indirectly) the operational decisions of each catcher vessel. We focus this study on shoreside production and catcher vessels and any mention hereafter refers to the shoreside, or inshore, sector of the pollock fishery (unless otherwise noted). Catcher vessels, 22–62 m in length, typically make 2 to 4 day trips. Given the freshness and quality standards that processors strive to meet, they often require catcher vessels to deliver fish to port within certain delivery windows. If a vessel misses its delivery window, the price paid for fish may plummet, as the pollock are relegated to low-value fish meal.

Vessel captains must decide when to begin a fishing trip by working backwards from the assigned window and production goals for their delivery. This requires an expectation of transit time, target fish location, how to avoid prohibited bycatch species that can shut down the fishery (Stram and Ianelli 2015; Reimer et al. 2017), and the amount of fishing time required to fill their holds. This creates a high value of communication among the approximately 70 vessels that fish within a season, although their co-operative and fishing strategies often differ. In addition to delivery windows, fishers must also cater to the product mix (e.g., roe, fillets, surimi, "head and gut") that their intended processor will make with the fish they deliver, which varies within and across seasons and years (Fell 2008; Strong and Criddle 2014). Because fish products are a function of fish size and the amount of time that it takes to deliver fish to port, the spatial distribution of the target species is a critical consideration for fishers. As the fishery landscape changes within and across years, the trade-offs that fishers must consider to balance delivery windows with fish size, product mixes, and freshness are continually reevaluated.

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 that 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 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 interannually 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 revenues. Given the stability of catches that result from vessels usually filling their holds, we focus our analysis 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, revenues, 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 short-run economic outcomes (e.g., catch rates and trip revenues minus fuel costs) 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.

Table 1. Data sets and their sources from which all behavioral, economic, and fishery landscape variables were derived or obtained.

Data set	Source
Vessel monitoring system	NOAA VMS database (Spalding 2016)
Fishery observer	North Pacific Groundfish Observer Program (AFSC 2016)
Fish tickets	Alaska Fisheries Information Network (ADFG 2015)
Fuel consumption	Amendment 91 Chinook Salmon Economic Data Report (www.psmfc.org/chinookedr/)
Processor production	Alaska Fisheries Information Network (ADFG 2015)
Price deflator	https://research.stlouisfed.org/fred2/series/GDPDEF#
Bering Sea bottom temperature	www.afsc.noaa.gov/RACE/groundfish/survey_data/
Fuel prices	Fisheries Economic Data Program (www.psmfc.org/efin/data/fuel_ak.txt)
Walleye pollock (*Gadus chalcogrammus*) abundance (age 3+ biomass)	Ianelli et al. 2015, Table 1.27
Total allowable catch	Ianelli et al. 2015, Table 1.2

Methods

Data

We incorporated several data sets from the Bering Sea pollock catcher vessel fleet (91 vessels) from 2003 to 2015. Compiled with their sources (Table 1), these data included vessel monitoring system (VMS) data, fishery observer data, fish tickets (landings data), vessel-level fuel consumption rates while transiting and fishing (see Supplementary Information[1] for more details), and processor production data. In addition to these fishery-dependent data sets, we explored four fishery landscape variables as drivers of fisher behavior (Table 1): average summer bottom temperature during the annual eastern Bering Sea groundfish survey, pollock abundance (age-3+ biomass), TAC, and fuel price (averaged from monthly surveys of fuel sellers for Dutch Harbor, Alaska). Economic data were adjusted to a base year of 2009 using an annual (seasonally adjusted) implicit price deflator for US gross domestic product. Analyses were performed using R version 3.3.0 (R Core Team 2016). See Supplementary Information for more details.

Trip-level fishing and short-run economic outcomes were extracted or derived from VMS, observer, fish ticket, or fuel consumption data (Table 2) (Watson and Haynie 2016). Vessel-level metrics were associated with each trip, including vessel length and each vessel's fishery co-operative (for more information: www.nmfs.noaa.gov/sfa/management/catch_shares/about/documents/bsai_pollock.pdf).

We examined net revenues and other fishing performance and economic outcomes (hereafter, fishing outcomes; Table 2) that underlie net revenues. The trade-offs associated with some of these outcomes help explain net revenues and expected fishing profits. Our measure for net revenues 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, demand, and freshness are determinants of price (Herrmann et al. 1996; Strong and Criddle 2014; Seung and Ianelli 2016). Available price data were aggregated annually (i.e., not resolved to the trip level) and were thus 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 (Criddle and Strong 2013). Vessels may use up to three 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. While the only cost component we considered was fuel, it is worth noting that some nonfuel variable costs may be similar regardless of the trip length and thus represent a larger portion of trip costs as trip lengths get shorter (i.e., as fuel costs decrease). Earnings are typically shared by vessel owners, skippers, and crew so labor is not included in our Costs term. Thus, our definition of net revenue is trip-level earnings (Price × Catch) minus estimated fuel costs (omitting capital costs and other expenses that are independent of fishing effort). Additionally, while fuel cost is obviously important, we also examine the ratio of fuel cost to gross earnings, a unitless measure (Criddle and Strong 2013) that facilitates comparison across vessels.

Our study 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 for surimi, thereby constraining vessels to shorter trips. Thus, production data were important for explaining fishery behavior. These data included the end-products produced (although 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 that 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, although the data provided production trends for processors and a linkage of these trends with each vessel and behavior.

Analyses

Our analyses relied on the hypothesis that changes in the fishery landscape lead to changes in fishers' spatial behaviors in the shoreside pollock catcher vessel fleet and that these changes would improve fishing outcomes. 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.

Characterizing spatial behaviors in the fishery

We characterized spatial behaviors as trip distances traveled by the shoreside 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 three and four processors, respectively) based on distinct trip distances in years with longer trips. We refer to these vessel groups as "Longer Trip Group" and "Shorter Trip Group" 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 versus vessel co-operatives.

[1]Supplementary data are available with the article through the journal Web site at http://nrcresearchpress.com/doi/suppl/10.1139/cjfas-2017-0315.

Table 2. Fishing and economic indicators calculated for each trip (left) and source or derivation (right).

Outcome	Derivation/source
Catch per trip	Fish ticket reported pounds of walleye 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/trip) (see Supplementary Information for details)
Catch per unit effort	Catch per trip/fishing effort
Catch per trip day	Catch per trip/trip duration (days)
Gross revenue per trip	Fish ticket reported value of trip
Gross revenue per trip-day	Gross revenue 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 revenue per trip	Gross earnings – fuel cost
Net revenue per trip-day	Net revenue per trip/trip duration
Ex-vessel price*	Gross revenue per trip/pounds landed per trip

Note: Some derivations include definitions from previous rows.

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

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:

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

where ε represents Gaussian errors. We performed stepwise 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 (Longer Trip Group and Shorter Trip Group) 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 et al. 2012)) 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).

Fishing outcomes across vessel groups and years

An important aspect of changes in fishing behavior is whether they are associated with different or more variable outcomes (Table 2). 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 among all of them. Rather, we expected fisher behaviors to buffer against changes in fishing outcomes, leading to weak correlations between several of the fishing outcomes and both the fishery landscape and trip distances. A lack of relationship can be difficult to demonstrate and indeed was not the central goal of our study. However, by comparing fishing outcomes and their relationships to landscape variables for the two groups in a similar manner, we sought to illustrate similarities and differences across vessel groups (Longer Trip Group and Shorter Trip Group).

We examined average fishing outcomes and the variability (coefficient of variation (CV)) of fishing outcomes for the two groups. The CV provides a unitless comparison across agents with different long-term means. It has also been used as a measure of economic risk exposure for fishers (e.g., Anderson et al. 2017; Ward et al. 2017), providing a valuable complement to average catches and revenues. We measured the Pearson correlations between the average annual fishing outcomes (Table 2) 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 fishery landscape or trip distances, we also measured correlations between the variability (CV) of fishing outcomes with the fishery landscape and trip distances. Simple pairwise correlations may fail to account for complex multivariate relationships, but this approach allows for more straightforward comparison between vessel groups while still setting the context for the subsequent discussion and analyses about how changes in the fishery landscape and fisher behaviors may relate to changes in fishing outcomes. 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.

Results

Characterizing spatial behaviors in the fishery

Trip distances were similar during winter A-seasons (January–May) across years, whereas during summer B-seasons (June–October), 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 (Fig. 1*a*). In contrast, summer B-season trip distances fluctuated depending on the year (Fig. 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 versus 223 nmi (1 nmi = 1.852 km)). The CV of trip distances for summer B-season trips was nearly double that of winter A-season trips (0.38 versus 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 Shorter Trip Group and a Longer Trip 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 Shorter Trip Group than in the Longer Trip Group, and the Shorter Trip vessels were typically smaller, made more trips (although not significantly more), and caught larger fish (Table 3).

In each year, trip distances and durations were less for the Shorter Trip Group 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.

Fig. 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 the Shorter Trip Group vessels (white) and Longer Trip Group vessels (black).

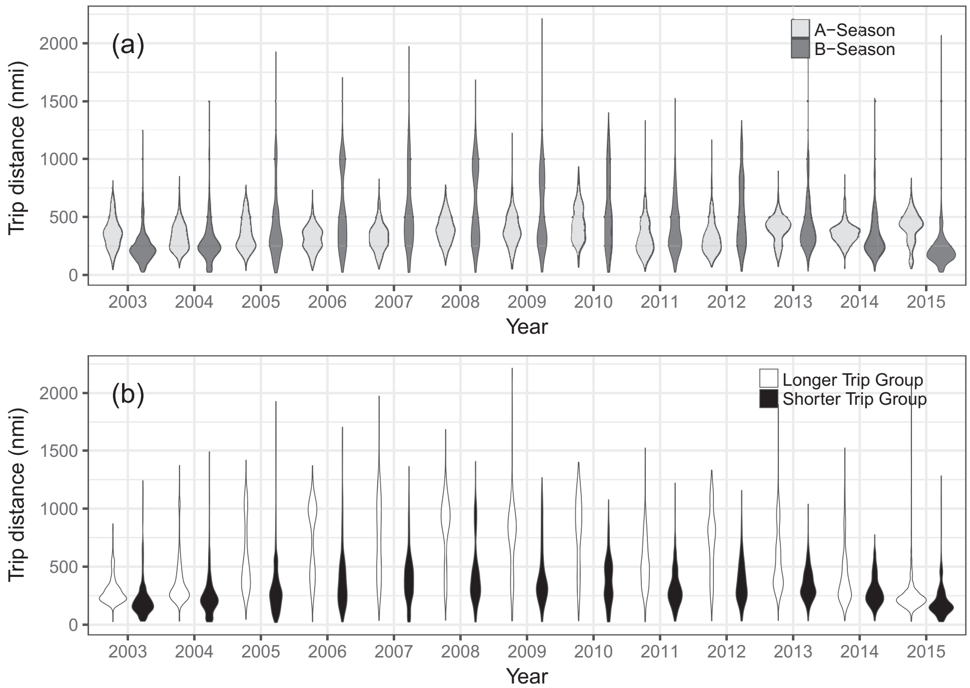


Table 3. Comparison of average (standard deviations) annual trip characteristics by vessel group.

	Shorter Trip Group	Longer Trip 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 mass (kg)	0.96 (0.15)	0.72 (0.10)

Note: Groups were significantly different (Mann–Whitney test, $P < 0.05$) for all metrics except number of trips.

The CVs of trip distances varied significantly across years (Supplementary Information Table S1).

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 the average annual first wholesale product value for the Shorter Trip Group was from fillet production, while only about 20% was from surimi. Meanwhile, the processors associated with Longer Trip Group vessels earned only about 30% from fillets and nearly 50% from surimi.

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 (Fig. 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 bottom temperature and abundance in the Bering Sea. Fuel price and TAC were not significant predictors on their own or when added to models with temperature or abundance. While not shown in eq. 1, average fish size was also explored as a covariate but was omitted because of its high degree of observed collinearity with pollock abundance (e.g., years with higher pollock abundance are characterized by large cohorts of younger fish, which reduce the average fish size). 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, Shorter Trip Group vessels, or Longer Trip Group vessels (Fig. 3; see Table S2 for model coefficients and diagnostics). In the cases of all modeled groups (Shorter Trip Group, Longer Trip Group, and all vessels), the lowest Akaike information criterion 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 Akaike information criterion for the model containing both abundance and temperature, we still include (Fig. 3; Table S2) 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 (Fig. 3). For example, all three groups (Shorter Trip Group, Longer Trip Group, and all vessels) 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 Shorter Trip Group vessels took longer trips. Distances during this year were not unusual for the Longer Trip 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 Longer Trip Group took much longer trips, leading to underestimated distances. When the Longer Trip Group was poorly fit (2006), the Shorter Trip 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 Longer Trip Group vessels were more sensitive to

Fig. 2. Several key characteristics of the fishery landscape and their anomalies, 2003–2015.

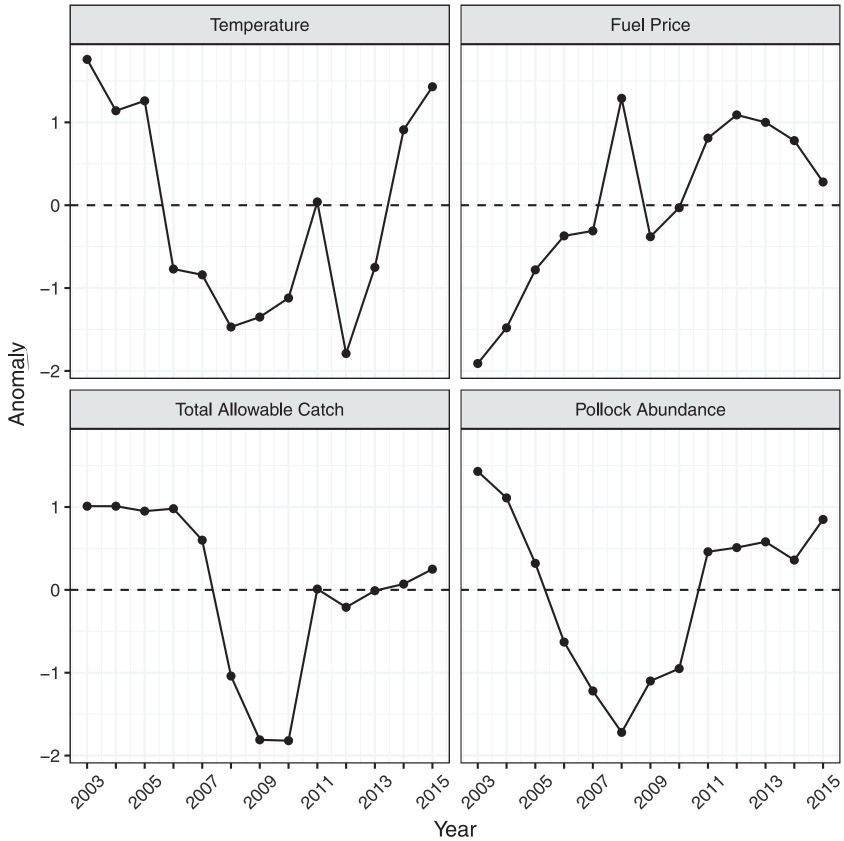
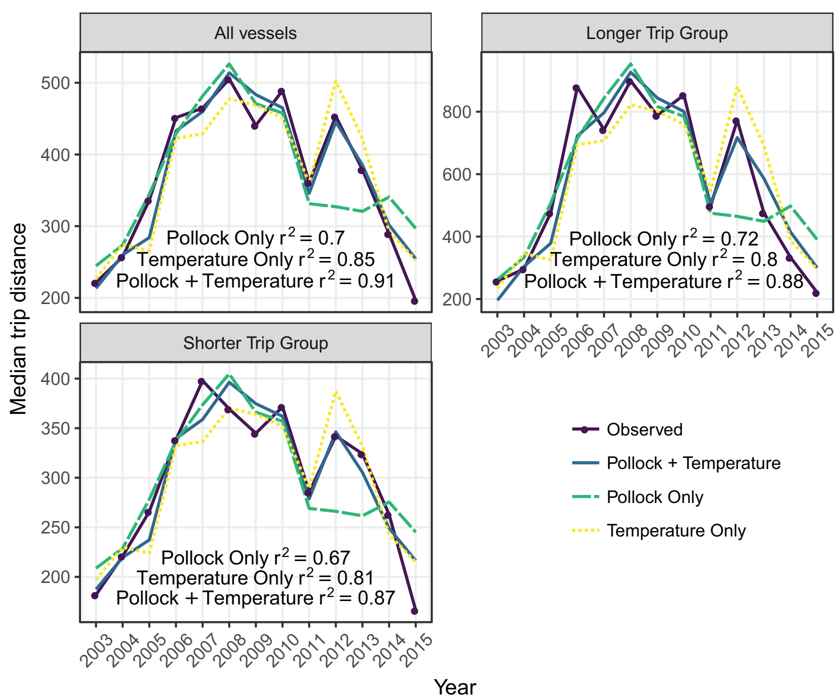
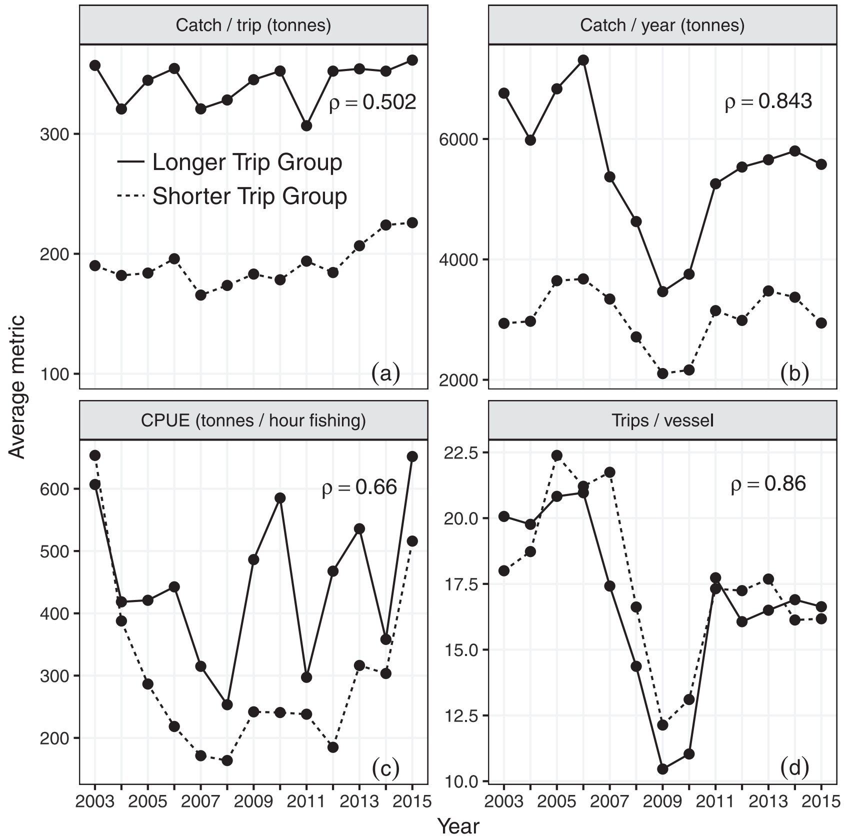


Fig. 3. Illustration of model fits to annual median summer B-season trip distances for all vessels (top left), Shorter Trip Group vessels (top right), and Longer Trip Group vessels (bottom left). Text values in each plot are the r^2 values from each model. [Color online.]



changes, in particular to changes in abundance (Fig. S1). Because the final models only included linear, first-order combinations of covariates, effects are also readily interpretable by coefficient values (Table S2), although we present sensitivity analyses for better interpretation and visualization of results (Fig. S1). 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

Fig. 4. Average fishing performance and behavior by year (summer B-season only) for the Shorter Trip Group vessels (solid lines) and Longer Trip Group vessesls (broken lines). Rho (ρ) values indicate Pearson correlations between the two groups.



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 was 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 Longer Trip Group vessels, (2) Shorter Trip Group vessels and all vessels responded similarly to perturbations, while the Longer Trip Group vessels were always more sensitive to change (i.e., had a greater change in median trip distance), and (3) for Longer Trip Group 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 Shorter Trip Group vessels (0.64 versus 0.38), Longer Trip Group vessels (0.62 versus 0.48), and all vessels groups (0.74 versus 0.47).

Fishing outcomes across vessel groups and years

There were generally weak relationships between fishing outcomes and the fishery landscape (including trip distances), although with several exceptions. The weak relationships support the expectation that changes in fishing behavior may help to buffer against environmental changes (although causation is not suggested through these pairwise correlations). Most notably, despite highly variable temperatures and abundance, average catch per trip for each group was relatively constant across years (Fig. 4) with relatively weak correlations with the environment or trip distance (Table 4). More importantly, average annual net revenues per trip showed remarkably weak correlations with the environment and trip distances. These relationships suggest that all groups adapted fishing strategies to changing environments, which were associated with sustained 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 (Fig. 1). Despite the Longer Trip Group always taking longer trips (in distance and duration), there was a range of variability in trip distances and duration across years (Table S1). Greater variability was seen for the Shorter Trip Group in many years and for many of the fishing outcome metrics, but there were a third more vessels in the Shorter Trip 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 (Fig. 4; Table 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 makes sense; fishers seek to fill their holds on each trip (independent of TAC) but the number of trips a vessel takes will be subsequently influenced by TAC. The strong relationship between catch per year and TAC for both vessel groups yielded 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 4).

The relationships between catch rates (catch per unit effort (CPUE)) and trip distance were different for the two vessel groups

Table 4. Relationships between fishing outcomes and both the fishery landscape and trip distances for vessels in the Shorter Trip Group and Longer Trip Group.

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

Note: Values are Pearson correlation coefficients (ρ) with dark-shaded boxes highlighting correlations with an absolute magnitude >0.7 and light shading between 0.3 and 0.7.

and across time. Average catch rates (CPUE) were more variable than catch per trip across years (Fig. 4) for the Longer Trip Group than for the Shorter Trip Group, which had a relatively strong relationship among CPUE, abundance, temperature, and trip distance (Table 4). However, not surprisingly, the relationships between CPUE and the fishery landscape were different within years versus across years. The average annual CPUE for Shorter Trip Group vessels was lowest during the years with the greatest average travel distances but within these years, CPUE across trips was higher when vessels traveled farther (Fig. S2). So during the coldest years with lowest abundance (2007–2010), Shorter Trip Group 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 (Fig. S2). Longer Trip Group vessels showed a similar positive relationship between distance and CPUE but for more years (2005–2013). Despite variability in the interannual average CPUE (Fig. 4*c*), the intraannual 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.

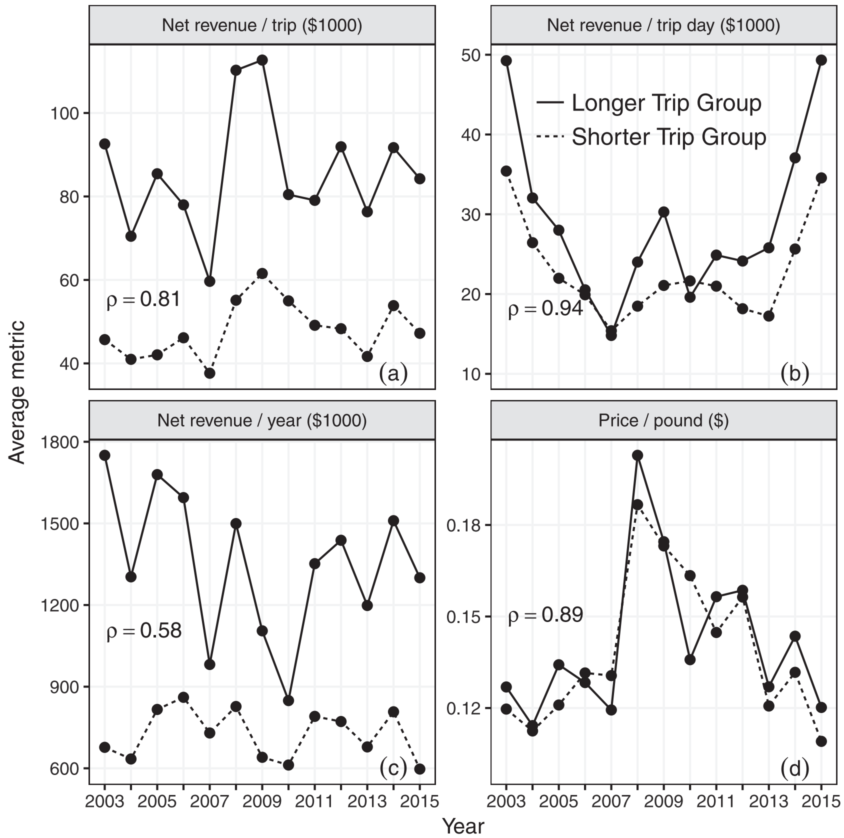
Average catches per trip were relatively stable over time (Fig. 4*a*) but average net revenues varied more (Fig. 5*a*). The strongest relationship between a fishery landscape variable and net revenues per trip was with TAC, likely reflecting some inverse relationship between TAC (i.e., supply) and ex-vessel price. Prices (shown for each group in Fig. 5*d*) were strongly related to TAC (Table 4) and net revenues per trip, in turn, were strongly related to ex-vessel price ($\rho = 0.76$ and 0.81 for the Shorter Trip Group and Longer Trip Group, respectively), which, by extension, links net revenues per trip to TAC. The covariance between vessel groups for net revenues per trip was relatively high, indicating that while vessel fishing strategies were different, they were similar relative to ex-vessel prices and they were similarly adaptive.

The annual-level (summer B-season only) average net revenues were not strongly related to any of the fishing outcomes. Average annual net revenues were much more variable across years for the Longer Trip Group (Fig. 5*c*), 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 S3), suggesting that adaptations in fishing strategies reduced revenue variability. When net revenues were standardized by the trip duration (i.e., net revenues per trip day; Fig. 5*b*), the covariance between groups was strikingly high ($\rho = 0.94$), and the relationships with temperature, average trip distance, and (to a lesser degree) abundance were strong (Table 4). While the Longer Trip Group yielded approximately double the net revenues per trip in some years (Fig. 5*a*), the greater travel times associated with those increased revenues led to similar net revenues rates (net revenues per trip-day) between the two vessel groups.

Vessels in the Longer Trip Group were typically larger (median = 38.8 m) than in the Shorter Trip 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 (Table S1). There were several years (2006, 2012–2013, and 2015) during which the Shorter Trip Group spent proportionally more on fuel due in part to their disproportionately lower CPUE (Fig. 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 Shorter Trip 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 Shorter Trip Group (Table S1).

Fish size varied by fishing location, impacting ex-vessel price and the products that can be made. We omitted fish size from Table 4 because the complicated lagged relationships between fish size and fish abundance confound correlations across years. Regressions of pollock size versus trip distance within each year illustrate their negative relationship and the higher average mass of fish during years with lower pollock biomass (Fig. S3). Shorter Trip Group vessels that primarily targeted fish for fillet production caught larger fish, a 240 g average difference in mean annual fish mass, with the largest fish typically caught nearer to port. When vessels traveled farther, they had higher catch rates but smaller fish. The Longer Trip Group also demonstrated more variable fish sizes than the Shorter Trip Group (Table S1). 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.

Fig. 5. Average annual (summer B-season only) economic performance for the Shorter Trip Group vessels (solid lines) and Longer Trip Group vessels (broken lines) groups. Rho (ρ) values indicate Pearson correlations between the groups.



Discussion

When pollock were abundant and water was warm, vessels across the shoreside catcher vessel fleet behaved similarly. In contrast, when abundance declined or temperature cooled, the fleet fractured into two groups of vessels exhibiting distinct spatial behaviors to best sustain their catches. These different responses of vessels to the changing fishery landscape helped vessels to buffer against lower and more variable annual net revenues.

Fisher responses were related to the processors to which vessels delivered fish. Processors more focused on surimi were associated with the Longer Trip Group vessels, which consisted of larger vessels that carry more fish and can thus be profitable on longer trips with greater fuel costs. The focus on surimi production for these vessels is also associated with smaller fish and longer delivery windows, which provide greater flexibility to search for pollock. The ability to target more productive fishing grounds with higher catch rates also reduces costs for these large vessels because more fuel is consumed during fishing than transiting (i.e., traveling farther for shorter tows may save fuel). Meanwhile, the Shorter Trip Group has maintained relatively stable annual revenues by targeting larger fish closer to port.

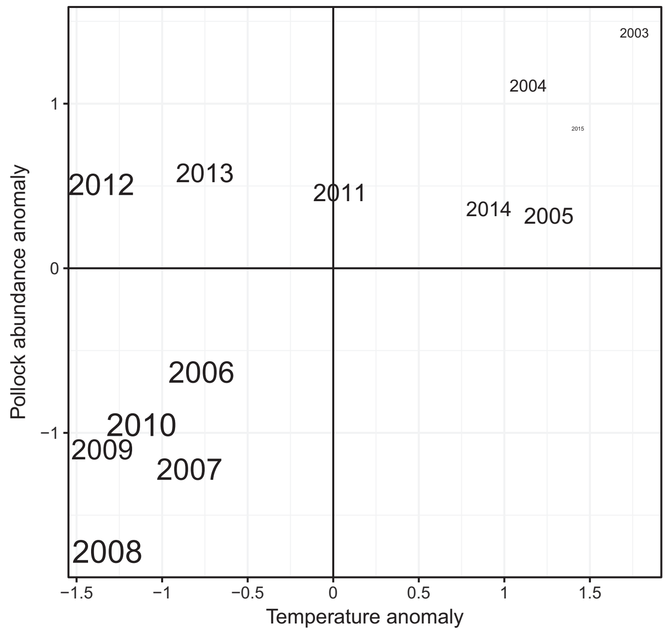
The implications of vessels' resiliency to change are particularly pertinent given that observations and projections of warming in the Bering Sea are associated with recruitment failures of pollock (Mueter et al. 2011) that may motivate changes in management (Ianelli et al. 2011) and impact pollock prices (e.g., Criddle et al. 1998; Seung and Ianelli 2016). We did not observe the climate-associated northward shift of fishers observed elsewhere (e.g., Pinsky and Fogarty 2012). Rather, some pollock vessels traveled farther north during colder years, illustrating complex interactions between markets and the unique environment of the Bering Sea.

Our findings have strong implications for how vessels may respond to future trends and variation 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 opportunity to resolve the dynamics of other fisheries amidst a changing fishery landscape.

Fishing location and the fishery landscape

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 (ρ = 0.94) than during the full time series (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 driven by 2005, where trip distances and temperature were less aligned (as also illustrated by model fits for the full time series in Fig. 3). The divergence of the distance–abundance relationship for the full time series thus occurs from 2012 to 2015, when average distances declined but abundance was relatively stable. During these years, the continued decline in trip distance was mirrored by increases in temperature (Figs. 1, 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 impacted by the temperature-mediated movements of fish and (2) temperature and abundance are tightly coupled drivers of fisher behavior that are difficult to disentangle. Extreme and lagged fluctuations in water temperatures and pollock year

Fig. 6. Illustration of the relationship between temperature and walleye pollock (*Gadus chalcogrammus*) abundance anomalies in each year shown by the labels. Label sizes are proportional to the median trip distance in each year, with larger labels representing longer median distances. Separate figures for each vessel group were similar.



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.

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 to 2005 were associated with very low juvenile pollock survival. These low-survival years led to missing year classes in the fishery during the cold years that followed (Coyle et al. 2011; Mueter et al. 2011). While our models examine only contemporaneous relationships, present conditions are the result 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 to 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 Shorter Trip Group vessels. With time, the decline of large pollock may also affect recruitment, impacting the entire fleet.

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 (Fig. 6, bottom right quadrant). The fishery has not yet experienced both a fishable 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. This was 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 Fig. 6.

Fishing outcomes across vessel groups and years

Despite both vessel groups maintaining relatively stable catches per trip (Fig. 4), the Longer Trip Group had higher but more variable annual revenues, while the Shorter Trip Group had lower but more stable average revenues. While there was little covariation between the two groups during the summer season in this period, net revenues of both groups varied substantially, with average variation in vessel-level annual revenues of 50% and 33% for the Longer Trip Group and Shorter Trip Group vessels, respectively (Fig. 5*c*). Notably, if 2003, 2004, and 2015 (i.e., the years with the shortest travel distances) were omitted from analysis, the covariation between the annual net revenue for the two groups would increase from $\rho = 0.58$ to $\rho = 0.89$. The impact of these years results from the drastically lower fuel to earnings ratio for the Longer Trip Group during warm, high-abundance years. When the Longer Trip Group does not travel farther, their ability to carry more fish shifts the proportions of their earnings and variable costs.

Annual net revenues were not strongly correlated with any single component of the fishery landscape or average trip distances (Table 4). Given that expected net revenues are a function of (Price × Catch) – Cost, the relationships of each component of this equation with the fishery landscape drive both net revenues and their variability (Table 4; Table S3) and vessels are choosing locations to balance these factors based on their size and product orientation. 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 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 seek to maximize expected profit, which is estimated by examining how vessels trade-off expected revenues 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 different decisions about spatial trade-offs 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 h 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. Our analysis points to the importance of including these complexities in future models of fisher behavior. Future work could also benefit from more precise, trip-level price data that could better explain the revenue from each trip.

Implications

Multiple strategies were prosecuted simultaneously within the shoreside pollock fishery, demonstrating the importance of factoring intrafleet and interannual 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, which may have implications for spatially explicit quota allocation and bycatch avoidance measures or for stock assessments that use fishery-dependent data.

Understanding fleet strategies is important for current management challenges such as salmon bycatch in the pollock fishery. Early versions of our models (not shown) explored the impacts of Chinook salmon (*Oncorhynchus tshawytscha*) bycatch on fisher spatial behaviors and found no significant relationships. However, it is worth noting that even if bycatch avoidance yielded spatial decisions on the scale of tens instead of hundreds of miles (and thus were not detectable by our approach), policy decisions related to bycatch avoidance may still play important roles in behaviors (Abbott et al. 2015; Reimer et al. 2017). The pollock fleet is constrained by vessel-level hard caps of Chinook salmon bycatch and there are rolling hotspot closures for Chinook and chum salmon (*Oncorhynchus keta*) bycatch (Ianelli and Stram 2015; Stram and Ianelli 2015) in addition to previous spatial restrictions. If pollock and salmon populations overlapped spatially more during warm years when the pollock fleet was more concentrated, we may expect greater impacts on both salmon stocks and the entire pollock fleet than if more overlap between salmon and pollock populations occurred in colder years, when the Shorter Trip Group and Longer Trip Group 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 (Haynie and Pfeiffer 2013; Pinsky and Mantua 2014). However, for fisheries with a high degree of specialization and automated processing, adaptation may 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 tonnes 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. Multiyear contracts stabilize revenue, but they also create an inertia that limits processors from switching to production that is optimized for the most readily available size of fish (Strong and Criddle 2014). Instead, adapting to changes in the fishery landscape may fall to those involved in the catching of fish rather than the processing of fish. 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. AFA vessels are not allowed to transfer quota between sectors (e.g., from the shoreside fleet to at-sea catcher processors), so if vessels that are more constrained in their ability to adapt (e.g., Shorter Trip Group vessels) are unable to catch all of their quota (as occurred in 2007 and 2011), some yield may be foregone (Criddle and Strong 2013). Alternatively, vessels may pursue longer seasons, in-sector leasing of quota, or other options for adaptation. Prices in the low-abundance years were some of the highest ever, and projections suggest that declines in abundance may be partially offset through increased prices (Strong and Criddle 2014; Seung and Ianelli 2016). However, the degree to which such price changes will affect vessels throughout fleets will depend upon the heterogeneities of vessel behaviors and markets.

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 of 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 fleets.

A key challenge in the development of integrated ecosystem assessments (e.g., Levin et al. 2009; DePiper et al. 2017) is identifying social and economic (i.e., human dimension) indicators of the impacts of a changing ecosystem on fisheries and processors. A range of metrics are available for both catch share (Brinson and Thunberg 2016) and noncatch share fisheries (Brinson et al. 2015). In our case, using catch, revenue, and VMS data, we are able to examine how a range of indices vary (Figs. 4 and 5). Importantly, the differences among these indices reveal several key lessons. First, as noted, vessels and processors have different strategies for adjusting their behavior, and this is reflected in the fishery outcomes. Second, indicators vary significantly among one another. When developing and utilizing these indicators, there is not a "one-size-fits-all" indicator and analysts must carefully consider what social and economic factors they are measuring and whether average values adequately capture human experiences. Future work should better examine how suites of indices best reflect long-term changes in fishing conditions.

Acknowledgements

Funding was from NOAA's Office of Fisheries Science and Technology through the Spatial Economics Toolbox for Fisheries (FishSET) Project, the North Pacific Research Board's Bering Sea Integrated Ecosystem Research Program, Alaska Sea Grant College Program R/112-04. K, and Pacific States Marine Fisheries Commission. K. Coutre, K. Criddle, C. Cunningham, K. Fenske, J. Gauvin, S. Kasperski, F. Mueter, M. Sigler, P. Sullivan, R. Suryan, E. Ward, and many pollock vessel captains, crew, and other industry professionals provided valuable contributions to the evolution of this project. Thanks for data from R. Lauth, AKFIN, and NOAA's Office of Law Enforcement. The findings and conclusions in the paper are those of the author(s) and do not necessarily represent the views of the National Marine Fisheries Service.

References

Abbott, J.K., Haynie, A.C., and Reimer, M.N. 2015. Hidden flexibility: institutions, incentives, and the margins of selectivity in fishing. Land Econ. **91**: 169–195. doi:10.3368/le.91.1.169.

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

Alaska Fisheries Science Center (AFSC). 2016. North Pacific (NORPAC) groundfish and halibut observer data dictionary December. 2007 – present. Metadata and access details available at https://inport.nmfs.noaa.gov/inport/item/7290.

Anderson, S.C., Ward, E.J., Shelton, A.O., Adkison, M.D., Beaudreau, A.H., Brenner, R.E., Haynie, A.C., Shriver, J.C., Watson, J.T., and Williams, B.C. 2017. Benefits and risks of diversification for individual fishers. Proc. Natl. Acad. Sci. U.S.A. **114**: 10797–10802. doi:10.1073/pnas.1702506114.

Bacheler, N.M., Ciannelli, L., Bailey, K.M., and Bartolino, V. 2012. Do walleye pollock exhibit flexibility in where or when they spawn based on variability in water temperature? Deep Sea Res. Part II Top. Stud. Oceanogr. **65–70**: 208–216. doi:10.1016/j.dsr2.2012.02.001.

Brinson, A.A., and Thunberg, E.M. 2016. Performance of federally managed catch share fisheries in the United States. Fish. Res. **179**: 213–223. doi:10.1016/j.fishres.2016.03.008.

Brinson, A.A., Thunberg, E.M., and Farrow, K. 2015. The economic performance of U.S. non-catch share programs. U.S. Dep. of Commer., NOAA Tech. Memo. NMFS-F/SPO-150.

Cheung, W.W.L., Lam, V.W.Y., Sarmiento, J.L., Kearney, K., Watson, R., Zeller, D., and Pauly, D. 2010. Large-scale redistribution of maximum fisheries catch potential in the global ocean under climate change. Global Change Biol. **16**: 24–35. doi:10.1111/j.1365-2486.2009.01995.x.

Coyle, K.O., Eisner, L.B., Mueter, F.J., Pinchuk, A.I., Janout, M.A., Cieciel, K.D., Farley, E.V., and Andrews, A.G. 2011. Climate change in the southeastern Bering Sea: impacts on pollock stocks and implications for the oscillating control hypothesis. Fish. Oceanogr. **20**: 139–156. doi:10.1111/j.1365-2419.2011.00574.x.

Criddle, K.R., and Macinko, S. 2000. A requiem for the IFQ in US fisheries? Mar. Pol. **24**: 461–469. doi:10.1016/S0308-597X(00)00025-7.

Criddle, K.R., and Strong, J. 2013. Dysfunction by design: the effects of limitations on transferability of catch shares in the Alaska pollock fishery. Mar. Pol. **40**: 91–99.

Criddle, K.R., Herrmann, M., Greenberg, J.A., and Feller, E.M. 1998. Climate fluctuation and revenue maximization in the eastern Bering Sea fishery for walleye pollock. N. Am. J. Fish. Manage. **18**: 1–10. doi:10.1577/1548-8675(1998)018<0001:CFARMI>2.0.CO;2.

DePiper, G.S., Gaichas, S.K., Lucey, S.M., Pinto da Silva, P., Anderson, M.R., Breeze, H., et al. 2017. Operationalizing integrated ecosystem assessments within a multidisciplinary team: lessons learned from a worked example. ICES J. Mar. Sci. **74**(8): 2076–2086. doi:10.1093/icesjms/fsx038.

Eales, J., and Wilen, J.E. 1986. An examination of fishing location choice in the pink shrimp fishery. Mar. Res. Econ. **2**(4): 331–351. doi:10.1086/mre.2.4.42628909.

Fell, H. 2008. Rights-based management and Alaska pollock processors' supply. Am. J Agric. Econ. **90**(3): 579–592.

Felthoven, R.G. 2002. Effects of the American Fisheries Act on capacity, utilization and technical efficiency. Mar. Res. Econ. **17**(3): 181–205. doi:10.1086/mre.17.3.42629363.

Fissel, B., Dalton, M., Felthoven, R., Garber-Yonts, B., Haynie, A.C., et al. 2015. Stock assessment and fishery evaluation report for the groundfish fisheries of the Gulf of Alaska and Bering Sea/Aleutian Islands area: economic status of the groundfish fisheries off Alaska. *Edited by* N.P.F.M. Council, Anchorage, Alaska.

Fox, J., and Monette, G. 1992. Generalized collinearity diagnostics. J. Am. Stat. Assoc. **87**: 178–183. doi:10.1080/01621459.1992.10475190.

Fox, J., Weisberg, S., Adler, D., Bates, D., Baud-Bovy, G., Ellison, S., and Heiberger, R. 2012. Package 'car'. R Foundation for Statistical Computing, Vienna, Austria.

Haynie, A.C., and Huntington, H.P. 2016. Strong connections, loose coupling: the influence of the Bering Sea ecosystem on commercial fisheries and subsistence harvests in Alaska. Ecol. Soc. **21**(4): 6. doi:10.5751/ES-08729-210406.

Haynie, A.C., and Layton, D.F. 2010. An expected profit model for monetizing fishing location choices. J. Environ. Econ. Manage. **59**(2): 165–176. doi:10.1016/j.jeem.2009.11.001.

Haynie, A.C., and Pfeiffer, L. 2013. Climatic and economic drivers of the Bering Sea walleye pollock (*Theragra chalcogramma*) fishery: implications for the future. Can. J. Fish. Aquat. Fish. Sci. **70**(6): 841–853. doi:10.1139/cjfas-2012-0265.

Herrmann, M., Criddle, K.R., Feller, E.M., and Greenberg, J.A. 1996. Estimated economic impacts of potential policy changes affecting the total allowable catch for walleye pollock. N. Am. J. Fish. Manage. **16**: 770–782. doi:10.1577/1548-8675(1996)016<0770:EEIOPP>2.3.CO;2.

Holland, D.S., and Sutinen, J.G. 2000. Location choice in New England trawl fisheries: old habits die hard. Land Econ. **76**(1): 133–149. doi:10.2307/3147262.

Hollowed, A.B., and Sundby, S. 2014. Change is coming to the northern oceans. Science, **344**(6188): 1084–1085. doi:10.1126/science.1251166. PMID:24904138.

Holsman, K.K., Ianelli, J., Aydin, K., Punt, A.E., and Moffitt, E.A. 2016. A comparison of fisheries biological reference points estimated from temperature-specific multi-species and single-species climate-enhanced stock assessment models. Deep Sea Res. Part II Top. Stud. Oceanogr. **134**: 360–378. doi:10.1016/j.dsr2.2015.08.001.

Ianelli, J.N., and Stram, D.L. 2015. Estimating impacts of the pollock fishery bycatch on western Chinook salmon. ICES J. Mar. Sci. **72**(4): 1159–1172. doi:10.1093/icesjms/fsu173.

Ianelli, J.N., Hollowed, A.B., Haynie, A.C., Mueter, F.J., and Bond, N.A. 2011. Evaluating management strategies for eastern Bering Sea walleye pollock (*Theragra chalcogramma*) in a changing environment. ICES J. Mar. Sci. **68**(6): 1297–1304. doi:10.1093/icesjms/fsr010.

Ianelli, J.N., Honkalehto, T., Barbeaux, S., Fissel, B., and Kotwicki, S. 2015. Assessment of the walleye pollock stock in the Eastern Bering Sea. *In* Stock assessment and fishery evaluation report for the groundfish resources of the Bering Sea/Aleutian Islands regions for 2015. North Pacific Fishery Management Council, Anchorage, Alaska. pp. 55–180. Available from http://www.afsc.noaa.gov/REFM/Docs/2016/EBSpollock.pdf.

Joo, R., Bertrand, A., Bouchon, M., Chaigneau, A., Demarcq, H., Tam, J., Simier, M., et al. 2014. Ecosystem scenarios shape fishermen spatial behavior. The case of the Peruvian anchovy Fishery in the Northern Humboldt Current System. Prog Oceanogr. **128**: 60–73. doi:10.1016/j.pocean.2014.08.009.

Joo, R., Salcedo, O., Gutierrez, M., Fablet, R., and Bertrand, S. 2015. Defining fishing spatial strategies from VMS data: Insights from the world's largest monospecific fishery. Fish. Res. **164**: 223–230. doi:10.1016/j.fishres.2014.12.004.

Kasperski, S., and Holland, D.S. 2013. Income diversification and risk for fishermen. Proc. Natl. Acad. Sci. U.S.A. **110**(6): 2076–2081. doi:10.1073/pnas.1212278110. PMID:23341621.

Levin, P.S., Fogarty, M.J., Murawski, S.A., and Fluharty, D. 2009. Integrated ecosystem assessments: developing the scientific basis for ecosystem-based management of the ocean. PLoS Biol. **7**(1): e1000014. doi:10.1371/journal.pbio.1000014.

Matulich, S.C., Sever, M., and Inaba, F. 2001. Fishery cooperatives as an alternative to ITQs: implications of the American Fisheries Act. Mar. Res. Econ. **16**(1): 1–16.

McIlgorm, A., Hanna, S., Knapp, G., Le Floc'H, P., Millerd, F., and Pan, M. 2010. How will climate change alter fishery governance? Insights from seven international case studies. Mar. Pol. **34**: 170–177. doi:10.1016/j.marpol.2009.06.004.

Mueter, F.J., Peterman, R.M., and Pyper, B.J. 2002. Opposite effects of ocean temperature on survival rates of 120 stocks of Pacific salmon (*Oncorhynchus* spp.) in northern and southern areas. Can. J. Fish. Aquat. Sci. **59**(3): 456–463. doi:10.1139/f02-020.

Mueter, F.J., Bond, N.A., Ianelli, J.N., and Hollowed, A.B. 2011. Expected declines in recruitment of walleye pollock (*Theragra chalcogramma*) in the eastern Bering Sea under future climate change. ICES J. Mar. Sci. **68**(6): 1284–1296. doi:10.1093/icesjms/fsr022.

Pfeiffer, L., and Haynie, A.C. 2012. The effect of decreasing seasonal sea-ice cover on the winter Bering Sea pollock fishery. ICES J. Mar. Sci. **69**: 1148–1159. doi:10.1093/icesjms/fss097.

Pinsky, M.L., and Fogarty, M. 2012. Lagged social–ecological responses to climate and range shifts in fisheries. Clim. Change, **115**(3–4): 883–891. doi:10.1007/s10584-012-0599-x.

Pinsky, M.L., and Mantua, N.J. 2014. Emerging adaptation approaches for climate ready fisheries management. Oceanography, **27**(4): 146–159. doi:10.5670/oceanog.2014.93.

R Core Team. 2016. R: a language and environment for statistical computing. R Foundation for Statistical Computing. http://www.R-project.org.

Reimer, M.N., Abbott, J.K., and Wilen, J.E. 2017. Fisheries production: management institutions, spatial choice, and the quest for policy invariance. Mar. Res. Econ. **32**(2): 143–168. doi:10.1086/690678.

Richardson, J.T.E. 2011. Eta squared and partial eta squared as measures of effect size in educational research. Educ. Res. Rev. **6**(2): 135–147. doi:10.1016/j.edurev.2010.12.001.

Schindler, D.E., Hilborn, R., Chasco, B., Boatright, C.P., Quinn, T.P., Rogers, L.A., and Webster, M.S. 2010. Population diversity and the portfolio effect in an exploited species. Nature, **465**: 609–612. doi:10.1038/nature09060. PMID:20520713.

Sethi, S.A., Reimer, M., and Knapp, G. 2014. Alaskan fishing community revenues and the stabilizing role of fishing portfolios. Mar. Pol. **48**: 134–141. doi:10.1016/j.marpol.2014.03.027.

Seung, C., and Ianelli, J. 2016. Regional economic impacts of climate change: a computable general equilibrium analysis for an Alaska fishery. Nat. Res. Mod. **29**(2): 289–333. doi:10.1111/nrm.12093.

Sigler, M.F., Napp, J.M., Stabeno, P.J., Heintz, R.A., Lomas, M.W., and Hunt, G.L. 2016. Variation in annual production of copepods, euphausiids, and juvenile walleye pollock in the southeastern Bering Sea. Deep Sea Res. Part II Top. Stud. Oceanogr. **134**: 223–234.

Spalding, K. 2016. NMFS VMS Program Headquarters, 1315 East West Highway, Silver Spring, MD 20910, USA.

Stabeno, P.J., Kachel, N.B., Moore, S.E., Napp, J.M., Sigler, M., Yamaguchi, A., and Zerbini, A.N. 2012. Comparison of warm and cold years on the southeastern Bering Sea shelf and some implications for the ecosystem. Deep Sea Res. Part II Top. Stud. Oceanogr. **65–70**: 31–45. doi:10.1016/j.dsr2.2012.02.020.

Stram, D.L., and Ianelli, J.N. 2015. Evaluating the efficacy of salmon bycatch measures using fishery-dependent data. ICES J. Mar. Sci. **72**(4): 1173–1180. doi:10.1093/icesjms/fsu168.

Strong, J., and Criddle, K.R. 2013. Fishing for pollock in a sea of change: a historical analysis of the Bering Sea pollock fishery. University of Alaska Sea Grant Press, Fairbanks, Alaska.

Strong, J., and Criddle, K.R. 2014. A market model of Eastern Bering Sea Alaska pollock: sensitivity to fluctuations in catch and some consequences of the American Fisheries Act. N. Am. J. Fish. Manage. **34**: 1078–1094. doi:10.1080/02755947.2014.944678.

van Putten, I.E., Kulmala, S., Thébaud, O., Dowling, N., Hamon, K.G., Hutton, T., and Pascoe, S. 2012. Theories and behavioural drivers underlying fleet dynamics models. Fish Fish. **13**(2): 216–235. doi:10.1111/j.1467-2979.2011.00430.x.

Ward, E.J., Anderson, S.C., Shelton, A.O., Brenner, R.E., Adkison, M.D., Beaudreau, A.H., Watson, J.T., Shriver, J.C., Haynie, A.C., and Williams, B.C.

2017. Effects of increased specialization on revenue of Alaskan salmon fishers over four decades. J. Appl. Ecol. doi:10.1111/1365-2664.13058.

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. doi:10.1371/journal.pone.0165173. PMID:27788174.

Wyllie-Echeverria, T., and Wooster, W.S. 1998. Year-to-year variations in Bering Sea ice cover and some consequences for fish distributions. Fish. Oceanogr. **7**(2): 159–170. doi:10.1046/j.1365-2419.1998.00058.x.

Zhang, J., and Smith, M.D. 2011. Heterogeneous response to marine reserve formation: a sorting model approach. Environ. Res. Econ. **49**: 311–325. doi:10.1007/s10640-010-9434-x.