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ARTICLE

Climatic and economic drivers of the Bering Sea walleye pollock (*Theragra chalcogramma*) fishery: implications for the future

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Abstract: This paper illustrates how climate, management, and economic drivers of a fishery interact to affect fishing. Retrospective data from the Bering Sea walleye pollock (*Theragra chalcogramma*) catcher–processer fishery were used to model the impact of climate on spatial and temporal variation in catch and fishing locations and make inferences about harvester behavior in a warmer climate. Models based on Intergovernmental Panel on Climate Change scenarios predict a 40% decrease in sea ice by 2050, resulting in warmer Bering Sea temperatures. We find that differences in the value of catch result in disparate behavior between winter and summer seasons. In winter, warm temperatures and high abundances drive intensive effort early in the season to harvest earlier-maturing roe. In summer, warmer ocean temperatures were associated with lower catch rates and approximately 4% less fishing in the northern fishing grounds, contrary to expectations derived from climate-envelope-type models that suggest fisheries will follow fish poleward. Production-related spatial price differences affected the effort distribution by a similar magnitude. However, warm, low-abundance years have not been historically observed, increasing uncertainty about future fishing conditions. Overall, annual variation in ocean temperatures and economic factors has thus far been more significant than long-term climate change-related shifts in the fishery's distribution of effort.

Résumé : Le présent article illustre comment les interactions du climat, de la gestion et des déterminants économiques d'une pêche influencent l'activité de pêche. Des données rétrospectives sur la pêche au goberge (*Theragra chalcogramma*) au navire-usine de la mer de Behring ont été utilisées pour modéliser l'impact du climat sur les variations spatiales et temporelles des prises et des lieux de pêche, et pour tirer des inférences sur le comportement des exploitants en cas de réchauffement climatique. Des modèles basés sur les scénarios du Groupe d'experts intergouvernemental sur les changements climatiques prédisent une diminution de 40 % de la glace marine d'ici 2050, ce qui entraînera une hausse des températures de la mer de Behring. Nous constatons que des variations de la valeur des prises se traduisent par des comportements différents selon la saison de pêche (hiver ou été). En hiver, des températures chaudes et de fortes abondances suscitent un effort intense au début de la saison afin de récolter les individus issus d'œufs à maturation précoce. En été, des températures océaniques accrues sont associées à des taux de prise plus faibles et à une réduction d'environ 4 % de l'activité de pêche dans les lieux de pêche plus nordiques, contrairement aux prévisions de modèles de type enveloppe climatique qui suggèrent que les pêcheurs suivront les poissons vers les pôles. Les variations spatiales des prix associées à la production ont une incidence semblable, en termes de magnitude, sur la répartition de l'effort. Cependant, le fait que des années plus chaudes de faible abondance n'aient pas encore été observées se traduit par une incertitude accrue concernant les conditions de pêches futures. Dans l'ensemble, les variations annuelles des températures océaniques et des facteurs économiques ont, à ce jour, eu un effet plus important que les changements à la répartition de l'effort de pêche associés aux changements climatiques à long terme. [Traduit par la Rédaction]

Introduction

The economic decision-making process makes predicting the effects of climate change on fisheries more complicated than the already complex task of predicting the effects of climate change on fish populations. In many regions, fish harvesters are important components of ecosystem dynamics. The fishing decisions of harvesters can be effectively modeled as a function of a variety of economic factors, including the spatial distribution of expected catches, fish and fuel prices, travel costs, and variation among fishing vessel capabilities (Bockstael and Opaluch 1983; Eales and Wilen 1986; Smith and Wilen 2003). However, predictions of how fisheries (as opposed to fish stocks) will respond to climate change have not included these economic components and have often come from large-scale models that predict shifts in the climate envelopes of species' ranges and changes in primary productivity (Cheung et al. 2010; Lehodey et al. 2003; Perry et al. 2005). This has led to predictions of fisheries following fish abundances toward the poles and potential increases in revenue due to higher productivity in high latitude regions.

Cheung et al. (2010) argue that global-scale projections of the effects of climate change on fisheries are useful for developing policy scenarios and contributing to assessments of marine-related socioeconomic issues. We argue, however, that the economic drivers of a fishery, as well as the management structure, are complex, vary on a local level, and are impacted by climate factors in many ways. Thus, when predicting how climate will affect a fishery, it is vital to consider the characteristics of the ocean dynamics, region, species, harvesting fleet, and management structure that are unique to particular fisheries. These characteristics determine the nature of interactions between harvesters and their target species. Ignoring or

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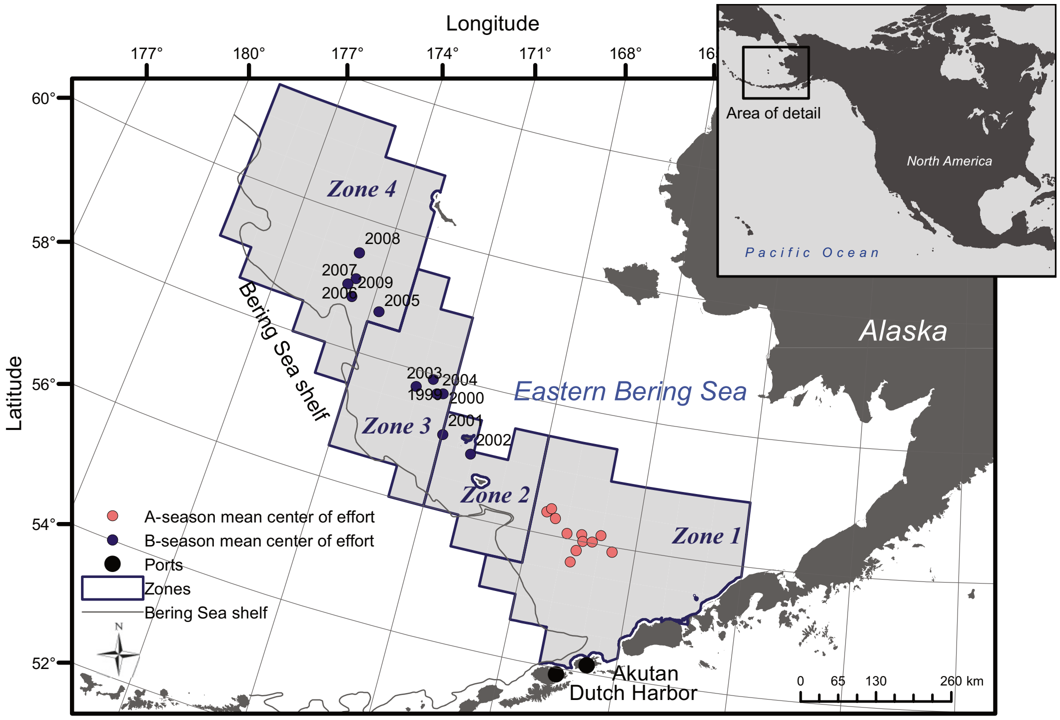
Fig. 1. The Eastern Bering Sea and the fishing areas of the catcher–processor fleet. Points represent the catch-weighted mean center of the distribution of fishing hauls by season. The borders of zones 1 through 4, which are referred to in the text, are shown.



abstracting from these details, as a global-scale model must do, may lead to inaccurate predictions of fishery adaptation.

In this paper, we explore the changes that have occurred in the timing and location of the catcher–processor sector of the Bering Sea (Alaska) walleye pollock (*Theragra chalcogramma*) fishery over 1999–2009, a period in which there has been considerable variation in ice cover, temperature, and total walleye pollock abundance. Polar and subpolar ecosystems are expected to continue to experience changes in seasonal sea ice cover and ocean properties because of climate change (Grebmeier et al. 2006; Overpeck et al. 1997). Analysis of fishing behavior during past warm climate regimes may be informative for predicting future fishing patterns in the walleye pollock fishery, as climate change is expected to decrease the extent of winter ice cover and increase the frequency of years characterized by warmer ocean conditions. For commercial walleye pollock harvesters, climate change may lead to vessels traveling farther and incurring greater fuel costs and a greater burden being placed on small vessels that are unable to travel as far. It may affect the abundance of fishable biomass and thus total allowable catches (TACs) and fishery revenue (Criddle et al. 1998; Ianelli et al. 2011*b*). Climate change may have implications for the complex marine ecosystem of the Bering Sea, of which walleye pollock is an integral part (Hunt et al. 2002; Springer 1992).

The premise of this paper is that the investigation of the mechanisms driving fish harvester behavior is essential to understanding patterns and changes in the distribution of fishing. A summary of the changes in the spatial distribution of the pollock catcher–processor fishery is useful for setting up the analyses. Since 1999, there has been a substantial shift in the distribution of fishing toward the northern reaches of the Bering Sea shelf off the coast of Alaska (Fig. 1), which at first glance corroborates predictions from climate envelope models. The mean center of the distribution of winter season fishing has remained stable, while the distribution of summer season fishing is centered much farther to the north in 2005–2009 than in 1999–2004. This change resulted from a shift in summer season effort. Effort in the most southern regions of the fishing grounds (zone 1 shown in Fig. 1) fell to nearly zero after 2005, while fishing in the northernmost region (zone 4 shown in Fig. 1) expanded (Fig. 2*b*). Fishing in the winter season underwent no such marked redistribution (Fig. 2*a*).

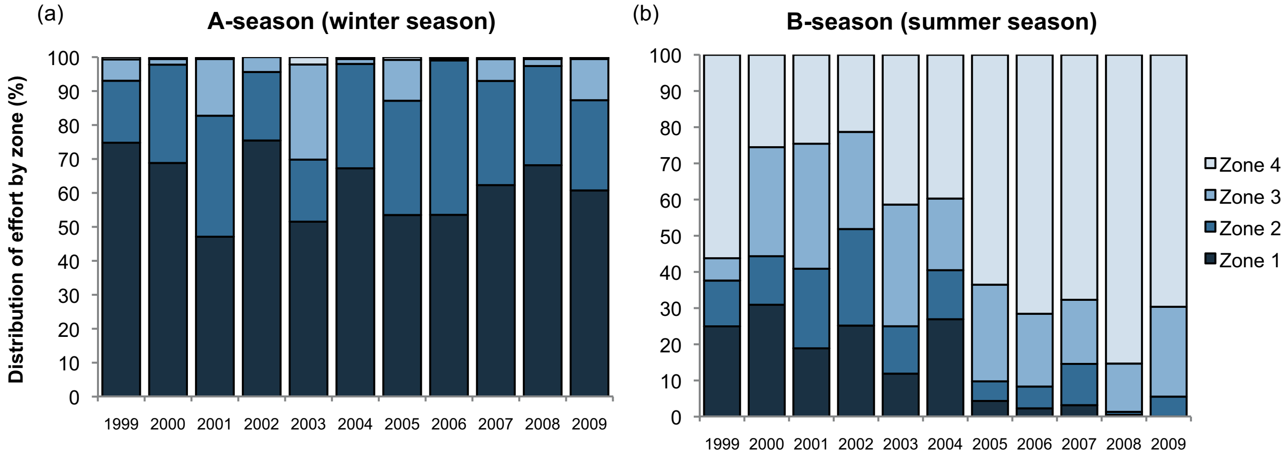
In this paper, we investigate the driving factors that have accompanied these changes, and whether they are related to climate variation. The "Background" section provides a description of the fishery and its characteristics. We then introduce a simple structural diagram that illustrates how climate may affect harvesters' decisions about when and where to fish and use it to guide our analysis. We find that while climate factors have had a role in the changes in the distribution of effort, these changes are inconsistent with the "northward march" prediction of climate envelope models for this particular fishery, because the northward shift occurred in the coldest years of the time period and was driven by oceanographic patterns and market conditions. We also look at the effect of climate and fishing location on the average distance traveled and distance-per-tonne of catch in a trip, proxies for travel costs. Finally, we investigate whether predictions can be made from the observed data about the future course of the timing and spatial distribution of the walleye pollock fishery as winter ice cover is reduced and the Bering Sea warms. This study integrates climatic, biological, economic, and institutional characteristics of an economically important fishery to empirically investigate the drivers of change in the fishery.

Materials and methods

Background

The Bering Sea walleye pollock fishery is the largest commercial fishery in the United States and has an annual product value of over $1 billion (Hiatt et al. 2011). The TAC of Bering Sea walleye pollock is split among several fishing sectors; our focus is on the offshore catcher–processor sector. The catcher–processor sector of the fishery consists of 16 large midwater–pelagic trawling vessels that catch approximately 50% of the annual Bering Sea walleye pollock TAC. The American Fisheries Act ended a seasonal race for fish in the fishery by allowing the formation of coopera-

Fig. 2. Change in the distribution of fishing effort by season and zone, 1999–2009. The location of the zones is displayed in Fig. 1.



tives and allocation of quota to individual vessels beginning in 1999. This transition to "catch share" management changed fishing dramatically as vessels went from catching as large a share of the common pool TAC as possible to maximizing the value of each fish caught as part of the vessels allocated share of TAC (Felthoven 2002; Wilen and Richardson 2008). Product recovery rates (the proportion of a fish that is processed into marketable products) increased and vessels slowed processing to a rate that optimized the flow of fish through the vessels' factories.

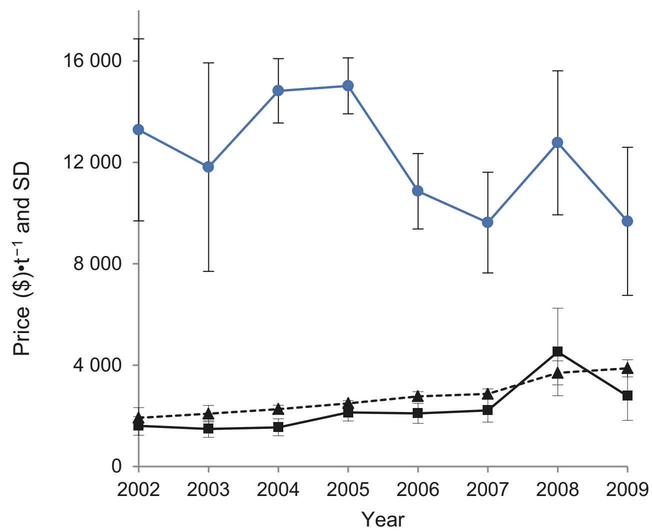
The walleye pollock fishery consists of two seasons: the A-season (winter season) begins on 20 January and the B-season (summer season) begins on 10 June. During the A-season, vessels target roe-bearing fish that have aggregated to spawn. The abundance and quality of roe varies spatially and generally decreases in value as the season advances and the roe becomes over-mature. The highest value roe occurs 3–4 weeks prior to spawning. Walleye pollock spawning in the Bering Sea has a seasonal spatial pattern, with the earliest spawning commencing in February (Bacheler et al. 2010; Ciannelli et al. 2007; Francis and Bailey 1983). Vessels follow the maturing roe such that roe is produced over the entire A-season. Roe is a high-value product in the Japanese consumer market and may sell for over \$20 000·t^{-1} for extremely high-quality lots; prices from 2003 to 2009 averaged \$12 000·t^{-1}. After roe is removed, the remainder of the fish is processed into other products. Depending on prices, roe can be a 50%–200% "bonus" on A-season fishing. The value of roe relative to other products has decreased over the time period considered (Fig. 3). On average, 50% of A-season revenue comes from roe, and total revenue per metric tonne of TAC is nearly 50% higher in the A-season.

In the B-season, schools of fish disperse along the outer Bering Sea shelf, where they feed and gain mass throughout the season. Surimi (an intermediate fish paste product used for imitation crab and other products) and fillets of different sizes and qualities are produced in the B-season and on average comprise 35% and 49% of seasonal revenue, respectively. Roe is encountered only in small quantities in B-season.

Data

The distribution of fishing is derived from haul-level data from the NOAA Fisheries' Alaska Fisheries Science Center's North Pacific Groundfish Observer Program. Information on the time, haul duration, exact location, species composition, and total tonnage of each haul is recorded by an onboard government-trained observer. Because the focus of this paper is the impact of climate on fishing behavior, we excluded fishery data before the incentive structure was transformed by the change to cooperative management in the fishery in 1999.

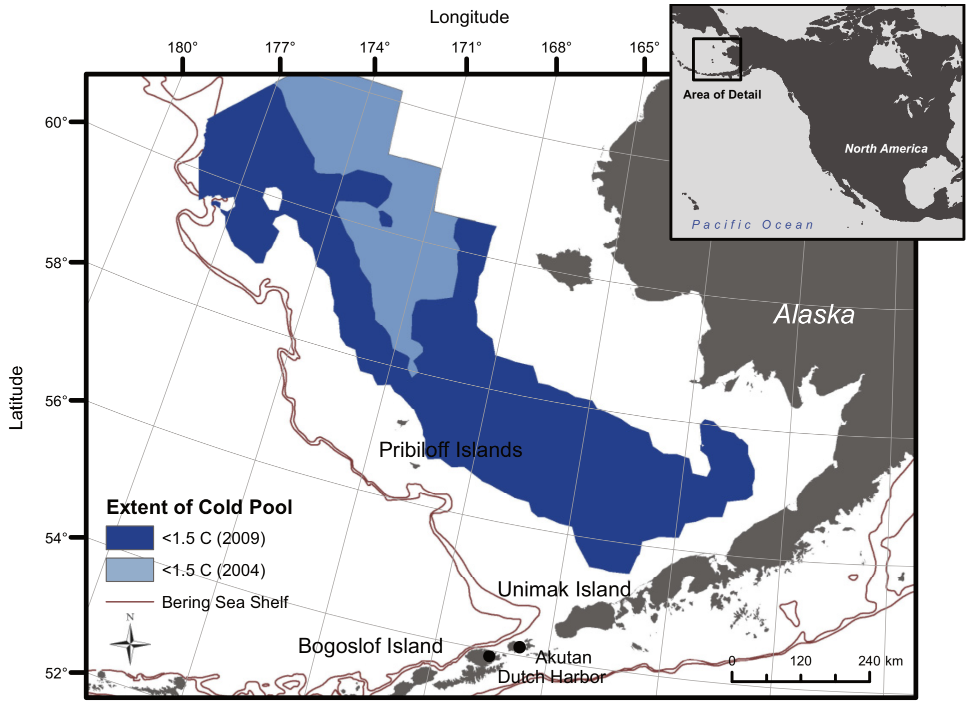
Fig. 3. Average annual prices for walleye pollock roe (circles), surimi (squares), and fillet (triangles). Standard deviations (SDs) shown are the SDs across vessels of the vessel-level average prices.



Fishery-independent data derived from an annual bottom trawl survey of the Eastern Bering Sea (conducted by the Alaska Fisheries Science Center groundfish stock assessment program in June and July; RACE 2011) is used as a basic measure of the productivity of a fishing location or expected catch per unit effort (CPUE). The survey timing corresponds with the beginning of the summer fishing season. The survey data were trimmed to the fishing area shown in Fig. 1, resulting in a dataset of approximately 200 sampled areas per year, weighted by sampling density, from 1990 through 2009. This longer time series is used for the analysis of empirical relationships among biological factors. CPUE by species (in t·ha^{-1} trawled) is measured at each survey station, allowing the construction of mean CPUE by spatial zone (Fig. 1).

Fishery-dependent CPUE was not used in this analysis to represent expected catch for a variety of reasons. First, it is contingent upon harvesters' decisions to fish in an area and could result in no observations of CPUE in areas when little fishing occurred. In the catcher–processor fleet, there exists the additional complication of the production process. Vessels do not necessarily maximize CPUE; according to interviews with vessel operators, vessels fish along the edge of walleye pollock aggregations to catch a large but manageable volume of fish. This optimizes flow through the fac-

Fig. 4. The extent of the cold pool in 2004 (a warm year) and 2009 (a cold year), as measured by the annual summer bottom trawl survey of the Eastern Bering Sea.



tory, which prioritizes constant catch rates. The resulting CPUE may be "hyper-stable", showing little variation in periods or areas of high and low abundance (Hilborn and Walters 1992). Finally, vessels have consistently heterogeneous average levels of CPUE, even for a given level of abundance because of their horsepower or net size or their ability to travel to the best fishing areas, necessitating standardization (Maunder and Punt 2004).

Total abundance of walleye pollock from 1990 to 2009 is obtained from estimates of the age 3+ (fishable) biomass in the Eastern Bering Sea modeled and estimated for the annual stock assessment process using data from the annual bottom trawl survey and a semi-annual acoustic survey (Ianelli et al. 2011*a*).

Prices were obtained from the Alaska Department of Fish and Game's Commercial Operator's Annual Report. Prices are annual, vessel-specific averages of prices received for each product type sold in that year, from 2002 to 2009. Weekly production data that include the amount of each product type produced are from NOAA Fisheries' Alaska Region. Vessel-level price data are very limited prior to 2002, so in analyses that include prices, parameters are checked for robustness to inclusion of the years prior to 2002. Analyses that do not include prices are checked for robustness to the exclusion of the years prior to 2002.

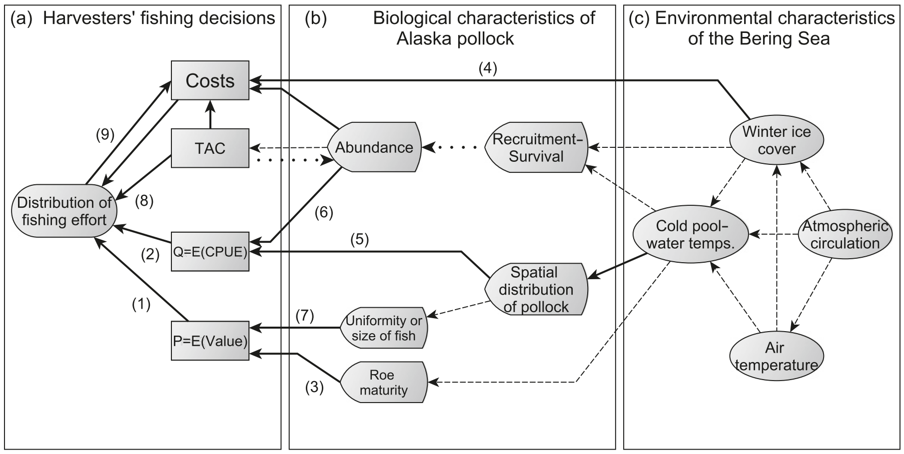
Winter conditions such as temperature, ice cover, and prevailing wind drive the characteristics of the ecosystem and persist through much of the year. The Bering Sea is partially ice-covered from December through April, and the extent of this sea ice impacts ocean conditions for the rest of the year. How far the sea ice extends into lower latitudes is determined by atmospheric temperatures and wind generated by the Aleutian Low Pressure System (Overland and Pease 1982). During the spring, the upper portion of the water column is warmed as air temperatures and solar insulation increase, but cold water remains at depth, creating a pool of arctic water, called the cold pool. Walleye pollock are a subarctic, pelagic species that generally avoid the cold pool (Kotwicki et al. 2005; Wyllie-Echeverria and Wooster 1998). The cold pool persists into the warm season; its size and persistence is determined by the extent of the winter ice cover (Grebmeier et al. 2006). Cold-year regimes are characterized by a very large cold pool that extends southward into the inner shelf toward the Alaska Peninsula, while in warm years the cold pool is much smaller (Fig. 4). The years 1999 and 2007–2009 were exceptionally cold years, while 2002–2005 were warm years in the Bering Sea. The size of the cold pool is measured as the percentage of the bottom trawl survey area <1.5 °C (as recorded by the annual bottom trawl survey). An ice cover index, which is the annual normalized anomaly from the average ice concentration for January–May, is obtained from the NOAA Bering Climate Project. Monthly average sea surface temperatures for the Bering Sea were obtained from the NOAA National Climate Data Center (NOAA 2012).

Methods

An illustrative diagram of the environmental, biological, and economic mechanisms through which climate may affect the distribution of walleye pollock fishing effort is provided (Fig. 5, derived from a more detailed figure in Haynie and Pfeiffer 2012). The arrows represent the direction of causality, and the solid lines represent mechanisms that are investigated in this paper. Each numbered link is referred to in the text. Dashed lines represent mechanisms that we make no attempt to model explicitly, either because they are environmental or biological mechanisms or because the available data are insufficient to test them. Dotted lines represent mechanisms that are likely to occur noncontemporaneously or have both year-of and lagged effects. For example, TAC may affect total abundance through both the contemporaneous removal of fish from the ecosystem and through its effects on recruitment, which may take several years to impact abundance. We do not attempt to model the lagged effects here.

A simple model of the harvesters' fishing location choice decision involves a harvester choosing an area to fish that will maximize the profit from fishing (Fig. 5*a*). This model is useful for focusing attention on how climate may directly impact the factors that influence how walleye pollock harvesters make decisions about when and where to fish by considering the characteristics

Fig. 5. Structural diagram of the effects of environmental characteristics on the distribution of fishing effort. The arrows represent the direction of causality, and the solid numbered lines represent mechanisms that are investigated in this paper. Dashed and dotted lines represent mechanisms that we do not model explicitly, either because they are environmental or biological mechanisms or because the available data are insufficient to test them. Dotted lines represent mechanisms that are likely to occur noncontemporaneously.



of potential choices, such as the quantity and value of fish they expect to catch and the cost of traveling to different areas.

Consider a harvester i who makes a choice between fishing locations j, $j = 1, \ldots, J$. The harvester will receive revenues from the quantity caught and the price received for the catch from the chosen location. The harvester must incur the cost per kilometre (costs) of traveling to the chosen location, which is distance D_j from port. All costs that vary by location choice are assumed to be captured in the costs parameter. The harvester's expected profit from fishing in location j is $E(\text{Profit}_{ijt}) = E(Q_{ijt}) \cdot E(\text{Price}_{ijt}) - \text{costs} \cdot D_{ijt}$, where $E(.)$ is the expectations operator, Q_j is the quantity of catch in location j, which is a function of the CPUE at location j, and Price_j is the unit value of fish caught in j that can implicitly incorporate the price of subproducts if production is spatially variable. In a fishery with catch shares such as the walleye pollock fishery, a harvester is constrained by his or her individual allocation of TAC. Thus, a harvester must choose a location to fish in each time period $t = 1,\ldots, T$, where T is the end of the season, to maximize expected total profit subject to the constraint that the total quantity of fish caught must be no greater than the vessel's share of the TAC, or $\sum_{t=1}^{T} Q_{it} \leq \text{TAC}_i$. A harvester will choose location j in time period t if the expected profit from j (expected revenues minus travel costs) is greater than that from all other alternative locations. All other things being equal, a harvester is less likely to travel to a more distant location because of greater travel costs (which could include fuel, the time cost of travel, or safety). However, an increase in $E(Q_j)$ and (or) $E(\text{Price}_j)$ would increase the probability of traveling to location j to fish, all other things being equal.

The manner in which vessels trade off these factors is complicated and variable across vessels and among years. The effect of TAC on distance traveled is ambiguous, because it constrains fishing (a vessel's TAC must be fished within the season) but is often correlated with abundance (because it is generally based on stock surveys and abundance projections), which may affect CPUE. We exploit several characteristics of the walleye pollock fishery to separately identify the effects of TAC from the effect of abundance through CPUE. In this fishery, individually allocated TAC is aggregated between vessels owned by the same company. If TAC is low, a company may choose to not fish one or several of its vessels. In addition, in the Bering Sea there is a 2 million t "ecosystem cap" that has constrained walleye pollock TAC to 1.5 million t to allow fishing for other species even when abundance would allow for a higher TAC. This results in variation of vessel-level TAC that is not completely correlated with variation in total abundance. Thus, an increase in TAC, holding other factors equal, makes $E(Q_j)$ more important relative to $E(\text{Price}_j)$ and travel costs because a harvester will be more constrained by season length. Any compensatory effect of $E(Q_j)$ increases can be captured through the effect of total abundance. TAC may be related to prices if the change in TAC is large enough to affect world prices (Herrmann et al. 1996). The sector supplies about 3% of the global whitefish fillet market but as much as 28% of the surimi market, so aggregate quantity changes could have some impact on the supply (FAO 2009), but individual catcher–processers are assumed to be price-takers. Given these assumptions, expected CPUE (which determines Q), expected prices, and travel costs are the main variable components in a harvester's decision-making process, while TAC constrains fishing.

We use a variety of models to link behavioral responses of walleye pollock harvesters to economic and climate factors. This analysis is not a structural model of micro-behavior, such as a spatial discrete choice model would be (Abbott and Wilen 2011; Eales and Wilen 1986; Haynie and Layton 2010). Limited data and complex structural assumptions that are unreasonable (using current methodology) for the walleye pollock catcher–processor fleet limit our ability to estimate this type of model. Rather, we take a reduced-form approach to analyze the relationships between climate factors and the distribution of fishing in the walleye pollock fishery through the mechanisms outlined in Fig. 5. Homoskedasticity is tested for, and heteroskedasticity-robust standard errors are used. The characteristics of the fishery, as well as the observed changes, give guidance about which mechanisms are important. Because of the differences in the value of walleye pollock between the A- and the B-seasons, the effects of climate are expected to vary by season.

A-season

The difference in the value per tonne of harvested catch (prices) in areas where roe-bearing fish are located causes harvesters to focus their effort on aggregations of prespawning walleye pollock in the A-season. The location of fishing depends on the timing, location, and progression of spawning. Large-scale spatial shifts are unlikely if spawning location depends on bathymetric and other physical features (Bacheler et al. 2010), although some spatial trade-offs exist between areas of high-recovery, lower-value roe and low-recovery, high-value roe. Processors produce roe in the A-season regardless of the prices of other products, though harvesters will concentrate more effort on roe if roe prices are high relative to other products (Paul et al. 2009). Rather, a more important variant in A-season fishing is the timing of the peak of roe value (link 3 in Fig. 5). Shifts in the temporal distribution of fishing may occur as harvesters choose when to begin fishing in the A-season. We explore several possible explanations for this choice. Biological evidence suggests that walleye pollock spawn earlier in warm years (Smart et al. 2012). However, ice advances from the Arctic into the Bering Sea from January through April and can restrict fishing in some areas. Ice is often at its greatest extent in March, so cold, high-ice years may prompt harvesters to start earlier if ice has the potential to interfere with fishing (link 4). In addition, they may be more likely to delay the start of the season if TAC is low (link 8). If TAC is high, vessels may expend more effort early in the season to have time to catch their entire allocation. We empirically estimated how these factors have influenced decisions about when to start fishing with a logit model:

$$(1)\qquad \Pr(\text{Early trip}_{it} = 1) = \frac{1}{\left(1 + \exp\left\{-\left[\beta_0 + \beta_1\text{TAC}_{it} + \beta_2\left(\text{Price}_{\text{roe}} \cdot \text{Price}_{\text{surimi}}{}^{-1}\right)_{it} + \beta_{30}\text{Ice}_t + \beta_4\text{LaggedSST}_t + \beta_4\text{Abundance}\right]\right\}\right)}$$

Early trip_{it} is a dichotomous variable equal to 1 if vessel i started fishing within the first 5 days of the opening of the A-season in year t, TAC_{it} is the vessel-specific seasonal total catch of walleye pollock (the fleet catches nearly 100% of their TAC each season, so total catch is similar to TAC), $(\text{Price}_{\text{roe}} \cdot \text{Price}_{\text{surimi}}{}^{-1})_{it}$ is the vessel-specific roe to surimi price ratio, Ice_t is the ice cover index, LaggedSST_t is the average sea surface temperature for several months prior to the start of the season, and Abundance_t is the estimated population of age 3+ walleye pollock. The environmental–biological mechanisms that lead to early walleye pollock spawning are not well enough understood to predetermine which months to include in the SST measure. Two seasonal temperature averages are presented here: the previous year's average summer SST (June–August) and the previous year's fall SST (September–December). Other combinations of the previous summer and fall SSTs were used as well, with similar results.

B-season: effect of climate on the distribution of walleye pollock biomass and CPUE

The analysis of the B-season is focused on how spatial variation in CPUE and prices, as well as total abundance, TAC, the timing of fishing, and other factors, affected the shift in fishing from the south to the north.

First, we focus on CPUE. The distribution of the target species affects spatial variation in expected CPUE, which is measured using fishery-independent estimates of CPUE. Water temperature patterns (the size of the cold pool) are expected to affect the spatial distribution of walleye pollock because they avoid the cold pool (Barbeaux 2012; Francis and Bailey 1983; Kotwicki et al. 2005). The mechanisms relating the size of the cold pool to CPUE differences are complicated; for example, the shape and timing of the cold pool may interact with the cold water avoidance behavior and affect migration patterns, resulting in varying levels of concentration of fish along the Bering Sea shelf. The cold pool may push walleye pollock out of the most northern fishing areas, it may concentrate fish that are in the north into a narrower band along the Bering Sea shelf (see Fig. 4), or it may concentrate fish over the entire fishing area. The spatial distribution of walleye pollock determines spatial expectations of CPUE (link 5). Because the most drastic changes in the distribution of fishing occurred in the most southern (zone 1) and the most northern (zone 4) regions of the fishing grounds, we focus on the CPUE differences between these zones that may have driven the changes in effort patterns and the shift of the mean center of the distribution of fishing to the north. The zone 4 to zone 1 ratio of CPUE is relevant because generally speaking, CPUE increases the farther north a vessel travels, but costs increase as well. As the CPUE ratio increases, a vessel is more likely to incur the increased travel costs to fish in the north. We estimate the linear regression:

$$(2)\qquad \text{Zone 4} \cdot \text{Zone 1}^{-1}\text{CPUE Ratio}_t = \beta_0 + \beta_1\,\%\text{Coldpool}_t + \beta_2\text{Abundance}_t + \varepsilon_t$$

where the Zone 4 · Zone 1^{-1} CPUE Ratio_t is the annual ratio of average bottom trawl survey CPUE from zones 4 and 1, and $\%\text{Coldpool}_t$ is the percentage of the survey area <1.5 °C. If fish are more concentrated in the north compared with the south by the cold pool, β_1 is expected to be positive. If fish are driven out of the northern fishing regions by the cold pool, β_1 is expected to be negative. High abundance is expected to increase CPUE (link 6), but it may not increase in all areas uniformly. In particular, the range of walleye pollock may expand in response to increased abundances (Holt et al. 1997). If β_2 is positive, increases in abundance increase CPUE in the north relative to the south, and if β_2 is negative, increases in abundance increase CPUE in the south relative to the north. If β_2 is zero, abundance increases CPUE uniformly.

B-season: value of the catch

Prices affect harvester behavior through the choice of a type of fish to target to produce a product to maximize expected profit. Both fish size and uniformity affect value, with larger fish typically but not always more valuable (it depends on product prices at a given time). Different sizes of fish are located in different areas of the fishing grounds in the B-season (Bailey et al. 1999; Lynde et al. 1986). Haul-level size uniformity of fish allows the onboard factory to recover more flesh. In a dynamic and constantly changing process that varies by vessel, vessels choose how to trade off expected lower levels of high-value fish with higher catch rates of lower-value fish. Thus, the prices that harvesters face can affect their decisions about where to fish (link 1).

We econometrically examine the role that spatial variation in fish value had on observed fishing locations. Intra-annual price data are not available, which limits the ability to estimate the relationship between a vessel's location choice and the value of the catch from each location. It also makes it more difficult to estimate a direct link between environmental factors and spatial variation in the value of the catch. Instead, we tested to determine if value varied depending on where it was caught. Using prices, production, and observer data, value per tonne ($\$\cdot t^{-1}$) of catch in a season (total amount of each product type, multiplied by the vessel average price of each product, summed and divided by total catch) was regressed on the percentage of vessel i's catch from zone 4 in year t ($\%\text{Zone }4_{it}$), before and after 2005 (to model the shift in fishing location):

$$(3)\qquad \text{Value} \cdot t_{it}^{-1} = \beta_i + \beta_t + \beta_1\,\text{Before 2005} \cdot \%\text{Zone }4_{it} + \beta_2\,\text{After 2005} \cdot \%\text{Zone }4_{it} + \varepsilon_{it}$$

Value t_{it}^{-1} is in natural logarithms so the coefficients are the proportionate change in value for a unit change in each independent variable. Before 2005 and After 2005 are 0–1 variables indicating the period. Year indicators allow the intercept to vary over time and control for differences in value that may be driven by relative prices, a vessel's effects allow the intercept to vary by owner, which controls for company-level product marketing decisions. The model is estimated as a fixed-effects panel data model (Cameron and Trivedi 2005). If either β_1 or β_2 is significantly different from zero, it indicates a value difference resulting from zone 4 fishing either before or after 2005.

The source of any value difference can be investigated. The location of fishing may affect production choices (i.e., the proportion of fish processed into surimi versus fillets), which may affect the value of the processed product. Three regressions are estimated with fixed-effects panel data models:

$$\text{(4)} \quad \text{ShareSurimi}_{it} = \beta_i + \beta_t + \beta_1 \text{ Before 2005} \cdot \text{\%Zone } 4_{it} + \beta_2 \text{ After 2005} \cdot \text{\%Zone } 4_{it} + \varepsilon_{it}$$

$$\text{(5)} \quad \text{Value} \cdot t_{it}^{-1} = \beta_i + \beta_t + \beta_1 \text{ Before 2005} \cdot \text{ShareSurimi}_{it} + \beta_2 \text{ After 2005} \cdot \text{ShareSurimi}_{it} + \varepsilon_{it}$$

$$\text{(6)} \quad \text{Product recovery rate}_{it} = \beta_i + \beta_t + \beta_1 \text{ Before 2005} \times \text{\%Zone } 4_{it} + \beta_2 \text{ After 2005} \cdot \text{\% Zone } 4_{it} + \varepsilon_{it}$$

where ShareSurimi_{it} is the share of vessel i's B-season production processed into surimi in year t. Equation 4 estimates how changes in fishing location affect production choices, and eq. 5 tests if production changes translate into changes in value. Year indicators control for differences in surimi production that may be driven by relative prices, and vessel fixed effects control for differences in vessels' production processes. Equation 6 estimates the product recovery rate (mass of processed products · mass of catch^{-1}) as a function of fishing location. If zone 4 fish are more uniform, recovery rates from zone 4 fishing could be higher relative to other zones, increasing value. The dependent variables in eqs. 4 and 6 are shares in the interval [0,1], so a fractional logit model was used, where $E(y|x)$ is modeled as a logistic function (Papke and Wooldridge 1993; Wooldridge 2002), $E(y|x) = \exp(x\beta)/[1 + \exp(x\beta)]$, and estimated using maximum likelihood. The estimated coefficients were exponentiated to obtain odds ratios. The odds ratio minus 1 is the proportionate change in the probability resulting from a unit change in an independent variable.

B-season: the role of climate and prices in the B-season effort distribution shift

After establishing the link between climate and spatial differences in CPUE and that prices must be included in a model of harvesters' decisions to avoid misspecification, we developed a reduced-form model of the share of effort that a vessel expends in zone 4, by trip, which is indexed by r ($\text{ShareZone } 4_{rit}$):

$$\text{(7)} \quad \text{ShareZone } 4_{rit} = \beta_i + \beta_1 \text{ColdPool}_t + \beta_2 \text{PriceZone } 4 \cdot \text{PriceZone1}_{it}^{-1} + \beta_3 \text{Abundance}_t + \beta_4 \text{TAC}_{it} + \beta_5 \text{Hauls} \cdot \text{Trip}_{rit}^{-1} + \beta_m \text{Month}_{rit} + \varepsilon_{rit}$$

The dependent variable is a share, so the fractional logit model was used and the estimates are presented as the odds ratio minus 1. The ratio $\text{PriceZone } 4 \cdot \text{PriceZone } 1_{it}^{-1}$ estimates the effect of vessel-level differences in average fish value between the north and the south, which depend on production choices and prices. The number of hauls in each trip ($\text{Hauls} \cdot \text{Trip}_{rit}^{-1}$) is included because longer trips may be more likely to be fished in zone 4. In this section of the paper, we treat prices and total abundance as exogenous. This allows us to estimate the effect that annual variation in the size of the cold pool and total abundance had on the proportion of vessels' effort expended in zone 4, assuming that their effects are through the ratio of north to south expected CPUE.

The results of eq. 7 are used to disaggregate the effect of the size of the cold pool from price effects to compare their magnitudes. To do this, consider two thought experiments. First, what was the effect of prices on the distribution of effort, if we could eliminate the effect of the cold pool? Second, what was the effect of the cold pool on the distribution of effort, if we could eliminate the effect of prices? To estimate the first, we compare the predicted distribution of effort after 2005 using historical prices with the prediction in which the price ratio was set equal to 1, which corresponds to eliminating any value differences between fish caught in zone 1 and zone 4. Then, holding the price ratio equal to one, we compared the predicted effort distribution assuming all years after 2005 were "typical" cold, average, or warm years. To define the "typical" cold, average, and warm year, we substituted the average size of the cold pool in each category (44.4%, 24.1%, and 10.0%, respectively) for the historical size (the results were not significantly different if we instead randomly drew from the distribution of each category). The difference between the prediction of zone 4 effort when all years are assumed "average" and when all years are assumed "cold" or "warm" represent the magnitude of the effect of the cold pool if prices had no effect on the spatial distribution of effort.

B-season: travel costs

Finally, one of the principal concerns related to climate change is that vessels will have to travel farther and incur the resulting higher costs (link 9). It may seem obvious that travel costs would be likely to increase as the proportion of fishing in the most northern zone increases, but vessels may adjust other aspects of fishing to mitigate travel costs. For example, they could travel less between hauls while fishing in the north. We estimated the linear panel data fixed-effects model:

$$\text{(8)} \quad \text{Dist} \cdot \text{Trip}_{rit}^{-1} = \beta_i + \beta_1 \text{\%Zone } 4_{rit} + \beta_2 \text{Coldpool}_t + \beta_3 \text{Num} \cdot \text{Hauls}_{rit} + \beta_4 \text{Abundance}_t + \beta_5 \text{TAC}_t + \varepsilon_{rit}$$

where $\text{Dist} \cdot \text{Trip}_{rit}^{-1}$ is the total distance (km) traveled in a trip, and $\text{\%Zone } 4_{rit}$ is the percentage of a trip fished in zone 4. A similar model with distance per tonne of catch per trip as the dependent variable was also estimated. Distance per tonne of catch per trip represents the average cost of travel. If harvesters can catch more fish by traveling farther, then their travel cost per tonne may remain constant. The estimated coefficients on total abundance and TAC demonstrate the effects of easier fishing (higher abundance, holding TAC constant) and the need to fish more intensively (higher TAC, holding abundance constant). If there are more fish present, the total distance traveled in a trip and distance per tonne is lower, because harvesters need to search less for acceptable rates of CPUE. If TAC is higher, holding abundance constant, harvesters need to fish faster to fish all of their TAC before the season ends. If the coefficient on $\text{\%Zone } 4_{rit}$ is positive and significant, then vessels incur greater travel costs (total and per tonne of catch) to fish in the north. The coefficient on Coldpool_t tests for an independent effect of the size of the cold pool on travel (independent from the effect of the cold pool on travel to the north, which was estimated using eq. 7 and embodied in eq. 8 through the inclusion of $\text{\%Zone } 4_{rit}$). A significant negative effect would indicate that given their choice of location, vessels travel less when the cold pool is larger, presumably because of the higher concentration of biomass caused by fish avoiding the cold pool.

Results

A-season

While there was no trend in the spatial distribution of A-season fishing, there is evidence that the temporal distribution of effort varied by temperature regime. Vessels choose when to fish to maximize their net revenues; if roe quality and quantity is expected to peak later in the season it would provide an incentive to

Table 1. Logit model of the effects of climate, total allowable catch (TAC), and prices on the probability of taking a fishing trip within the first 5 days of the opening of the A-season.

	(1) Probability of an early trip	(2) Probability of an early trip
Lagged summer SST	2.190** (0.69)	
Lagged fall SST		1.147* (0.47)
TAC (vessel-specific, thousand t)	0.348** (0.10)	0.344** (0.10)
Ratio of roe to surimi prices (average of t and $t-1$)	−0.175 (0.24)	−0.562** (0.19)
Total abundance (million t of age 3+)	−0.254 (0.19)	−0.234 (0.17)
Ice cover index	−0.050 (0.21)	−0.581** (0.10)
Constant	−17.444** (6.25)	−3.652 (3.14)
Observations	176	176
Pseudo-R^2	0.444	0.415

Note: *, $p < 0.05$; **, $p < 0.01$. Standard errors are in parentheses and are clustered by vessel. General linear mode (GLM) yields very similar results. Years included are 1999–2009. Columns contain alternative specifications of sea surface temperature (SST).

begin fishing later in the season. The warmest years (2003–2005) had consistently high effort at the season's start. Cold years were more heterogeneous; some vessels delayed the start of the season by up to 2 weeks in some of the coldest years.

The factors correlated with a vessel's decision to start a fishing trip within 5 days of the opening of the A-season include SST, TAC, ice cover, and roe prices (Table 1). The probability of early fishing increased with higher lagged SST (which may promote early spawning), higher TAC (harvesters must start fishing earlier to have time to fish their allocation), and a higher contemporaneous ice cover index (harvesters may be restricted from some fishing grounds as ice advances later in the spring). If roe prices are low relative to other products, the temporal targeting of roe is less important. Total walleye pollock abundance does not significantly affect the decision to start fishing within 5 days of the season opening.

B-season

Effect of climate on the distribution of walleye pollock biomass and CPUE

In contrast with the A-season, a dramatic change in the distribution of effort has occurred in the B-season (Fig. 1). The correlation among the ratio of north to south CPUE, the size of the cold pool, and abundance appears to be strong, especially after 1999 (Fig. 6). Using the entire time period, the relationships are empirically significant (Table 2). As the size of the cold pool increases by 1% (from a mean of 31%), the ratio of CPUE in zone 4 to CPUE in zone 1 increases by 0.023 (at the mean ratio of 1.737) (Table 2, column 2). This is evidence for a concentration of fish in the north in the region outside the cold pool on the Bering Sea shelf in cold years when the cold pool is large. Correlates of the size of the cold pool, such as the ice cover index, the timing of ice retreat, average bottom temperatures, and average sea surface temperatures were used as alternative climate indicators, with similar results (only the ice cover index is shown, in column 4). As biomass increases, the CPUE ratio decreases, evidence that walleye pollock expand into the south during periods of high abundance (Table 2, column 3). However, the size of the cold pool is collinear with biomass ($r = -0.39$), and with only 20 years of data we cannot identify each effect separately very well (Table 2, column 1). In addition, there have been few low-abundance study years in our dataset (4 years: 2006–2009), and in particular, there were no warm years with low walleye pollock abundance. This makes it impossible to predict the CPUE ratio in warm, low-abundance years without making very strong assumptions.

Value of the catch

To examine the role that spatial variation in prices had in the observed changes in the fishery, we tested to see if fish caught in zone 4 were more valuable (i.e., processed into products with a higher total value), which would help to explain the shift in the distribution of effort toward the north beginning in 2005 (Table 3, column 1). While there was no significant value premium for fish caught in zone 4 in the period after 2005, there was a small value penalty for fish caught in zone 4 relative to other areas before 2005 (Table 3). This 0.4% penalty (~$3.2·t^{-1}) for a 1% increase in zone 4 fishing would have made it slightly less likely for vessels to fish in the north before 2005. This difference disappeared after 2005.

Columns 2–4 explore the source of the disappearance in the value penalty for fish caught in zone 4. The location of fishing may affect production choices (the proportion of fish processed into surimi versus fillets), which may affect the value of the processed product. Column 2 contains estimates of eq. 4, the effect of fishing in zone 4 on surimi production. A 1% increase in zone 4 fishing led to a greater-than-proportionate (1.7%) increase in the share of catch processed into surimi, before 2005. This effect was absent after 2005. Column 3 displays estimates from eq. 5, the value difference from producing a higher proportion of surimi. Before 2005, producing 1% more surimi led to a 0.6% decrease in value per tonne of catch (approximately $4.8·t^{-1}). This effect disappeared after 2005. Finally, we tested if there was a difference in the recovery rate from catch in zone 4 relative to other zones, before and after 2005, but the effect was not significant (Table 3, column 4). These results indicate that before 2005, fishing in zone 4 decreased the value of catch because a greater percentage of fish was processed into surimi at a lower value. This would have decreased the propensity to fish in the north, given constant CPUE. Neither effect was significant after 2005. Before 2005, the zone 4 penalty may have disappeared because of increasing surimi prices (Fig. 3) or an increasing propensity to produce fillet from zone 4 fish, especially given high fillet prices in 2008 (Paul et al. 2009 estimated a higher own-price elasticity for fillet than for surimi).

The role of climate and prices in the B-season effort distribution shift

The preceding sections have demonstrated that the distribution of walleye pollock in the Bering Sea is related to variation in the size of the cold pool, total abundance, and prices. Harvesters make decisions about where to fish based on trade-offs among expected CPUE, expected prices, and travel costs, so the distribution of effort in the fishery is related to climate, at a minimum, through the size of the cold pool and its effect on CPUE.

The share of effort that a vessel expends in zone 4, by trip, is expected to increase when the cold pool is larger, because of the resulting higher concentration of biomass in the north relative to the south. More northern fishing is observed in years in which the cold pool was large, when the price ratio was high, and when abundance was low (Table 4). The effect of abundance occurs through both the effect on the spatial distribution of the stock (toward the south in high abundance years, decreasing the north/south CPUE ratio), and through overall CPUE. An increase in vessel-specific TAC (holding abundance constant) has no statistically significant effect on the probability of zone 4 fishing.

We disaggregated the effects of the size of the cold pool and price variation (Table 5). The magnitude of the overall change in effort distribution resulting from the size of the cold pool was similar to the impact of prices. To see this, consider the first column of Table 5, which predicts the percentage of effort in zone 4 using the historical (observed) cold pool size. Holding the price ratio equal to one isolates the predicted percentage of effort due to other factors in zone 4 after 2005 if prices had no effect on the spatial distribution of effort. Predicted effort falls by 3.9%, from 69.1% to 65.2%. This difference is similar if we assume that all years

Fig. 6. Time series of the ratio of average CPUE in fishing zones 4 (the northern region) and 1 (the southern region) (black line), the size of the cold pool (percentage of the area surveyed by bottom trawl survey with temperature <1.5 °C) (dashed line), and the abundance of age 3+ walleye pollock (grey line). Abundance is normalized to the year of minimum abundance (2008).

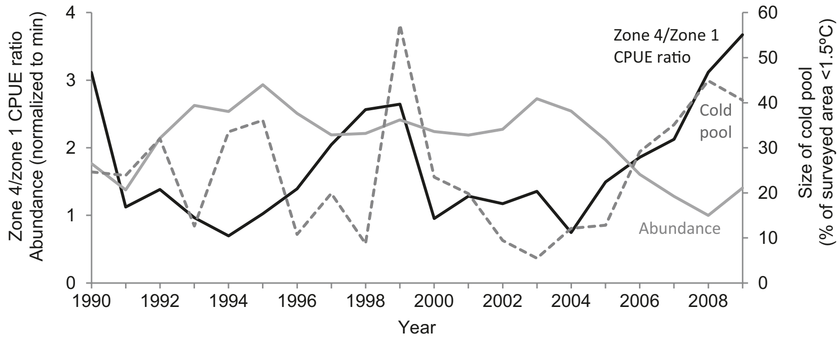


Table 2. Relationship between the ratio of average zone 4 to average zone 1 CPUE, the size of the cold pool (or in column 4, the ice cover index), and total abundance.

	(1) Zone 4/Zone 1 CPUE ratio	(2) Zone 4/Zone 1 CPUE ratio	(3) Zone 4/Zone 1 CPUE ratio	(4) Zone 4/Zone 1 CPUE ratio
Size of cold pool (% of surveyed area)	0.013 (0.009)	0.023* (0.009)		
Ice cover index				0.249* (0.103)
Total abundance (million t of age 3+)	−0.188* (0.076)		−0.230** (0.070)	−0.145* (0.074)
Constant	3.076** (0.956)	0.953** (0.285)	3.862** (0.729)	3.025** (0.741)
Observations	20	20	20	20
Adjusted R^2	0.374	0.232	0.342	0.476

Note: *, $p < 0.05$; **, $p < 0.01$. Standard errors are in parentheses. Homoskedasticity cannot be rejected. Data is from the bottom trawl survey, 1990–2009. Columns present alternative specifications.

Table 3. Regressions of the effect of fishing in zone 4 on the value of catch, before and after 2005.

	(1) Value (ln of \$·t^{-1} catch)	(2) Share of production made into surimi	(3) Value (ln of \$·t^{-1} catch)	(4) Recovery rate (t production/t catch)
% of catch in zone 4 (before 2005)	−0.004** (0.001)	0.017** (0.003)		−0.001 (0.001)
% of catch in zone 4 (after 2005)	0.0008 (0.001)	0.002 (0.003)		0.003** (0.001)
% of production surimi (before 2005)			−0.006** (0.001)	
% of production surimi (after 2005)			−0.002 (0.001)	
Vessel effects		Included		Included
Owner effects	Included		Included	
Annual effects	Included	Included	Included	Included
Constant	6.190* (0.052)	−2.201** (0.392)	6.308** (0.066)	−0.783** (0.067)
N	117	159	117	159
R^2 or pseudo-R^2	0.88	0.14	0.83	0.01

Note: *, $p < 0.05$; **, $p < 0.01$. Robust standard errors are in parentheses. Homoskedasticity cannot be rejected. Columns (1) and (3) use data from 2002–2009 because of price data limitations before 2002 and are estimated as semi-logs so the coefficients can be interpreted as the proportionate change in value from a unit change in the independent variables. Columns (2) and (4) use data from 1999 to 2009, are estimated as a fractional logit model, R^2 is pseudo-R^2, and the coefficients represent the proportionate change in value from a unit change in the independent variables. Results do not change significantly if 1999–2001 are dropped to match the time period used for columns (1) and (3), which include prices.

after 2005 were cold, average, or warm. This can be compared with the effect of the size of the cold pool by holding the price ratio equal to one and comparing the predicted share of effort in zone 4 had each of the years after 2005 been typical cold, average, or warm years. Predicted effort in zone 4 is 4.2% greater in cold years compared with average (64.5%–60. 3%) and 3.1% lower in warm years compared with average years (60.3%–57.2%). These results indicate that both the increase in the price ratio and the increasing number of cold years after 2005 helped to create the observed shift in the distribution of effort toward the north after 2005.

Travel costs

The characteristics of a trip, including the proportion of a trip spent fishing in the north, are empirically related with the distance traveled in a trip (Table 6, column 1) and the travel cost (distance) per tonne of catch (Table 6, column 2). Total distance per trip is a proxy for total cost per trip, while distance per tonne per trip is a proxy for the average cost of a trip. A 1% increase in the percentage of fishing occurring in zone 4 increased the distance traveled in a trip by 0.4% (~10 km) and the distance per tonne of catch by 0.3%. This implies that walleye pollock catcher–processor harvesters incurred a higher cost in terms of total travel and distance traveled per tonne to fish in the north, but the effect on total distance was very slightly mitigated by catching a larger quantity of fish per kilometre traveled. Holding the choice of the percentage of a trip to spend in the north constant (which is affected by the size of the cold pool as discussed in the previous section), a 1% increase in the size of the cold pool decreased the

Table 4. The role of climate, prices, abundance, and TAC in the share of a fishing trip spent in the northernmost region (zone 4).

	(1) Share of trip fished in zone 4	(2) AME: EY/EX† (95% CI)	(3) Mean of indep. variable (SD)
Size of cold pool (% of surveyed area)	0.012* (0.01)	0.18% (0.11, 0.34)	30.3 (20.1)
Price ratio (zone 4 to avg. of zones 1 and 2)	0.894** (0.27)	0.51% (0.21, 0.81)	1.1 (0.3)
Total abundance (million t of age 3+)	–0.269** (0.04)	–1.21% (–1.58, –0.85)	8.8 (2.3)
TAC (vessel-specific, thousand t)	0.027 (0.01)	0.33% (–0.02, 0.67)	23.7 (7.7)
No. of hauls·trip^{-1}	0.007 (0.006)		44.0 (17.0)
Monthly effects	Included		
Vessel effects	Included		
Constant	0.019** (0.017)		
N	1009		
Pseudo-R^2	0.25		

Note: *, $p < 0.05$; **, $p < 0.01$. Robust standard errors are in parentheses, except for column (3), which shows standard deviation (SD). The model is estimated as a fractional logit, and the coefficients can be interpreted as the proportionate change in value from a unit change in the independent variables.

†Average marginal effect (AME) is presented as EY/EX (the elasticity) at the sample means and can be interpreted as the percent change in the share of a trip fished in zone 4 resulting from a 1% increase in the dependent variable. Years included are 1999–2009.

Table 5. Prediction of the average percentage of trip effort directed to zone 4, after 2005, using the historical north to south price ratio and substituting the price ratio equal to 1 after 2005.

	Historical cold pool	All years after 2005, cold	All years after 2005, average	All years after 2005, warm
Prediction of percentage of effort in zone 4 after 2005, historical prices	69.1%	68.6%	64.6%	61.6%
Prediction of percentage of effort in zone 4 after 2005, price ratio = 1	65.2%	64.5%	60.3%	57.2%

Table 6. Determinants of distance traveled in a trip and travel cost per tonne of catch.

	(1) Distance·trip^{-1} (log of km)	(2) Distance·t^{-1}·trip^{-1} (log of km·t^{-1})	(3) Mean of indep. variable (SD)
% of fishing in zone 4	0.004** (0.00)	0.003** (0.00)	48.9 (41.8)
Size of cold pool (% of survey area)	–0.003** (0.00)	–0.002* (0.00)	30.3 (20.1)
No. of hauls	0.010** (0.00)	–0.013** (0.00)	44.0 (17.0)
Total abundance (million t of age 3+)	–0.039** (0.01)	–0.048** (0.01)	8.8 (2.3)
TAC (vessel-specific, thousand t)	–0.001 (0.00)	–0.012** (0.00)	23.8 (7.7)
Constant	7.414** (0.11)	1.095** (0.15)	
Vessel fixed effects	Included	Included	
N	1009	1009	
R^2	0.421	0.391	

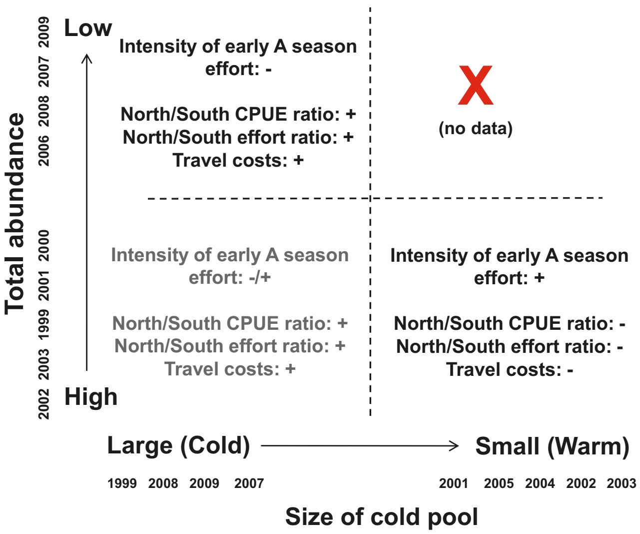
Note: *, $p < 0.05$; **, $p < 0.01$. Robust standard errors are in parentheses, except for column (3), which shows standard deviation (SD). Models are in semi-logs so the coefficients represent the proportionate change in distance from a unit change in the independent variables from their means. Heteroskedasticity has been modeled using feasible generalized least squares; the % of fishing in zone 4 and the number of hauls were included in the weighting model because they caused a majority of the heteroskedasticity. Results from a GLM are similar.

distance traveled in a trip by 0.3% and distance per tonne per trip by 0.2%. This indicates that the concentration of fish caused by a larger cold pool results in less travel, independent from fishing location choice. The regressions also include the effect of the total number of hauls in a trip, total abundance, and vessel-specific TAC. Higher abundance decreased both total distance traveled and distance per tonne, because harvesters needed to search less for acceptable rates of CPUE when abundance was high. The coefficients on TAC estimate the effect of the need to fish more intensively. Higher TAC is associated with a lower distance per tonne, but no change in total distance traveled per trip. This may be because vessels took longer trips and caught more fish on each trip when TAC was high, negating the distance-related costs of fishing more intensively.

Discussion

We have shown that the distribution of fishing in the walleye pollock catcher–processor fishery is influenced by a variety of economic factors and that these economic factors vary with changes in environmental conditions. The mechanisms that determine fishing patterns are specific to this ecosystem and the fishing fleet. For example, if one failed to account for distinct economic drivers that characterize the two seasons of the Bering Sea walleye pollock fishery, the **annual** mean center of the distribution of fishing would obscure the changes taking place in the fishery. Without disaggregating the seasons, one would see a distribution of effort centered in the middle of the fishing grounds, with a small degree of northward shift over 1999–2009. In reality, high prices from roe-bearing fish relatively close to port dominate higher CPUE that might be found elsewhere in A-season fishing, while B-season fishing is driven by the trade-offs vessels make among spatially and temporally variable CPUE, prices, and travel costs. Each of these factors can be affected by climate, and the resulting aggregate distribution of fishing is a function of individual harvesters' location choices over the fishing seasons. However, several complexities inherent in this system push the modeling

Fig. 7. Summary of the effects of the size of the cold pool and total walleye pollock abundance on the intensity of early A-season (winter season) effort, B-season (summer season) CPUE, B-season effort, and B-season travel costs. Years in the sample characterized by varying abundance and cold pool levels are listed on the horizontal and vertical axes.



problem beyond the state of the art in spatial discrete choice modeling of fishing locations. Walleye pollock are an extremely mobile species, making the temporal stability of endogenously estimated expected CPUE used in discrete choice models problematic. In addition, catcher–processors make decisions over multi-week trips that involve trading off constant flow through the factory with the possibility of higher catch rates at the expense of lost processing time. Finally, the environment impacts the fishing process in a complex and temporally and (or) spatially lagged manner, often at uncertain scales. While these issues are the subject of ongoing research, this paper presents a robust and informative reduced-form analysis of economic drivers of the fishery and how they are related to local climate conditions. Understanding these mechanisms is an important foundation for future integrated modeling efforts.

This paper also identifies one of the difficulties in predicting the effects of climate change in complicated systems with limited historical data. Although 20 years of historical biological survey data and 11 years of fishery data were used, separately identifying the effects of many important variables is difficult. For example, separate identification of TAC, ice cover, and lagged temperatures in the A-season, or identification of the CPUE ratio, total abundance, and the size of the cold pool in the B-season, is problematic because we simply have no data on warm, low-TAC and low-abundance years. Figure 7 illustrates this point by showing the years in our economic dataset in which total abundance was relatively high and low and years in which the cold pool was small and large, along with the key results of the preceding analysis. There was no correspondence between low-abundance, small-cold-pool (warm) years, and only 1 year of correspondence between high-abundance and large-cold-pool (cold) years. Because biological evidence suggests that the predicted increased frequency of warmer climate regimes may result in decreased abundances (Hunt et al. 2011; Mueter et al. 2011), this lack of correspondence represents a major limitation in predicting how the behavior of the catcher–processor walleye pollock fleet will be affected by climate change. Given the current state of knowledge and available data, out-of-sample forecasting results would be highly speculative. If a warmer future has characteristics different from those that have been historically observed, the potential for surprises increases.

The scenarios for which data correspondence does occur provide insight into how economic drivers of the fishery affect the distribution of effort and how these factors are related to climate. The identifiable effects of annual climate variation on A-season fishing are temporal rather than spatial. Biologically, walleye pollock are shown to mature earlier in the season in warm years (Smart et al. 2012), and we find that lagged SST affects the proportion of vessels actively fishing for walleye pollock at the beginning of the A-season. Paul et al. (2009) found complementary results. Harvesters consider the shift in the peak of the highest value roe, but are also influenced by TAC and the timing of the maximum extent of winter ice. There is evidence that vessels need to start fishing earlier to catch their share of the quota when TAC is high; however, warm years in the sample have also been high-TAC years, so we cannot reliably separate their effects. The data and analysis from the A-season suggest that we are unlikely to see major changes in the location of fishing unless there is a (currently unforeseen) regime shift that greatly affects the spatial distribution of spawning.

In the B-season the shift in the spatial distribution of effort is related to climate through the cold pool and its effect on the spatial distribution of fish. However, the effect can be enhanced or mitigated by the spatial variation in the value of fish. The spatial distribution of fish is also dependent upon total abundance, which is affected by climate through a lagged process of recruitment and survival. Cold years with large cold pools had higher B-season CPUE in the north relative to the south. This effect was amplified by relatively low survey abundances in recent cold years (2007–2009). The combined effects of a large cold pool and low abundance caused a divergence between CPUE in the north and CPUE in the south and helped to explain the shift in the distribution of fishing to the north. The change in the distribution of value complemented this shift. Increasing and more variable surimi prices drove the disappearance of a value penalty for fishing in zone 4 after 2005.

There has been substantial speculation as to whether climate change will affect commercial fishing through increased travel costs if fisheries shift north and farther from their traditional ports. We find evidence of increased travel per trip and distance traveled per tonne of fish caught that is associated with the shift to zone 4 fishing; however, increases in zone 4 fishing are contemporaneously associated with **colder**, low-abundance years. We also find that TAC has an effect on travel beyond abundance. High abundance reduces search travel, as expected, but high TAC, holding abundance constant, makes vessels less willing to expend travel time for marginal improvements in CPUE or prices. In contrast with more general climate-envelope models, our analysis of the economic drivers of the fishery with the available data suggest that a warming trend will lead to a more southerly distribution of fishing effort by the catcher–processor sector **if abundance remains high**. This will be driven by the smaller ratio of north to south CPUE, which is driven by a smaller cold pool. In reality, although climate models forecast a warming trend, variation in annual temperatures is predicted to remain high (IPCC 2007). Figure 7 makes it obvious that our findings are not adequate to make an informed prediction about the distribution of the fishery in warm, low-abundance years.

It is critical to recognize the importance of management institutions in shaping the behavior of harvesters and their response to changes in the factors that drive them, including climate. The creation of catch shares in the walleye pollock catcher–processor fishery in 1999 completely changed the fishery's incentives, so much so that it is impossible to use data from both periods to analyze the effects of climate without accounting for the change. Before this change in management, the race to fish caused vessels to fish at full intensity from the moment of season opening, making time spent traveling rather than fishing much more expensive. Catch share management allows vessels, companies, and cooperatives to make spatial and temporal trade-offs to maximize value. Ongoing institutional changes will continue to impact the fishery. For example, the implementation of catch shares in the west coast groundfish fishery enables vessels that fish in both the walleye pollock fishery in the Bering Sea and the whiting fishery off of Washington and Oregon to coordinate efforts in both regions. Changes in salmon bycatch regulation will also continue to impact the timing and location of fishing in the Bering Sea. The design of management institutions to be flexible to the potential impacts of climate change is an important policy objective. For example, anticipating changes in the spatial distribution and abundance of the stock (or changes in their variance) and incorporating them into stock assessments and management choices could help avoid unintended overfishing. If enough information on spatial stock dynamics and costs were available, the stock could be managed (in terms of the determination of total annual TAC by the regulating body) to achieve maximum economic yield rather than the current policy of maximum sustainable yield (Dichmont et al. 2010). Allowing flexibility in the timing and location of harvesters choices (by reducing spatial and seasonal limitations, for example) can reduce unnecessary costs imposed by the limitations. Even if regulations were originally efficiently designed, climate-related impacts on fish and fisheries can make existing regulations extremely costly.

Ultimately, the entire marine ecosystem, of which fisheries are an integral part, is being affected by changing climate. In this research we show that there are a variety of causes of the observed changes in walleye pollock fishing, and market conditions have larger impacts on the fishery distribution than trends in climate over the study period. Just as ignoring interactions between species can lead to erroneous predictions about the effect of climate change on the range and abundance of species (Davis et al. 1998), ignoring the interaction between human apex "predators" and their target species can lead to similarly inaccurate predictions. In some fisheries, excellent data concerning economic drivers of the fishery is available. Improving the quality and quantity of economic data and using it to support ecosystem studies of fisheries will result in research that can better inform management in the face of climate change.

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References

Abbott, J.K., and Wilen, J.E. 2011. Dissecting the tragedy: a spatial model of behavior in the commons. J. Environ. Econ. Manage. **62**(3): 386–401. doi:10.1016/j.jeem.2011.07.001.

Bacheler, N.M., Ciannelli, L., Bailey, K.M., and Duffy-Anderson, J.T. 2010. Spatial and temporal patterns of walleye pollock (*Theragra chalcogramma*) spawning in the eastern Bering Sea inferred from egg and larval distributions. Fish. Oceanogr. **19**(2): 107–120. doi:10.1111/j.1365-2419.2009.00531.x.

Bailey, K.M., Quinn, T.J., Bentzen, P., and Grant, W.S. 1999. Population structure and dynamics of walleye pollock, *Theragra chalcogramma*. Adv. Mar. Biol. **37**: 179–255. doi:10.1016/S0065-2881(08)60429-0.

Barbeaux, S.J. 2012. Scientific acoustic data from commercial fishing vessels: Eastern Bering Sea walleye pollock (*Theragra chalcogramma*). Ph.D. thesis, School of Aquatic and Fisheries Sciences, University of Washington, Seattle.

Bockstael, N.E., and Opaluch, J.J. 1983. Discrete modelling of supply response under uncertainty: the case of the fishery. J. Environ. Econ. Manage. **10**(2): 125–137. doi:10.1016/0095-0696(83)90021-9.

Cameron, A.C., and Trivedi, P.K. 2005. Microeconometrics: methods and application. Cambridge University Press, Cambridge.

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**(1): 24–35. doi:10.1111/j.1365-2486.2009.01995.x.

Ciannelli, L., Bailey, K.M., Chan, K.-S., and Stenseth, N.Chr. 2007. Phenological and geographical patterns of walleye pollock (*Theragra chalcogramma*) spawning in the western Gulf of Alaska. Can. J. Fish. Aquat. Sci. **64**(4): 713–722. doi:10.1139/f07-049.

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): 1–10. doi:10.1577/1548-8675(1998)018<0001:CFARMI>2.0.CO;2.

Davis, A.J., Jenkinson, L.S., Lawton, J.H., Shorrocks, B., and Wood, S. 1998. Making mistakes when predicting shifts in species range in response to global warming. Nature, **391**: 783–786. doi:10.1038/35842. PMID:9486646.

Dichmont, C.M., Pascoe, S., Kompas, T., Punt, A.E., and Deng, R. 2010. On implementing maximum economic yield in commercial fisheries. Proc. Natl. Acad. Sci. **107**(1): 16–21. doi:10.1073/pnas.0912091107. PMID:20018676.

Eales, J., and Wilen, J. 1986. An examination of fishing location choice in the pink shrimp fishery. Mar. Resour. Econ. **2**(4): 331–351.

FAO. 2009. Fisheries and aquaculture statistics. Rome.

Felthoven, R.G. 2002. Effects of the American Fisheries Act on capacity, utilization and technical efficiency. Mar. Resour. Econ. **17**(3): 181–206.

Francis, R.C., and Bailey, K. 1983. Factors affecting recruitment of selected gadoids in the northeast Pacific and East Bering Sea. *In* From year to year. *Edited by* W.S. Wooster. Washington Sea Grant, Seattle, Wash. pp. 35–60.

Grebmeier, J.M., Overland, J.E., Moore, S.E., Farley, E.V., Carmack, E.C., Cooper, L.W., Frey, K.E., Helle, J.H., McLaughlin, F.A., and McNutt, S.L. 2006. A major ecosystem shift in the northern Bering Sea. Science, **311**(5766): 1461–1464. doi:10.1126/science.1121365. PMID:16527980.

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. 2012. Why economics matters for understanding the effects of climate change on fisheries. ICES J. Mar. Sci. **69**(7): 1160–1167. doi:10.1093/icesjms/fss021.

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**(4): 770–782. doi:10.1577/1548-8675(1996)016<0770:EEIOPP>2.3.CO;2.

Hiatt, T., Dalton, M., Felthoven, R., Fissel, B., Garber-Yonts, B., Haynie, A., Kasperski, S., Lew, D., Package, C., Sepez, J., and Seung, C. 2011. 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.

Hilborn, R., and Walters, C.J. 1992. Quantitative fisheries stock assessment: Choice, dynamics and uncertainty. Chapman and Hall, New York.

Holt, R.D., Lawton, J.H., Gaston, K.J., and Blackburn, T.M. 1997. On the relationship between range size and local abundance: back to basics. Oikos, **78**(1): 183–190. doi:10.2307/3545815.

Hunt, G.L., Stabeno, P., Walters, G., Sinclair, E., Brodeur, R.D., Napp, J.M., and Bond, N.A. 2002. Climate change and control of the southeastern Bering Sea pelagic ecosystem. Deep Sea Res. Part II: Top. Stud. Oceanogr. **49**(26): 5821–5853. doi:10.1016/S0967-0645(02)00321-1.

Hunt, G.L., Coyle, K.O., Eisner, L.B., Farley, E.V., Heintz, R., Mueter, F., Napp, J.M., Overland, J.E., Ressler, P.H., Salo, S., and Stabeno, P.J. 2011. Climate impacts on eastern Bering Sea foodwebs: a synthesis of new data and an assessment of the Oscillating Control Hypothesis. ICES J. Mar. Sci. **68**(6): 1230–1243. doi:10.1093/icesjms/fsr036.

Ianelli, J.N., Barbeaux, S., Honkalehto, T., Kotwicki, S., Aydin, K., and Williamson, N. 2011*a*. Assessment of the walleye pollock stock in the Eastern Bering Sea. *In* 2011 North Pacific Groundfish Stock Assessment and Fishery Evaluation Reports North Pacific Fisheries Management Council, Anchorage, Alaska. pp. 51–168.

Ianelli, J.N., Hollowed, A.B., Haynie, A.C., Mueter, F.J., and Bond, N.A. 2011*b*. 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.

IPCC. 2007. Contribution of Working Groups I, II, and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. *In* Climate Change 2007: Synthesis Report. *Edited by* R.K. Pachauri and A. Reisinger. IPCC, Geneva, Switzerland.

Kotwicki, S., Buckley, T.W., Honkalehto, T., and Walters, G. 2005. Variation in the distribution of walleye pollock (*Theragra chalcogramma*) with temperature and implications for seasonal migration. Fish. Bull. (NOAA), **103**(4): 574–587.

Lehodey, P., Chai, F., and Hampton, J. 2003. Modelling climate-related variability of tuna populations from a coupled ocean–biogeochemical–populations dynamics model. Blackwell Science Ltd. pp. 483–494.

Lynde, C.M., Lynde, M.V.H., and Francis, R.C. 1986. Regional and temporal differences in growth of walleye pollock (*Theragra chalcogramma*) in the eastern

Bering Sea and Aleutian Basin with implications for management. NMFS Northwest and Alaska Fisheries Science Center, Seattle, Wash.
Maunder, M.N., and Punt, A.E. 2004. Standardizing catch and effort data: a review of recent approaches. Fish. Res. **70**(2–3): 141–159. doi:10.1016/j.fishres.2004.08.002.
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.
NOAA. 2012. National Data Climate Center [online]. Available from http://www.ncdc.noaa.gov/oa/climate/research/sst/oi-daily-information.php [accessed 1 May 2012].
Overland, J.E., and Pease, C.H. 1982. Cyclone climatology of the Bering Sea and its relation to sea ice extent. Monthly Weather Review, **110**(1): 5–13. doi:10.1175/1520-0493(1982)110<0005:CCOTBS>2.0.CO;2.
Overpeck, J., Hughen, K., Hardy, D., Bradley, R., Case, R., Douglas, M., Finney, B., Gajewski, K., Jacoby, G., Jennings, A., Lamoureux, S., Lasca, A., MacDonald, G., Moore, J., Retelle, M., Smith, S., Wolfe, A., and Zielinski, G. 1997. Arctic environmental change of the last four centuries. Science, **278**(5341): 1251–1256. doi:10.1126/science.278.5341.1251.
Papke, L.E., and Wooldridge, J. 1993. Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. National Bureau of Economic Research Cambridge, Mass., USA.
Paul, C.J.M., de O.,Torres, M., and Felthoven, R.G. 2009. Fishing revenue, productivity and product choice in the Alaskan pollock fishery. Environ. Resour. Econ. **44**(4): 457–474. doi:10.1007/s10640-009-9295-3.
Perry, A.L., Low, P.J., Ellis, J.R., and Reynolds, J.D. 2005. Climate change and distribution shifts in marine fishes. Science, **308**(5730): 1912–1915. doi:10.1126/science.1111322. PMID:15890845. PMID:15890845.
RACE. 2011. Groundfish assessment program [online]. Available from http://www.afsc.noaa.gov/RACE/groundfish/default.php [accessed 2011].
Smart, T.I., Duffy-Anderson, J.T., and Horne, J.K. 2012. Alternating temperature states influence walleye pollock (*Theragra chalcogramma*) early life stages in the southeastern Bering Sea. Mar. Ecol. Progr. Ser. **455**: 257–267. doi:10.3354/meps09619.
Smith, M.D., and Wilen, J.E. 2003. Economic impacts of marine reserves: the importance of spatial behavior. J. Environ. Econ. Manage. **46**(2): 183–206. doi:10.1016/S0095-0696(03)00024-X.
Springer, A.M. 1992. A review: Walleye pollock in the North Pacific — how much difference do they really make? Fish. Oceanogr. **1**(1): 80–96. doi:10.1111/j.1365-2419.1992.tb00026.x.
Wilen, J.E., and Richardson, E.J. 2008. Rent generation in the Alaskan pollock conservation cooperative. Food and Agriculture Organization, Rome. pp. 361–368.
Wooldridge, J.M. 2002. Econometric analysis of cross section and panel data. The MIT Press, Cambridge and London.
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.