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Full length article Predicting the distribution of red king crab bycatch in Bering Sea flatfish trawl fisheries

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Abstract

Declining Bristol Bay red king crab (BBRKC) abundance has triggered recent closures of this iconic Bering Sea fishery and raised interest in bycatch in non-directed fisheries as a possible conservation concern. One particular concern is the effectiveness of static closed areas for bycatch fisheries in an era of climate warming and widespread distribution shifts. However, spatial data for supporting management decisions concerning bycatch is lacking, as fisheries-independent data are collected only in the summer, and the relationship to BBRKC distribution in the fall/winter/spring, when most bycatch occurs, is unknown. We filled this information gap by using fishery-dependent data to build predictive models of BBRKC bycatch distribution in non-pelagic trawl groundfish fisheries in the data-poor seasons. We trained Boosted Regression Tree models for bycatch occurrence and abundance of four BBRKC sex-size/maturity categories, and evaluation metrics indicated good to excellent predictive ability across all models. We found that flatfish directed-fishery CPUE, summer survey CPUE for BBRKC and flatfish, and depth were important predictors for bycatch occurrence and abundance. Physical variables (ice cover and temperature) were generally less important. We also found strong correlations between the mean latitude of

observed bycatch and the summer survey for BBRKC, highlighting the ability of summer survey data to predict non-summer bycatch distributions. BBRKC bycatch prediction is a tractable problem, and our results are the first step towards operating models that may be used to evaluate proposed management actions. We also conclude that northward shifts in fishery-independent and -dependent data suggest the possible value of reassessing decades-old static closure areas for managing BBRKC bycatch.

Introduction

Scientific advice for management decisions may be affected by a disconnect between the seasonal availability of fisheries-independent data and the seasonal timing of fisheries, when distribution and abundance data are most needed for making appropriate management decisions. Fisheries-independent data are usually collected through research surveys over standardized (and usually large) areas (Dennis et al., 2015). Surveying yearround is often impossible due to cost and weather conditions outside the summer months, especially in high-latitude systems. In situations when the seasonal timing of surveys limits the availability of fisheries-independent data, fisheries-dependent data from onboard observers, industry-reported logbooks, or fishing receipts may provide the best available information for understanding the biology of species caught in directed fisheries or as bycatch (Crear et al., 2021, Karp et al., 2023). One important consideration when using fisheries-dependent data is that sampling effort is driven by the factors regulating fishing behavior and location of fishing grounds, such as the abundance of a target species, the desire to avoid bycatch species, or distance traveled from port (Karp et al., 2023). These effects typically lead to violation of the statistical assumption that sampling locations have been chosen independently of the response variable (Conn et al., 2017, Diggle et al., 2010, Pennino et al., 2019). In spite of these concerns, fisheries-dependent data have been shown to complement fisheries-independent data to fill critical knowledge gaps for species occurrence and abundance (Pecquerie et al., 2004, Pinto et al., 2019, Rufener et al., 2021). Fisheries-dependent distribution models may produce results that are comparable to models informed by random sampling (Ducharme-Barth et al., 2022), especially when fisheries-independent data are not sampling a biased subset of climatic conditions for the species of interest (Karp et al., 2023). In some cases, fisheries-dependent data may even outperform fisheries-independent data for modeling temporal changes in species distributions (Pennino et al., 2016). Given appropriate attention to underlying issues of sampling design, distribution information derived from fisheries-dependent data may provide useful insight to support management decisions outside of the data-rich survey

season (Rufener et al., 2021), such as where and when bycatch hotspots of a non-target species occur (Shirk et al., 2023, Ward et al., 2015).

Bristol Bay is a large embayment (~72,500 km²) in the southeast part of the Bering Sea. The Bristol Bay stock of red king crab (*Paralithodes camtschaticus*; hereafter BBRKC) has historically been one of Alaska's most valuable shellfish fisheries, with an ex-vessel catch value of US \$73 million in 2021 (Garber-Yonts et al., 2023). Abundance for this stock has been assessed annually since 1975 with a fisheries-independent summertime bottom trawl survey. While this time series provides a wealth of data for understanding summer BBRKC distribution, fisheries-independent information on the distribution in other seasons is lacking. This is a crucial gap not only because interactions with bycatch fisheries primarily occur in non-summer months, but also because a long-term decline in recruitment has driven the stock to historically low levels of abundance in recent years, prompting closures of the directed fishery during the 2021/22 and 2022/23 seasons (Palof, 2023). This decline of an iconic fishery has heightened interest in the potential need for conservation measures to protect the stock during a period of depressed abundance. This interest has particularly focused on the distribution of BBRKC bycatch in groundfish fisheries during the fall/winter/spring seasons in order to evaluate the efficacy of static closure areas which were established in the 1990s based on BBRKC distribution data from the summer survey (Ackley and Witherell, 1999). To evaluate whether these closures are still effective, there first needs to be an understanding of where bycatch is occurring and how this has changed since closed areas were established. Changes in BBRKC

distribution are particularly important given the potential for long-term range shifts as the Bering Sea warms, and the potential for seasonal movements by BBRKC, which are poorly documented but thought to cover 100s of kilometers (Evans et al., 2012, Loher and Armstrong, 2005, Szuwalski et al., 2021, Zacher et al., 2018). BBRKC are also known to have sex- and size-specific distribution patterns that may be important for the effectiveness of closed areas (Zacher et al., 2023). In addition, catchability in the trawl gear used for the summertime survey is known to vary with size and sex (Palof, 2023). Similar dynamics may also affect bycatch rates in commercial trawl fisheries, which is an additional, important consideration for evaluating BBRKC bycatch and the utility of closed areas. However, to date, no analysis has been published that: 1) evaluates BBRKC bycatch in a predictive modeling capacity; 2) covers decadal time scales relevant to existing closure areas; 3) covers the fall/winter/spring data-poor seasons; and 4) accounts for sex- and size-dependent distribution patterns.

Here, we address these knowledge gaps using boosted regression tree (BRT) models trained on fisheries-dependent data to predict the distribution of BBRKC bycatch in non-pelagic flatfish trawl fisheries (hereafter "flatfish trawl fisheries"). This approach differs from modeling a target and bycatch species separately and evaluating bycatch risk based on their overlap in distribution (e.g., Hazen et al., 2018). Our approach is an extension of Species Distribution Model (SDM) techniques, which have been effectively applied towards addressing various bycatch issues, including evaluating the utility of static and dynamic closure areas for reducing bycatch (Hazen et al., 2018, Smith et al., 2021), relating bycatch hotspots to environmental conditions and understanding hotspot trends through time (Shirk et al., 2023, Ward et al., 2015), predicting bycatch of species across a broad range of movement patterns and bycatch rates (Stock et al., 2020), and demonstrating the underlying utility of bycatch data for projecting species distributions in novel scenarios (Murray and Orphanides, 2013, Pan et al., 2023). SDMs infer statistical relationships between predictor variables and species occurrence (presence/absence) and/or abundance, which in turn aids understanding of the variables that influence the distribution of response variables such as crab bycatch. SDMs can also use those inferred relationships to generate predictions of where bycatch will occur over space and time.

Our goal is to build predictive models of BBRKC bycatch to support management decisions about the utility of existing or proposed conservation measures for the stock. Our specific objectives are to 1) build distribution models for legal male, immature male, mature female, and immature female BBRKC bycatch in flatfish trawl fisheries; 2) evaluate model predictive performance; and 3) assess spatio-temporal variability in bycatch and important model covariates for predicting bycatch for each sex-maturity category. Our study contributes timely insight regarding the distribution and drivers of BBRKC bycatch and represents the first step towards developing predictive tools for evaluating future bycatch scenarios.

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Section snippets

Selection of focal fisheries and study area

We chose flatfish trawl fisheries due to high rates of bycatch with this gear type (Cunningham and Cates, 2022). We then conducted an exploratory evaluation of the flatfish trawl fisheries and seasons that produce the largest amounts of bycatch for BBRKC based on bycatch totals from the years 1997–2023, using the database of bycatch data documented by onboard observers in groundfish fisheries managed by the U.S. Federal Government in Bristol Bay (details below). This analysis indicated that…

Results

Across sex-size/maturity categories, mean catch per hour for BBRKC bycatch in flatfish trawl fisheries was generally highest between 1999 and 2013 (Fig. 3), subsequently decreasing and then peaking again in 2017–2021, followed by another decline in 2022, and then an uptick in 2023. Legal males and mature females (Fig. 3A and C, respectively) were caught as bycatch at roughly twice the rate as immature males and females (Fig. 3B and D, respectively).

Delta model components (occurrence and…

Discussion

Our results show that predicting BBRKC bycatch distribution is a tractable problem, as models for all four sex-size/maturity categories performed very well in out-of-sample prediction and exhibited spatial alignment with observed bycatch despite changes in fishing behavior through time. Our analyses also show northward shifts for observed BBRKC bycatch and survey CPUE with important differences among sex-size/maturity categories, highlighting the potential value of dynamic management actions…

Utility for management

The northward shift in bycatch and survey CODs provides an indication that dynamic management could be considered for BBRKC, but the nature of any such management measures (e.g., dynamic or redefined closed areas), along with a cost-benefit analysis for their effectiveness, is beyond the scope of this study. However, our models do demonstrate that BBRKC bycatch distribution can be predicted out-of-sample, and not simply post-hoc, and we believe that this proof of concept provides a tool for…

CRediT authorship contribution statement

Emily Ryznar: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Michael A. Litzow:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization.…

Declaration of Competing Interest

The authors have no conflicts of interest to disclose in relation to the manuscript "Predicting the distribution of red king crab bycatch in Bering Sea flatfish trawl fisheries".…

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