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Variability in somatic growth over time and space determines optimal season-opening date in the Oregon pink shrimp (*Pandalus jordani*) fishery

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Highlights

3-5 bullet points, 85 characters, including spaces, per bullet point

* Size at recruitment varied across time and space in the Oregon pink shrimp fishery
* Optimal season opening dates depended on location, year, and fishing mortality rate
* No drivers of size at recruitment were identified from candidate variables

Abstract

Will provide in next draft

Keywords

Somatic growth, revenue per recruit, shrimp, crustacean, environmental drivers

1 Introduction

In fisheries, there is an important trade-off between waiting to catch individuals until they are large, and thus have a higher yield per individual, and catching individuals earlier in their lives when they are small, but catch rates are higher because there has been less opportunity for them to die from non-fishing causes (e.g., predation). Failing to allow individuals to grow large enough to maximize yield is known as “growth overfishing” (Hilborn and Walters, 1992). In populations with weak stock-recruit relationships, as are common in large marine ecosystems, recruitment overfishing can only occur at extremely low spawning biomasses (Szuwalski et al., 2014; Sellinger et al., 2024). Especially for opportunistic species with high natural mortality, fast growth, and variable recruitment, growth overfishing is therefore a key consideration for management, although ecosystem responses to low biomass do likely occur well before recruitment overfishing (King and McFarlane, 2003; Caillouet et al., 2008; Cury et al., 2011).

Somatic growth in marine populations is highly variable, but often difficult to characterize. Somatic growth variability has major implications for population dynamics and productivity, sometimes comparable to variability in early life history survival (Stawitz et al., 2015; Stawitz and Essington, 2019). This variability, in turn, influences optimal fishery management policies in important ways (Lorenzen, 2016). However, identifying environmental and density-dependent drivers of growth, as with many marine population processes, has proven difficult largely due to data limitation and the complexity of the marine environment (Stawitz et al., 2015). In addition, most studies on growth variability in marine populations have focused on finfish due to their hard structures that can be reliably aged. Because of the difficulty in ageing, relatively few studies have quantified somatic growth variability in wild crustacean populations or attempted to identify drivers of that variability. Lab studies have identified many common factors such as temperature and food supply, as well as potentially important drivers in the future such as ocean pH (see Chang et al., 2012 for review). The more limited *in situ* research indicates that, as with finfish, somatic growth variability can be notable and have consequences for fishery production and management (Brylawski and Miller, 2006; McMahan et al., 2016).

Seasonal forecasting that provides actionable decision support can reduce uncertainty and manage business risks in both aquaculture and wild capture fisheries (Hobday et al., 2016). However, in order to take advantage of these gains, reliable indicators that tie forecasts to population dynamics must be identified. A number of barriers exist in using operational forecasting in ecology and resource management. These can be categorized by data limitation (repeated measures, timely), probabilistic limitations (quantifying uncertainty and skill), model limitations (structural uncertainty, data-model assimilation techniques), and social limitations (training, culture, professional incentives) (Dietze et al., 2018). However, our ability to move past these challenges and provide and assess the skill of seasonal-scale forecasts is key to adaptive management in the age of climate change (Walters and Hilborn, 1978; Brodie et al., 2023).

For at least two decades, managers and participants in the Oregon pink shrimp (*Pandalus jordani*) fishery have been faced with a challenge to maximize revenue and yield each year and avoid growth overfishing within a highly dynamic population. The fishery would thus benefit from seasonal forecasts. In 2004, a study found that to maximize revenue per recruit, season openings should be delayed under high fishing mortality rates, but not under low fishing mortality rates, even though the current early opening date maximized *yield* per recruit across all fishing mortality rates (Gallagher et al., 2004). Since 2004, the Oregon Department of Fish and Wildlife has pursued several lines of research to better understand shrimp population dynamics as part of becoming the first Marine Stewardship Council certified shrimp fishery. A virtual population analysis now allows for more rigorous estimation of fishing mortality rates and recruitment once a year class has been fished for three years (Hannah and Jones, 2014a). In addition, a number of reports have summarized the variability in growth, recruitment, and their relationship to density-dependent and density-independent (i.e., environmental) factors (Hannah, 2011; Hannah and Jones, 2014b, 2016; Groth and Hannah, 2018; Groth, 2022). Despite the new research, the question of when the fishery should open each year still remains a key question for managers, and the industry often elects to delay the start of the fishing season for several weeks in years when individuals are small. Finally, because pink shrimp are short-lived and fast-growing, length-frequency analysis is a reasonable approach to understand variability and drivers of somatic growth, unlike many other crustacean species (Chang et al., 2012).

In this study we 1) use multivariate autoregressive state space models to quantify variation in shrimp size-at-age across time and space in the Oregon pink shrimp fishery, 2) test whether environmental or density-dependent factors can improve predictions of shrimp length-at age, and 3) apply the growth model to a revenue per recruit analysis to explore how variation in shrimp growth across time and space impacts optimal management decisions on when to open the shrimp fishery. This information is intended to help managers identify default dates to open the fishery across its spatial range, as well as identify factors that may help adaptively manage the opening date as growth, abundance, and fishing effort vary across years.

2 Materials and Methods

*Oregon Pink shrimp*

Pink shrimp (*pandalus jordani*) mate in fall. Females carry externally fertilized eggs from around October to March. During this time, the fishery is closed largely to protect the population’s reproductive capacity. Females release larvae in March and April after which the fishery opens. Larvae exist in the water column during the spring and summer, and then settle to the seafloor where they begin occasionally showing up in trawl catches as age-0s in September and October. Fishery recruitment is generally measured as the cohort strength of age-1 shrimp the following spring, one year after they were released as larvae. The first reproductive season is the winter between their first and second years (right?) (Hannah and Jones, 2014a). Pink shrimp are also protandrous hermaphrodites with sexually dimorphic growth (females are larger), and year class strength impacts the observed sex ratios (Charnov and Hannah, 2002).

Pink shrimp is a state-managed fishery and the population is not well-sampled by any fishery-independent survey. In addition to restricting fishing while females are brooding, the fishery is mainly managed by size (maximum count per pound), the number of permitted vessels, and the gear that vessels may use. Managers conduct a virtual population analysis annually, allowing estimation of recruitment following a cohort’s third year being available to the fishery (Hilborn and Walters, 1992). After the third year, all individuals in the cohort are assumed to have been caught or died of other causes. While the fishery legally operates from April 1 to October 31, fishing is sometimes delayed if individuals are perceived as too small, and there are currently debates about whether to make this delay a permanent feature. Fishing vessels originate from all three West Coast states (Washington, Oregon, California), but the fishery is centered around Oregon, with X% of landings occurring on vessels permitted in Oregon. Data from the fishery are collected within 12 distinct state areas across the three states (Figure 1). Although shrimp, like other shellfish, cannot be aged from hard tissues, each age class is clearly visible as a mode in length-frequency plots, and ages are assigned based on year-, month-, and sex-specific nadirs in the frequency plot. Because the three age classes are clearly defined in the length-frequency plots, this is considered a sufficiently reliable method (Chang et al., 2012).

*Drivers of population dynamics*

Shrimp population dynamics have previously been found to be correlated with sea level height and the Bakun upwelling index (Hannah, 2011; Rothlisberg and Miller, 1983). The strength and timing of upwelling of cold deep nutrient-rich waters impacts the temperature shrimp experience, ocean transport during the larval stage to adult habitat, and quantity and quality of food resources. For this analysis, we used the coastal upwelling transport index (CUTI) and biologically effective upwelling transport index (BEUTI) calculated monthly and averaged across 42, 45, and 47°N, the approximate latitudinal range of the data, and from March through June, the key spring upwelling period (Jacox et al., 2018). These upwelling indices are improved measures of upwelling strength relative to the Bakun index and are more relevant for marine organisms (Jacox et al., 2018). In addition, shrimp from large year classes may be smaller and skinnier due to competition with conspecifics.

*Growth model*

Variability in growth over time and space was estimated using a multivariate autoregressive state-space model (e.g., De Valpine, 2003; Stawitz et al., 2015; Table 1). Let *La,c,r* be length of age *a* (in months) shrimp from the cohort *c* in state area (region) *r*. Then:

Where *µL1* is the average length of age 1 shrimp in April, *α0* and *α1* describe the average monthly growth increment, *αs* is the magnitude of the seasonality component, and*ma* is the month of the year for shrimp of age *a* months (cycles back to 1 at the end of the year). To align *m* with the seasonal cycle of growth, *m* = 1 corresponds with March. The seasonality component was included due to a cyclical pattern initially observed in process errors, as crustaceans commonly experience temperature-driven seasonal growth variation (Chang et al., 2012). is the observed average length of shrimp of age *a* (in months) from cohort *c* caught in state area *r* as measured by port samplers*.* We furthermore assume that process errors (*ε*), observation errors (*δ*), and spatial variation (*γ*) are all normally distributed with mean zero and standard deviations *σL1* (*ε1*, variability of size at recruitment in April), *σp* (*εa*, *a* ≠ 1, variability of process errors after recruitment), *σo* (*δ,* variability of observation error), and *σr* (*γ*, regional variability). Note that this model is akin to a discretized version of the differential equation for the Von Bertalanffy growth model:

Where *α0* is analogous to *kL*∞ and *α*1 is analogous to 1-*k*.

We fit the above model in a Bayesian framework via markov chain monte carlo (MCMC) conducted by Stan (Stan Development Team, 2022) and implemented with the Rstan package (Stan Development Team, 2020) in R (R Core Team, 2021). We subtracted the mean observed length from the data before fitting to improve numerical stability. We ran four chains for 4000 iterations each, retaining the final 2000 draws. Convergence was determined based on R-hat, using the accepted threshold of 1.05, and by ensuring effective sample sizes of at least 100 (Vehtari et al., 2021).

The model fit to equations 1-3 indicated high variability in size at recruitment across space and time (i.e., high estimates of *σL1* and *σr* relative to all variance estimates). Thus, environmental covariates were included in a way that modified size at recruitment:

Where ***X****c* is a vector of environmental covariates during the period that impacts size at recruitment of cohort *c*, ***β*** is a vector of estimated parameters quantifying the impact of the covariates on size at recruitment, and the *T* superscript indicates the vector transpose. For simplicity and due to computational limitations of the Bayesian model, ***X****c* was either a scalar representing a single covariate, or a vector of length two, representing a single covariate and its quadratic term. CUTI and BEUTI were lagged by one year (i.e., upwelling impacts larval age-0 growth which is observed when they recruit to the fishery the next year). Variables were standardized by subtracting the mean and dividing by the standard deviation.

Model selection was conducted using Pareto smoothed importance sampling leave one out cross validation (PSIS-LOO CV), which efficiently approximates leave one out cross validation from MCMC samples (Vehtari et al., 2017, 2022b), and implemented by the loo R package (Vehtari et al., 2022a). While this does not explicitly account for the autoregressive nature of the data, there are limited methods available for reliable and computationally tractable Bayesian model selection.

*Bioeconomic model*

The estimated growth model was then used as an input into a revenue per recruit model used to assess the impact of growth and different season opening dates on expected revenue (Tables 1, 2). Specifically, we looked at the revenue per recruit curves of opening dates between April 1 and June 1 in bimonthly increments (i.e., April 1, April 15, May 1, etc.).

A revenue per recruit model begins with a population with one recruit, projects that single recruit through a population model, and then sums expected revenue over the lifetime of that recruit. Thus, the number of shrimp per recruit at age *a* = 0 months, *N0,* is assumed 1. The model was implemented in bimonthly increments because of the set of opening dates tested, but all time units are in months. Thus, the number of shrimp per recruit at age *a* + 0.5 months is:

Where *Ms* is the monthly natural mortality rate during season *s*, *I*open is an indicator variable that is equal to 1 if the fishery is open and 0 otherwise, and *F* is the presumed monthly fishing mortality rate. Catch in numbers during each bimonthly period follows the Baranov catch equations and is

Season *s* is either summer (April-October), when natural mortality is higher or winter (November-March), when natural mortality is lower (Gallagher et al., 2004). Because of the seasonal nature of both fishing and natural mortality, there is no straightforward analytical solution for the plus group. Few shrimp survive past their third summer, so expected revenue was assumed to be zero at this point. The virtual population analysis used to manage the fishery makes the same assumption (Hannah and Jones, 2014a).

Obtaining yield in weight from catch in numbers required a length-age relationship, fit above, and a length-weight relationship. Shrimp in the middle of the month were assigned length based on their age at the start of the month. A weight-length power relationship was fit to available Oregon Department of Fish and Wildlife (ODFW) data from 2014-2021 as a linear model on a log-log scale using ordinary least squares regression and then bias corrected. Total yield per recruit was calculated as yield summed across all bimonthly age increments.

Processors generally pay higher prices per pound for shrimp when the count per pound is lower (i.e., when individual shrimp are larger). We accounted for this in our revenue per recruit model by fitting a linear model of ex vessel price as a function of count per pound, including each year-month combination as an additional fixed effect to account for market effects on price. The model was fit to data from shrimp tickets in PacFIN (Pacific Fishery Information Network; https://pacfin.psmfc.org/) between 2016-2020 matched with biological port sampling data on count per pound available from ODFW. As expected, count per pound had a negative effect on price. For more details on the price model, see supplemental materials.

3 Results

Shrimp size at age varied across both time and space (Figure 2). Across years, the largest shrimp age 2 and older tended to be observed in cohorts that recruited prior to 2000. This trend over time was not as apparent for age 1 shrimp. Growth slowed somewhat during the winter months. Across space, there is a clear pattern of smaller shrimp at age in more northerly state areas, particularly areas 30 and 32 which cover most of the Washington state coastline. Across both years and state areas, average size at recruitment varied by approximately 2-3 mm over the observed data.

The model generally fit the data well, and convergence diagnostics indicate that the model successfully converged and produced an adequate effective sample size for all key parameters; mixing was worst for the size at recruitment and process variance (Fig. S1, Table 3). The model does not estimate slowing down of growth at older ages, as indicated by the estimate of *α1* close to 1, although model the model does tend to estimate decreasing process errors as age increases (Figs. S1, S2). Various approaches were tried to make process errors centered around zero for all ages (e.g., informative priors on *α1*), but this slowed mixing, and the model consistently estimated *α1* close to 1. The two largest variance estimates described variability in size at recruitment across time, *σL1*, and across space, *σr* (Table 3). The smallest variance estimate was for process error, which is the monthly variation in the growth increment that is shared across all areas. The observation variance, which includes both actual sampling error and true differences in size at age across state areas unexplained by size at recruitment, was larger than the process variance.

None of the variables tested to influence size at recruitment (CUTI, BEUTI, log-recruitment) markedly improved the expected log predictive density (ELPD) over a base model that relied on random variation about a mean size at recruitment (Table 4). The model with a single linear term for CUTI had the highest (best-fitting) ELPD, and the base model with no covariates had the lowest ELPD. However, the difference between these two models was 3.6 log-density units. In general, differences in the ELPD of less than four units are considered small, and differences greater than four should be compared to the standard error of the difference (Sivula et al., 2023). The mean of the posterior distribution of the CUTI effect indicated a 0.112 mm decrease in length at recruitment for every 1 unit increase in standardized CUTI during the spring of larval release. This result suggests slower growth under stronger upwelling of cool nutrient-rich waters. However, the 95% credible interval was (-0.345, 0.125), indicating the effect was ambiguous. Therefore, because no variables substantially improved the model, subsequent results are from the base model with no covariates.

Using the growth model to inform the revenue per recruit model indicated that an opening date of April 1 maximized expected revenue per recruit up until a fishing mortality rate of around 0.2 mo-1 (Fig. 3). Under high fishing pressure, later opening dates were more beneficial. At no fishing mortality rate were intermediate opening dates beneficial; the date that maximized revenue per recruit was always the earliest (April 1) or latest (June 1). Changing the natural mortality rate, a highly uncertain parameter, shifted this inflection point. Higher natural mortality rates pushed the inflection point to higher fishing mortality and lower revenue while lower natural mortality rates pushed the inflection point to lower fishing mortality and higher revenue. Estimates of actual monthly fishing mortality in the fishery averaged around 0.1 mo-1 during the fishing season from 1980-2011, ranging from approximately 0.03 to 0.2 (Hannah and Jones, 2014a).

Across space, a wider range of fishing intensities supported later opening dates in state areas farther north, particularly areas 30 and 32 which cover most of Washington state (Fig. 4). These northern areas, where shrimp tended to be smaller, also supported less revenue per recruit overall, though total revenue and profits depend on a variety of additional factors such as catch rates and market forces. On the other hand, the early April 1 opening was optimal across the entire range of observed fishing mortality rates for southern fishing areas that served as habitat for the largest size shrimp.

Size at recruitment has varied substantially across time, and this has also had economic implications for the fishery (Fig. 5). For year classes with large shrimp, such as 1991, an early opening was optimal regardless of fishing mortality rate. For years with small shrimp, such as 2011, the best opening date was ambiguous and depended on the fishing mortality rate. An early opening was optimal at lower fishing mortality rates, but a delayed opening was better at higher fishing mortality rates, with an inflection point right (i.e., all opening dates are similarly optimal), around the long-term average fishing mortality rate of 0.1. Thus, if fishing mortality is low (e.g., harvesters are not incentivized to fish due to low prices, high costs, or other opportunities, a large year class overwhelms fishing capacity) or average, an early opening date is best. If fishing mortality is high, however, the optimal decision on opening depends on the size of the shrimp.

Accounting for spatial *and* temporal variation illustrated that both factors operated jointly in determining optimal opening dates (Fig. 6). In years where shrimp recruited at small sizes (e.g., 2011), it was generally beneficial to postpone opening in northern areas (e.g., area 32), whereas the optimal opening date in southern areas with larger shrimp (e.g., area 19) depended on the fishing mortality rate. In years where shrimp recruited at large sizes (e.g., 1991), the early opening date was optimal in areas with large shrimp within the observed fishing mortality range, but the optimal opening date depended on the fishing mortality rate in the areas with small shrimp.

4 Discussion

Our analysis and modeling can help provide advice to managers on when to optimally open the fishery, accounting for variability in growth across years and across the population’s spatial range. Decision-makers are best prepared to account for this heterogeneity if they have information on the size of the shrimp recruiting to the fishery in a given year (e.g., from a test fishery), and a proxy for how strong they expect fishing mortality to be relative to past years (based on factors such as shrimp prices, fuel costs, fishery CPUE, etc.). In years with small shrimp, managers can optimize revenue per recruit by delaying opening until June in northern state areas and delaying in southern state areas if proxies indicate fishing mortality will be average to high. If fishing mortality is expected to be low, southern areas are slightly better off opening the fishery in April, but the differences are small and may not warrant the additional complexity. In years with average size shrimp the April 1 opening produced either optimal revenue per recruit or similar revenue per recruit to other opening dates, for state areas 12-29; this is the case across fishing mortality rates. In the most northerly areas 30 and 32, if fishing mortality is expected to be high, there is a clear benefit to delaying the opening to June. If fishing mortality is expected to be low or average, there may be a slight benefit to opening in April, but the differences in revenue per recruit are small across opening dates. Finally, in years with large shrimp, the early April 1 opening date is generally a good option across all state areas. Notably, we did not find support for intermediate opening dates between April 1 and June 1.

We did not identify any density-dependent or density-independent covariates of size at recruitment that improved model predictions and could promote seasonal forecasting and assist with management decisions on when to open the fishery. There are several possible explanations for this result, and they need not be mutually exclusive. First, growth could respond non-linearly to drivers, or the effects of drivers may only arise when accounting for interactions among them. Machine learning methods like boosted regression trees would be better-suited to infer these types of effects, but require larger datasets than were available and are not well-suited to mechanistic models like the one we fit (Ward et al., In review). Second, we may not have selected the correct divers to test. Identifying appropriate oceanographic drivers of marine population dynamics is notoriously difficult (Myers, 1998; Brooks and Deroba, 2015; Haltuch et al., 2019). A more thorough review of shrimp life history and its relationship to local oceanography may be needed to identify appropriate drivers. For example, while upwelling is highly correlated with temperature, directly including temperature may have been better (Rothlisberg, 1979). Sea surface temperature, possibly relevant for pelagic larval stages, is available for the entire time series modeled. However, including bottom layer temperature, relevant for settled juveniles, would require eliminating years at either the beginning or end of the time series, depending on the oceanographic modeling product. Finally, growth could be a truly stochastic and unpredictable process. Others?

This study contributes to an existing body of work on the ecology and management of Oregon pink shrimp in two key ways. First, while annual growth indices summarized across cohorts and months have been derived to explore the influence of density-dependent and density-independent factors on growth, no work to date has explored growth variability in a mechanistic fashion such as the one employed here, more directly modeling the data as they were collected (Hannah and Jones, 2014b, 2016; Groth and Hannah, 2018; Groth, 2022). Our approach did require more complex models with extra parameters compared to the simpler regression approach used to model the derived growth index. Although we were less likely to identify spurious drivers using our approach, and the results can provide more actionable management guidance, we also had less statistical power to identify true drivers, which bore out in the results. Second, previous work studying when to open the fishery looked at the joint impact of natural mortality, fishing mortality, and the response metric- revenue versus yield per recruit (Gallagher et al., 2004). We chose to use the metric more relevant to the fishing fleet (revenue per recruit), and added a new dimension to the analysis in its place: size at recruitment. This allowed us to provide more dynamic advice over both time and space, giving managers information they can use to adaptively manage the fishery.

Validating lab studies to understand growth variability in wild crustacean populations has often been limited by the difficulty in determining reliable ages of wild-caught individuals. A large number of studies have explored impacts of density-dependent and density-independent factors on growth in controlled laboratory settings (see Chang et al., 2012 for review). Intensive tagging studies have shed light on growth variability in real-world conditions, but these are generally limited to data-rich populations with long-term fishery-independent monitoring programs (e.g., McMahan et al., 2016). Using ages determined from length-frequency distributions is not a gold standard and can result in biased estimates of biological reference points, particularly when confounded with estimation of mortality rates in stock assessments (Fournier et al., 1991). However, such ages can still be a valuable and sufficient source of information on somatic growth in management-relevant contexts for appropriate species. Pink shrimp in Oregon are short-lived and fast-growing with good long-term fishery-dependent data, but limited fishery-independent monitoring, making them an excellent candidate for the application of length-frequency-derived ages. We were able to use these ages to quantify variability of growth over time and space, and to develop models that suggest when is optimal to open the fishery in different locations and years.

The models used in this study made a number of assumptions that may have influenced our conclusions. First, results of our revenue-per-recruit model are dependent on the fishing mortality rate that the fishery prosecutes. However, the fishing mortality rate is extremely difficult to control in a short-lived population such as shrimp because the population biomass generally changes much more rapidly than it can be assessed. Proxies for the fishing mortality rate may be able to be approximated using early season catch rates to identify relative year class strength, and in-season data on fishing effort. Second, the shrimp population distribution generally stratifies by age, and harvesters capitalize on this by fishing larger age-2 and age-3 year classes early in the season and smaller age-1 year classes later in the season. Our revenue per recruit model assumes constant monthly fishing mortality on each year class within and across seasons. This means that they fishery may effectively be delayed in most years for newly recruited shrimp, in particular, and monthly fishing mortality rates when the year classes are being targeted may be higher than the range reported. Finally, shrimp are protandrous hermaphrodites and sexually dimorphic, but we did not account for either of these factors. Furthermore, more primary females are observed when the age-2 and age-3 year classes are weak (Charnov and Hannah, 2002), and these primary females tend to be larger than primary males. Accounting for variation in the sex ratio could make the average size at recruitment more predictable. For example, if the age-2 and age-3 year classes are known to be weak, the age-1 year class may have an above-average proportion of primary females, leading to a larger size at recruitment. In addition, the relative number of primary females could influence the process error estimates across the cohort’s lifespan (e.g., more primary females means shrimp have already reaped the “female size bump” and there is less growth during older life stages). Other caveats I could include: condition factor (Scott, is there anything to cite on this?), ageing methods, other? But am also trying not to have this paragraph be half of the discussion so if you suggest adding something consider also suggesting taking something out…

5 Conclusions

Pink shrimp was the fifth most important fishery species on the U.S. West Coast over the last decade in terms of revenue, and it can be a key source of income for participants in some years (Free et al., 2023). For example, during the 2014-2016 marine heatwave when key fisheries such as salmon experienced precipitous declines, strong recruitment prior to the heatwave coupled with high prices set by global markets allowed for record revenue from the pink shrimp fishery. Therefore, sustainable fishery management that prioritizes population and ecosystem health while also seeking to maximize fishing revenue can help sustain and stabilize local coastal economies by allowing them to rely on a diversity of fisheries (Kasperski and Holland, 2013; Sethi et al., 2014; Oken et al., 2021). The work in this study can help inform when the fishery opens each year in different management areas along the coast, giving targeted advice on when and where it should be delayed, thus helping to maximize fishing revenue each year. However, temporal diversification, that is, spreading fishing activities evenly across year, is also a key way that harvesters reduce risk and make full use of their fishing capital (Oken et al., 2021; Abbott et al., 2023). Changing the time of year that the shrimp fishery operates may impact the temporal diversity that it provides. Harvesters themselves have initiated discussions on delaying the opening of the shrimp fishery. However, as with many fishery management decisions, the fishing community should have an opportunity to respond to any significant changes to the timing of the fishery to ensure their goals and priorities are being considered (Wiber et al., 2004).

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