Grand title

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Abstract

Key words

Introduction

Diverse resource portfolios can reduce revenue variability and financial risk incurred due to the large fluctuations in productivity and profitability of exploited natural populations (Kasperski and Holland 2013). Variability in fishing revenue declines for individuals (Anderson et al. 2017), vessels (Kasperski and Holland 2013), and communities (Sethi et al. 2014, Himes-Cornell and Hoelting 2015, Cline et al. 2017) when groups maintain a diverse portfolio of fishing activities by targeting different species or geographic areas. However, the ability to build diverse fishing portfolios has declined as limited access and catch share programs have increasingly constrained access to fisheries. This is particularly the case for younger fishers who were not gifted fishing permits when access first became limited (Kasperski and Holland 2013, Himes-Cornell and Hoelting 2015, Holland and Kasperski 2016, Holland et al. 2017).

The ecological dynamics and life histories of the populations that comprise resource portfolios mediate the extent to which diverse portfolios benefit income patterns and risk. First, population synchrony can play a role. Synchronous populations tend to respond in the same direction to shared drivers or have similar exploitation histories (Baum and Worm 2009, Hansen et al. 2013), whereas asynchronous populations tend to be competitors or respond in opposite directions to a shared driver (Hare et al. 1999, Gonzalez and Loreau 2009, Loreau and Mazancourt 2013, Selden et al. 2018). Populations that vary asynchronously or independently of one another yield a more temporally stable aggregate biomass than populations that vary synchronously (Doak et al. 1998), and this stability in biomass can lead to greater stability in the revenue that the portfolio of populations generates (Hilborn et al. 2003, Schindler et al. 2010). Second, variability itself can be driven by life history. Long-lived species with “slow” life histories tend to exhibit smaller interannual variations in biomass than “fast” short-lived species (Warner and Chesson 1985, Winemiller and Rose 1992). Finally, phenology often determines timing of the fishing seasons so that populations are protected during periods that are particularly important for reproduction and growth (e.g., molting, carrying of egg sacs). Portfolios that both stabilize *and* increase revenue should take advantage of differences in timing of seasons within the year to enable fuller use of fishing capital. Both natural (Schindler et al. 2013) and human predators can benefit from taking advantage of these phenological portfolios.

An extensive social-ecological modeling literature has demonstrated that managing fisheries without regard to the interactions between ecological dynamics and human behavior can undermine biological sustainability and reduce the benefits fishers and society derive from the ecosystem (see Nielsen et al. 2018 for review). For example, vessels in multispecies fisheries can intentionally alter their fishing behavior to avoid species with lower natural productivities and achieve more optimal harvest patterns (Kirkley and Strand 1988, Squires and Kirkley 1991), and accounting for ecological interactions, such as predation, can generate new fishing opportunities (Oken and Essington 2016) and lead to different estimates of management targets (Collie and Gislason 2001, Overholtz et al. 2008, Holsman et al. 2016). However, there has been relatively little focus of this literature on how the management of access rights and the ability of fishers to diversify influences returns. While diversification may have a cost in terms of efficiency, the natural variability of fisheries means that idealized systems include a mix of specialist and generalist individuals (McKelvey 1983, Smith and McKelvey 1986). Acknowledging the costs and benefits of diversification, Sanchirico et *al*. (2008) applied financial portfolio theory to fisheries and generated an efficient frontier of catch allocations that minimize variability and maximize returns; however, the correlation patterns were based on correlations in historical gross revenue and had no mechanistic ecological basis.

The California Current Large Marine Ecosystem (CCLME) provides an ideal model system to explore how ecological dynamics and management decisions combine to impact the profitability and risk of alternative fishing portfolios and overall fishery performance. Many fisheries in the CCLME are highly interdependent, sharing linkages through both exposure to common environmental drivers and cross-participation of fishers. Climate variability is a strong component of the CCLME (Schwing et al. 2010), especially due to ENSO events (Jacox et al. 2016) and the Pacific Decadal Oscillation (Mantua et al. 1997, Hare and Mantua 2000). In addition, physical changes associated with warming and ocean acidification could increase and transform previous patterns of climate variability (Black et al. 2014). Climate cycles and oceanic conditions influence the productivity of many commercially valuable species across scales through impacts to recruitment, growth and spatial distribution (Black et al. 2010, Schwing et al. 2010, Hazen et al. 2013, Shanks 2013, Stachura et al. 2014, Stawitz et al. 2015), indirectly linking their dynamics. Participation of fishers in multiple fisheries within the California Current provides additional connectivity of dynamics among the component populations. Although the strength of this cross-participation varies among fishing ports, it represents an important linkage at the coastwide scale (Fuller et al. 2017).

We develop a simulation model that is roughly based on the fisheries for three key species in the CCLME. We use this model to explore how synchrony of productivity combined with ease of access and movement among fisheries combine to affect profitability and variability in income for fishers. Understanding the consequences of management strategies in conjunction with the ecological dynamics of the fish stocks and the participation decisions of fishers is daunting. Simulation models that capture the key characteristics of this system can help overcome data limitations and provide insights into the dynamics of these complex socioecological systems. We simulated annual recruitment and population dynamics and weekly fishery participation decisions for six permit portfolios that target some combination of Dungeness crab (*Metacarcinus magister*), Chinook salmon (*Oncorhynchus tshawytscha*) and groundfish (characterized by Sablefish: *Anoplopoma fimbria*) off the U.S West Coast. We used the model to vary the number of fishers holding a diverse permit portfolio under alternative correlations in recruitment of the populations. We consider how changes in the ease of access affect the profitability and variability in profits for the different fleets at individual and aggregated levels when recruitment among the populations is synchronous, asynchronous, or independent.

Methods

We built a simulation model three species (crab, salmon, and groundfish) which are linked by cross-participation of fishing vessels and shared productivity dynamics (Table 1). We tested scenarios that altered the cross-participation dynamics by adjusting the number of vessels with permits for more than one fishery and tested scenarios that altered the productivity dynamics by adjusting the synchrony among the three populations. We simulated fisheries for 50 years and ran X 50-year simulations under each scenario. The model was written in R version 3.5.1 (R Core Team 2018) and code is available online (https://github.com/okenk/CC\_bioecon).

*Focal fisheries*

Despite limits on the number of participants, vessels participating in Dungeness crab fisheries race to catch available crabs as quickly as possible. Nearly all legal-size males are caught in a matter of weeks, and catch rates decline rapidly as fishers deplete the population. Most fishers exit before the fishery legally closes and participate in other fisheries or outside work. The timing of this exit varies substantially among years and vessels due to variability in the opening dates, abundance of crab, and individual cost incentives. Crab recruitment is largely driven by environmental conditions during the larval phase, and they display little to no stock-recruit relationship (Shanks and Roegner 2007, Shanks 2013) so we modeled recruitment as a random lognormal variable with temporal autocorrelation to emulate observed regime-like patterns, described below. The biomass available to the fishery is simply the biomass corresponding to the year’s recruitment. We assume crab fisheries open on December 1 (start of the model year) and close on August 14.

Ocean troll fisheries for salmon on the U.S. West Coast are mainly based on hatchery fish, but less abundant wild stocks mix with the hatchery fish and also appear in catches. Like crab, salmon fisheries display high interannual variability and have been subject to several large closures in recent years designed to protect threatened or endangered wild stocks (Richerson and Holland 2017, Richerson et al. 2018). Because the majority of the ocean salmon harvest is of hatchery origin, biomass available to the fishery depends mainly on hatchery production and survival rates, not the number of fish that returned to spawn (Shelton et al. 2018). Thus, we again modeled recruitment without a stock-recruit relationship as a random lognormal variable with temporal autocorrelation where biomass available to the fishery is equal to the year’s recruitment. Salmon fisheries experience much less depletion through the season than crab fisheries. We assume salmon fisheries open on May 1 and close on October 31.

The groundfish fishery is relatively stable in comparison to crab and salmon, as it targets longer-lived species and exerts much lower fishing mortality rates (e.g., Johnson et al. 2015). Because the biomass of available groundfish in a given year depends on both new recruitment to the population and whatever biomass survived and grew from the previous year, we modeled the groundfish populations using a delay-difference model, described below. Groundfish fisheries operate year-round.

*Weekly fishery participation model*

Each week of the year, vessels in the model each consider their costs and anticipated revenue and decide whether it would be profitable to fish. If it is profitable to fish in more than one fishery, they also choose which fishery to participate in.

Costs of fishing were divided into annual fixed costs for each species *s* () that were automatically incurred every year (e.g., permits, boat and gear maintenance) and weekly variable costs for each species *s* and vessel *v* (*cs,v*) that were only incurred if a vessel chose to fish for a particular species in a given week (e.g., fuel, bait, labor). Variable costs varied among vessels according to a lognormal distribution to mimic disparities in fishing efficiency and introduce differences in participation decisions among vessels during the season.

Fishers were assumed to have perfect knowledge of the available biomass each week, and catchability was held constant with no interference among vessels. Revenue for a vessel fishing for species *s* in week *w* of year *y,* *rs,y,w* was then:

where *qs* is the catchability of species *s* (proportion of the population harvested by one vessel in one week) and *Ps,y,w* is the price per unit biomass of species *s* in week *w* of year *y*. Prices were held constant for groundfish and salmon, so fishers also had perfect knowledge of the revenue and profit they would earn in a week for those populations. A linear demand function was built for crab to better mimic real dynamics of the Dungeness crab fishery. Compared with a constant price, this function led to much higher population depletion by the end of the season and increased the temporal overlap between the actualized crab and salmon fisheries. Prices for Dungeness crab (*Pd,y,w*, subscript *d* for Dungness)increased linearly as catches fell once total weekly catches (*Cd,y,w*) were below 10% of average recruitment biomass (product of average recruitment and weight at recruitment, ):

This functional form ensures continuity at the threshold. Fishers used the crab prices from the previous week to calculate expected revenue and profit for the upcoming week. In the first week of the year, we assumed fishers already had perfect knowledge of recruitment, and they calculated expected prices based on the demand function, assuming that every vessel holding a crab permit would fish for crab in the first week (which usually occurs).

Each week every fisher then calculated their expected marginal profits (*rs,y,w* – *cs,v*) for each fishery that was open and for which they held a permit, and either fished in the most profitable fishery or, if no fishery was profitable (*rs,y,w* – *cs,v* < 0 for all species *s*), did not fish that week. For vessels holding multiple permits, variable costs across fisheries were correlated (i.e., efficiency across fisheries is correlated for each vessel at a correlation of *ρc*):

where *σc2*, the diagonal of Σ*c*, is the variance of the log of the weekly variable cost (shared for all three fisheries) and all off-diagonal entries in Σ*c* are equal to *ρcσc2*. Bold symbols are vectors comprised of the value of that variable for each species. The mean parameter, ***c***, is further described in the parameterization section.

For each 50-year simulation, we calculated the mean and standard deviation of both profit and revenue and the coefficient of variation of revenue for each vessel. We also computed those same statistics for revenue and profits summed over the entire fleet, and we computed the mean, standard deviation, and coefficient of variation for total revenue summed over each species. Tracking profits for each species and vessel simultaneously was more memory-intensive, and profits and revenues tended to show similar patterns in the cases where we tracked both.

*Salmon and crab population models*

Salmon and crab populations were modeled as random recruitment deviations with no dynamics explicitly linking biomasses from one year to the next. Thus, recruitment for species *s* in year *y* was:

where  is average recruitment for species *s*, *εy,s* is an autocorrelated normal random variable, the second term in the exponent is a bias correction which ensures the expectation of the entire exponentiated term is 1, and *σR,s* is the unconditional standard deviation of *εs*.

When recruitment is independent among populations,

where *ϕs* is the strength of autocorrelation (between zero and one) for species *s*.

*Groundfish population model*

The groundfish population is simulated based on a Deriso-Schnute delay-difference model with a Beverton-Holt stock-recruit relationship (Schnute 1985). This allows for changes in age structure, an advance from simpler surplus production models, but restrictively assumes selectivity and maturity are knife-edged and occur at the same age (Hilborn and Walters 1992, Quinn and Deriso 1999). Although biomass dynamics in this model can be simulated with a single complex equation, for ease, we equivalently modeled both abundance (*N*) and biomass (*Bg,* subscript *g* for groundfish) (Hilborn and Walters 1992). For comparability with the crab and salmon populations, we assumed these dynamics occurred at an annual time scale:

where *Sy* is total per capita survival in year *y*; *α* and *β* are the intercept and slope, respectively, of a Ford-Walford plot (i.e., plot of weight at age vs. weight at age - 1); *ωk* is the weight at age *k*; *k* is the age at both recruitment to the fishery and maturity; and *Ry,g* is the recruitment to the fishery of groundfish in year *y*. We assumed a Beverton-Holt stock-recruit relationship using the steepness parameterization, so that:

where *h*, *R0*, and *B0* are steepness (percent of unfished recruitment occurring at 20% of unfished biomass, i.e., “resilience”), unfished recruitment, and unfished biomass, respectively, *Hy* is the proportion of the biomass that was harvested in year *y*, and *εy,g* is a random recruitment deviation in year *y* for groundfish modeled in the same way as described in the previous section. This model formulation presumes that reproduction occurs after fishing and before natural mortality. Unfished biomass is calculated based on equilibrium conditions as *R0*/*κ* where *κ* is the following growth-survival constant:

*Parameterization*

Because we were interested in comparing revenue and profit patterns across different scenarios, but were not attempting to accurately represent the actual values of the revenue and profit earned, many scaling parameters were set to unit values for simplicity (Table 2). Examples of such parameters are average recruitment, price per unit weight, and weight at recruitment.

We included six different possible permit portfolios in our model: three portfolios where vessels specialize in a single fishery (crab, salmon, and groundfish) and three portfolios where vessels hold permits for more than one fishery (crab-salmon, crab-groundfish, and crab-salmon-groundfish). We only model multi-fishery portfolios that include crab because crab is the highest grossing fishery, and we wanted to keep the total number of portfolios to a manageable level. [Do most vessels that participate in multiple fisheries fish for crab? Is there a citation for this?]

To maintain equilibrium in fishery participation (i.e., on average no entry or exit) and permit costs, we set total costs in an average recruitment year equal to total revenue for a marginal fisher (95th percentile of variable cost distribution) who might be considering entry into the fishery. For crab and salmon, we ensured this condition by using a root-finding routine that projected a single fishery in an average year. The routine solved for the mean variable cost given the profitability constraint, fixed costs, and catchability. To avoid monte carlo error in the root-finding algorithm, the routine deterministically assigned vessel-specific variable costs based on quantiles of the lognormal distribution. For simplicity, this variable cost calculation was done independently for each fishery (i.e., vessels did not have other fishing options during the calculations), and was based on a fleet consisting of the same number of vessels as held permits for the fishery in the baseline “medium access” scenario (Table 3, described in “Scenarios” section). For simplicity, crab prices in the algorithm were held constant at 1 rather than use the demand function. We manually adjusted *qs* and to achieve an acceptable annual ratio of variable costs to fixed costs for an average fisher (X for crab, X for salmon) and acceptable patterns of depletion over the year (Figure X).

Because the groundfish population dynamics respond to the fishery dynamics, tuning the fishery parameters was more a complex process. First, catchability was set so that when all vessels with groundfish permits in the baseline scenario participated in the fishery for 40 weeks of the year (40 was chosen since vessels do not actually fish every week of the year in reality), total yield is equal to the yield that leads the population to equilibrate at 40% of the unfished biomass (the actual management target). We then manually fixed the mean variable cost and solved for the fixed cost such that the same marginal vessel described above had no net profit at 40% of the unfished biomass under equilibrium age structure. The mean variable cost was tuned to achieve an acceptable annual ratio of variable to fixed costs in an average year with a population equilibrated at 40% of the unfished biomass (X). We also needed to ensure our assumption that all vessels fish for 40 weeks would occur given the cost structure, as no constraint actively prevented vessels from leaving the fishery earlier in the year. We calculated the revenue of the vessel with the highest variable costs (costs once again calculated deterministically based on quantiles) in the 40th week of the year and checked that the revenue was greater than the vessel’s variable cost. Finally, because the parameterization of this cost structure was quite complex and involved many calculations and assumptions, we visually checked that the fishery was roughly in equilibrium and that the groundfish population did not consistently tend to grow or decline during the simulations (Fig. SX).

We assumed the groundfish population had equilibrated at 40% of its unfished biomass at the start of each simulation. The groundfish growth parameters *α* and *β* were calculated by taking the weight at age from the Sablefish stock assessment’s age-length and length-weight relationships (Johnson et al. 2015) and estimating a linear regression through the resulting points (which are almost, but not exactly, linear). We fixed weight at recruitment (age 4), to 1, as with salmon and crab. Age at recruit was chosen blah. Steepness was taken from the stock assessment. Unfished recruitment was set at 0.5 so that blah.

*Scenarios*

We used the model described above to test how revenue and profit patterns changed under different ecological conditions (synchrony of productivity) and management strategies (access of individuals to diverse fishing portfolios).

The first set of scenarios varied the correlation in recruitment deviations among the three populations. When recruitment was correlated among species, recruitment deviations became autocorrelated *multivariate* normal random variables (called a vector autoregressive model):

where indicates elementwise multiplication, bold symbols are vectors comprised of the value of that variable for each species, and Σ is the covariance matrix. The diagonal of Σ was defined by the variance term of the normal distribution in equation X. The off-diagonals were defined as:

where *ρR,i,j* is the correlation in log recruitment deviations between species *i* and *j*. Note when recruitment among all populations is independent, as it is in the baseline parameterization, *ρR,i,j* = Σ*i,j* = 0 for all *i* and *j*, and equations X and Y become equivalent. We tested scenarios with *ρR,i,j* = -0.5, 0, and 0.5, using the same value for all three pairwise correlations (i.e., *ρR,i,j = ρR*). We tried using a magnitude greater than 0.5 but it is not mathematically possible to simulate three random variables that all have stronger negative correlations.

The second set of scenarios varied the number of vessels holding permits for a single fishery versus multiple fisheries while keeping the total number of vessels constant. We considered three scenarios: easy, medium, and hard access, with the number of specialist vessels increasing as access grows more difficult (Table 3). Finally, we tested the interaction between synchrony and permit access by running the easy and hard access scenarios under both synchronous and asynchronous recruitment.

Results

More access:

1. Decreases average profits and revenue of individuals within a fleet: less fish per person
2. Decreases crab revenue because derby fishery floods markets, prices are low
3. Increases salmon and groundfish revenue because more permits means more fish caught
4. Increases variability of salmon and groundfish revenue (CV & SD)
5. Decreases inequality in mean revenue because more people have access to high value fishery
6. Decreases profit/revenue SD within a fleet for anyone who has a crab permit
7. Decreases revenue CV across all individuals (except also eliminates groundfish specialist hump near zero)
8. Decreases *spread* of revenue CV distribution for crab and crab/salmon fleets— decreases instances of high *and* low variability individuals/simulations (which?)
9. Complicated impact on total summed revenue/profits. No/minimal change in variability.

Asynchrony:

1. No impact on mean profit/revenue of individuals
2. No impact on mean or variability of profit/revenue by species
3. Decreases individual profit/revenue variability for those in fleets with crab & salmon in permit portfolio.
4. Decreases total summed profit/revenue variability

Note that looking at the interaction of synchrony and access generally results in intuitive additive results.

Discussion

1. Summary of key results
2. Tradeoff between returns and variability. Catch shares reduce variability *within* year, but erosion of portfolios can increase variability *among* years.
3. Different patterns at different levels of aggregation (entire fleet, stock, individual). Choose the right metric.
4. Life history + synchrony patterns jointly determine the best portfolios to reduce variability.
5. This kind of model is fairly novel.
6. Caveats
7. Future research, broad conclusions.

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