Title: Overcoming challenges of harvest quota allocation in spatially structured populations

Running Title: Harvest allocations for spatially structured populations

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#### Abstract

Ignoring spatial population structure in the development of fisheries management advice can affect population resilience and yield. However, the resources required to develop spatial stock assessment models that match the spatial scale of management are often unavailable. As a result, quota recommendations from spatially aggregated assessment models are commonly divided among management areas based on empirical methods. We developed a spatially explicit simulation model to 1) explore how variation in population structure influences the spatial distribution of harvest that produces maximum system yield, and 2) contrast the performance of empirical quota allocation methods in approximating ideal spatial harvest strategies. Spatial scenarios that included post-recruitment movement resulted in a broader range of spatial management options (e.g., setting regional total allowable catch) that achieved near maximum system yield compared to scenarios without movement. Stochastic projections showed that using the proportion of total survey biomass in each management area to spatially allocate quota performed best for maximizing system yield when the true spatial structure was unknown, considerably outperforming equal allocation and allocation based on a recruitment index. However, with all methods, area-specific harvest rates sometimes led to unintended depletion within management units. Improved data and understanding of spatial stock dynamics can reduce the need for ad hoc approaches for spatial harvest allocation, allow for a greater range of management options, and increase the efficacy of spatial management procedures.


Keywords: Stock Assessment, Spatial Management, Connectivity, Population Structure, Catch Allocation, Harvest Rate

## 1. Introduction

Fish populations often exhibit spatial variability in biological characteristics (e.g., growth, maturity, fecundity, natural mortality, and movement) that arise from interactions with ecological and environmental processes, which influence population dynamics and create challenges for the development of sustainable fisheries management strategies (Ricker 1958; Jackson et al., 2010; Hanselman et al., 2015; Vincenzi et al., 2016; Kerr et al., 2017b). Yet, fishery management procedures commonly ignore spatial variability by assuming average population demographics (homogeneity) within or across management units. Management units are often conveniently defined (e.g., political boundaries) rather than aligning with known biological characteristics of the resource, which can create additional spatial heterogeneity through regulatory measures (Riess et al. 2009; Cope and Punt, 2011; Kerr et al., 2014; Hanselman et al., 2015). Recent advances in the understanding of spatial population structure and movement patterns (e.g., see Berger et al., 2017c) indicate a need to address spatial heterogeneity when providing management advice, such as defining biological reference points and associated catch quotas (Thouzeau et al., 1991; Rätz and Lloret, 2003; Melville-Smith and de Lestang, 2006; Jackson et al., 2010; Williams et al., 2012; Hanselman et al., 2015; Vincenzi et al., 2016). Additionally, it may be necessary to define regional-scale management procedures due to jurisdictional boundaries for shared stocks (e.g., regional management agencies, state, or international), fleet dynamics (van der Lee et al., 2014), socioeconomic considerations (e.g., cost of travel to fishing grounds; Thiault et al., 2017); resource distribution (Hanselman et al. 2016), and/or the existence of biological structure (Kerr et al., 2017a).

Population components defined by spatially varying life history characteristics can have differential responses to management actions, and not accounting for this variability may inhibit the ability to meet desired management objectives. For example, because long-lived, slowgrowing fish generally have a lower reproductive output compared to short-lived, fast-growing fish, they cannot sustain high harvest levels (Musick, 1999). Additionally, connectivity dynamics can confound the efficacy of management actions depending on the timing of those actions and the scale at which they are applied in relation to fish movement (McGilliard et al., 2015). Harvest rate differences among management units can differentially impact the size and age classes that move compared to those that remain resident within a single fishing mortality regime (Guan et al., 2013; Lee et al., 2017). These challenges demonstrate the need to understand and account for the interactions among movement dynamics and biological variability when considering spatial management procedures, such as TAC specifications (Kerr et al., 2014; Goethel et al., 2016; Goethel and Berger, 2017).

The increasing availability and quality of spatially resolved information regarding population structure, connectivity, and demographics has led to the development of population models which better represent the complex spatiotemporal nature of a fishery resource (Berger et al., 2017b, Goethel and Berger, 2017; Kerr et al., 2017a; Punt et al., 2017; Thorson et al., 2017; Truesdell et al., 2017). Various simulation studies have explored the impact of alternative spatial population processes on the estimation of population parameters used for setting management advice, including movement (Hulson et al., 2011; Goethel et al., 2015; Vincent et al., 2017), mortality (Johnson et al., 2015), growth (Punt, 2003), and recruitment (Hulson et al., 2013;

Denson et al., 2017). These theoretical studies have elucidated the importance of understanding spatial variability when identifying biological reference points (Ying et al., 2011; Goethel and Berger, 2017) and also highlighted the management implications of ignoring or misidentifying spatial population structure (Kerr et al., 2014; Goethel et al., 2016). For example, Goethel and Berger (2017) demonstrated that spatially explicit harvest strategies that maximize system yield were highly dependent on the combination of spatial population structure, connectivity patterns, movement rates, and productivity. Misdiagnosing either movement patterns or population structure led to depletion within management units and an overall loss of system-wide yield. Similarly, ignoring fleet dynamics (e.g., effort aggregation) has been shown to be as detrimental to the resource as ignoring resource distribution and connectivity dynamics (Fu and Fanning, 2004; Goethel and Berger, 2017).

Although spatial population structure has increasingly been acknowledged in fishery stock assessment frameworks over the last two decades (Fournier et al., 1998; Cope and Punt, 2011; Taylor et al., 2011; Berger et al., 2012; Methot and Wentzel, 2013; Goethel et al., 2015; Li et al., 2015; Punt et al., 2015; Vincent et al., 2017), relatively few spatially explicit stock assessments have been implemented for setting harvest limits (Berger et al., 2017a; Punt, 2017). Spatially explicit assessments require high quality, spatially informed data as well as rates and patterns of connectivity (Fournier et al., 1998; Taylor et al., 2011; Goethel et al., 2011, Taillebios et al., 2017), but these data are often limited or not available for many populations (Berger et al., 2017b). Given the limited number of applied spatial assessment models, spatial management procedures are often implemented without estimates of population parameters (e.g., spawning
stock biomass or fishing mortality) at the scale of desired management actions (Cope and Punt, 2011; Goethel et al., 2016; Kerr et al., 2017b). The resulting mismatch across the assessmentmanagement interface often leads to $a d h o c$ approaches for spatially allocating catch quotas, because catch projections are based on the broader management domain (e.g. assessment area) which creates the need for a method to sufficiently allocate catch to the smaller management units (Goethel et al., 2016; Berger et al., 2017b). Spatial catch allocation methods typically ignore inherent variation in biological processes of the managed resource and often rely on empirical approaches for dividing quotas across management units (e.g., allocations based on regional survey abundance; Hanselman et al., 2016). Despite the wide application of quota allocation methods, there has been limited exploration into whether these methods are able to ensure sustainable harvests when a fishery resource exhibits spatial heterogeneity in demography and complex population structure.

We used stochastic projection models to quantify how spatial heterogeneity and connectivity among population components influenced management quantities (e.g. maximum sustainable yield reference points) for marine fish. We also evaluated whether selected empirical or ad hoc spatial quota allocation methods could approximate the distribution of catch that achieved the maximum sustainable harvest when the true spatial dynamics were assumed to be unknown. Specifically, the objectives were to, 1) compare optimal spatial harvest strategies across alternative population spatial structures and demographic parameterizations, and 2) assess the performance of several empirical quota allocation methods using common data sources for allocating system-level quotas to smaller spatial management units. Collectively, the study
objectives aim to offer guidance on whether a particular method for spatial quota allocation performs best when information on the underlying spatial dynamics is limited.

## 2. Methods

Research objectives were evaluated using stochastic projection models extended from spatially explicit modeling framework presented by Goethel and Berger (2017). The study design consisted of two distinct modeling components, one for each of our two primary objectives. Simulation models were developed loosely based Pacific hake and Alaskan sablefish, which represent different species with distinct life history characteristics. A 'hake-like' model was developed to mimic a mid-water semi-pelagic species of intermediate longevity and a 'sablefishlike' model was designed to mimic a longer-lived groundfish species. These two species (hereafter referred to as 'hake' and 'sablefish') provide a basis for examining two-area (hake) and three-area (sablefish) models with spatial differences in natural mortality, recruitment, growth, maturity, and movement based on either empirical data or hypothesized processes. An important distinction between the two example species was how the stock recruitmentrelationships were parameterized. The model assumptions mimicked those applied the most recent stock assessment such that the hake example assumed a Beverton-Holt stock-recruitment relationship (steepness value $=0.814$ ), and sablefish assumed no density dependence in the stock recruit relationship (constant recruitment with annual deviations). In the sablefish example,
recruitment is de-coupled from the spawning stock biomass, removing any effect of area-specific differences in maturity or fecundity.

Connectivity for the hake model applied a largely unidirectional ontogenetic movement pattern, while the sablefish model applied a multi-directional movement pattern. Both simulation models were conditioned with input parameters available from recent stock assessments. If input parameters were not directly available, hypothesized values were used based on ongoing research. The results from these models should be interpreted relative to each other in order to gain comparative insight and not to inform management actions. A detailed description of model inputs is provided in Appendix A.

Throughout this paper, definitions pertaining to spatial structure and movement follow those defined in Goethel and Berger (2017). The 'biological domain' of a system was defined as the entire spatial extent of the biological resource (Fig. 1). Spatial structure of the resource was specified within the biological domain, which may consist of multiple biological populations and/or areas. A 'population' represented a single reproductive unit within which all fish are able to reproductively mix and recruitment dynamics were modeled using a single stock-recruit function. A population may reside in a single homogeneous area or be distributed across multiple areas with variable life history traits or fishery processes among the different areas. An 'area' represented the geographic extent over which a biological or fishery process is homogeneous. Movement could occur among areas (assuming a Markovian process) and once a fish moved it assumed the life history and reproductive dynamics of that area or population. Following these definitions, we modeled three alternative types of spatial structure: panmictic, spatial
heterogeneity, and metapopulation. The panmictic structure was modeled as a single population occupying a single area where all fish were assumed to be homogeneously distributed across space (Fig 1a). Spatial heterogeneity was modeled assuming a single population that resided across two or more areas (Fig. 1b). A metapopulation consisted of multiple, demographically distinct populations connected through movement. Each population within a metapopulation occurred in a single area and maintained a unique stock-recruit function, while reproductive mixing was assumed to occur only with fish of the current resident population (Fig. 1c). Once fish moved into a new population, they adopted the reproductive traits for that population. For simplicity, we assumed that the spatial extent of the management units aligned with the spatial extent of the biological units (populations or areas) defined in the biological domain.

The terms 'apportionment' and 'allocation' are often used interchangeably, however, in this study we apply each term to describe a separate process in our modeling framework. 'Apportionment' is defined as the partitioning of population-level recruitment across areas (specifically when spatial heterogeneity is modeled) and 'allocation' refers to the process of partitioning system-wide quota among individual management units.

### 2.1. Influence of spatial heterogeneity on spatial harvest strategies

To determine how differing population spatial structures and demographic parameterizations influence the spatial distribution of harvest that maximized equilibrium system yield (i.e., spatial harvest strategy, analogous to system-wide maximum sustainable yield, MSY), we conducted a suite of simulations across a range of underlying assumptions regarding spatial
structure and connectivity. Scenarios were developed that explored plausible demographic configurations and were parameterized for both example species using stock assessment outputs and/or the current best understanding of each species' biology (see Appendix A). Model outcomes were compared relative to a reference scenario parameterized as a single population with spatial heterogeneity (Spatial; Table 1) which represented the most likely population structure and demography for the example species. Model comparisons focused on four primary aspects; 1) specification of population structure, 2) spatial biological or fishery heterogeneity, 3) spatial recruitment dynamics, and 4) connectivity patterns (Table 1). Metrics used to compare model scenarios included the area- and population-specific equilibrium values for yield, harvest rate ( $u$ : yield/biomass), and depletion (terminal spawning biomass/unfished equilibrium spawning biomass for each spatial unit). The area-specific yield that collectively achieved the overall maximum system yield ('spatial harvest strategy') was the primary metric for model comparisons.

Maximum system yield was found using a grid search across combinations of areaspecific fishing mortality rates ranging from 0 to 7.0 in increments of 0.025 and 0.050 (Goethel and Berger, 2017) for hake and sablefish, respectively. All simulated population trajectories began at unfished equilibrium abundance levels and the population dynamics for each scenario were simulated for 200 years, which was sufficient to reach equilibrium. Simulations were conducted using AD Model Builder (Fournier et al., 2012) and R (R core team 2016) statistical computing software programs. Models can be found at (https://github.com/KatelynBosley/SPASAM/tree/master/Spatial_BRP_project).

### 2.1.1 Spatial MSY Scenarios

## Population Structure

Three population structures were compared to determine the impact of varying population structure on spatial harvest strategies (Table 1). Model types included spatial heterogeneity (Spatial), metapopulation (Metapop), and the panmictic (Panmictic) structures. The panmictic structure consisted of only one population with one area, therefore area-specific input parameters from the Spatial scenario were aggregated for the Panmictic scenario. For the Metapop scenario, each population maintained an identical steepness value, but area-specific virgin recruitment $\left(R_{0}\right)$ was scaled to provide population-specific recruitment matching areaspecific recruitment specified in the Spatial scenario. No additional changes to the metapopulation models were made relative to the Spatial scenario.

Biological and Fishery Heterogeneity
Alternative selectivity (Alt_Selectivity) and maturity (Alt_Maturity) scenarios were developed to examine how different parameterizations influenced spatial harvest strategies. The Alt_Selectivity scenario assumed constant selectivity for sablefish (verses spatially-varying selectivity in the Spatial scenario) and spatially varying selectivity for hake (verses constant selectivity in the hake Spatial scenario). These scenarios allowed comparison of both spatially varying and constant selectivity assumptions across the two life-history types (see Fig. S1 and S2 for the alternate selectivity ogives). An Alt_Maturity scenario was developed for hake that
assumed constant maturity across areas as opposed to spatially varying maturity specified in the Spatial scenario (see Fig. S3 for alternate maturity ogives). The comparison of these two maturity scenarios for hake allowed exploration of how the population dynamics were influenced by spatial patterns in maturity.

## Recruitment Dynamics

Alternative recruitment scenarios were explored by specifying different recruitment apportionment values (Alt_Apport) to simulate a change to the distribution of recruits across space. The alternate apportionment values for the hake model provided a less skewed division of recruits among the two areas relative to the Spatial model (Table S1). For the sablefish model, alternate apportionment values were obtained by reversing values for Areas 1 and 3 (Table S1).

## Movement

Examination of alternative movement parameterizations included scenarios that induced a higher residency rate relative to that of the Spatial model (Hi_Residency; Tables S3 and S4) and another that did not include movement among areas (Spatial_NM). Additionally, scenarios were specified without movement for the alternate selectivity (Alt_Selectivity_NM) and alternate maturity models (Alt_Maturity_NM) to explore the interaction of spatially varying demographics when connectivity did not exist among areas.

### 2.2. Spatial allocation of quota using empirical methods

For our second modeling component, we compared several methods for spatially allocating system-level catch to smaller management units. The purpose of these explorations was to mimic approaches to spatial quota allocation where spatially explicit assessment models are untenable, but spatial quota management may be needed to account for observed spatial structure in the population or socioeconomic factors that necessitate sub-dividing harvest across the species range. Performance of each allocation method was based on how well the method could approximate the expected spatial distribution of catch and biomass (based on the spatial harvest strategy identified for a given population structure as described in Section 2.1).

For all total allowable catch (TAC) allocation scenarios, the population dynamics were simulated for 200 years in order to reach equilibrium conditions and area-specific catch levels were determined by the allocation of a system-wide ( $S$ ) catch. The system quota for an assumed population structure was calculated by multiplying the system-level harvest rate (aggregated catch divided by aggregated biomass across all areas) that maximized system yield ( $u_{S, \text { max_ }_{-} Y}$; based on the value from the associated run in Section 2.1.1) by the system-level biomass $\left(B_{S}\right)$ in the current year of the simulation. This approach assured that quotas did not exceed system-wide biomass, which would cause overall population extinction. An area-specific TAC was then calculated based on the system yield and a management unit (i) allocation factor (Alloc_Bi) given by:

$$
\begin{equation*}
=u_{S, \max _{-} Y} * B_{S,} * \quad l l o c_{-} B \tag{1}
\end{equation*}
$$

The allocation factor could either be determined from observed data (e.g., the ratio of area-specific biomass to total population biomass) or input as a fixed proportion (e.g., equal allocation among areas). The allocation fraction was calculated as the relative ratio of the observed index (Obs_I) for the given management unit to the observed index for the entire system.

$$
\begin{equation*}
l l o c_{-} B,=O b s_{-} I_{,-1} / O b s_{-} I_{S,-1} \tag{2}
\end{equation*}
$$

The three different catch allocation methods were evaluated based on their ability to replicate optimal TAC allocations (using Eq. 1). All allocation methods were evaluated by applying system-level yield from the Spatial and Spatial_NM scenarios (determined in Section 2.1) for both example species. The resulting area-specific yield and biomass from the TAC allocation scenarios were then compared to the values associated with the spatial harvest strategies derived in Section 2.1. The single population with spatial heterogeneity model configuration was applied because it represents the most common population structure modeled for marine fishes. The three TAC allocation methods we applied were 1) the use of an observed survey biomass index Alloc_Survey and Alloc_Survey_NM), 2) an observed recruitment index (Alloc_Rec_Index, Alloc_Rec_Index_NM) and, 3) equal allocation (Alloc_Equal, Alloc_Equal_NM). The survey biomass index was calculated as the area-specific biomass scaled by the input catchability parameter $(q)$ with measurement error $(C V=0.2)$ assuming a lognormal error structure. The biomass index was simulated to occur mid-year such that the TAC allocation
factor ( lloc_B, ) applied each year was based on the abundance index from the previous year ( $y$-1; i.e. a one year lag for the implementation of the spatial harvest allocation). The observed recruitment index was determined as the number of area-specific recruits with applied lognormal measurement error ( $C V=0.5$ ).

To demonstrate the impact of incorrect specification of population structure, TAC allocation based on the survey biomass index was applied using system-level harvest values $\left(u_{S, \max _{-} Y}\right)$ from the panmictic model (Alloc_Survey_Panmictic) and the metapopulation model (Alloc_Survey_Metapop) when the true dynamics were simulated as a single population with spatial heterogeneity. A final comparative scenario applied TAC allocation based on survey biomass when the true population structure was a metapopulation, but the population structure was misdiagnosed as a single population with spatial heterogeneity (i.e., using the incorrectly specified system-level harvest rates from the Spatial models described in Section 2.1; Sim_Survey_Metapop).

For each scenario, the Newton-Raphson method was used to iteratively tune the model until the spatially explicit fishing mortality rates for each year (y) corresponded to the areaspecific TAC values within a $0.1 \%$ error threshold (see Goethel and Berger, 2017). Scenarios were comprised of 100 independent model runs to encapsulate random variation in indices. The performance of each allocation method was then assessed by comparing the relative percent difference (RPD) in area-specific management quantities (i.e., harvest rate and depletion) between models that applied the TAC allocation methods (i.e. observed) and the comparable scenario that maximized system yield from objective 1 (i.e. true). The TAC allocation methods
were evaluated based on whether the observed data sources could be used to approximate the spatial harvest strategies derived from objective 1 .

## 3. RESULTS

### 3.1 Impact of spatial heterogeneity on spatial harvest strategies

Differences in population dynamics, demographics, selectivity, and movement led to vastly different approaches to system harvest for both species. The Spatial model for the hake example, which assumed a unidirectional ontogenetic movement pattern, suggested that Area 1 (nursery) should not be fished and Area 2 should have high fishing pressure (Fig. 2). The sablefish Spatial model allowed greater mixing among areas and results indicated that a spatially balanced harvest strategy was optimal. In general, system-wide harvest rates and depletion levels associated with maximum system yield were similar across scenarios, but the area-specific harvest rates required to achieve them differed substantially due to the underlying heterogeneity in spatial processes (Fig. 2).

## Population Structure

System-wide harvest rate and depletion for the hake single-area Panmictic model were not substantially different from the Spatial model (Table 3, Fig. 2). The spatial harvest rates from the Metapop model were elevated relative to those for the Spatial model (Table 3), which resulted in lower area-specific and system-wide depletion values (i.e. fewer fish). Specification of population-specific stock-recruit relationships was a major factor influencing the difference
between the Spatial and Metapop scenarios. For the hake example, maturity ogives differed between the populations with the age at $50 \%$ maturity lower for one population relative to the other (Fig S3). This difference led to a $14 \%$ reduction in terminal system-level spawning stock biomass for the Metapop scenario relative to the Spatial scenario. The sablefish example produced results similar to hake when comparing the Panmictic scenario to the Spatial, but it was not sensitive to the metapopulation assumption (Metapop model outputs were almost identical to the Spatial model).

## Biological and Fishery Heterogeneity

Changing maturity from spatially varying (Spatial) to constant across areas (Alt_Maturity) for the hake reduced both system-wide and area-specific harvest rates and depletion levels (Fig. 2). This resulted from an $8.2 \%$ reduction in system-wide spawning biomass when using the Area 2 maturity ogive (Fig. S3) in both areas, which produced fewer mature, younger fish.

Assuming constant selectivity across areas in the sablefish model (Alt_Selectivity) resulted in a sharp change in the spatial harvest strategy that maximized yield with essentially no fishing in Area 2 and an increase in harvest rate for Area 1 (Area $1 u_{, \text {max_ }_{-}}$was 0.10 and 0.23 for the Spatial and Alt_Selectivity scenarios, respectively; Fig. 2c). Despite no fishing in Area 2, depletion levels remained consistent across all areas ( $\sim 0.25$ ). Similarly, adding spatial heterogeneity in selectivity for hake resulted in a marked shift in the spatial harvest strategy
relative to the Spatial scenario. Shifting selectivity in Area 2 so that fish are selected at older ages, produced a spatial harvest strategy with significantly lower area-specific and system-level depletion levels (Fig. 2).

## Recruitment Dynamics

The Alt_Apport scenario for the hake example showed little influence on system-wide and area-specific depletion (Fig 2). Altering recruitment apportionment caused a slight reduction in the system-level harvest rate ( $u_{S, m_{a_{-} Y}}$ was 0.2 and 0.25 in the Alt_apport and Spatial scenarios, respectively; Fig. 2) and the harvest rate in area 2 was reduced by $9 \%$ relative to the Spatial model. Altering recruitment apportionment for sablefish produced a more spatially balanced harvest strategy resulting in depletion levels that were relatively uniform across the three areas ( $\sim 0.25$; Fig. 2).

## Movement

Simulations of both example species showed area-specific harvest rates and depletion levels were approximately uniform when movement did not occur among areas (Spatial_NM; Table 3, Fig. 2). Modeling movement in the Spatial scenarios led to harvest rates that varied widely by area causing spatial variation in depletion levels (Table 3, Fig. 2). In the hake example, unequal recruitment apportionment combined with a strong unidirectional, ontogenetic movement pattern created a situation where fish recruited to Area 1 and then migrated to Area 2 as they matured. For sablefish, recruitment apportionment and movement in the Spatial scenario
were more similar across areas resulting in a more spatially uniform harvest strategy relative to the hake example (Table 3). As expected, the high residency (Hi_Residency) models for both example species resulted in less spatial variation of in harvest levels compared to the Spatial scenario, with outcomes similar to scenarios not including movement (Fig. 2). Despite less spatial variation in harvest rates, depletion levels were similar to those from the Spatial scenario indicating the importance of other sources of heterogeneity (i.e. maturity and selectivity) in deriving spatial harvest strategies.

Comparison of yield vs. harvest rate isopleths for the Spatial and Spatial_NM scenarios showed conspicuous differences in the shape of the yield surface (Fig. 3). Modeling movement among areas resulted in a broader, plateau-like surface indicating many combinations of spatial harvest can produce in yields close to the maximum. Yield isopleths from scenarios that did not model movement showed fewer combinations that achieved near maximum yield (Fig. 3). For example, the Spatial_NM scenario for hake produced a steep surface (with small areal peak) indicating that the harvest rate in Area 1 would need to remain near 0.3 and greater than 0.15 in Area 2 achieve near maximum yield (Fig. 3a). The addition of movement resulted in a diagonal plateau of harvest rate combinations across the two areas (Fig. 3b), where $68.5 \%$ of the harvest rate combinations produced $<=90 \%$ of the maximum yield compared to $46.9 \%$ without movement. Similarly, the sablefish example produced an essentially flat-topped yield surface over which the maximum system yield was realized through a broad range of area-specific harvest combinations across the three areas when movement was modeled (Fig. 3d). This result
differed from the well-defined peak and a smaller range of harvest rates (around 0.2 for all areas; Fig 3c) that achieved near maximum yield without movement.

### 3.2. Allocation of harvest quota to spatial management units

Spatial allocation of quota based on empirical methods performed well, often resulting in area-specific depletion levels that were within $25 \%$ of the ideal level. Overall, results across allocation methods were similar between example species, which allowed generalizations to be made across the two life-history types we examined.

None of the methods we tested for allocating catches were able to exactly reproduce the spatial harvest strategy that maximized system-level yield, but most approaches were able to approximate harvest rates within a $50 \%$ difference from expected without causing high levels of area-specific depletion (Fig. 4; Tables S4-S7). Spatially allocating TACs based on relative survey biomass (Alloc_Survery,_Alloc_Survey_NM) performed the best, particularly when no movement occurred among areas (median RPD $<60 \%$ in all areas, Fig. 4). When the underlying population dynamics included movement, the equal apportionment method (Alloc_Equal) performed as well as using the survey biomass (median RPD $<112 \%$ in all areas, Fig. 4). However, applying an equal harvest allocation to the parameterizations without movement (Alloc_Equal_NM) led to substantial differences in harvest rates and caused area-specific depletion. Interestingly, the simulated dynamics when movement did not occur caused some area-specific quotas to be greater than the available biomass (Table 4), ultimately driving one management area (hake; Area 2) or two management areas (sablefish; Areas 2 and 3) to collapse.

The lack of available biomass resulted in overall underutilization of the resource with only $91 \%$ and $82 \%$ of the expected system-wide TAC harvested for hake and sablefish, respectively. Allocating the TAC using a recruitment index (Alloc_Rec_Index, Alloc_Rec_Index_NM) performed poorly for both example species and exhibited the largest range of area-specific differences for both harvest rate and depletion (Tables S4-S7, Fig. 4).

For both example species, applying the harvest rate for a panmictic population when simulating spatial heterogeneity (Alloc_Survey_Pan) resulted in a slightly more conservative management approach and lower depletion levels (as indicated by the positive RPD in Fig. 4). The hake example was more sensitive to incorrectly assuming metapopulation structure (Alloc_Survey_Met), which caused more fish to be removed from the system and resulted in higher system-level depletion (Fig. 4). When applying population-level harvest rates to a model that simulated metapopulation dynamics (Sim_Survey_Metapop), slight loss of yield caused stock status to increase (population became less depleted). Because the sablefish example did not assume a stock-recruit relationship, outcomes from the metapopulation scenarios were identical to the models that assumed a single population with spatial heterogeneity (Spatial).

## 4. Discussion

The development and application of spatially explicit assessment models has been driven by the need to provide management advice at finer spatial scales. Unfortunately, the data are often not available or lack sufficient resolution to apply these spatially explicit modeling approaches when providing management advice. We employed a suite of stochastic projection
models to demonstrate the importance of accounting for connectivity and spatial heterogeneity when deriving spatial harvest strategies that achieve maximum sustainable resource utilization. This work builds on the findings of Goethel and Berger (2017) by incorporating spatial variation in fishery selectivity and demographics using example species that exhibit different life history types. We also evaluated the consequences of applying empirical methods for spatial quota allocation over a range of assumptions regarding the spatial complexity of a biological resource.

Previous simulation studies have shown that subtle differences in the shape of the selection curve can have large impacts on maximum sustainable yield for panmictic populations (Scott and Sampson, 2011; Goethel and Berger, 2017). Thus, it was not surprising that spatial heterogeneity in selectivity or life-history parameters influenced spatial harvest strategies. Results from Alt_Selectivity scenarios for both example species demonstrated that relatively small changes in selectivity can have a large impact on management quantities, especially when movement occurs. We also found that interactions between maturity rate and selectivity pattern can have a strong influence on the population dynamics, resulting in spatial harvest strategies that are not intuitive. Connectivity among management units can further complicate the determination of harvest strategies derived from yield-based management metrics. Model projections applied over the two life history types provided an example of these challenges, showing that the combination of area-specific harvest rates that achieved maximum equilibrium system yield were largely influenced by movement and less by the underlying form of spatial population structure (e.g., panmictic, spatial heterogeneity, or metapopulation). Collectively, these results indicate that specifying the correct form of spatial population structure may not be
as critical as understanding movement patterns and spatial heterogeneity in the fishery (e.g., selectivity curves) and other demographic parameters (e.g., maturity) when developing spatial reference points for management advice.

A unique and important finding of our study showed that connectivity among management units results in numerous spatial harvest rate combinations that nearly achieve maximum system yield with similar levels of overall depletion. Unlike the scenarios without movement, yield isopleths showing spatial harvest combinations for models that incorporated connectivity generally had a moderate slope with a broad plateau instead of a single well-defined peak characteristic of maximum equilibrium system yield curves. The movement of fish across areas leads to the effective dispersal of fishing effort over the model domain, which causes correlation among area-specific harvest strategies (Guan et al., 2013; Kerr et al., 2014; Goethel and Berger, 2017). The plateau-like yield surfaces from our simulations showed a range of harvest strategies with similar overall management outcomes, elucidating the potential for greater flexibility in the distribution of fishing effort across space when developing management plans. When movement exists among populations or areas, it may be possible to define a range of area-specific harvest rates that are able to achieve the same overall goals (i.e., maintaining a system-level target population size, MSY). In some cases, it may be more important to weigh socioeconomic considerations (e.g., regional equality in TAC allocations, annual stability in the allowable biological catch, costs of travel to the fishing grounds) in the evaluation of alternative spatial management decisions. Our results suggest that the interaction between ontogenetic movement patterns, recruitment dynamics, spatial variation in demographics, and fishery
selectivity can lead to spatial harvest strategies that may not meet management objectives, particularly when applying strict MSY-based, area-specific harvest limits. This is demonstrated by scenarios from the hake example that recommend exploitation predominantly in one area. When connectivity dynamics are assumed, the application of spatial models can facilitate the development of optimal management strategies by incorporating both ecological and economic considerations.

Spatial harvest strategies produced by the hake example illustrated some of the challenges associated with attempting to allocate system-level TACs to smaller spatial management units. It is a common approach to use a relative index of abundance for defining catch allocations across management units. However, when a population displays ontogenetic movement patterns that interact with maturity and fishery selectivity, some portion of the biomass will remain in areas that, from a maximum system yield perspective, should not be harvested. This implies that allocation methods ignoring age structure may not be appropriate for populations with complex age-based movement patterns and it may be necessary to explicitly account for age-specific abundance when evaluating management goals. Similarly, the allocation scenarios showed that Area 1 in the sablefish example was consistently overharvested due to the low harvest rate required to maximize system yield. Despite the tendency to overharvest certain areas regardless of the allocation method, system-level depletion was not strongly biased. This result suggests that system-wide spawning stock biomass and population trajectories may not be significantly impacted unless the overfished area contains a large portion of the total mature biomass.

Evaluation of catch allocation methods showed that incorrect specification of areaspecific catch limits did not result in significant depletion regardless of underlying population structure. Given this general result, the survey index allocation method is likely to perform sufficiently for developing management advice when it is impossible to directly account for spatial population structure in stock assessments, a conclusion that is also supported by Hintzen et al. (2015). If high quality and reliable surveys are not available or residency rates are known to be low, then the equal or 'fixed' allocation method may be preferable. In general, the equal allocation method performed nearly as well as the survey index allocation method and provides an appealing alternative because it requires a lower investment in resources. However, the equal allocation method can be more risk-prone in terms of local depletion when connectivity among areas (or populations) is limited. Application of equal allocation to scenarios without connectivity led to overfishing in at least one area for both example species. As a result, areaspecific TACs derived from equal allocation methods may be too high when a population exhibits spatial heterogeneity, potentially causing an overall loss of yield and/or unbalanced harvest of population components thereby inhibiting management goals and reducing population resiliency (Kell et al., 2009). Overall, our results illustrate some of the challenges that can arise from the implementation of a constant catch or fixed-ratio strategy if the spatial dynamics of a resource are unknown. When applying any allocation method, it is advisable to consider the spatial differences that may result from the interaction between age-specific movement and fishery selectivity (i.e., availability).

Our study evaluated TAC allocation approaches that represent either currently applied methods or theoretical alternatives for overcoming the challenge of spatial TAC allocation. Division of quota based on survey index has been applied to as an $a d$ hoc approach designed to match spatial and temporal variation productivity with fishery harvest (e.g. sablefish, Hanselman et al., 2016) whereas fixed-ratio allocation has been applied to facilitate resource distribution across political boundaries (e.g. Pacific Hake, Berger et al. 2017a). Although recruitment indices have not yet been used to spatially allocate catch, there is increasing interest in using juvenile survey data to better estimate population productivity and inform stock assessment models (Schweigert et al., 2009; Field et al. 2010; Buchheister et al., 2016). Our results showed that TAC allocation based on a recruitment index performed poorly, but both our example species displayed a high degree of connectivity among areas and they were intermediate to long-lived. It is possible that a juvenile survey with sufficient spatial and temporal resolution may perform better for species that exhibit greater within-area residency and that are shorter-lived (e.g. herring). Future work should examine alternative TAC allocation approaches, including the recruiement index, given different life history types to determine if longevity plays a role in how these methods perform.

There are several caveats and limitations to our modeling approach for evaluating the performance of TAC allocation methods. Generally, the population dynamics and catch allocation simulations we applied were a simplification of most real-world catch allocation situations. For example, the TAC allocation equations included an estimate of biomass from the same year in which the quota allocation procedure is applied. In practice, estimates of biomass
may not available for the same year that a management procedure is put into effect.
Implementation of our approach would then need to apply biomass parameters with a greater time-lag to derive TAC allocation fractions for a given year or input a projected biomass estimate. We did not explore how timing differences between data availability and the implementation of spatial management can influence TAC allocation performance; however, future work could refine our approach by taking into consideration the timeframe in which empirical data is available and processed relative to when spatial management procedures are enacted. Additionally, our approach to spatial quota allocation assumed that the exploitation rate and biomass are known perfectly, without error, which would be impossible to know in a realworld application. Not considering these important sources of error in our modeling framework produces 'best case' scenarios which may not encompass the full range of plausible outcomes.

Finally, there is the inherent difficulty associated with including spatially varying biological parameters such as growth, maturity, and fecundity when concomitantly modeling Eulerian or box-transfer movement. In some cases, a flux of fish that transition from the biological characteristics of one area to another in a given time step results in unrealistic biological changes (e.g., going from mature to immature or an instantaneous reduction in size), and the range of impacts these assumptions have on management performance is yet to be fully understood (Goethel and Berger, 2017). These challenges are not unique to our study as the Eulerian approach to modeling movement is quite common. Lagrangian approaches such as individual-based modeling are a more flexible alternative but tend to be data-intensive (Turchin, 1998; Kerr and Goethel, 2014; Goethel et al., 2016). Despite these simplifications in our
modeling approach, our results broadly indicate that understanding the spatial structure and connectivity of fishery resources is important for achieving successful spatial management of fisheries, even under best-case circumstances.

This study provides insight into the performance of different catch allocation schemes under a range of spatial population and fishery regimes, but a comprehensive analysis using closed-loop feedback simulations, such as a management strategy evaluation (MSE; Smith, 1994; Smith et al., 1999; Butterworth and Punt, 1999; Punt et al., 2001), is needed to adequately provide specific management advice that is robust to system uncertainties. In an MSE, objectives are predefined and the consideration of trade-offs are made explicit, which allows the choice of management options while acknowledging trade-offs and risk (Kell et al., 2005; Mapstone et al., 2008). Exploring these methods within an MSE or simulation-estimation framework would provide a more complete examination of how spatial processes and simplified stock assessment assumptions (e.g. panmictic) influence management performance for a given stock, and would highlight whether the applied harvest allocation method is able to achieve the overall management goals (e.g., resource and fishery sustainability). Moreover, the integration of spatially complex simulation models into an MSE framework could provide feedback on how socioeconomic information could be incorporated to supplement biological information for setting spatial TAC allocations.

The increasing use of species distribution models along with demographically structured population and fleet dynamic models are providing improved ways to incorporate spatial complexities into management advice (Berger et al., 2017b). As spatially resolved data becomes
more available, and statistical research and computing power continue to advance, the ability to incorporate spatial processes throughout the assessment-management framework will reduce the need to rely on $a d h o c$ approaches to harvest allocation.

## 5. Conclusions

Spatial assessment-management frameworks can improve management performance (Punt et al., 2015; Goethel and Berger, 2017; Punt, 2017; Punt et al., 2017), but implementation often demands reliable spatial data to inform models and management decision making. Given the limited application of spatial stock assessments for providing management advice (Berger et al., 2017b), there remains a need to identify robust approaches to TAC allocation (Kerr et al., 2014; Goethel et al., 2016). Our results demonstrate that with high levels of movement among population components of a biological resource, it may not be critical to determine an ideal spatial harvest strategy for the desired reference point. Because of this flexibility, the spatial allocation methods that we evaluated did not negatively impact resource sustainability. When yield curves are well-defined and peaked, the empirical approaches to TAC allocation may be more risk-prone. In these circumstances, it may be prudent to evaluate the performance of alternative approaches, such as adaptive management or application of precautionary catch buffers, within a dynamic modeling framework.

We recommend that future simulation work evaluate how TAC allocation methods perform over a range of harvest levels and spatial population dynamics while also including additional sources of error (both process and measurement error) expected from true fishery data.

Generally, the application of stochastic projection models can provide insights into how robust TAC allocation methods are to variability in spatial processes and can highlight best approaches for how they can be applied within a fishery management framework.

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Table 1: Description of scenarios used to determine the management implications of misdiagnosing spatial processes. Each scenario was evaluated for both hake and sablefish unless otherwise noted. The Spatial model was applied as the reference model for model comparisons because it represented the most likely population dynamics for the example species.

| Scenario | Description |
| :---: | :---: |
| Includes movement | Panmictic structure |
| Panmictic | Single population with spatial heterogeneity (reference model) |
| Spatial | Metapopulation structure |
| Metapop | Alternate selectivity |
| Alt_Selectivity | Alternate maturity (hake only) |
| Alt_Maturity | Alternate recruitment apportionment |
| Alt_Apport | High residency |
| Hi_Residency |  |
| No movement | Spatial Model without movement |
| Spatial_NM | Alternate selectivity without movement |
| Alt_Select_NM | Alternate maturity without movement (hake only) |
| Alt_Maturity_NM |  |

812 Table 2. Description of TAC allocation scenarios.Population Structure indicates population structure assumed in the stochastic projection. $u_{m_{a x} Y}$ describes the scale of harvest rate applied to the management area. TAC Allocation Method describes the approach used to allocate the proportion of the system wide TAC to the smaller spatial management units within the system.

| Scenario | Description | Population Structure | $u_{\text {max_Y }}$ | TAC Allocation Method |
| :---: | :---: | :---: | :---: | :---: |
| Alloc_Survey | Survey Allocation | Spatial | Population | Survey Biomass |
| Alloc_Survey_NM | Survey Allocation - No Movement | Spatial | Population | Survey Biomass |
| Alloc_Rec_Index | Rec Index Allocation | Spatial | Population | Recruit Index |
| Alloc_Rec_Index_NM | Rec Index Allocation - No Movement | Spatial | Population | Recruit Index |
| Alloc_Equal | Equal Allocation | Spatial | Population | Equal Distribution |
| Alloc_Equal_NM | Equal Allocation - No Movement | Spatial | Population | Equal Distribution |
| Alloc_Survey_Panmictic | Panmictic $u_{S, \text { max_ } Y}$ | Spatial | Panmictic | Survey Biomass |
| Alloc_Survey_Metapop | Metapopulation $u_{S, \text { max_ } Y}$ | Spatial | System Metapop | Survey Biomass |
| Sim_Survey_Metapop | Spatial Heterogeneity $u_{S, \text { max_Y }}$ | Metapopulation | Population | Survey Biomass |

815 Table 3. Spatial harvest rates that achieve maximum system yield ( $u_{\text {max_ }}$ ) and associated depletion levels for hake and sablefish scenarios with and without movement for alternative population structures.

| Hake |  | Movement |  | No Movement |  |
| ---: | :---: | :---: | :---: | :---: | :---: |
| Model Scenario | Area | $u_{m x_{-} Y}$ | Depletion | $u_{m x_{-} Y}$ | Depletion |


| Panmictic (Panmictic) | - | - | - | 0.23 | 0.32 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Spatial Heterogeneity (Spatial \& Spatial_NM) | 1 | 0.00 | 0.53 | 0.25 | 0.31 |
|  | 2 | 0.53 | 0.21 | 0.25 | 0.30 |
|  | Total | 0.25 | 0.31 | 0.25 | 0.31 |
| Metapopulation (Metapop) | 1 | 0.00 | 0.50 | - | - |
|  | 2 | 0.58 | 0.20 | - | - |
|  | Total | 0.27 | 0.29 | - | - |


| Sablefish |  | Movement |  | No Movement |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Model Scenario | Area | $u_{m \times-Y}$ | Depletion | $u_{m} x_{-} Y$ | Depletion |
| Panmictic (Panmictic) | - | - | - | 0.18 | 0.24 |
|  | 1 | 0.10 | 0.29 | 0.20 | 0.23 |
| Spatial Heterogeneity | 2 | 0.17 | 0.24 | 0.20 | 0.24 |
| (Spatial \& Spatial_NM) | 3 | 0.33 | 0.21 | 0.21 | 0.24 |
|  | Total | 0.20 | 0.24 | 0.20 | 0.23 |
|  | 1 | 0.10 | 0.29 | - | - |
| Metapopulation | 2 | 0.17 | 0.24 | - | - |
| (Metapop) | 3 | 0.33 | 0.21 | - | - |
|  | Total | 0.20 | 0.24 | - | - |

820 Table 4: Spatial harvest rates ( $u$ ) and proportional TAC allocations for scenarios that maximize system yield (based on results from the Spatial and Spatial_NM scenarios) compared to TAC allocation scenarios that spatially distribute catch according to the survey biomass index (Survey) and equivalent (Equal) catch allocation methods. Prop_TAC represents the true proportion of catch derived from each scenario. Values from the equal apportionment scenario without movement ${ }^{*}$ ) caused collapse in at least one area due to the allocated quota exceeding available biomass. Under the equal allocation scenario, values in parenthesis indicate the terminal areaspecific depletion levels.

| Species | Maximum System Yield |  |  |  | Survey ${ }^{\dagger}$ |  |  |  | Equal |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Movement |  | No Movement |  | Movement |  | No Movement |  | Movement |  | No Movement* |  |
|  | $u$ | TAC proportion | $u$ | TAC proportion | $u$ | TAC proportion | $u$ | TAC proportion | $u$ | TAC proportion | $u$ | TAC proportion |
| Hake |  |  |  |  |  |  |  |  |  |  |  |  |
| Area 1 | 0.00 | 0.00 | 0.25 | 0.80 | 0.21 | 0.41 | 0.25 | 0.80 | 0.26 | 0.50 | 0.13 | 0.76* (0.49) |
| Area 2 | 0.53 | 1.00 | 0.25 | 0.20 | 0.28 | 0.59 | 0.24 | 0.20 | 0.24 | 0.50 | 0.46 | 0.24* (0.19) |
| System | 0.25 |  | 0.25 |  | 0.25 |  | 0.25 |  | 0.25 |  | 0.16 |  |
| Sablefish |  |  |  |  |  |  |  |  |  |  |  |  |
| Area 1 | 0.10 | 0.18 | 0.20 | 0.42 | 0.19 | 0.31 | 0.20 | 0.42 | 0.20 | 0.33 | 0.08 | 0.43* (0.63) |
| Area 2 | 0.17 | 0.25 | 0.20 | 0.30 | 0.19 | 0.29 | 0.19 | 0.30 | 0.23 | 0.33 | 0.44 | 0.28* (0.09) |
| Area 3 | 0.33 | 0.57 | 0.21 | 0.28 | 0.20 | 0.39 | 0.20 | 0.27 | 0.17 | 0.33 | 0.37 | 0.29* (0.08) |
| System | 0.20 |  | 0.20 |  | 0.20 |  | 0.20 |  | 0.20 |  | 0.15 |  |

${ }^{\dagger}$ median values

Figure 1. Schematic showing the hierarchical structure of the biological and management components within the system for the three population structures (a-c) that were modeled. For simplicity, the management and biological spatial components are aligned in the current study.


Panmictic


Spatial Heterogeneity


Metapopulation


SABLEFISH



Figure 3. Isopleths representing a 3-dimensional yield surface as a proportion of the systemwide maximum given spatial harvest rate combinations for $\operatorname{Spatial}$ _NM ( $\mathrm{a}, \mathrm{c}$ ) and Spatial (b,d) scenarios. For the three-area sablefish model, the two spatial dimensions that best illustrate the primary findings are shown (Areas $1 \& 2$ ). Isopleths showing yield surfaces across alternate spatial dimensions are shown in Fig. S8. The plot area shows fishing mortalities less than 7.0. Inset values indicate the proportion of spatial harvest rate combinations that achieved $>=90 \%$ of system-wide maximum yield.


Harvest Rate

Figure 4. The relative percent difference (RPD) in harvest rate (a,c) and depletion (b,d) comparing results from TAC allocation method scenarios to values that achieve maximum system yield as derived in objective 1. For the hake example, Area 1 values for Spatial model comparisons represent the true harvest rates (e.g. $20=0.2$ ), because $u_{\text {max_ } Y}$ was zero and therefore the calculation of RPD for Area 1was undefined. The scenarios that do not include movement are shown relative to the Spatial_NM model. The metapopulation scenarios are shown relative to the Metapop model. A full description of model scenarios are provided in Table 2.


## Appendix A: Description of Species Used for Model Scenarios

For this study, we identified two species that have spatially varying life history characteristics and where management advice relies on spatial allocation of catch quotas, Pacific hake (Merluccius productus), and sablefish (Anoplopoma fimbria) in Alaskan waters, which represent intermediate and long-lived species, respectively. The two species show potential to have spatial variability in natural mortality, recruitment, growth, maturity, and ontogenetic movement, which may impact population dynamics, productivity, and thus spatial harvest strategies. The models for both species were conditioned with input parameters that were available directly from the most recent stock assessment and further structured using hypotheses and ongoing research regarding the spatial population dynamics of the species. All results presented in this study should be interpreted relative to each other to gain comparative insight and not used directly to inform management for either species.

## Hake

Pacific hake (or Pacific whiting) is a semi-pelagic, schooling, migrating species that ranges from southern Baja California to southern Alaska (Hamel et al., 2015; Berger et al., 2017a). The spatial distribution of Pacific hake is largely defined by ontogenetic movement, where larger (older) adults tend to migrate further north than smaller (younger) individuals. The most recent stock assessment assumed a single panmictic (homogeneous) population, with timevarying fishery selectivity to capture annual differences in the availability of fish by age that results from high recruitment variation and ontogenetic movement (Taylor et al., 2014; Berger et
al., 2017a). Catch advice is provided based on projections from the panmictic assessment model, and quotas are then allocated to Canada and the United States (northern and southern management units) based on a fixed ratio derived from historical catches and specified by the Pacific Whiting Treaty (2004). Given the ontogenetic movement of fish along a general northsouth gradient, the impact of fishing differentially affects the population depending upon where the majority of the harvest is occurring, the time of year that it occurs, and the distribution of age-classes in a specific year.

Our reference model for hake (Spatial: see Table 1 in the main text) was structured as a single population with spatial heterogeneity with the population distributed across two areas (United States, Area 1, and Canada, Area 2; see Fig. A1). The model was age-structured (15 age classes with the last as a plus group) and incorporated ontogenetic migrations with age-specific movement rates. Age-based movement rates were hypothesized using available acoustic survey and fishery-dependent catch-at-age data by area because formal tagging or other animal tracking experiments have not been conducted for this species. A single Beverton-Holt stock-recruitment function was applied using population-wide spawning stock biomass to inform future recruitment, which was subsequently apportioned to each area ( $80 \%$ to the United States and $20 \%$ to Canada). Recruitment apportionment values were consistent with the spatial distribution of age-1 observations in the acoustic survey (J. Clemons, NW Fisheries Science Center, NOAA, pers. comm.) and evidence that spawning predominantly occurs further south (Area 1; Ressler et al., 2007). Area-specific maturity ogives were also specified in the model and were based on previous spatial estimates (Taylor et al., 2014). All remaining parameters were spatially and temporally invariant and were obtained directly from the most recent stock assessment (Berger et
al., 2017a). These include natural mortality ( $M=0.226$ ), stock-recruitment steepness ( $h=0.814$ ), average virgin recruitment ( $R_{0}=3.13$ billion), and fishery and survey selectivity ogives (Fig. A2), and survey catchability ( $q=1$ ).

## Sablefish

Sablefish are bottom-dwelling groundfish capable of long-distance migrations along the west coast of the United States and Canada. Movement rates within Alaskan federal waters and between Alaska state and federal waters are well characterized for the species (Wolotira et al., 1993; Hanselman et al., 2015). Sablefish exhibit an ontogenetic movement pattern where younger fish inhabit shallower nearshore habitats and move to deeper offshore waters as they age. Currently, Alaskan federal waters are assessed as a panmictic stock using a single area assessment model (Hanselman et al., 2016). Catch projections based on the results of the panmictic stock assessment have traditionally been used to set the total catch for the entirety of Alaskan federal waters. Allocation to each of six management units was then determined using a 5-year exponential weighting scheme of relative survey and fishery indices of abundance, where older surveys carry less weight. However, high variability in yearly allocations was problematic which lead to the establishment of fixed allocation ratios beginning in 2013.

The reference model constructed for the sablefish (Spatial: see Table 1 in the main text) assumed a single population distributed across three spatial areas (West, Area 1; Central, Area 2; East, Area 3; see Fig. A3) matching those specified in a spatially explicit stock assessment model currently in development (K. Fenske, AK Fisheries Science Center, NOAA, per. comm.). The West area combines the Bering Sea, Aleutian Islands, and Western Gulf of Alaska; the Central
area is the Central Gulf of Alaska, and the East area combines the West Yakutat and East Yakutat/Southeast management areas (Fig. A3). The model was age-structured (31 age classes with the last as a plus group) and included movement rates derived from the Hanselman et al. (2015) tagging analysis of age $2+$ sablefish, which was simplified to develop a single age- and time-invariant movement matrix and standardized to exclude movement out of Alaskan federal management areas. A stock-recruitment function is not specified in the Alaskan sablefish assessment because some of the largest recruitment events have come from periods of low stock biomass (Hanselman et al., 2016). Therefore, the simulation model follows the current assessment where annual recruitment was fixed as an overall population-level mean ( $R_{0}=15.54$ million). Recruitment was then apportioned based on the proportion of age- 2 fish that were estimated to be in each of the three areas ( $44 \%$ to Area 1, 30\% to Area 2, and $26 \%$ to Area 3). Biological parameters for the sablefish model were derived from data collected during longline surveys and from outputs of the spatially explicit stock assessment model (K. Fenske, AK Fisheries Science Center, NOAA, per. comm.). Fishery selectivity ogives represented the average of male and female selectivity-at-age for each area (Fig. A4). Survey selectivity-at-age (Fig. A4) and catchability $(q=8.70)$ parameters were from the current sablefish assessment (Hanselman et al., 2015). Spatial estimates for the proportion of mature females-at-age were derived using visual observations from a longline survey (Sasaki, 1985; Fig. A4). Natural mortality was assumed to be constant across space, time, and age ( $M=0.1$ ).

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Figure A1. Map of the Northeastern Pacific showing hypothesized hake age-dependent movement rates and recruitment apportionment by area. Area 1 corresponds to waters off the continental United States and Area 2 encompasses the waters off British Columbia, Canada.


Figure A2. Maturity and selectivity ogives for hake Spatial (Area 1 and Area 2) and Panmictic model structures. The maturity ogive varied by area in the hake Spatial model while both survey and fishery selectivity were spatially consistent throughout the system.


Figure A3. Map showing sablefish movement rates and recruitment apportionment rates by area. Area 1 includes the Bering Sea, Aleutian Islands, and western Gulf of Alaska; Area 2 is the central Gulf of Alaska; and Area 3 includes the West Yakutat and East Yakutat/Southeast subareas.


Figure A4. Maturity and selectivity ogives for sablefish Spatial (Areas 1, 2, and 3) and Panmictic model structures. The maturity and fishery selectivity ogives varied by area in the Spatial sablefish model while survey selectivity remained spatially consistent throughout the system.


