STAFF SUMMARY FOR DECEMBER 6-7, 2017

21. RED ABALONE FISHERY MANAGEMENT PLAN

Today's Item **Information ☒** **Action ☐**

Receive update from DFW on fishery management plan (FMP) process for red abalone.

Summary of Previous/Future Actions

• FGC supports red abalone FMP development per MRC recommendation	Oct 8, 2014; Mt. Shasta
• DFW updates on FMP process and timeline	2015-2016; MRC meetings
• Update on FMP process and timeline	Mar 23, 2017; MRC, San Clemente
• Update on FMP process and timeline	Jul 20, 2017; MRC, Santa Rosa
• **Update on FMP process and timeline**	**Dec 6-7, 2017; San Diego**

Background

At its Oct 2017 meeting, FGC requested to receive an update from DFW on progress in developing the red abalone FMP. Throughout the FMP development process, DFW has provided updates at MRC meetings on stakeholder input and next steps.

Today DFW will provide an update on red abalone FMP progress, as informed by recent conditions in the fishery, and discuss the possible role of various survey methods related to harvest control rules.

Significant Public Comments

- The Nature Conservancy (TNC) submitted two comments regarding abalone FMP development. First, at the July MRC meeting, TNC highlighted using citizen science as a means to efficiently inform an adaptive management framework for red abalone (Exhibit 1). The second letter (Exhibit 2) requests that DFW consider using the described harvest control proposal within the abalone FMP.
- Mendocino County Fish & Game Commission recommends that data streams and management approaches that use the best available science be considered in the FMP and to consider employing more citizen science as a cost-effective means to gather more and better data on red abalone (Exhibit 3).
- Seven members of the scientific community encourage FGC to consider two things when reviewing the abalone FMP: (1) all proposed harvest control rules should be subjected to a peer review process by independent scientists and (2) as the standard-bearer for testing harvest control rules, Management Strategy Evaluation is a formal evaluation process using computer simulation that should be used in the peer review process. (Exhibit 4)

Exhibits

1. Email from The Nature Conservancy, received Jul 7, 2017
2. Email from The Nature Conservancy, dated Nov 22, 2017

3. Letter from Mendocino County Fish & Game Commission, received Nov 21, 2017
4. Email from University of California at Santa Barbara, University of Miami, and others, received Nov 22, 2017

Motion/Direction (N/A)

The Nature Conservancy
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July 7, 2017

Mr. Eric Sklar, President
California Fish and Game Commission
1416 Ninth Street, Room 1320
Sacramento, CA 95814

RE: Agenda Item 6B, Red abalone – Update on fishery management plan development

Dear President Eric Sklar and MRC Members,

The Nature Conservancy is working to build innovative, collaborative solutions to promote healthy ocean ecosystems and thriving marine fisheries in California. Given the inherent value of the red abalone recreational fishery, and the vulnerability of the species and coastal ecosystems to changing ocean conditions, it is critical that we manage this resource more effectively. Yet, the current management framework is largely seen as inflexible, relies exclusively on limited data generated from state-led density and recruitment surveys.

Since the California Department of Fish and Wildlife (CDFW) initiated the development of a fishery management plan for the recreational red abalone fishery in late 2014, the Conservancy's team has worked closely with fishery stakeholders and with world-class fishery scientists. **These collaborations have yielded promising new data streams and data collection tools, as well as a harvest control rule, that can be incorporated into the red abalone fishery management plan currently in development.** We believe that these new management tools and approaches will facilitate more nimble management and long-term conservation of red abalone in the future.

<u>Generating New Data Streams to Inform Management</u>
The Nature Conservancy is developing new, cost-effective harvester and 3rd party generated data streams capable of capturing high-quality data on abalone length. As proven in extensive peer-reviewed science and demonstrated in invertebrate fisheries around the world, robust information on length can be invaluable for management. It can inform estimates of spawning potential ratio (SPR), which can be used to inform assessments and management decisions for data-poor resources like red abalone.

In working to generate a length database for red abalone, we first partnered with Reef Check, CA and its volunteer citizen scientists. In consultation with CDFW, we have also co-developed an abalone specific protocol and facilitated the uptake of this strategy by hosting diver trainings and public forums. Citizen science data collection shows great promise in creating a management-ready dataset for red abalone, particularly given Reef Check divers can collect abalone length measurements at more than five times the rate of the state. **In the span of just over a year, we have generated an unprecedented length database for this resource (approximately 7,000 individual measurements), improved spatial representation of the current sampling scheme (sampling across 17 sites), and there is increased interest in participation by Reef Check divers for this season.**

Additionally, the Conservancy and partners are piloting a mobile application that will allow the approximately 25,000 recreational abalone divers in California to easily collect high-quality length information on abalone at the point of capture. This mobile app has the potential to both modernize the report card process for collecting abalone data and inform near real-time stock status models. **In-depth feedback received thus far from recreational divers has been positive and constructive criticism received has resulted in some key revisions to the mobile app, which is anticipated to be ready for use by late summer 2017.**

<u>New Frameworks for Transparent Decision-Making</u>
The Conservancy has worked with scientists and our partners to develop a new climate-ready, adaptive framework for red abalone. Building off the concept described by Dr. Natalie Dowling, a renowned expert in data-limited harvest strategies, during a 2016 public workshop co-hosted with CDFW, the Conservancy has finalized a harvest control rule that uses a two-tier decision tree to integrate multiple streams of information (including density surveys, individual length, report card landings, and an El Niño environmental indicator) to assess stock status and generate catch limits to manage at the preferred spatial scale deemed suitable for management by CDFW.

To evaluate the effectiveness of our proposed red abalone harvest control rule against status quo management approaches, fisheries modeling expert Dr. Bill Harford completed a comprehensive Management Strategy Evaluation (MSE). **Results from the MSE indicate that the proposed harvest control rule performs best over long and short time periods when both landings and length data are included and density data is excluded. The harvest control rule is also robust under perfect storm conditions (i.e., harmful algal blooms, El Niño, kelp die-off, poaching, fishing pressure). Use of multiple streams of data in the proposed harvest control rule help to reduce the risk of stock collapse while maximizing yields and maintaining stability under a range of normal and extreme environmental conditions.**

The Conservancy appreciates the Commission's leadership on this important issue. We look forward to continuing to work collaboratively with CDFW, harvesters, and scientists to improve management of data-poor fisheries like red abalone and to develop a fishery management plan that enhances climate-readiness in this fishery.

Sincerely,

Tom Dempsey
Senior Fisheries Project Director
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November 22, 2017

Mr. Eric Sklar, President
California Fish and Game Commission
1416 Ninth Street, Room 1320
Sacramento, CA 95814

Re: Agenda Item on Red Abalone Fishery Management Plan

Dear President Sklar,

In advance of the October 2017 Commission meeting, a group of stakeholders, including The Nature Conservancy, submitted a collaborative harvest control rule (HCR) proposal and formally requested that the proposal be considered for inclusion in the red abalone fishery management plan (FMP), and undergo peer review alongside any harvest control rule proposal put forth by the California Department of Fish and Wildlife (CDFW).

To inform the Commission's evaluation of the collaborative HCR proposal, as well as any future peer review process, we have attached a report summarizing the management strategy evaluation (MSE) used to assess the collaborative HCR, including the specifications of the operating model and metrics used to evaluate HCR performance against management objectives. The most recent version of the collaborative HCR proposal incorporates feedback from CDFW and ensures a conservative approach to resource management under the recent extreme environmental conditions, thereby ensuring full stock recovery, while still maintaining access to the resource. Results from the MSE clearly show that under extreme environmental conditions the collaborative HCR proposal can adjust catch to levels that reduce the possibility of stock collapse while continuing to maintain the recreational fishery. In the absence of extreme environmental conditions, it can also maintain stock productivity and catch at levels that approach maximum sustainable yield.

As the Commission develops their recommendation to CDFW on the necessary content to include in the Red Abalone FMP, we urge you to include the collaborative, harvest control rule proposal. Such collaborative proposals leverage the expertise of a diverse array of stakeholders, including academic researchers, non-profits, and divers, and align with mandates in the California Marine Life Management Act that support use of the best available science and stakeholder engagement in discussions around and development of content to include in fishery management plans.

Sincerely,

Alexis Jackson

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An indicator-based decision tree for managing the northern California red abalone fishery

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November 2017

Executive summary

Selection of a management strategy for the red abalone fishery is a process that requires objective and transparent evaluation of alternative approaches. Here we have built a hierarchical decision tree that was originally designed at a public meeting in collaboration with fishery stakeholders and the Department of Fish and Wildlife. The Decision Tree has been refined over the past year and a half based on feedback from the CDFW and interested fishermen. Our model results provide an opportunity for Commissioners, members of the public and independent scientists to review the specification and performance of this approach. We recommend that all possible management strategies under consideration in the Fishery Management Plan be subjected to the same guidelines for transparency and evaluation of performance as the approach undertaken here.

The Decision Tree management strategy evaluated in this report incorporates landings data from each of 56 sites reported by fishermen as well as length frequency information collected by both CDFW and Reef Check, California at 15 sites. The decision tree can easily accommodate length frequency data from additional sites as they become available. The management strategy evaluation clearly shows that the decision tree can adjust catch to levels that reduce the possibility of stock collapse while continuing to maintain a fishery under extreme environmental scenarios. In the absence of extreme environmental conditions, the decision tree can maintain stock productivity and catch at levels that approach maximum sustainable yield.

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1. Introduction

Data-limited fisheries management typically proceeds in the absence of quantitative stock assessment, relying instead on simpler indicators derived from monitoring data that inform decision-making. Circumstances contributing to data limitations are varied, but can arise for example, where fine-scale spatial stock structure is at odds with feasible scales of data collection, or where an overwhelming number of fishers and landing sites prevents comprehensive monitoring (Butterworth et al., 2010; Dowling et al., 2015a; Prince et al., 2008). These data limitations are familiar circumstances facing management of the northern California recreational fishery for red abalone (*Haliotis rufescens*). The fishery operates between San Francisco and the Oregon border, is estimated to be worth US$40 million and includes approximately 25,000 registered fishers. In addition to its value, awareness of historical collapses of other California abalone species has cultivated considerable interest in monitoring and management of this resource (Braje, 2016; Erlandson et al., 2005; Reid et al., 2016).

The red abalone fishery is regulated under the State of California Department of Fish and Wildlife (CDFW) Abalone Recovery and Management Plan (CDFW, 2005). But recently, a diver-based survey of red abalone density, that is heavily relied upon for regulatory decision-making, was subject to scientific review. This review was convened by California's Ocean Science Trust and recommended fundamental improvements to assessment and management (OST, 2014). Following this review, the CDFW initiated a plan to re-visit its approach to decision-making. In support of this initiative, non-governmental organizations, including The Nature Conservancy, have worked closely with recreational fishers to expand data collection and to explore management strategy options. For instance, cost-effective length composition monitoring of red abalone has been successfully implemented in collaboration with the citizen scientist group Reef Check, California (Freiwald et al., 2016).

Candidate management strategies have also been developed that emphasize connections between resource monitoring, data analysis used in calculating indicator values, and the use of indicator-based harvest control rules (HCRs). Monitoring designs can profoundly affect indicator reliability, and consequently, the scientific merit of management decisions (e.g., Smith et al., 2011). Data analysis can vary from summary statistics of survey abundance, fishery catch-per-unit-effort, or population size composition, to statistical estimation of stock depletion, reproductive potential, and fishing mortality rates (Apostolaki and Hillary, 2009; Carruthers et al., 2015; Dick and MacCall, 2011; Gedamke and Hoenig, 2006; Geromont and Butterworth, 2015a; Hordyk et al., 2015c; Klaer et al., 2012; Martell and Froese, 2012). HCRs must be able to cohesively integrate indicators and correctly guide regulatory changes towards the achievement of fishery objectives (Dowling et al., 2015a; Harford and Babcock, 2016). Indicator-based HCRs have already been implemented for some Australian abalone fisheries and this type of approach is thought to promote stakeholder buy-in relative to less-transparent *ad hoc* decision-making (Campbell et al., 2007; Prince et al., 2008; Wilson et al., 2010).

Formulating management strategy options for red abalone required addressing spatial variability in red abalone growth, survival, and reproductive success between relatively localized habitat patches (e.g., sites < 1000 m apart) (Emmett and Jamieson, 1988; Geibel et al., 2010; Haaker et al., 1995; Leaf et al., 2007; McShane and Naylor, 1995; Nash, 1992; Sloan and Breen, 1988). Globally, it is well established that the small-scale meta-population dynamics of abalone species need to be accommodated in management strategy design (Bedford et al., 2013; Mayfield et al., 2012; Prince, 2005; Saunders et al., 2008; Shepherd and Brown, 1993). Problematically, within the northern California red abalone fishery, less than 50% of fishing sites along the coastline are monitored, aside from recording of catches, and many sites differ with respect to fishing pressure. Thus, in relying on existing data streams and their inherent limitations, management strategy design accommodated site-specific signals about resource changes where this information was available, while also attempting to guide TAC adjustments along the entire coast (Fig. 1). Because the northern California coastline consists of approximately 56 fishing sites, it was also necessary to offer built-in flexibility to generate regional TACs, as aggregates of fishing sites. Regional TACs were necessary to support implementation of regulatory tactics for recreational fishing, as well as to reasonably accommodate fishery enforcement. Tactical regulation of red abalone catches currently includes a ban on scuba, a minimum shell length of 178 mm (7 inch) for possession, seasonal and area closures, and daily and annual bag limits.

During initial development of management strategies, we recognized that design complications could not be simply addressed through expert judgement alone (Butterworth et al., 2010). Accordingly, simulation testing was carried out through management strategy evaluation (MSE; Butterworth, 2007; Butterworth and Punt, 1999; Punt et al., 2016; Sainsbury et al., 2000; Smith et al., 1999). MSE examines the collective performance of data collection, data analysis, and decision-making in the currency of whether fishery objectives are expected to be achieved over various time horizons. By comparison, treatment of any isolated aspect of a strategy, viewed independent from its intended use in decision-making, is merely an abstraction from the objective of sustainable management (Harford and Babcock, 2016). The effects of uncertainty on decision-making are also explicitly addressed in MSE, for instance, by replicating the error structure or bias of a monitoring program and propagating this (potentially unreliable) information into application of a HCR. MSE is also well suited to examining management reactions to changing environmental conditions because MSE simulates recursive decision-making through time, where each decision in supplied with updated information, and thus, each decision is a reaction to new information (A'mar et al., 2010; Punt et al., 2014).

Through MSE and through feedback from stakeholders and scientists, our initial specification of a multi-indicator management strategy was refined. Indicators derived from density surveys, catches, length frequency distributions, and an index of environmental conditions were initially considered in contributing to a hierarchically structured decision tree (Harford et al., 2017). Like other incremental harvest strategies, the decision tree determined the direction of TAC adjustments and iteratively modified TACs in small steps until catches stabilized around target reference points (Hordyk et al., 2015a; Prince et al., 2011). The results of the initial MSE produced concerns that density surveys could be unreliable, resulting from patchily-distributed red abalone and modest sampling intensity (see Kashiwada and Taniguchi, 2007). Unreliable density estimates sometimes led to erroneous TAC adjustments that produced a non-negligible probability of site biomasses falling to low levels. We therefore do no recommend the use of density surveys in this updated model specification. Similarly, in the initial model specification, anomalies of the El Nino Southern Oscillation index were used as an empirical indicator, recognizing that red abalone growth and survival can vary dramatically in response to climate variation and its effects on kelp biomass (e.g., *Nereocystis luetkeana*), which is red abalone's main dietary constituent (Cavanaugh et al., 2011; Jiao et al., 2010; Rogers-Bennett et al., 2011; Tegner et al., 2001; Tegner and Dayton, 1987). However, this environmental index was subsequently excluded in this updated model specification because in reality, mechanistic linkages between red abalone biology and environmental conditions are difficult to confirm and because environmental indices typically fail to improve management performance unless mechanistic relationships are well established (A'mar et al., 2010; Punt et al., 2014). Beneficial data streams that were included in this harvest control rule were catch histories and length frequency distributions, which offered potential to avoid undesirably low biomass levels and to maintain sustainable catches that were commensurate with long-term attainment of maximum sustainable yield (MSY). Length frequency distributions were used to calculate spawning potential ratio (SPR), which is a measure of the state of reproductive potential of the stock (Goodyear, 1993; Hordyk et al., 2015c). Catch histories were used in a Monte Carlo method, known as catch-MSY, to estimate current harvest rates relative to a harvest rate reference point (Froese et al., 2017; Martell and Froese, 2012).

Development of candidate management strategies also highlighted complexities about how to specify reference points, against which indicators are compared (Harford et al., 2017). For indicators derived from catch histories and length frequency distributions, reference points could be established based on optimality criteria or precautionary principles, which are commonly obtained from per-recruit analysis (Beverton and Holt, 1957). Conversely, the use of the diver-based density survey required that a density reference point be chosen without knowledge of corresponding stock status. In some circumstances relative abundance-based HCRs have been demonstrably useful for fishery management (Hilborn, 2002; Little et al., 2011; Pomarede et al., 2010). Nevertheless, reference points based on target or limit exploitation rates and reproductive potential can reflect, to some extent, disparate fishery objectives than those related to relative abundance indicators, especially when the latter need to be established without an understanding of the underlying stock status. MSE also highlighted the potential for incompatibility or antagonism among indicators used in multi-indicator decision framework when reference points did not reflect a cohesive vision for meeting fishery objectives. This means that if, by happenstance, a historical density reference point reflected an aggressively depleted stock condition, while an SPR reference point was established based on a much less depleted target, then these reference points could hinder achievement of any policy objective.

Our initial MSE also contrasted red abalone vulnerability to severe environmental conditions (i.e., climate variability, harmful algal blooms) in conjunction with fishery exploitation and poaching, which highlighted precautionary considerations for delineating management reference points. Under normal environmental conditions and fishing operations, indicators derived from catch histories and length frequency data maintained biomass levels that approached maximum sustainable yield (B_{MSY}) and catches that approached MSY. However, under scenarios involving harsh environmental circumstances, MSE demonstrated the consequences of degree of precaution in reference point selection, with less precautionary reference points (e.g., an SPR reference point of 0.4 rather than 0.6) enhancing stock declines during environmental conditions that were unfavorable to red abalone.

In this study, we evaluated the performance of an updated decision tree based on catch histories and length frequency data using MSE, according to the following objectives. First, we highlighted the effects of specifying historical stock dynamics on future HCR performance, as historical conditions are often highly uncertain in data-limited circumstances (i.e., Harford et al., 2016). Second, we evaluated the cumulative effects of fishing and harsh environmental conditions on decision tree performance, as red abalone are known to be vulnerable to climate fluctuations and harmful algal blooms; each of which can induce changes to survival, growth, and reproductive success (Harley and Rogers-Bennett, 2004; Rogers-Bennett et al., 2012; Tegner et al., 2001). Third, we reconciled capacity for achievement of fishery objectives in relation to practical impediments of data availability and data quality by contrasting decision tree performance against a reference strategy that optimally guided achievement of fishery objectives under perfect information (Cadrin and Pastoors, 2008; Dowling et al., 2015b).

2. Methods

In conducting the MSE, we first developed an operating model that simulated red abalone stock dynamics and resource monitoring. Alternative operating model scenarios were developed by modifying structural modeling equations or parameter values. These alternative scenarios were used to reflect uncertainties about red abalone ecology, historical state of the resource, and future environmental conditions. We then developed a decision tree, which consisted of the set of instructions used to determine routine adjustments to red abalone TACs. We then developed an implementation algorithm that addressed the spatial and temporal distribution of fishing effort, and thus, determined how removals at individual sites would occur in relation to regional TACs. Simulation runs were then conducted under each of the specified simulation scenarios and performance of the decision tree was measured in relation to achievement of common fishery management objectives (Punt, 2017).

Operating model

Spatial distribution of red abalone

Stock dynamics were a spatially-explicit representation of red abalone inhabiting the northern California coastline. Abalone were distributed along a 1-dimensional array consisting of 56 sites, each of which corresponded to recreational fishing locations that span a total distance of approximately 540 km (334 miles) from San Francisco to the California-Oregon border (Tables 1 & 2). Given that each site corresponded to an area of one-to-tens of kilometers, we did not model site connectivity because larval dispersal and adult movement likely occur on much smaller spatial scales. Short larval durations of abalone species typically act to minimize dispersal distances from 10s to 100s of meters (Leighton, 2000; McShane et al., 1988; Prince et al., 1987; Shepherd and Brown, 1993). While potential for long distance larval dispersal has been suggested (Rogers-Bennett et al., 2016; Watson et al., 2010), most evidence demonstrates that nearly all new recruits come from parents located within several hundred meters (Gruenthal et al., 2007; Saunders et al., 2008; Temby et al., 2007). Adult movement over various time scales is also thought to be limited to 100s of meters (Ault and Demartini, 1987; Coates et al., 2013). In addition, we did not represent separation between deep water habitat that is inaccessible to free-diving fishers and shallow water areas where fishing occurs.

Temporal dynamics of red abalone

The red abalone stock was initialized for the year 2002 and historical temporal dynamics were modeled for the time period of 2002 to 2016, using actual site-specific catches, before projecting the stock forward for 25 years during which time the decision tree determined annual TAC adjustments. Temporal dynamics were calculated for each site using length-structured population dynamics, which is an approach well-suited for modeling species that are difficult to age, like marine invertebrates (Breen et al., 2003; Haddon, 2011). Length-based models account for survival, growth, and reproduction through time by assigning individuals to length classes or length bins. Numbers-at-length matrices differ from numbers-at-age matrices because the latter tracks specific cohorts as they transition between age classes, while the former probabilistically tracks transitions between length classes where individuals from several cohorts are likely to be found in any given length bin (Haddon, 2011). Red abalone were classified according to 59 length bins from 5 mm to 300 mm, in 5 mm increments. For a given site l and simulation replicate *k*, the matrix algebra involved in calculating the progression of individuals between length bins, according to an annual time step, *j*, was (for brevity *k* and *l* subscripts are omitted):

$$\mathbf{N_{j+1}} = \mathbf{G_j}\left(\mathbf{S_j}\mathbf{N_j}\right) + \mathbf{R_j}, \tag{1.1}$$

where **N** is the abundance vector with 59 length classes, **G** is the square growth transition matrix with upper triangle of zeros preventing negative growth in length, **S** is the zero square matrix with only diagonal elements having non-zero values, and **R** is the recruitment vector with 59 length classes. The growth matrix specified how numbers-at-length would transition probabilistically into other length classes based on a Gaussian probability density function with expected growth increment in mm obtained from a von Bertalanffy function (i.e., expected growth increment is $\Delta L_{i,j,k,l} = \left(L\infty_{j,k,l} - Lbin_i\right)\left(1-\exp(-K_{j,k,l})\right)$, where *K* is Brody growth coefficient, $L\infty$ is average maximum size, and *Lbin* is the lower bound of each length bin) and standard deviation of 8.5 mm (Rogers-Bennett et al., 2007). Because we modeled temporal and spatial variation in growth and natural mortality, parameters related to these processes have subscripts indicating length bin *i*, year *j*, simulation replicate *k*, and location *l*. In the subsequent section (**Methods: *Operating Model:*** *Environmentally-driven life history variation*), we describe our approach for generating environmentally-driven spatial and temporal variation in life history parameters.

Reproductive dynamics served the dual roles of determining the number of newly recruiting individuals and determining the patterns of emergence of mature red abalone from crevices onto exposed substrates. At each site, a logistic maturity function ($Mat_{i,k,l}$) was parameterized based on average maximum size ($\bar{L}\infty_{k,l}$) and using a Beverton-Holt life history invariant relationship, such that, $L50_{k,l} = \bar{L}\infty_{k,l} \times 0.6$ and $L95_{k,l} = L50_{k,l} \times 1.15$, where *L50* and *L95* are the lengths associated with 50% and 95% probabilities of maturity, respectively (Jensen, 1996; Prince et al., 2015). Eggs-per-female was a power function of length (*fec_i =2.85exp(-((Lmids$_i$-215)^2/(2888)))0.5*; *Lmids* is mid-point of each length bin) with a descending right limb reflecting the possibility of reproductive senescence (Rogers-Bennett et al., 2004). Numbers of recruits at each site were calculated according to the Beverton-Holt stock-recruitment function that was re-parameterized using steepness (*h*):

$$R_{j,k,l} = \left(\frac{0.8 R_{0,k,l} h B_{j-1,k,l}}{0.2 B_{0,k,l} (1-h) + (h-0.2) B_{j-1,k,l}} \right) \exp\left(\mathrm{Normal}\left(0, {\sigma_{j,k,l}}^2\right) - {\sigma_{j,k,l}}^2 \big/ 2 \right), \tag{1.2}$$

where σ is standard deviation of lognormal recruitment deviates, B_0 is unfished reproductive output (i.e., egg production), and B is a measure of reproductive output in year j-1:

$$B_{j-1,k,l} = \sum_i Mat_{i,k,l} \times fec_i \times N_{i,j-1,k,l} \tag{1.3}$$

Steepness was specified as 0.6, as abalone species tend to display weak compensatory recruitment at low stock size and this value is similar to those assumed in abalone stock assessments (Fu, 2014; Gorfine et al., 2005; Rossetto et al., 2013; Zhang et al., 2007). Age 1 recruits ($R_{i,j}$) populated length bins of the recruitment matrix ($\mathbf{R_j}$) according to a Gaussian probability density function with expected length of 26 mm (based on the global average von Bertalanffy parameters used in simulation runs: $L\infty$=254 mm shell length, K=0.108 year^{-1}, t_0=0) and a standard deviation of 8.5 mm (Rogers-Bennett et al., 2007). The second role of reproductive ecology was in specifying emergence-at-length from a cryptic existence within crevices as juveniles onto exposed substrates as mature adults (Prince et al., 1988). Site-specific emergence-at-length probability was specified equal to site-specific maturity-at-length probability. Emergence affected the availability of red abalone to divers conducting surveys of length frequency distributions and the availability to the fishery.

Survival (S) consisted of natural mortality (M) and fishing mortality (F) and was calculated at the beginning of each time step:

$$S_{i,j,k,l} = \exp\left(-M_{i,j,k} - sel_{i,k,l} F_{j,k,l}\right), \tag{1.4}$$

where sel is selectivity and is a function of availability to free-divers, based on emergence, and knife-edge possession beginning at 178 mm total length. For a given l and k, $S_{i,j}$ populated the diagonal of the corresponding survival matrix ($\mathbf{S_j}$). We used the mortality-at-length curve of Leaf et al. (2008) that describes natural mortality as being 0.65 year^{-1} for shell lengths less than 50 mm, 0.05 year^{-1} for length greater than 245 mm, and a decreasing logistic function in between. Catch in numbers (C_N) was calculated:

$$C_{N,i,j,k,l} = \frac{sel_{i,k,l} F_{j,k,l}}{\left(M_{i,j,k} + sel_{i,k,l} F_{j,k,l}\right)} \left(1 - S_{i,j,k,l}\right) N_{i,j,k,l}. \tag{1.5}$$

Environmentally-driven life history variation

Water temperature has been shown experimentally to have negative effects on red abalone gamete production, body condition, survival rates, and somatic growth rates (Moore et al., 2011; Perez, 2010; Vilchis et al., 2005). In a related observational study, Jiao et al. (2010) reported negative changes to $L\infty$ in relation to warm-phase temperature anomalies of the El Nino Southern Oscillation index. Likewise, trends in food availability, especially related to climate- and storm-induced variability in kelp biomass (e.g., *Nereocystis luetkeana*), have been implicated in changes to red abalone survival and growth (Cavanaugh et al., 2011; Rogers-Bennett et al., 2011; Tegner et al., 2001; Tegner and Dayton, 1987).

Spatial variation was simulated by generating site-specific mean asymptotic length ($\bar{L}\infty_{k,l}$) and Brody growth coefficient ($\bar{K}_{k,l}$) according to a multivariate Gaussian distribution ($\mathrm{MVN}(\mu,\Sigma)$) with $\mu=\left(\bar{L}\infty=254,\bar{K}=0.108\right)$ and Σ calculated using a 3% coefficient of variation (CV) on $\bar{L}\infty$ and a 10% CV on $\bar{K}$ (Jiao et al., 2010; Rogers-Bennett et al., 2007). Maturity ogives were then calculated based on site-specific growth patterns, thus enabling growth and reproductive characteristics to co-vary at each site (Prince et al., 2015).

Temporal variation in several life history parameters was simulated to be driven by an index of the El Nino Southern Oscillation (ENSO) known as the Ocean Nino Index, which measures surface temperature anomalies (NOAA, 2017). Life history parameters $L\infty$ and *M* co-varied with the ENSO index according to Gaussian bivariate probability distributions. Specification of temporal life history variation proceeded by first generating time series of ENSO anomalies. During the time period of 2002 to 2016, we used actual ENSO autumn season means (i.e., Sept, October, November averages). During the projection time period, we randomly selected toroidal-like segments of the autumn season ENSO index from the time period of 1950 to 2016 and applied these segments to projections to preserve patterns of temporal autocorrelation in this index. ENSO indices informed the bivariate sampling distributions according to specified Pearson correlation coefficients, which determined relationship strength and direction with life history parameters. Correlations were -0.5 for $\bar{L}\infty_{k,l}$ and 0.5 for natural mortality and reflected correlations reported between kelp biomass and a regional climate signal (Cavanaugh et al., 2011), which we assumed would similarly influence red abalone. Having multiple life history parameters co-vary with ENSO anomalies produced demographic responses that were more systematic in response to environmental change than having life history parameters vary independently of one another. Also, empirical data were informative about total variance of life history parameters, but were less informative about sources contributing to this variation (Geibel et al., 2010; Jiao et al., 2010; Leaf et al., 2007). Thus, by constructing relationships with the ENSO index based on bivariate probability distributions we could conserve the total variance of life history parameters, while assigning a partial influence of this variation to a climate-based driver. Thus, the resulting temporal variation in life history parameters varied partially in response to ENSO anomalies and partially as a site-specific stochastic process, producing localized trends in stock dynamics that varied between sites. Temporal variation around the parameter $\bar{L}\infty_{k,l}$ was specified with a CV of 0.1 (Jiao et al., 2010). Experimental comparisons of red abalone survival between ambient conditions and those representing a severe el Nino warm phase (Moore et al., 2011; Vilchis et al., 2005) were used to specify changes in the survival fraction (i.e., where survival = exp(-*M*)) up to 50% under the most extreme conditions. This was accomplished using a Gaussian distribution with mean zero and standard deviation 0.25. Fractional changes in the average natural mortality-at-length from ENSO anomalies was applied to all length classes.

Recruitment deviations were lognormal with a standard deviation of 0.2. Deviations were independent of other environmental signals. We also simulated recruitment failures (generated independently for each site and simulation run) to reflect studies that have reported apparent absences of red abalone recruitment (Karpov et al., 1998; Rogers-Bennett et al., 2016; Tegner et al., 1989). These events were generated as a Bernoulli random variable with recruitment failure probability of 0.25, or occurring on average, once per every four years.

Time-varying natural mortality increases caused by harmful algal blooms were generated as separate sequences of events that affected either the northern fishing sites (Mendocino, Humboldt, and Del Norte counties) or the southern fishing sites (Sonoma and Marin counties). This approach reflected the pattern of a recent red tide event as well as evidence about large-scale oceanographic conditions initiating these events (Anderson et al., 2008; Rogers-Bennett et al., 2012; Trainer et al., 2000). A discrete Markov process produced Bernoulli random variables according to a transition matrix, **P**, of conditional probabilities (Minkova and Omey, 2014):

$$\mathbf{P} = \begin{pmatrix} 1-\pi\left(1-\rho_M\right) & \pi\left(1-\rho_M\right) \\ q\left(1-\rho_M\right) & 1-q\left(1-\rho_M\right) \end{pmatrix} \tag{1.6}$$

where π is the probability of an episodic natural mortality event, q is $1-\pi$, and ρ_M is the correlation between episodic natural mortality events (Feller, 1971).Given a current state, $\theta_t = 1$, the conditional probability of $\theta_{t+1} = 1$ is equal to: $1-q\left(1-\rho_M\right)$. Actual bloom events that were severe enough to cause human deaths have been reported at least every four years prior to the Second World War, while blooms associated with marine mammal or bird illness have been reported annually since 1998 (Lewitus et al., 2012; Price et al., 1991). Thus, we specified events to occur once every four years on average, with a probability that one event would be proceeded by another event in the following year (and so on) with a probability of 0.5. Event occurrence was multiplied by event magnitude, which was drawn from a uniform probability distribution with minimum of 0.15 year^{-1} and maximum of 0.35 year^{-1}. An exception to the probabilistic generation of red tide events was during 2011, where we imposed a natural mortality increase of 0.29 year^{-1} to sites in Sonoma county and southward to reflect a reported severe event (Rogers-Bennett et al., 2012).

Simulated monitoring of red abalone

Simulated observation of catches at each site occurred without error. Observation of length frequency distributions was simulated at 15 unique sites that are routinely monitored by either CDFW and Reef Check California (CDFW, 2005; Freiwald et al., 2016). Lengths were observed as a multinomial process with an effective sample size of 200 individuals, which is a sampling variance assumption that is common to fisheries modeling (Hulson et al., 2012). Availability of length classes to the simulated survey was affected by site-specific emergence. Both Reef Check and CDFW do not annually sample all 15 sites and selection of sampling sites is not coordinated. During the time period of 2002 to 2016 the actual schedule of sampling events was imposed on simulation runs. During the projection time period, 9 of 13 sites monitored by Reef Check were randomly selected annually and 3 of 10 sites monitored by CDFW were likewise randomly selected.

Indicator-based decision tree

The red abalone decision tree used catches (numbers of legal sized red abalone) and length frequency distributions to inform TAC adjustments (Table 3). The decision tree represented the pre-specified process of linking each possible combination of indicators derived from catches and length frequency data to red abalone status (Fig. 2). Delineating red abalone status at a site based on indicator combinations reflected population biology of red abalone, propensity for environmental perturbations, and past management experience with other abalone species (Prince, 2005; Prince et al., 2008). Each possible status had a corresponding TAC adjustment, which ranged between -20% and +20% in increments of 10, including zero TAC change. In instances where length frequency data or catches became unavailable, break-out rules were specified to cope with the remaining data stream (Table 4).

Catches were available for each site and were used to in the catch-MSY approach of (Froese et al., 2017) to calculate the ratio of last year's exploitation rate (*U*) to the exploitation rate associated with production of MSY-level catches. This approach uses a site-specific catch history within a numerical routine that estimates the intrinsic rate of increase *r*, unfished vulnerable biomass *B0*, and depletion in the terminal year. A uniform prior probability distribution for *r* was specified according to life-history-based resiliency (Froese and Pauly, 2011). A uniform prior probability distribution for *B0* was specified following the procedure outlined in Froese et al. (2017). Estimation proceeded by sampling and retaining *r* and *B0* parameter combinations that met simple criteria about stock depletion. Point estimates of *r*, *B0*, and current depletion were used to calculate $U_{MSY}=r/2$. Current *U* was calculated as the catch in the final year divided by *B0* times current depletion. The exploitation ratio was used to indicate whether catches were considered high (i.e., U/U_{MSY} was greater than 1.0), low (i.e., U/U_{MSY} was less than 0.75), or stable ($0.75 < U/U_{MSY} < 1.0$).

Length frequency data was used to calculate spawning potential ratio (SPR) according to the LB-SPR method (Hordyk et al., 2015b, 2015c, 2015a). The SPR describes the reproductive potential of an exploited stock relative to its reproductive potential in an unexploited state (Goodyear, 1993; Restrepo and Powers, 1999). The theoretical basis for the LB-SPR method is that mortality will affect both SPR and the length frequency distribution of the stock. Thus, in the absence of a direct measure of total mortality and fishery selectivity, sampling of length frequency distributions can be used to infer current SPR, given a few additional life history parameters (Hordyk et al., 2015b). The maximum likelihood LB-SPR estimation routine requires input parameters of *M/K*, asymptotic length, coefficient of variation of asymptotic length, and a logistic maturity curve (Hordyk et al., 2015c). For all sites, *M/K* and the coefficient of variation of asymptotic length were specified as 0.9 and 0.1, respectively, which conformed to life history expectations for abalone species (Prince et al., 2015). Because emergence is thought to reflect site-specific maturation trends (e.g., Prince et al., 1988), and because we simulated emergence coincident with maturation, logistic maturity parameters (*L50* and *L95*) were obtained from the emergence trends captured in the left-hand side of the length frequency distribution (Fig. 3). Using all length bins less than or equal to the mode of the length frequency distribution, a cumulative distribution function (CDF) was constructed and scaled such that the mode was the 95% percentile. The *L95* was specified as the mode and the *L50* input parameter was specified as the 50% percentile of CDF. Asymptotic length was calculated as *L50* divided by 0.6, based on the Beverton-Holt life history invariant (Jensen, 1996; Prince et al., 2015).

Ideally, status would always be based on site-specific length frequency data. But while catches were available at each site, length frequency data was only available at several sites in any given year. Because monitoring at all 15 sites did not occur annually, any site where length frequency sampling occurred within the previous three years was considered to have a current SPR estimate. If a site was sampled more than once during the previous three years, the most recent sampling event was used. For sites where monitoring did not occur, the mean SPR from sampled sites within the region (Sonoma county and southward or Mendocino county and northward) was applied. SPR was compared to a set of SPR reference points to determine red abalone status at a given site. When reproductive potential was between 0.66 and 0.54 it was considered stable. The target reference point of 0.6 was chosen to represent a MSY-based target, with a 10% variation around this target considered stable. Above 0.66 reproductive potential was considered high and between 0.54 and 0.3 it was considered low. The SPR limit reference point of 0.3 was selected to trigger more severe catch reductions to support rebuilding towards the SPR target. Using an SPR-based reference point enabled TAC adjustments to avoid both undesirably low stock sizes (i.e., recruitment overfishing) and high stock sizes (i.e., under-utilization of the red abalone resource).

Spatial allocation of fishing

Given the practical challenges associated with managing site-specific TACs, site-specific TACs were summed and implemented as regional TACs. Two regions were defined using the Sonoma-Mendocino county line, with one region consisting of Mendocino and northward (i.e., Mendocino, Humboldt, and Del Norte counties) and the other consisting of Sonoma and southward (i.e., Sonoma and Marin counties). Regional TACs were simulated to be removed (harvested) without error; however, implementation error occurred at the level of site-specific removals. We utilized a spatial effort allocation model that increased or decreased regional effort as necessary to achieve removal of the regional TAC, while maintaining the relative spatial distribution of effort commensurate with simulated 2016 effort distribution. This effort allocation model reflected the idea that each site would continue to maintain its relative popularity into the foreseeable future, despite local abundance changes. In initial model development we considered alternative effort allocation models; however, resulting simulation results did not vary dramatically between model formulations and thus we opted to utilize only a single effort allocation framework in this updated model specification (Harford et al., 2017)

Performance testing

Performance testing was a factorial combination of two decision tree variants, two historical abundance trends, and two future scenarios about environmental conditions. Decision trees differed with respect to TAC adjustments made during stock rebuilding, with a slow rebuild scenario applying more modest TAC reductions than a faster rebuilding scenario with larger TAC reductions (Table 3). To specify historical abundance trends, a process of model tuning to actual catches and SPR estimated from length frequency distributions was carried out. Because trends in SPR from 2002-2016 differed between length frequency datasets collected by CDFW and Reef Check, two distinct historical abundance trends emerged:

Historical scenario 1: *high but declining abundance, negative survival trend in historical data.*

Historical scenario 2: *low but stable abundance.*

In simulating historical scenario 1, depletion at each site was initialized at 0.8 and continued to decline in a reasonably similar manner to expectations based on SPR estimates obtained from Reef Check length frequency data. In simulating historical scenario 2, low but stable abundance, depletion at each site was initialized at 0.2. Technical details of model tuning can be found in Appendix B: Simulated stock reconstruction and historical trends.

The two scenarios about future environmental conditions involved simulating (1) the frequency and magnitude of future ENSO anomalies and (2) ENSO anomalies in addition to severe episodic harmful algal blooms, and episodic recruitment failure. Collectively simulating all of these influences on red abalone abundance reflected a suite of conditions to which the actual red abalone stock is, at times, simultaneously subjected.

Projections of HCRs were implemented for 25 year durations and 100 replicate simulations were carried out. All time- and space- varying stochastic parameter values were generated ahead of simulation runs and applied in parallel against all HCRs to ensure that all evaluations occurred against the same sequences of events to avoid chance differences inherent in a sample of random draws from affecting performance outcomes (Punt et al., 2016). In all simulation runs, the minimum harvest length was seven inches (178 mm). The reference HCR was a constant fishing mortality rule using $F_{60\%SPR} = 0.13$ year^{-1}, as determined from equilibrium stock characteristics (see Appendix A).

Four performance measures were specified. First, we measured the effect of the decision tree on spawning biomass trends by calculating the ratio of projected biomass to the biomass in 2016. Second, we calculated the ratio of projected catches to the catches in 2016. Third, we calculated the ratio of projected biomass to B_{MSY}. Finally, we calculated the ratio of projected catches to MSY. These performance metrics were calculated separately for each site and each simulation run at years 10 and 25 of the projection time period. Performance metrics are presented as the central tendency and dispersion of measures made at 56 sites times 100 simulation runs.

3. Results

Using the fishing site called Van Damme, we illustrate here the process of generating historical stock dynamics and then projecting stock dynamics forward according to a specified HCR (Fig. 4). Under historical conditions described as low but stable abundance, historical trends fluctuate according to stochastic effects on recruitment, survival, growth, and catch histories (Figs. 4A & B). During projections, recovery occurs towards B_{MSY}. The functioning of the decision tree can be observed as follows. A reduction in catches during the early part of the projection time period is followed by gradual catch increases as biomass returns to more sustainable levels. Time lags are apparent between the changes in biomass and subsequent detection of these changes and TAC adjustments (see Appendix D for more details on time lags). The effect of the responsiveness of the decision tree is also observed under the historical condition described as high but declining (Figs. 4C & D). In comparison to the scenario of historically stable abundance, catch reductions that facilitate rebuilding are not detected and triggered as rapidly, and thus, recovery does not occur to the same extent over a 25-year projection period. This illustration demonstrates how simulation testing via MSE was executed in a manner consistent with the study objectives. First, two scenarios reflecting historical conditions were imposed, although in each simulation run stochastic elements caused fluctuations in abundance trends. Second, the cumulative effects of fishing and environmental conditions are observed in red abalone dynamics as well as in the application of the decision tree. Third, practical considerations of management strategy design are collectively revealed via MSE, particularly as the illustrated management strategy integrates several complexities related to data availability and data quality and implements TAC adjustments, all while unpredictable environmental fluctuations occur.

Short-term (10 year) and long-term (25 year) projections suggested a clear rebuilding trade-off between maintaining catches and achieving increases in stock biomass (Figs. 5 & 6). For demonstration, the natural rate of stock recovery in the absence of fishing was simulated (i.e. the fishery was simulated to be closed for 25 years). Two HCRs (slow rebuild and fast rebuild) were compared to fishery closure. Under typical ENSO-driven survival and growth patterns as well as recruitment variability, rebuilding to B_{MSY} is unlikely in 10 years, even with no fishery (Fig. 5). Recovery in the absence of fishing is likely to occur within 25 years (Fig. 6A). The problem of achieving timely stock recovery is exacerbated by the episodic occurrence of more severe environmental events, like red tide-induced mortality increases and recruitment failure (Fig. 6C & D) and by rapidly declining abundance prior to implementing a HCR, which requires a greater time frame to sufficiently rebound towards B_{MSY} (Fig. 6B). Given the desirability to maintain an active fishery, the trade-off becomes one of catch reductions to improve stock recovery in the near and production of yields commensurate with MSY in the longer-term. The slow rebuild decision tree produces catches most similar to the reference HCR ($F_{60\%SPR}$ with perfect information), while enabling the stock to increase towards B_{MSY} (Fig. 5A). The fast rebuild decision tree offers accelerated rebuilding, most similar to that which can be achieved by closing the fishery, although fast rebuild imposes a dramatic reduction in catches during rebuilding. These trade-offs can also be illustrated using performance metrics that reflect changes to the stock in relation to the simulated state of the stock in 2016 (Figs. 7 & 8). Relative biomass and relative catches (in numbers) highlight the same patterns of recovery and trade-offs that impose fishery reductions to rebuild the stock towards a more sustainable stock size.

The results of the MSE are somewhat alarming with respect to prospects for stock recovery under severe conditions that include red tide mortality events and recruitment failure (Fig. 5C, 5D, 6C, 6D). It is important to recognize that these projections exist at the confluence of initially low stock sizes and the propensity for episodic events in the future that we specified. Since fishery closure results in almost no instances of stock recovery under these severe conditions within 25 years, the inability of the decision tree variants to enable recovery should not be interpreted as poorly designed HCRs. Instead, failure to recover – under severe future environment – is the consequence of the simulated stock becoming depleted to problematically low levels before the decision tree is implemented.

4. Discussion

The decision tree was designed and tested by a group of fishery stakeholders in the red abalone fishery as a viable approach to meeting objectives of fishery management. The decision tree is a harvest control rule that relies on the interaction between two independent assessment methodologies to recommend TAC adjustments based on two independent data sources. As such, it is imperative that these stock assessment methods (SPR and catch-MSY) be evaluated in terms of the capacity to meet management objectives when combined in the decision tree framework, and not independently. The operating models were designed to be sufficiently complex to enable determination of trends in decision tree performance in support of development of a fishery management plan. The operating model reflected the most current estimates of life history parameters (Kashiwada and Taniguchi, 2007; Leaf et al., 2008; Rogers-Bennett et al., 2004, 2007). We incorporated life history variation in space and time in a manner consistent with empirical and experimental evidence and we considered not only stochastic variation, but also systematic variation linked to an environmental signal (Cavanaugh et al., 2011; Jiao et al., 2010; Leaf et al., 2007). Consequently, our performance testing reflected scenarios where red abalone were subject to combined detrimental influences of fishery exploitation and harsh environmental conditions (Harley and Rogers-Bennett, 2004). We simulated each site as an isolated component of the larger red abalone stock, which is consistent with expectations related to larval dispersal and adult movement (Ault and Demartini, 1987; Coates et al., 2013; Gruenthal et al., 2007; Saunders et al., 2008; Temby et al., 2007).

Under two historical depletion trends, declining and stable, both of which resulted in expectations of a rather depleted red abalone stock in 2016, the decision tree variants demonstrated an ability to correctly gauge stock status and implement stock rebuilding. These results were most evident when future environmental conditions were expected to follow typical ENSO-driven survival and growth patterns as well as recruitment variability. Following rebuilding, the decision tree sequentially increased TACs, to the benefit of the fishery. Furthermore, the decision tree shifted biomass and catches toward MSY-related targets under typical environmental conditions. The two decision tree variants differed in magnitude of TAC reductions implemented during rebuilding and we emphasize that these decision trees trade-off the extent to which shorter-term reductions in TACs are tolerable against the extent to which rapid stock rebuilding is desirable. As a precaution and as an illustration of the potential vulnerability of red abalone to episodic natural morality events (i.e., harmful algal blooms) or localized recruitment failures, the stock could take longer than 25 years to recover if these unfortunate events do occur.

The design of decision-tree was aimed at addressing four practical policy considerations about the red abalone fishery. First, site-specific indicators informed decision-making, while also enabling catch adjustments along the entire coastline. Second, indicators consisted of the most cost-effective and reliable existing data sources, rather than exploring alternate or new data streams. Third, flexibility was maintained in the framework to accommodate monitoring at additional sites, should monitoring programs expand. Fourth, TAC adjustment algorithms remain flexible to be implemented at aggregate regional spatial scales as a means to reasonably accommodate enforcement activities and specification of tactical regulations (e.g., bag limits).

From the perspective of formulating a management strategy for the red abalone fishery that accommodates small-scale meta-population dynamics, using an indicator derived from site-specific length frequency data offers some practical solutions to on-going challenges. Measurement of site-specific indicators, especially given considerable variation in localized abundance trends, is known to be paramount to successful management of abalone fisheries (Geibel et al., 2010; McShane and Naylor, 1995; Prince, 2005; Prince et al., 2008). Because diver-based observation of length frequency distributions can be systematically expanded to accommodate monitoring at additional sites, coverage of the coastline can be improved without requiring major changes to a fishery management plan. Note that the SPR indicator that is derived from length frequency data is compared to a biological baseline that is independent of historical conditions (i.e., an SPR reference point). To the contrary, where red abalone density surveys have been previously used to inform decision-making, the existing 8-10 sampling sites have been criticized as not being indicative of red abalone abundance along the entire coastline, nor does averaging historical conditions across sites constitute an acceptable coast-wide density reference point (OST, 2014). The status quo practice under the ARMP is to calculate a historical reference density as an average across three sites, which is then compared to a current average across 8-10 recently sampled sites (CDFW, 2005). The approach used in the ARMP appears to confound temporal changes in density with site-specific causes of density changes, like fishing, local habitat conditions, and local productivity. Adding more density survey sites could address the spatial coverage issue only if survey precision was increased and if contemporary density estimates were compared only to historical density at the same site. Of course, this would require a “shifting baseline” of reference density conditions as new sites are added, which is not a desirable component of a fishery policy.

Reliance on length frequency data also arguably better addresses sampling design principles when it comes to the red abalone stock. Length frequency distributions measure relative changes in size structure, and are not dependent on reliable counts. Therefore, length-frequency sampling appears to be less affected by depth-oriented movement or re-distribution of red abalone as long as diver searches adhere to sampling designs that reflect the entire depth range of habitats and as along as post-exploitation sized individuals are not subject to size-based differences in detection probability. Density surveys appear to be more problematic in this regard, as unless specifically accounted for using stratified random sampling, or some other scheme, and corresponding statistical calculation procedures are used (e.g., see Cochran, 1977), year-to-year movement of red abalone between deep and shallow habitats can be difficult to separate from changes in total abundance. Lastly, there remains an unresolved complication pertaining to whether habitat conditions, including instances of low kelp density, affect the detection probability or 'catchability' during density surveys. Problematically, when detection probability is not accounted for in sampling of animal populations, the magnitude of bias in density can co-vary with environmental conditions (Guillera-Arroita et al., 2010; Monk, 2014; Royle and Dorazio, 2009).

The cohesive functioning of indicators reflecting exploitation status (from catch-MSY) and reproductive potential of the stock (from LB-SPR) are worth pointing out. Simply put, catch histories are available for all sites, and thus, an indicator of exploitation status is made available via the catch-MSY approach. But this indicator alone is limited to fishery exploitation status, rather than indicating the overall cumulative fishery and environmental effects that determine whether recruitment overfishing is likely to be occurring. The SPR calculation estimated using LB-SPR provides an indication of recruitment overfishing. When SPR levels trigger TAC reductions, the exploitation status indictor works as a mitigating factor that recognizes when fishery exploitation has been sufficiently reduced to theoretically induce stock rebuilding. Thus, since rebuilding is a slow process, the fishery exploitation indicator prevents ad nauseam TAC reductions and instead recognizes when reductions should be sufficient for rebuilding. Collectively, the SPR and fishery exploitation indicators work non-antagonistically and reflect target reference points (i.e., SPR of 0.6 and harvest rate of 0.75 – 1.0 time F_{MSY}), while also enabling avoidance of limit reference points (i.e., SPR < 0.3 and harvest rate > F_{MSY}).

The development of this decision tree reflected the categorization of the red abalone fishery as being data-limited. As it was applied here, MSE provided guidance on decision tree design, and in doing so, illustrated how the use of indicator-based approaches requires pragmatism. In addition, MSE revealed the central importance of examining red abalone vulnerability to environmental conditions in conjunction with fishery exploitation (Harley and Rogers-Bennett, 2004; Rogers-Bennett et al., 2012; Tegner et al., 2001). Accordingly, we demonstrated that the application of data-limited methods should be made cautiously and be subjected to simulation testing. Data-limited approaches can often rely on simplifications of complex stock dynamics, and therefore, can sometimes result in poor management performance (Carruthers et al., 2014; Fulton et al., 2016; Hordyk et al., 2015a). Furthermore, data availability and data quality must be balanced against expectations about achievement of fishery objectives. But despite challenges faced in developing and implementing data-limited management strategies, some data-limited methods have been shown to be on par in achievement of fishery objective with more complex approaches requiring quantitative stock assessment (Geromont and Butterworth, 2015b). Like the application we have presented herein, relating changes to indicator values to corresponding changes in fish stock status is a particular strength of indicator-based approaches and has the potential to provide clarity in decision-making and development of fisheries policy (Campbell et al., 2007; Prince et al., 2008; Wilson et al., 2010). We recommend the results and conclusions drawn from this work be subjected to independent peer review and evaluated against any alternative harvest control rule put forth by CDFW or other stakeholders for consideration in the red abalone fishery management plan.

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6. Figures

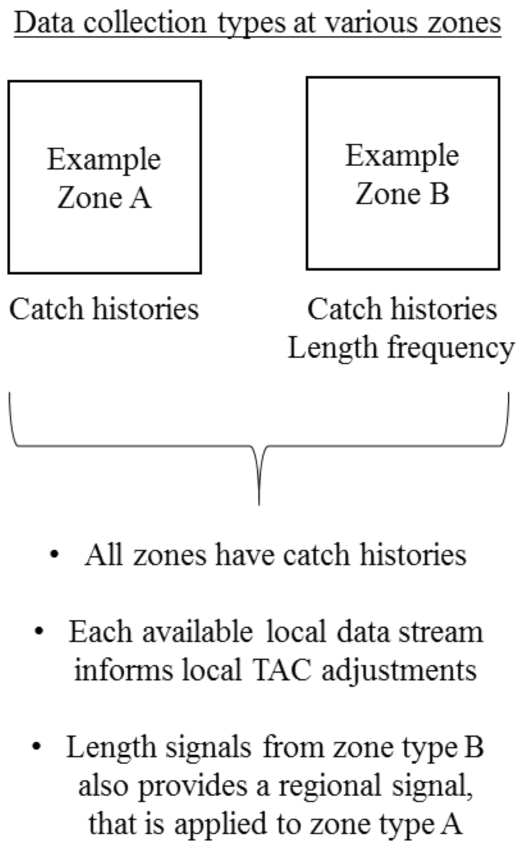


Figure 1. Data availability and its influence on harvest control rule design.

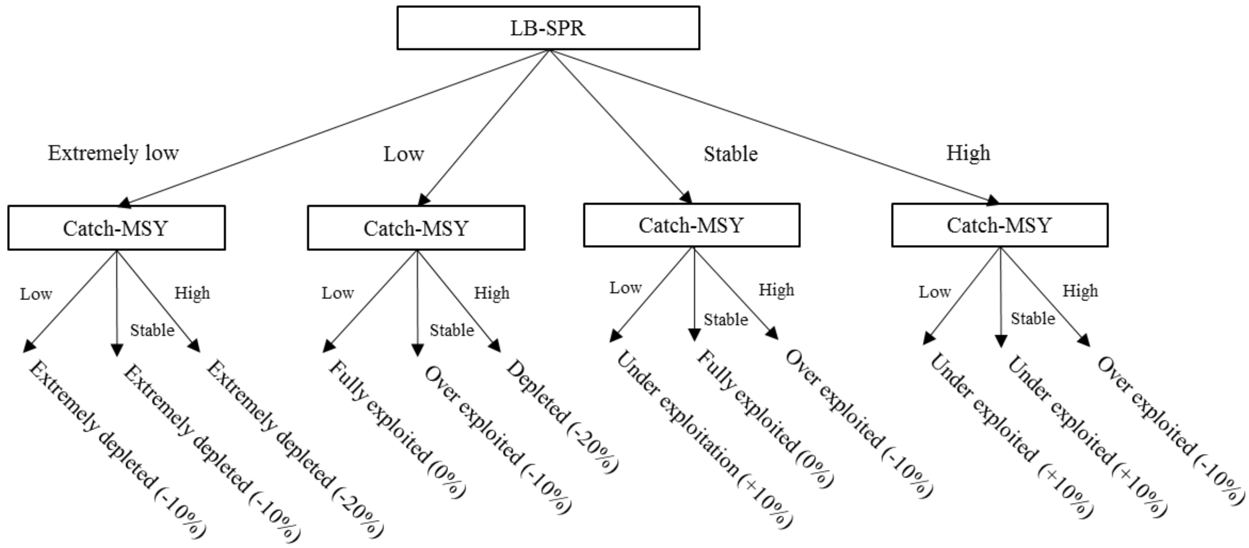


Figure 2. Decision tree.

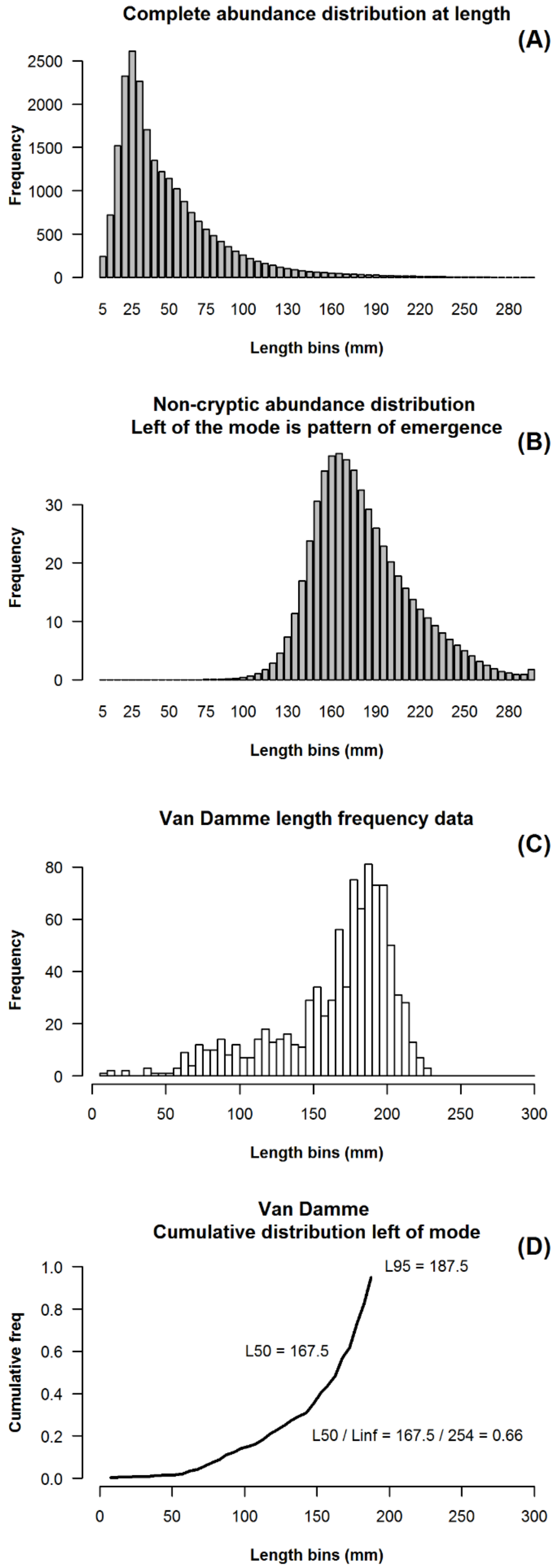


Figure 3. Simulated patterns of red abalone emergence (A & B) and empirical pattern from Van Damme (C) used in calculating maturity parameters *L50* and *L95* (D). Note that ratio $L50/L\infty$ is similar to expectation from Beverton-Holt life history invariant.

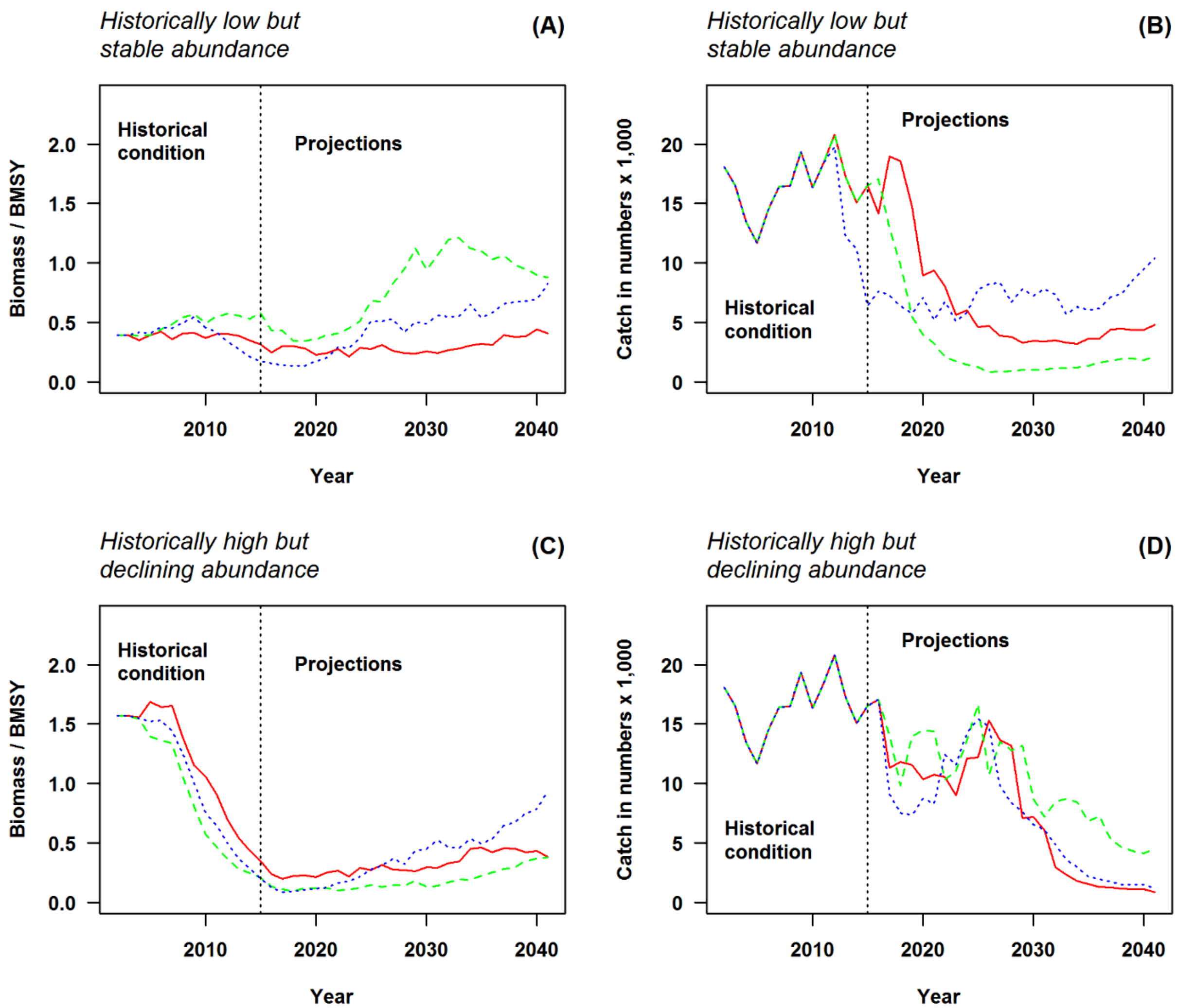
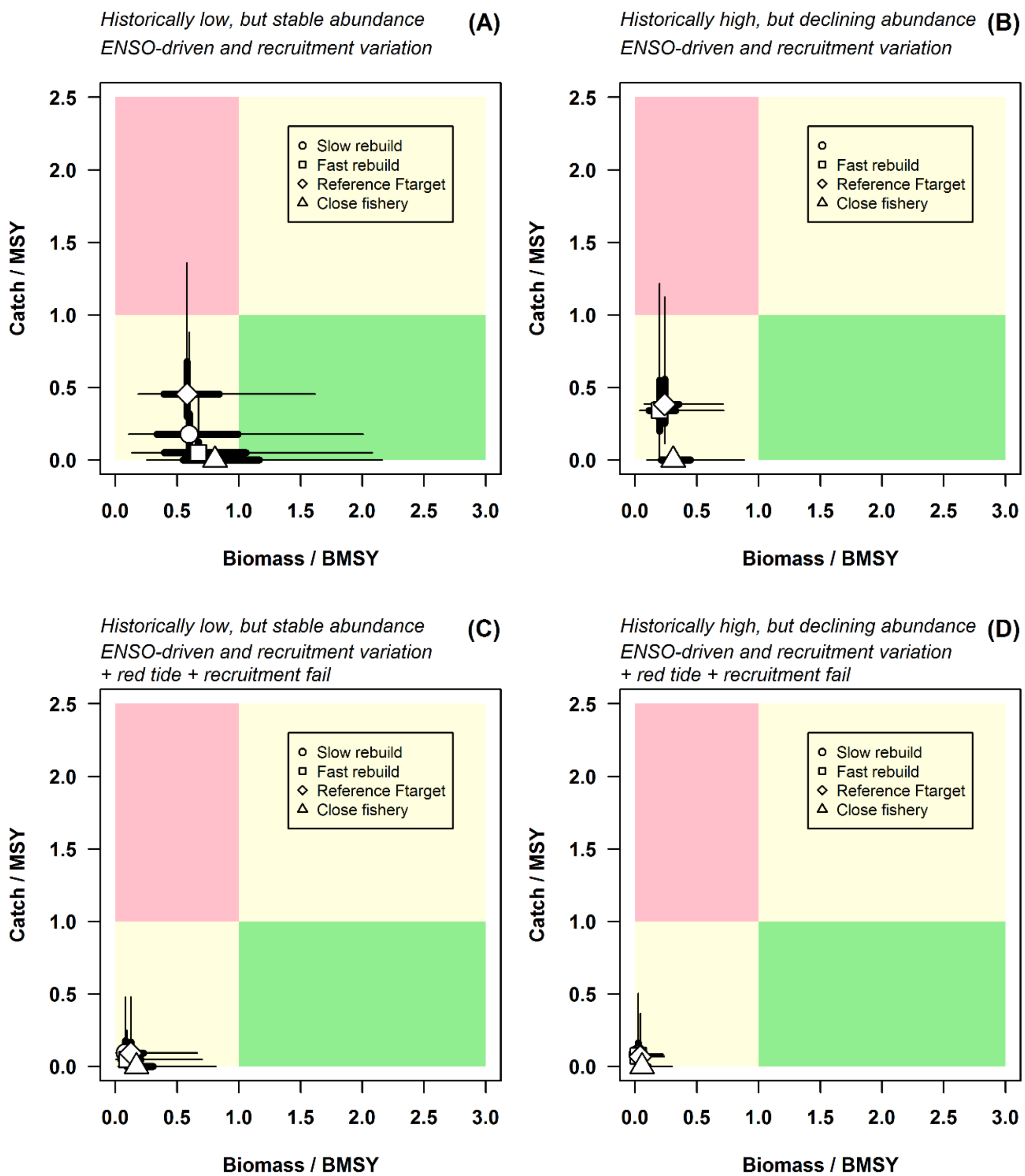
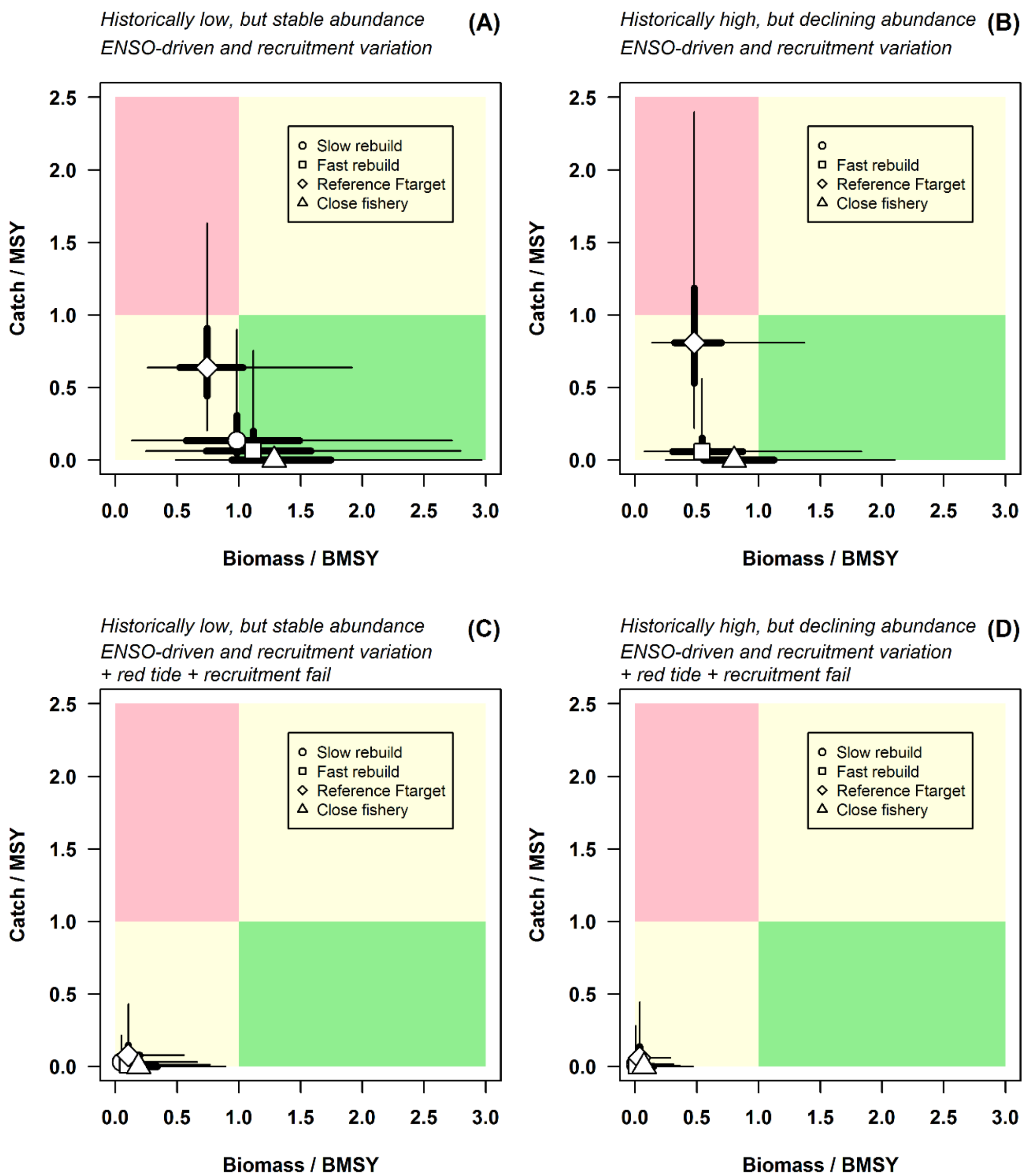


Figure 4. An example of the processes involved in MSE that consist of generating historical stock dynamics and then projecting these stock dynamics forward according to a specified management strategy. Historical conditions differ between plots with (A) and (B) reflecting low but stable historical stock size and (C) and (D) reflecting high but declining historical stock size.



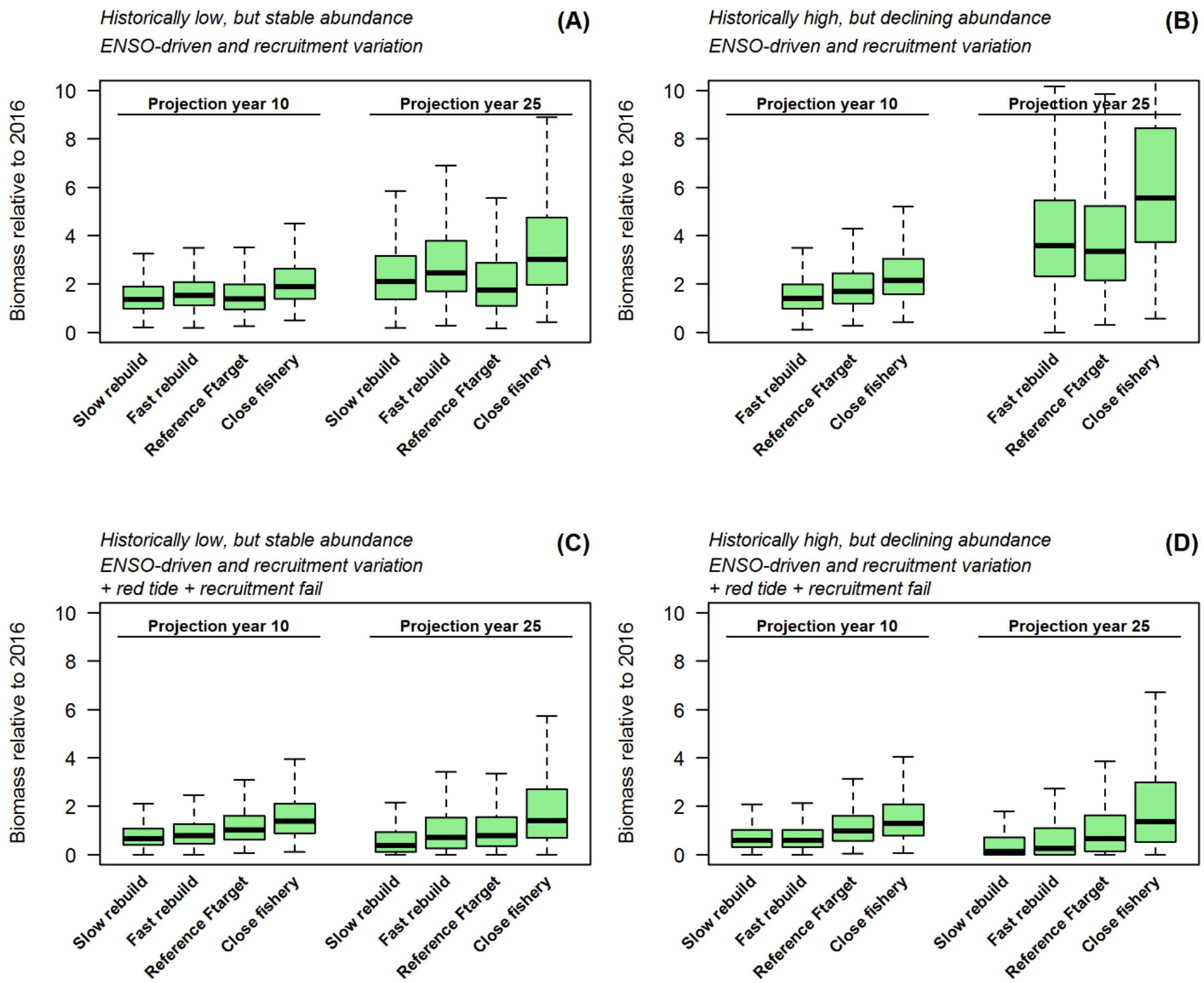
Note: Plot 5B does not show slow rebuild decision tree, this will be updated in follow-up report.

Figure 5. Trade-off plot illustrating performance at year 10 of projections for two decision trees (slow rebuild and fast rebuild) and two reference strategies (no fishery and perfect implementation of $F_{60\%SPR}$). Plots indicate different historical conditions and different environmental conditions that affect both historical conditions and projection time period.



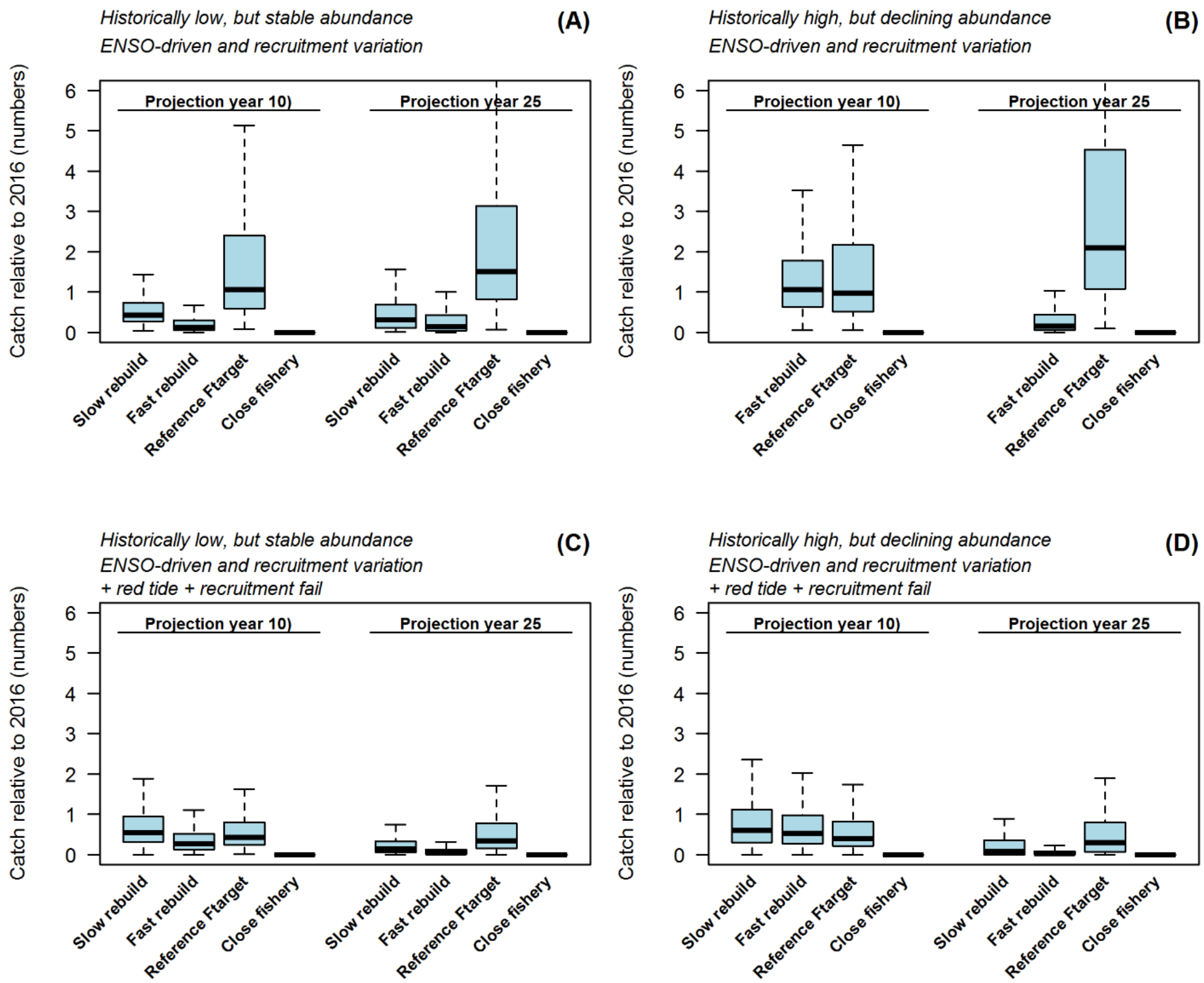
Note: Plot 6B does not show slow rebuild decision tree, this will be updated in follow-up report.

Figure 6. Trade-off plot illustrating performance at year 25 of projections for two decision trees (slow rebuild and fast rebuild) and two reference strategies (no fishery and perfect implementation of $F_{60\%SPR}$). Plots indicate different historical conditions and different environmental conditions that affect both historical conditions and projection time period.



Note: Plot 7B does not show slow rebuild decision tree, this will be updated in follow-up report.

Figure 7. Changes in projected spawning biomass relative to 2016 level for two decision trees (slow rebuild and fast rebuild) and two reference strategies (no fishery and perfect implementation of $F_{60\%SPR}$). Plots indicate different historical conditions and different environmental conditions that affect both historical conditions and projection time period.



Note: Plot 8B does not show slow rebuild decision tree, this will be updated in follow-up report.

Figure 8. Changes in projected catches (in numbers) relative to 2016 level for two decision trees (slow rebuild and fast rebuild) and two reference strategies (no fishery and perfect implementation of $F_{60\%SPR}$). Plots indicate different historical conditions and different environmental conditions that affect both historical conditions and projection time period.

7. Tables

Table 1. Summary of sites in Del Norte, Humboldt, and Mendocino counties. Catches are in numbers of abalone.

Site	Region	Mean Catch 2002-2016	Catch 2016	No-take Zone	Reef Check Sampling	CDFW Sampling
Crescent City	1	135	79			
Other Del Norte	1	45	6			
Patrick’s Point	1	585	343			
Trinidad	1	326	198			
Punta Gorda	1	788	182			
Shelter Cove	1	3041	1557			
Other Humboldt	1	619	209			
Bear Harbor	1	386	282			
Usal	1	239	77			
Hardy Creek	1	1373	669			
Abalone Point	1	2871	1445			
Westport	1	1805	974			
Bruhel Point	1	645	188			
Kibesillah	1	572	0	✓		
MacKerricher	1	4690	3204			
Glass Beach	1	5475	5685		✓	
Georgia Pacific	1	7316	5627			
Todds Point	1	7259	6272			✓
Hare Creek	1	4605	2949			
Mitchell Creek	1	2685	2290			
Jughandle	1	5714	6464			
Caspar Cove	1	6597	6283		✓	✓
Russian Gulch	1	7097	8110		✓	✓
Jack Peters Gulch	1	3792	8404			
Mendocino Hdlnds	1	10371	12222		✓	
Gordon Lane	1	3140	4424			
Van Damme	1	16525	17051		✓	✓
Dark Gulch	1	4636	5941			
Albion Cove	1	7688	6016			
Salmon Creek	1	1654	1449			
Navarro River	1	3306	2447			
Elk	1	8193	6506			
Point Arena Lighthouse	1	4387	1010		✓	
Arena Cove	1	8993	4040		✓	✓
Moat Creek	1	9592	5132			
Schooner Gulch	1	539	161			
Saunders Landing	1	701	0	✓		
Anchor Bay	1	4965	3785			
Robinson Point	1	1327	1414			

Table 2. Summary of sites in Sonoma and Marin counties. Catches are in numbers of abalone.

Site	Region	Mean Catch 2002-2016	Catch 2016	No-take Zone	Reef Check Sampling	CDFW Sampling
Gualala Point	2	850	321			
Sea Ranch	2	10803	5723		✓	✓
Black Point	2	244	26			
Stewarts Point	2	1098	153			
Rocky Point	2	232	39			
Horseshoe Cove	2	1038	0	✓		
Fisk_Mill Cove	2	5542	1415			
Salt_Point State Park	2	8555	4197		✓	✓
Ocean Cove	2	4293	2897		✓	✓
Stillwater Cove	2	3747	3147		✓	
Timber Cove	2	7625	3681			✓
Fort Ross	2	28672	2366		✓	✓
Jenner	2	2515	963			
Bodega Head	2	902	263		✓	
Tomales Point	2	1968	561			
Point Reyes	2	281	31			
Other Marin	2	424	124			

Table 3. Rationale for the decision tree based on indicators of spawning potential ratio (SPR) and exploitation rate calculated via catch-MSY approach. Two decision trees are described that differ with respect to rebuilding red abalone abundance with it is at low levels.

SPR indicator	**Catch-MSY indicator**	**Exploitation status**	**TAC adjustment**	**Explanation**
Slow rebuild				
High	High	Over exploited	-10%	Watch and wait
High	Stable	Under exploited	+10%	SPR high under stable catches
High	Low	Under exploited	+10%	Possibly restrictive management
Stable	High	Over exploited	-10%	SPR stable, but fishing is increasing
Stable	Stable	Fully exploited	0%	SPR stable around reference
Stable	Low	Under exploited	+10%	Possibly restrictive management
Low	High	Depleted	-20%	Recruitment overfishing possible
Low	Stable	Over exploited	-10%	Recruitment overfishing possible
Low	Low	Fully exploited	0%	Recruitment overfishing possible
Extremely low	High	Very depleted	-20%	Rebuild abundance
Extremely low	Stable	Very depleted	-10%	Rebuild abundance
Extremely low	Low	Very depleted	-10%	Rebuild abundance
Fast rebuild				
High	High	Over exploited	-10%	Watch and wait
High	Stable	Under exploited	+10%	SPR high under stable catches
High	Low	Under exploited	+10%	Possibly restrictive management
Stable	High	Over exploited	-10%	SPR stable, but fishing is increasing
Stable	Stable	Fully exploited	0%	SPR stable around reference
Stable	Low	Under exploited	+10%	Possibly restrictive management
Low	High	Depleted	-20%	Recruitment overfishing possible
Low	Stable	Over exploited	-10%	Recruitment overfishing possible
Low	Low	Fully exploited	0%	Recruitment overfishing possible
Extremely low	High	Very depleted	-20%	Rebuild abundance
Extremely low	Stable	Very depleted	-20%	Rebuild abundance
Extremely low	Low	Very depleted	-20%	Rebuild abundance

Table 4. Break-out rules in instances where length frequency data or catch time series are not available or not included in the analysis.

Indicator	TAC adjustment
Catch history	
High	-10%
Stable	0%
Low	+10%
Length frequency data (for either fast and slow rebuilding)	
High	+10%
Stable	0%
Low	-10%
Extremely low	-20%

Appendix A. Equilibrium characteristics and fishing mortality reference points

Per-recruit analyses have been widely applied to abalone species and used to derive eggs-per-recruit or biomass-per-recruit based reference points (Leaf et al., 2008; McShane and Naylor, 1995; Nash, 1992; Rogers-Bennett and Leaf, 2006; Shepherd and Baker, 1998). Here, we used the operating model to generate per-recruit metrics as a means to summarize characteristics of the red abalone stock. The surplus production relationship was calculated using average stock dynamics parameters: K=0.108, Linf=254, logistic maturity L50=0.6Linf, L95=1.15L50, M-at-length according to Leaf et al. (2007), fecundity-at-length from Rogers-Bennet et al. (2004), Beverto-Holt stock-recruitment with steepness 0.6, fishery availability-at-length equal to logistic maturity, and possession knife-edge at 178 mm (7 inches) shell length (Fig. A1 and Table A1).

Table A1. Fishing mortality reference points obtained from equilibrium characteristics of the simulated red abalone stock. SSB is spawning output in eggs, SSB0 is unfished egg production, SPR is spawning potential ratio.

Referernce point	Fishing mortality rate	SPR	SSB/SSB0	Catch biomass / MSY
$F_{SPR60\%}$	0.13	0.60	0.51	0.99
F_{MSY}	0.17	0.54	0.45	1.00
$F_{SPR40\%}$	0.43	0.40	0.28	0.93

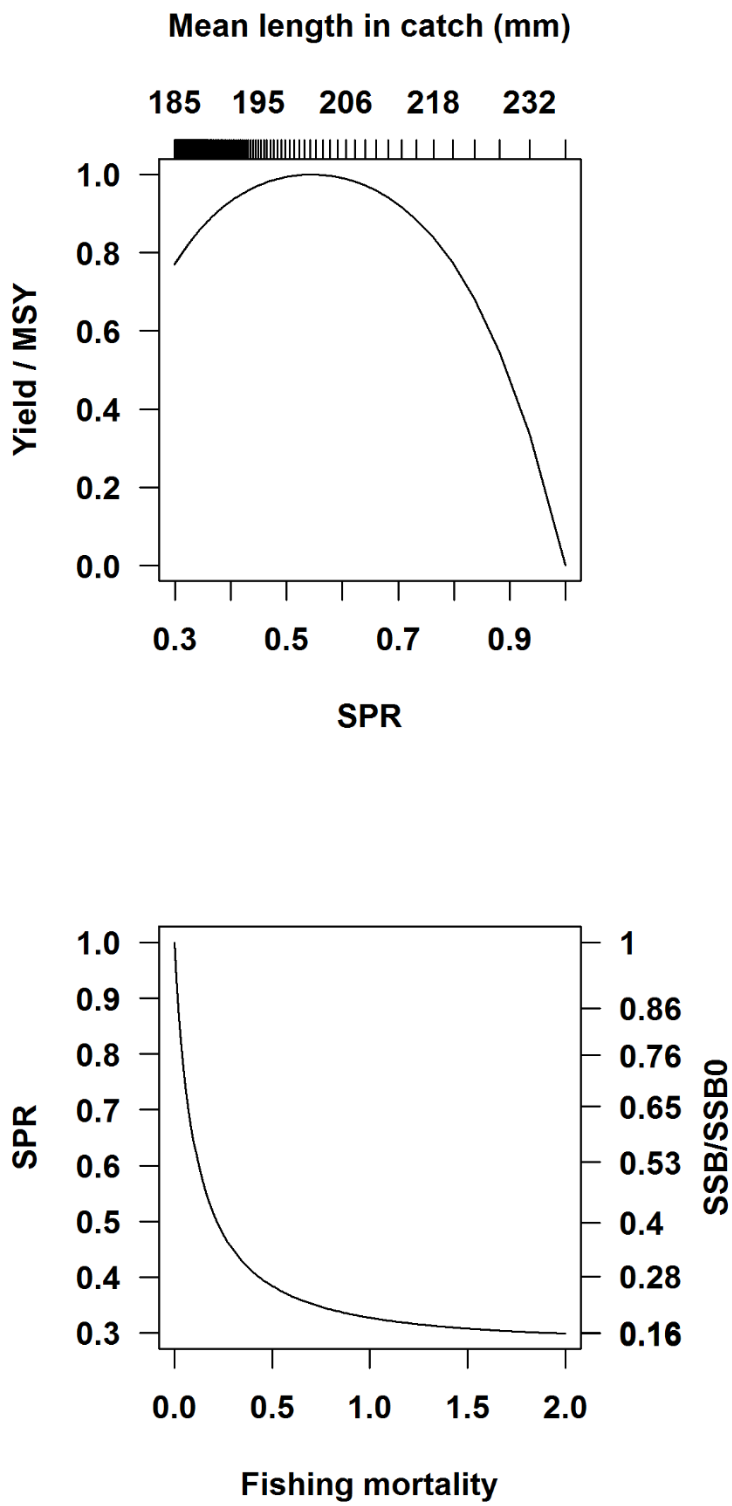


Fig. A1. Equilibrium yield curve versus SPR and mean length in the catch (upper) and reproductive output (SPR and *SSB/SSB0*; lower) for simulated red abalone stock dynamics. SSB is spawning output in eggs, SSB0 is unfished egg production, SPR is spawning potential ratio, calculations produced based on f assuming fishery selectivity at 178 mm (7 inches).

Appendix B. Simulated stock reconstruction and historical trends

Background

Like other data-limited fisheries, historical trends in abundance are not well established for red abalone. Simulated historical trends are required in most MSEs because simulated data collection is conducted in relation these historical trends. Accordingly, we re-constructed red abalone stock dynamics from 2002 to 2016 by adjusting initial depletion (the same value was used for each site). Tuning was conducted such that simulated red abalone characteristics were reasonably consistent with the following characteristics derived from actual data collected by CDFW and Reef Check:

- Reproduction of catches between 2002 – 2016
- CDFW annual site-specific estimates of SPR calculated from length frequency data
- Reef Check annual site-specific estimates of SPR calculated from length frequency data

Technical details

In producing simulated reconstructions, all sites were initialized using the same specified depletion. The actual catch from 2002 was used to scale relative length structure (associated with the specified depletion level) to absolute abundance and in scaling other parameters like unfished recruitment (*R0*). After initialization, actual annual catches between 2002 and 2016 were reproduced by the simulations unless catches exceeded vulnerable abundance. Tuning was conducted using deterministic stock dynamics to elicit the average historical trend, prior to running stochastic simulations. This means that no stochastic recruitment variation occurred. Effects of the ENSO index on life history parameters was included according to the expected relationships between these variables. No red tide events were simulated with the exception of the 2011 severe red tide event, with an approximate mortality increase of 0.29 year^{-1} , was forced to occur at sites in Sonoma and Marin counties (Rogers-Bennett et al., 2012)). Note that while tuning demonstrates deterministic trends, implementing these reconstructions in MSE simulation runs did include stochastic processes, and thus, each simulation run produced a somewhat unique reconstruction, while also ensuring that observed catches were reproduced.

In producing SPR estimates from actual datasets collected by CDFW and Reef Check (for comparison with simulated stock dynamics), several input parameters are required for the LB-SPR method. We considered three different estimation routines that differed with respect to parameter inputs. LB-SPR fitting steps were applied separately to each site and year and separately to Reef Check & CDFW data. There were three steps and each fitting routine differed in step #3.

1. Truncate observed length frequency at 178 mm
2. Bin length comp in 5 mm bins
3. Specify LB-SPR input parameters (see three different approaches, described below)

Fit 1: Histology-based and using LVB from van Damme applied to every site/yr.

```
MyPars@CVLinf=0.1
MyPars@Walpha=1x10-4
MyPars@Wbeta=3.03
MyPars@Linf <- 254
MyPars@L50 <- 118
MyPars@L95 <- 130
MyPars@MK<-0.9
MyPars@L_units <- "mm"
```

Fit 2: Use LVB only, rely on B-H constants for other parameters, apply to every site/yr

```
MyPars@CVLinf=0.1
MyPars@Walpha=1x10-4
```

MyPars@Wbeta=3.03

MyPars@Linf <- 254

MyPars@L50 <- 0.6*254

MyPars@L95 <- 0.6*254*1.15

MyPars@MK<-0.9

MyPars@SL50 <- 160

MyPars@SL95 <- 195

MyPars@L_units <- "mm"

Fit 3: Empirical cumulative density of age comp.

i. Get full length comp (all sizes) 5 mm and up.
ii. For a given site, pool data from all years, allowing most comprehensive view of left side of the length comp distribution.
iii. Find the main mode.
iv. Set main mode = L95 (length at 95% maturity).
v. Using length comp =< main mode, build empirical cumulative distribution using 5 mm bins.
vi. Main mode becomes the 100% probability of the cumulative distribution. Re-scale the cumulative distribution so that main mode is 95% probability.
vii. Find the 50% probability, set L50 equal to this length bin.
viii. Linf = L50*1.66

Now we have site-specific Linf, L50 and L95 derived from the pattern of emerging abalone at length.

MyPars@CVLinf=0.1

MyPars@Walpha=1x10-4

MyPars@Wbeta=3.03

MyPars@Linf <- Linf

MyPars@L50 <- L50

MyPars@L95 <- L95

MyPars@MK<-0.9

MyPars@SL50 <- 160

MyPars@SL95 <- 195

MyPars@L_units <- "mm"

Tuning results

In model tuning a complication arose between producing stock dynamics that were consistent with SPR trends estimated from actual length frequency distributions collected by CDFW and Reef Check (Fig. B1). Sites sampled by CDFW indicated low SPR (often < 0.3) but consistent SPR through time. Sites sampled by Reef Check suggest SPR was higher earlier in the time series, but declined rapidly to low levels (often < 0.3) by 2016. This situation occurred primarily because the largest abalone observed by Reef Check were either not observed or observed in lower proportions in CDFW sampling (Fig. B1). This inconsistency led to the development of two scenarios about historical stock trends between 2002 and 2016:

Historical scenario 1: *high but declining abundance, negative survival trend in historical data*

Historical scenario 2: *low but stable abundance.*

Tuning to *high but declining abundance* resulting in initial depletion of 0.8 (where depletion is the level of spawning biomass relative to unfished spawning biomass). To produce this trend, we also had to introduce a time-varying natural morality trend that consisted of decreasing survival by 20% during the final 10 years of the historical time period. Without this exogenous mortality source, specified catches nor el Nino events alone could produce the downward SPR trajectory observed in the Reef Check dataset (Figs. B2 and B3). Tuning to *low but stable abundance* resulted in initial depletion of 0.2 (Figs. B4 and B5).

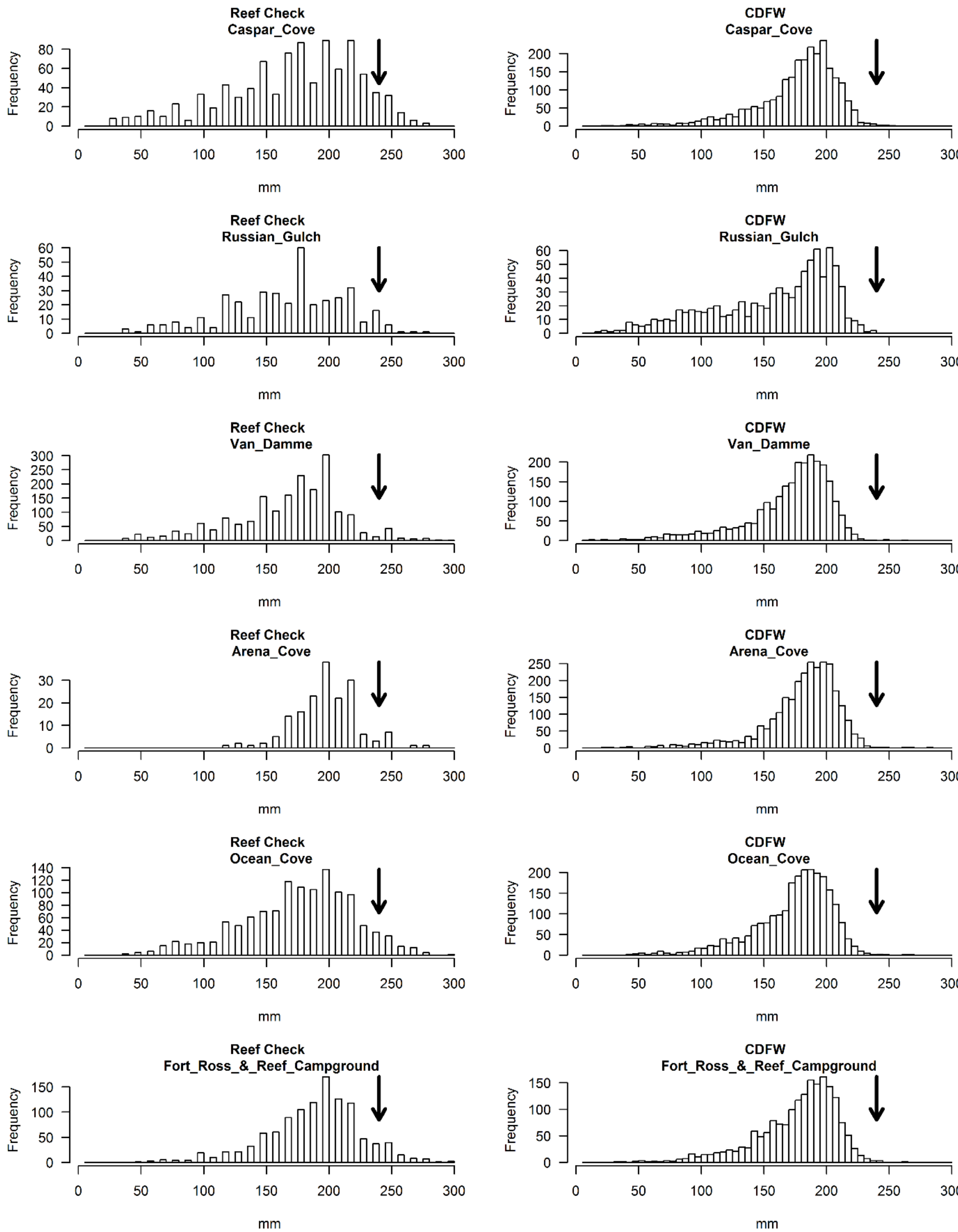


Figure B1. Histograms of observed length composition as sampled by Reef Check and CDFW at corresponding sites (rows). Sample collections at each site are pooled across site visits between 2007 and 2015. Arrows point to largest size classes.

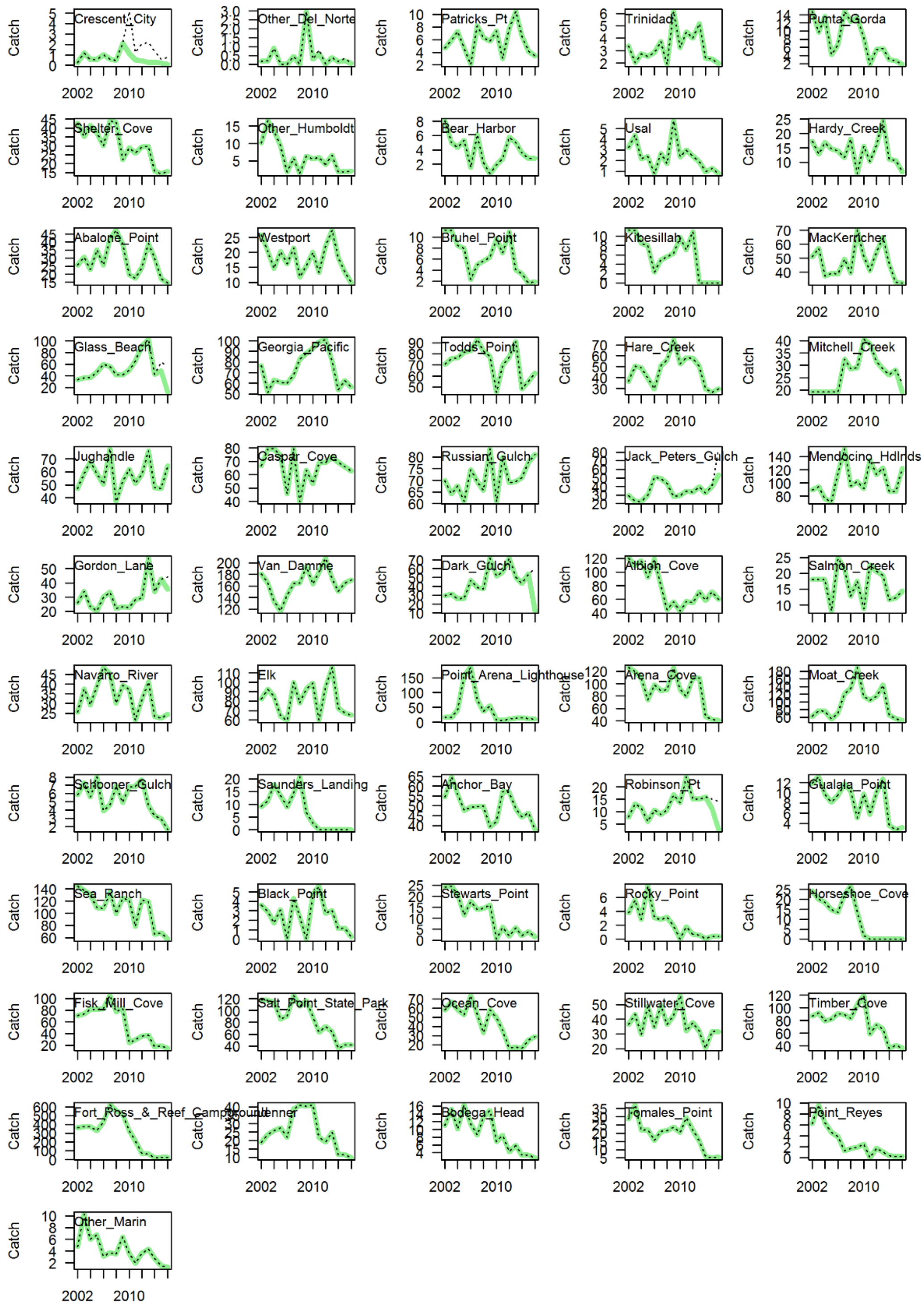


Figure B2. Historical scenario 1 (*high but declining abundance*). Simulated catches (in number of red abalone times 100; thick transparent lines) versus actual catches (thin dotted lines) during stock reconstruction.

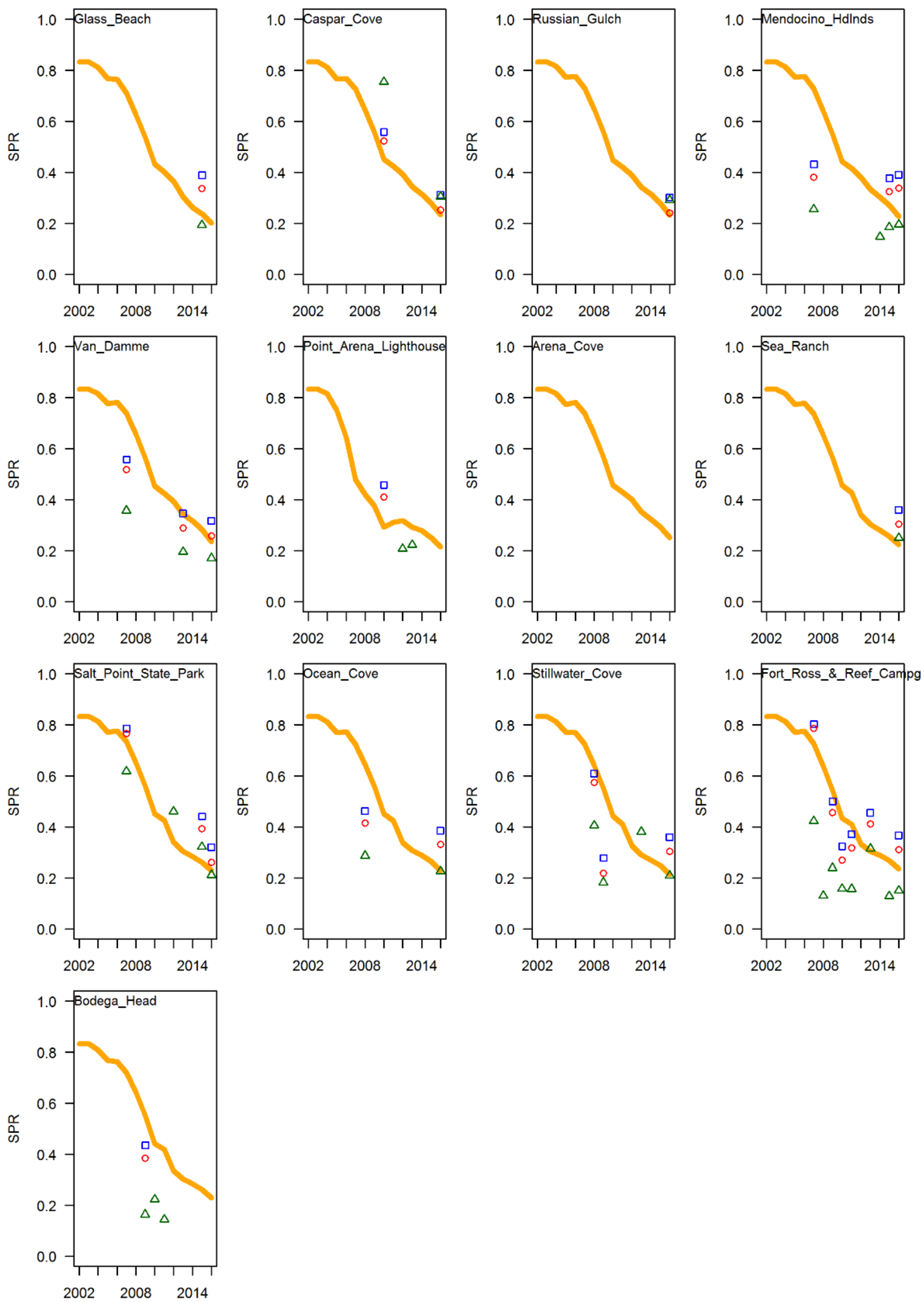


Figure B3. Historical scenario 1 (*high but declining abundance*). Simulated SPR trends (thick lines) and point-estimates of SPR from Reef Check length frequency distributions. Blue squares are estimates from fit #1, red circles are from fit #2, and green triangles are from fit #3.

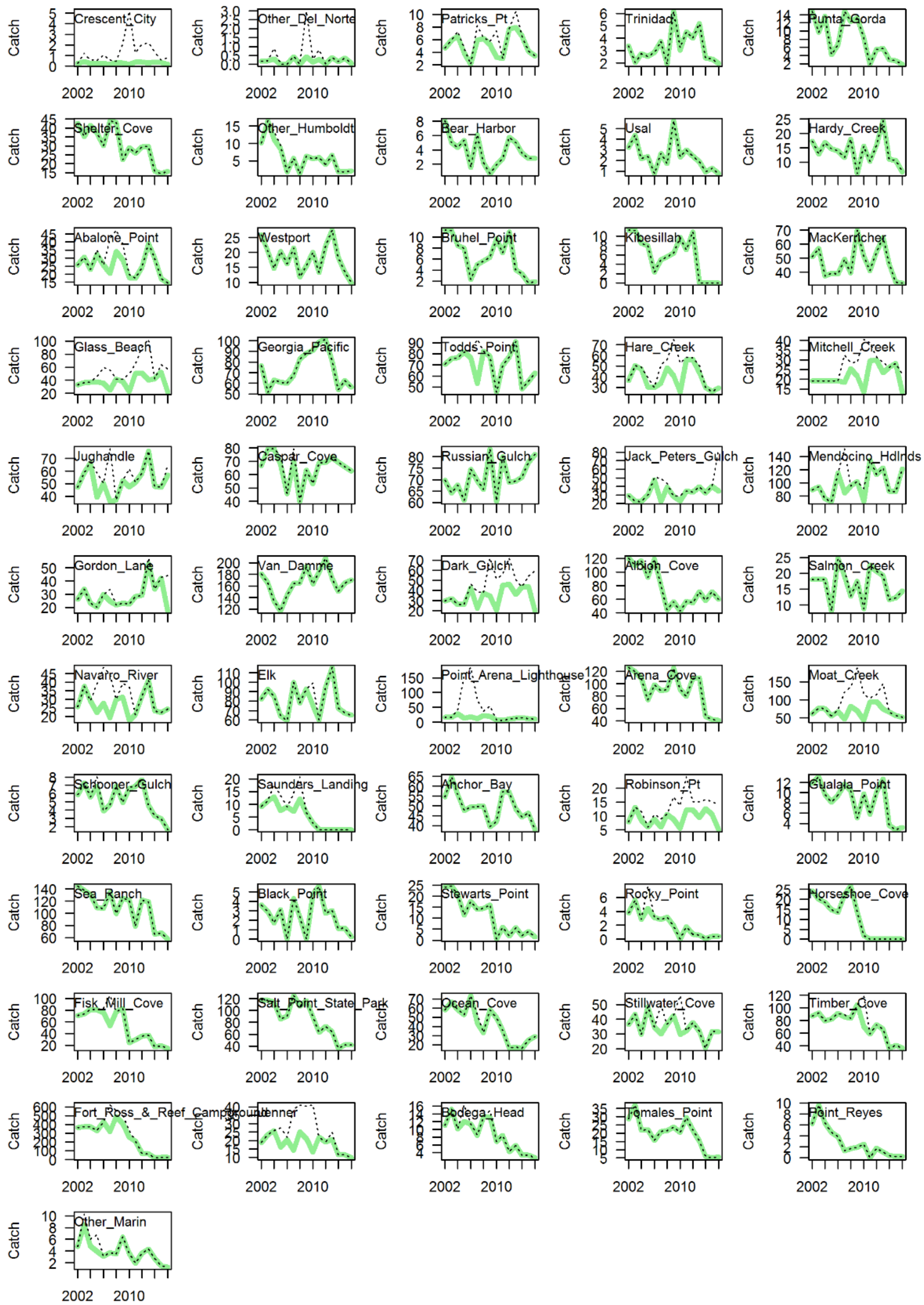


Figure B4. Historical scenario 2 (*low but stable abundance*). Simulated catches (in number of red abalone times 100; thick transparent lines) versus actual catches (thin dotted lines) during stock reconstruction.

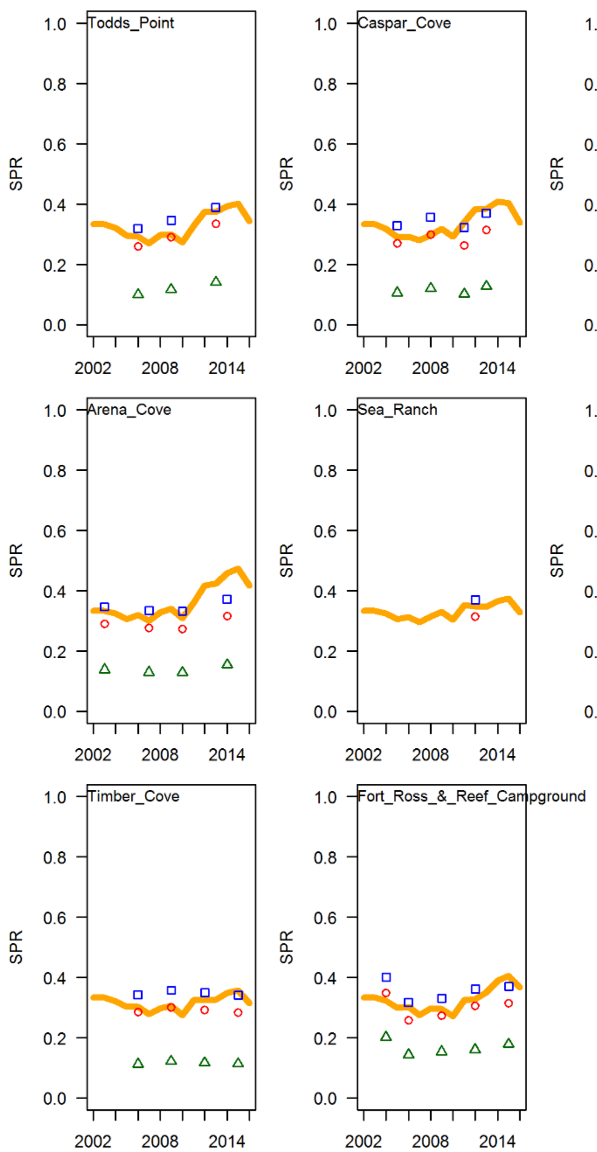


Figure B5. Historical scenario 2 (*low but stable abundance*). Simulated SPR trends (thick lines) and point-estimates of SPR from CDFW length frequency distributions. Blue squares are estimates from fit #1, red circles are from fit #2, and green triangles are from fit #3.

Appendix C. Hypothetical application of the decision tree

As with any stock assessment, we are continuing to refine and review the methodology and reserve the right to modify this section and its results as necessary.

Below is a step-by-step summary of the application of the indicator-based decision tree to actual datasets, with the terminal year of data collection being 2016. A hypothetical calculation of 2017 TACs is also provided.

Step 1. Gather datasets

1. Gather catch histories (numbers of red abalone) for 56 fishing sites from 2002 – 2016.
2. Identify sampling sites where length frequency sampling has occurred within the last 3 years.
3. Gather length frequency these sampling from sites, but include all sampling events prior to and including 2016

Step 2. Calculate current harvest rate at each site using catch-MSY

- Uses catch histories from each of 56 fishing sites
- Parameter inputs (names reflect those used in catch-MSY):
    - r prior: uniform (0.05, 0.5)
    - B0 prior, as per Froese et al. 2017. This varies by site.
    - Parameters to determine resilience:
        - minAge=8; maxAge=50; K=0.108

Step 3. Calculate SPR using LB-SPR method

- Uses length frequency data gathered as stated above.
- Analysis for each site is carried out separately (do not pool data across sites)

1. Find L50 and L95, which are parameters of the logistic maturity curve and indicate the lengths at which 50% and 95% of the abalone at a site are mature.
    - Pool length data from all years, allowing most comprehensive dataset reflecting the left side of the length comp distribution.
    - Find the main mode of this distribution.
    - Set main mode = L95 (length at 95% maturity).
    - Using length comp =< main mode, build empirical cumulative distribution (5 mm bins).
    - Thus, main mode becomes the 100% probability of the cumulative distribution. Re-scale the cumulative distribution so that main mode is 95% probability.
    - Find the 50% probability, set L50 equal to this length bin.
    - Linf = L50/0.6

2. Apply LB-SPR method to estimate SPR
    - Subset length frequency data from only the most recent sampling year.

- Truncate observed length frequency at 178 mm
- Bin length comp in 5 mm bins
- Specify LB-SPR input parameters:
    - L50, L95, and Linf as calculated above
    - M/K=0.9; CVLinf=0.1;
    - L-W conversion parameters: beta=3.03; alpha=0.0001 (mm to g conversion)
- If sampling did not occur at a site, the mean SPR from sampling sites within its region (Sonoma county and southward or Mendocino county and northward) was applied.
- Calculate SPR ratio as SPR estimate / 0.6; where 0.6 is the SPR reference point.
- The SPR ratio indicates whether reproductive potential was considered high (i.e. ratio > 1.1), was considered low (ratio < 0.9), and in between 0.9 and 1.1 it was considered stable.

Step 4. Apply the decision tree to each site, determining local adjustment relative to 2016 TAC.

- Note that because this management strategy is novel, site-specific TACs were not necessarily identified in previous management strategies. Thus, as a starting point, 2016 site-specific catches were used as initial TACs, from which 2017 TACs were calculated

Step 5. Calculate regional TACs by summing across site-specified TACs

Table C1. Slow rebuild decision tree - TAC calculations for Mendocino, Humboldt, and Del Norte counties using catch histories (2002 – 2016) and from length frequency data (most recent site visit within last 3 years). 2017 TAC calculation is for demonstration only.

Site	Region	U/U_{MSY}	SPR	Harvest rate status	SPR status	Adjustment	2016 Catch	2017 TAC
Crescent City	1	0.6655837	0.5	Low	Low	0	79	79
Other Del Norte	1	0.3101644		Low	extremely low	-0.1	6	5
Patrick's Point	1	0.4789021		Low	extremely low	-0.1	343	309
Trinidad	1	0.5533836		Low	extremely low	-0.1	198	178
Punta Gorda	1	0.2368731		Low	extremely low	-0.1	182	164
Shelter Cove	1	0.326394		Low	extremely low	-0.1	1,557	1,401
Other Humboldt	1	0.301346		Low	extremely low	-0.1	209	188
Bear Harbor	1	0.3508368		Low	extremely low	-0.1	282	254
Usal	1	NA		NA	extremely low	-0.1	77	69
Hardy Creek	1	0.3641383		Low	extremely low	-0.1	669	602
Abalone Point	1	0.3632512		Low	extremely low	-0.1	1,445	1,301
Westport	1	0.4059291		Low	extremely low	-0.1	974	877
Bruhel Point	1	NA		NA	extremely low	-0.2	188	150
Kibesillah	1			NA	NA	NA	0	0
MacKerricher	1	0.43104		Low	extremely low	-0.1	3,204	2,884
Glass Beach	1	1.3422904		High	extremely low	-0.2	5,685	4,548
Georgia Pacific	1	0.6465173		Low	extremely low	-0.1	5,627	5,064
Todds Point	1	0.5659898		Low	extremely low	-0.1	6,272	5,645
Hare Creek	1	0.5596426		Low	extremely low	-0.1	2,949	2,654
Mitchell Creek	1	0.74787		Low	extremely low	-0.1	2,290	2,061
Jughandle	1	0.2285531		Low	extremely low	-0.1	6,464	5,818
Caspar Cove	1	0.1760962	0.3	Low	Low	0	6,283	6,283
Russian Gulch	1	0.2276864	0.29	Low	extremely low	-0.1	8,110	7,299
Jack Peters Gulch	1	0.5030301		Low	extremely low	-0.1	8,404	7,564
Mendocino Hdlnds	1	0.2156431	0.19	Low	extremely low	-0.1	12,222	11,000
Gordon Lane	1	0.2301862		Low	extremely low	-0.1	4,424	3,982
Van Damme	1	0.1945215	0.17	Low	extremely low	-0.1	17,051	15,346
Dark Gulch	1	0.3900723		Low	extremely low	-0.1	5,941	5,347
Albion Cove	1	0.4481624		Low	extremely low	-0.1	6,016	5,414
Salmon Creek	1	0.5481317		Low	extremely low	-0.1	1,449	1,304
Navarro River	1	0.5470234		Low	extremely low	-0.1	2,447	2,202
Elk	1	0.147326		Low	extremely low	-0.1	6,506	5,855
Point Arena Lighthouse	1	0.5942807		Low	extremely low	-0.1	1,010	909
Arena Cove	1	0.3630416	0.15	Low	extremely low	-0.1	4,040	3,636
Moat Creek	1	0.6571551		Low	extremely low	-0.1	5,132	4,619
Schooner Gulch	1	0.2289149		Low	extremely low	-0.1	161	145
Saunders Landing	1			NA	NA	0	0	0
Anchor Bay	1	0.1417376		Low	extremely low	-0.1	3,785	3,407
Robinson Point	1	0.3304633		Low	extremely low	-0.1	1,414	1,273
Average SPR			0.27					
Totals							133,095	119,834
TAC percent change								-9.96325933

Table C2. Fast rebuild decision tree - TAC calculations for Mendocino, Humboldt, and Del Norte counties using catch histories (2002 – 2016) and from length frequency data (most recent site visit within last 3 years). 2017 TAC calculation is for demonstration only.

Site	Region	U/U_{MSY}	SPR	Harvest rate status	SPR status	Adjustment	2016 Catch	2017 TAC
Crescent City	1	0.6655837	0.5	Low	Low	0	79	79
Other Del Norte	1	0.3101644		Low	extremely low	-0.2	6	5
Patrick's Point	1	0.4789021		Low	extremely low	-0.2	343	274
Trinidad	1	0.5533836		Low	extremely low	-0.2	198	158
Punta Gorda	1	0.2368731		Low	extremely low	-0.2	182	146
Shelter Cove	1	0.326394		Low	extremely low	-0.2	1,557	1,246
Other Humboldt	1	0.301346		Low	extremely low	-0.2	209	167
Bear Harbor	1	0.3508368		Low	extremely low	-0.2	282	226
Usal	1	NA		NA	extremely low	-0.2	77	62
Hardy Creek	1	0.3641383		Low	extremely low	-0.2	669	535
Abalone Point	1	0.3632512		Low	extremely low	-0.2	1,445	1,156
Westport	1	0.4059291		Low	extremely low	-0.2	974	779
Bruhel Point	1	NA		NA	extremely low	-0.2	188	150
Kibesillah	1			NA	NA	NA	0	0
MacKerricher	1	0.43104		Low	extremely low	-0.2	3,204	2,563
Glass Beach	1	1.3422904		High	extremely low	-0.2	5,685	4,548
Georgia Pacific	1	0.6465173		Low	extremely low	-0.2	5,627	4,502
Todds Point	1	0.5659898		Low	extremely low	-0.2	6,272	5,018
Hare Creek	1	0.5596426		Low	extremely low	-0.2	2,949	2,359
Mitchell Creek	1	0.74787		Low	extremely low	-0.2	2,290	1,832
Jughandle	1	0.2285531		Low	extremely low	-0.2	6,464	5,171
Caspar Cove	1	0.1760962	0.3	Low	Low	0	6,283	6,283
Russian Gulch	1	0.2276864	0.29	Low	extremely low	-0.2	8,110	6,488
Jack Peters Gulch	1	0.5030301		Low	extremely low	-0.2	8,404	6,723
Mendocino Hdlnds	1	0.2156431	0.19	Low	extremely low	-0.2	12,222	9,778
Gordon Lane	1	0.2301862		Low	extremely low	-0.2	4,424	3,539
Van Damme	1	0.1945215	0.17	Low	extremely low	-0.2	17,051	13,641
Dark Gulch	1	0.3900723		Low	extremely low	-0.2	5,941	4,753
Albion Cove	1	0.4481624		Low	extremely low	-0.2	6,016	4,813
Salmon Creek	1	0.5481317		Low	extremely low	-0.2	1,449	1,159
Navarro River	1	0.5470234		Low	extremely low	-0.2	2,447	1,958
Elk	1	0.147326		Low	extremely low	-0.2	6,506	5,205
Point Arena Lighthouse	1	0.5942807		Low	extremely low	-0.2	1,010	808
Arena Cove	1	0.3630416	0.15	Low	extremely low	-0.2	4,040	3,232
Moat Creek	1	0.6571551		Low	extremely low	-0.2	5,132	4,106
Schooner Gulch	1	0.2289149		Low	extremely low	-0.2	161	129
Saunders Landing	1			NA	NA	0	0	0
Anchor Bay	1	0.1417376		Low	extremely low	-0.2	3,785	3,028
Robinson Point	1	0.3304633		Low	extremely low	-0.2	1,414	1,131
Average SPR			0.27					
Totals							133,095	107,748
TAC percent change								-19.0439911

Table C3. Slow rebuild decision tree - TAC calculations for Sonoma and Marin counties using catch histories (2002 – 2016) and from length frequency data (most recent site visit within last 3 years). 2017 TAC calculation is for demonstration only.

Site	Region	*U/UMSY*	SPR	Harvest rate status	SPR status	Adjustment	2016 Catch	2017 TAC
Gualala Point	2	0.4291862		Low	extremely low	-0.1	321	289
Sea Ranch	2	0.4071729	0.25	Low	extremely low	-0.1	5,723	5,151
Black Point	2	0.149921		Low	extremely low	-0.1	26	23
Stewarts Point	2	0.1409166		Low	extremely low	-0.1	153	138
Rocky Point	2	0.1787852		Low	extremely low	-0.1	39	35
Horseshoe Cove	2	0		NA	NA	NA	0	0
Fisk_Mill Cove	2	0.2965497		Low	extremely low	-0.1	1,415	1,274
Salt_Point State Park	2	0.3244974	0.21	Low	extremely low	-0.1	4,197	3,777
Ocean Cove	2	0.3988714	0.23	Low	extremely low	-0.1	2,897	2,607
Stillwater Cove	2	0.5228199	0.21	Low	extremely low	-0.1	3,147	2,832
Timber Cove	2	0.3358609	0.11	Low	extremely low	-0.1	3,681	3,313
Fort Ross	2	0.0970061	0.15	Low	extremely low	-0.1	2,366	2,129
Jenner	2	1.006257		High	extremely low	-0.2	963	770
Bodega Head	2	0.3208284		Low	extremely low	-0.1	263	237
Tomales Point	2	0.3047123		Low	extremely low	-0.1	561	505
Point Reyes	2	0.0920407		Low	extremely low	-0.1	31	28
Other Marin	2	0.2803942		Low	extremely low	-0.1	124	112
Average SPR			0.19					
Totals							25,907	23,220
TAC percent change								-10.37

Table C4. Fast rebuild decision tree - TAC calculations for Sonoma and Marin counties using catch histories (2002 – 2016) and from length frequency data (most recent site visit within last 3 years). 2017 TAC calculation is for demonstration only.

Site	Region	*U/UMSY*	SPR	Harvest rate status	SPR status	Adjustment	2016 Catch	2017 TAC
Gualala Point	2	0.4291862		Low	extremely low	-0.2	321	257
Sea Ranch	2	0.4071729	0.25	Low	extremely low	-0.2	5,723	4,578
Black Point	2	0.149921		Low	extremely low	-0.2	26	21
Stewarts Point	2	0.1409166		Low	extremely low	-0.2	153	122
Rocky Point	2	0.1787852		Low	extremely low	-0.2	39	31
Horseshoe Cove	2	0		NA	NA	NA	0	0
Fisk_Mill Cove	2	0.2965497		Low	extremely low	-0.2	1,415	1,132
Salt_Point State Park	2	0.3244974	0.21	Low	extremely low	-0.2	4,197	3,358
Ocean Cove	2	0.3988714	0.23	Low	extremely low	-0.2	2,897	2,318
Stillwater Cove	2	0.5228199	0.21	Low	extremely low	-0.2	3,147	2,518
Timber Cove	2	0.3358609	0.11	Low	extremely low	-0.2	3,681	2,945
Fort Ross	2	0.0970061	0.15	Low	extremely low	-0.2	2,366	1,893
Jenner	2	1.006257		High	extremely low	-0.2	963	770
Bodega Head	2	0.3208284		Low	extremely low	-0.2	263	210
Tomales Point	2	0.3047123		Low	extremely low	-0.2	561	449
Point Reyes	2	0.0920407		Low	extremely low	-0.2	31	25
Other Marin	2	0.2803942		Low	extremely low	-0.2	124	99
Average SPR			0.19					
Totals							25,907	20,726
TAC percent change								-20.00

Appendix D. Technical aspects of LB-SPR

This appendix is structured as a series of questions and answers related to technical aspects of the LB-SPR method for estimating spawning potential ratio (SPR) from length frequency data.

Question 1: does LB-SPR produce reliable SPR estimates under steady-state conditions?

We conducted simulation testing to evaluate the extent to which the SPR produced by the more complex operating model of red abalone agreed with the SPR estimates produced by LB-SPR. The input parameters needed for LB-SPR matched those used in the simulated data produced by the operating model, which allowed us to ask whether the simpler structural equations used in LB-SPR would produce reliable SPR estimates. We simulated equilibrium length distributions using the red abalone operating model that corresponded to "true" simulated SPR levels of 0.3, 0.4, 0.5, 0.6, and 0.7. Finally, we fit these simulated length frequencies (i.e., observed lengths sampled from multinomial distribution with effective sample size of 200 individuals, actual sample size 400 individuals). We repeated this process 100 times.

Answer: Yes, LB-SPR produces reasonable reliable SPR estimates.

At low simulated SPR, the estimated SPR tends to be negatively biased, but nevertheless often correctly indicates the overly depleted state of the stock. There is a positive bias at high simulated SPR, which likely reflects differences between the LB-SPR estimation routine and the red abalone operating model, namely in terms of the stock-recruitment relationship (i.e., steepness = 0.6) (Fig. D1).

Question 2: do changes to length frequency data lag behind actual changes to underlying spawning biomass (or SPR)?

It is well established that size-based indicators respond slowly to changes in fishing mortality, which can sometimes lead to delays in triggering TAC changes (Punt et al., 2001; Shin et al., 2005; Wayte and Klaer, 2010). As a demonstration of this effect, we simulated a 100-year projection using the HDT with only the LB-SPR indicator. This simulation was carried out under completely deterministic conditions (i.e., no stochastic recruitment and no temporal environmental variation or life history variation)

Answer: Yes.

Cyclic behavior of spawning biomass can emerge from delays in changes to length frequency distributions, which are then picked up and acted upon by the harvest control rule (Fig. D2).

Question 3: how to dynamically changing recruitment, growth and survival affect SPR estimation?

This is a complex question that was best addressed using the simulated outcomes of MSE. In the MSE, we retained SPR estimates that were calculated at each time step and we also recorded the true simulated SPR. Thus, we could compare how SPR trends were estimated with respect to changing stock size as well as in response to environmental fluctuations.

Answer: Some care must to taken in employing LB-SPR, but the careful integration of this approach with other indicators and an appropriate harvest control can produce reasonable management outcomes.

We first simulated stable but low historical abundance, followed by stock rebuilding in years 15 through 40 for 100 simulation runs (Fig. D3). This scenario highlights that at low simulated SPR, the estimated SPR tends to be slightly negatively biased, but nevertheless often correctly indicates the overly depleted state of the stock. There is a positive bias at high simulated SPR, which likely reflects differences between the LB-SPR estimation routine and the red abalone operating model, namely in terms of the stock-recruitment relationship (i.e., steepness = 0.6).

We then simulated declining historical abundance, followed by stock rebuilding in years 15 through 40 for 100 simulation runs (Fig. D4). During very rapid stock declines, changes in biomass outpace changes in length composition, and consequently biased SPR estimates are produced. The stabilizing of the length composition does result in reasonable SPR estimates, reduction of TACs, and stock rebuilding. Again, the examination of assessment methods in isolation inevitably will identify challenges facing any data limited assessment method. We therefore stress the need to consider the assessment pieces within the integrated harvest control rule and whether the integration and subsequent decision-making meets target management objectives.

Question 4: Does increased natural mortality cause a decrease in SPR and is this decrease detected by the LB-SPR fitting routine?

We simulated a stock in a stable state for 10 years, followed by an increase in M on all length classes of 0.1 $year^{-1}$. We then returned the natural mortality to its baseline rate for a subsequent 10 years. During this 30-year time period, fishing mortality was held constant at F_{MSY}. The resulting trends in stock dynamics demonstrate a simulated decline in SPR, followed by a rebounding once natural mortality was returned to its baseline rate (Fig. D5). We then simulated the observation of length frequency data at various points during this 30 year duration and used the LB-SPR fitting routine to estimate SPR (following the procedure used in the MSE for estimating SPR). We plotted the percent bias in SPR between the estimated values and true simulated values.

Answer:

Yes, SPR changes owing to period changes in natural mortality and this effect is detected using the LB-SPR fitting routine (Fig. D5). During the initial 10-year stable state, a negative bias is evident, as we have demonstrated in other plots in this appendix. During stock decline, the SPR estimate lags behind the changes in stock size, but later adjusts. Importantly, when natural mortality increases are driving changes in stock size, these changes will be picked up by the LB-SPR method. As noted previously, the examination of assessment methods in isolation inevitably will identify challenges facing any data limited assessment method. We therefore stress the need to consider the assessment pieces within the integrated harvest control rule and whether the integration and subsequent decision-making meets target management objectives.

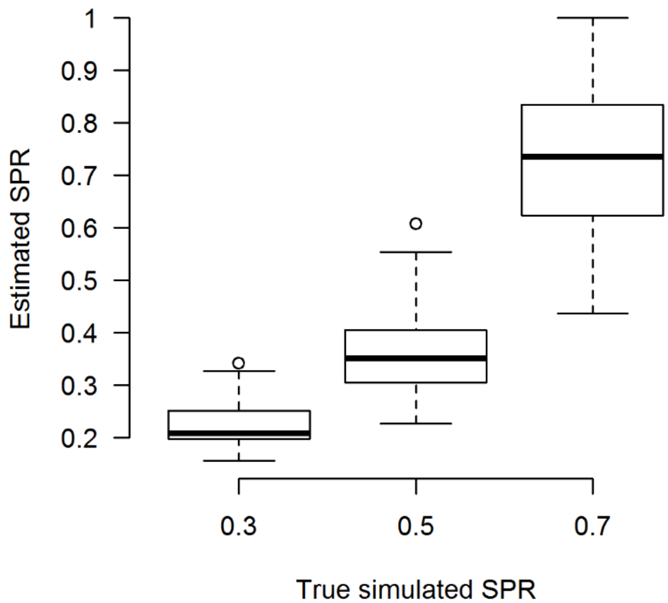


Figure D1. Comparison of “true” simulated SPR to estimates obtained from the LB-SPR fitting approach under steady-state or equilibrium conditions.

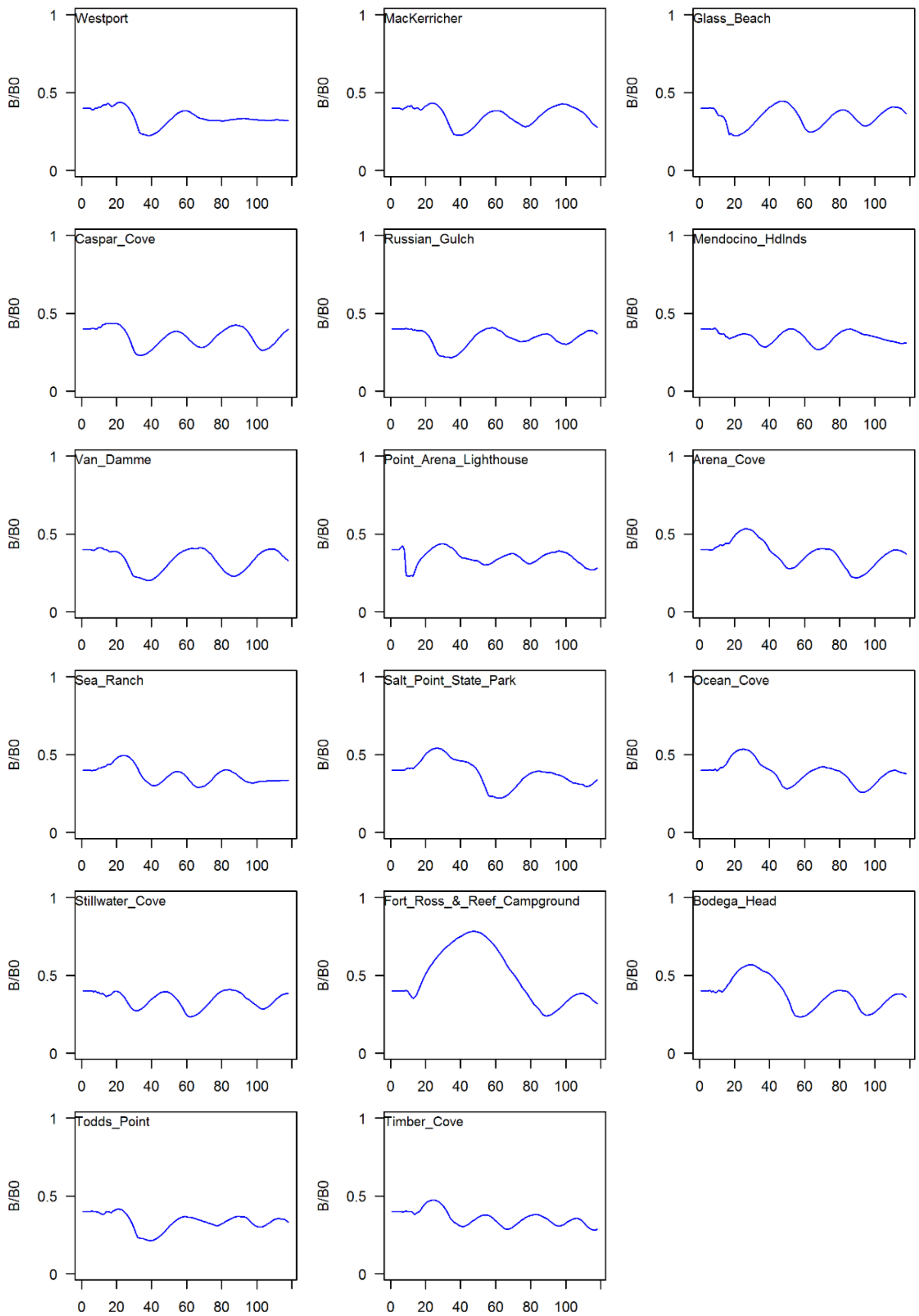


Figure D2. Depletion trends (spawning B / B0) based on deterministic projections using only the LB-SPR indicator in the decision tree.

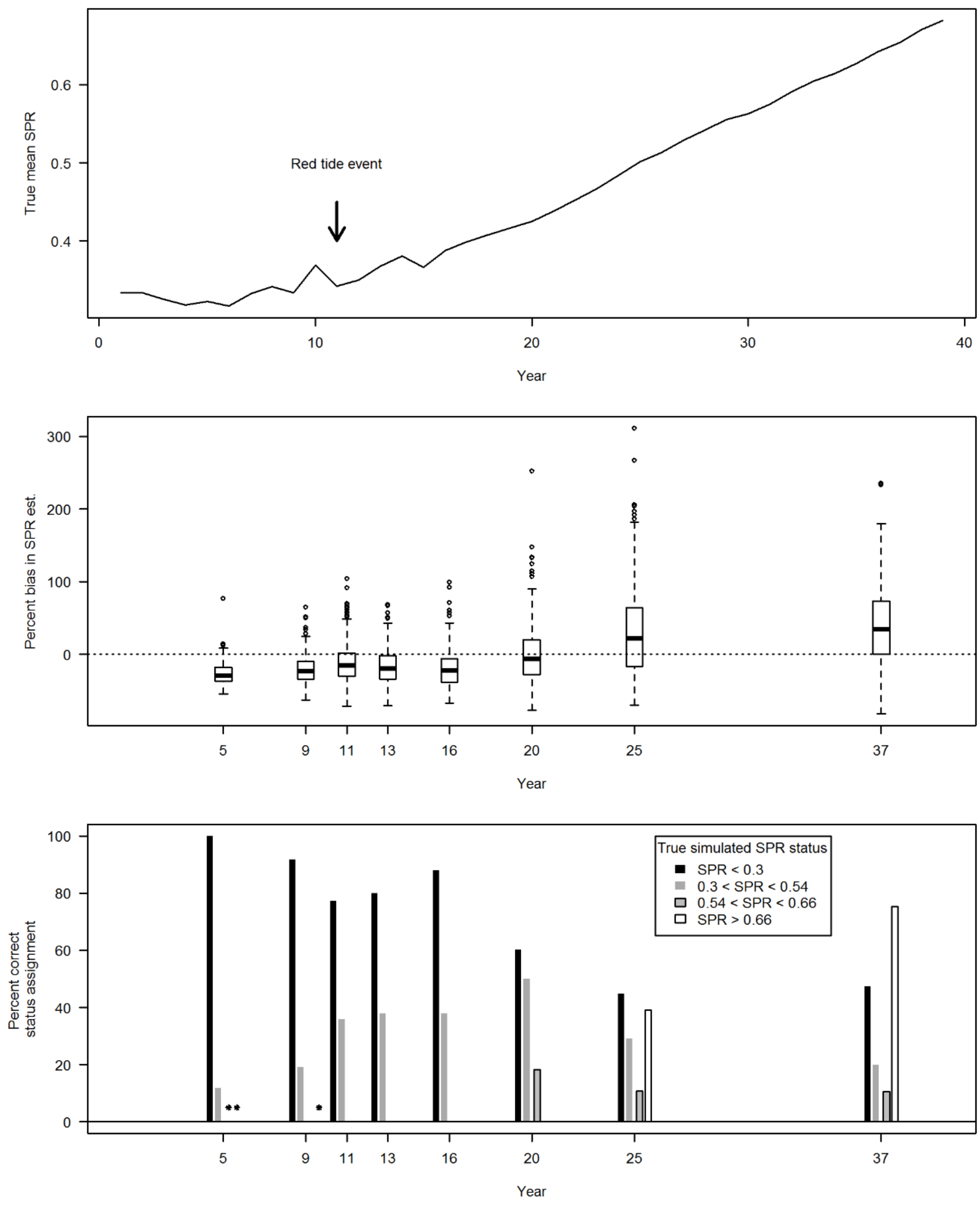


Figure D3. Summary of SPR estimation reliability under historically low but stable abundance. Upper panel is average SPR trend in 100 simulation runs, middle panel is percent bias boxplots in select years of simulation runs, and lower panel is the percent of instances of SPR estimates being correctly assigned to a status category. Asterisks indicate no true simulated instances of a status category.

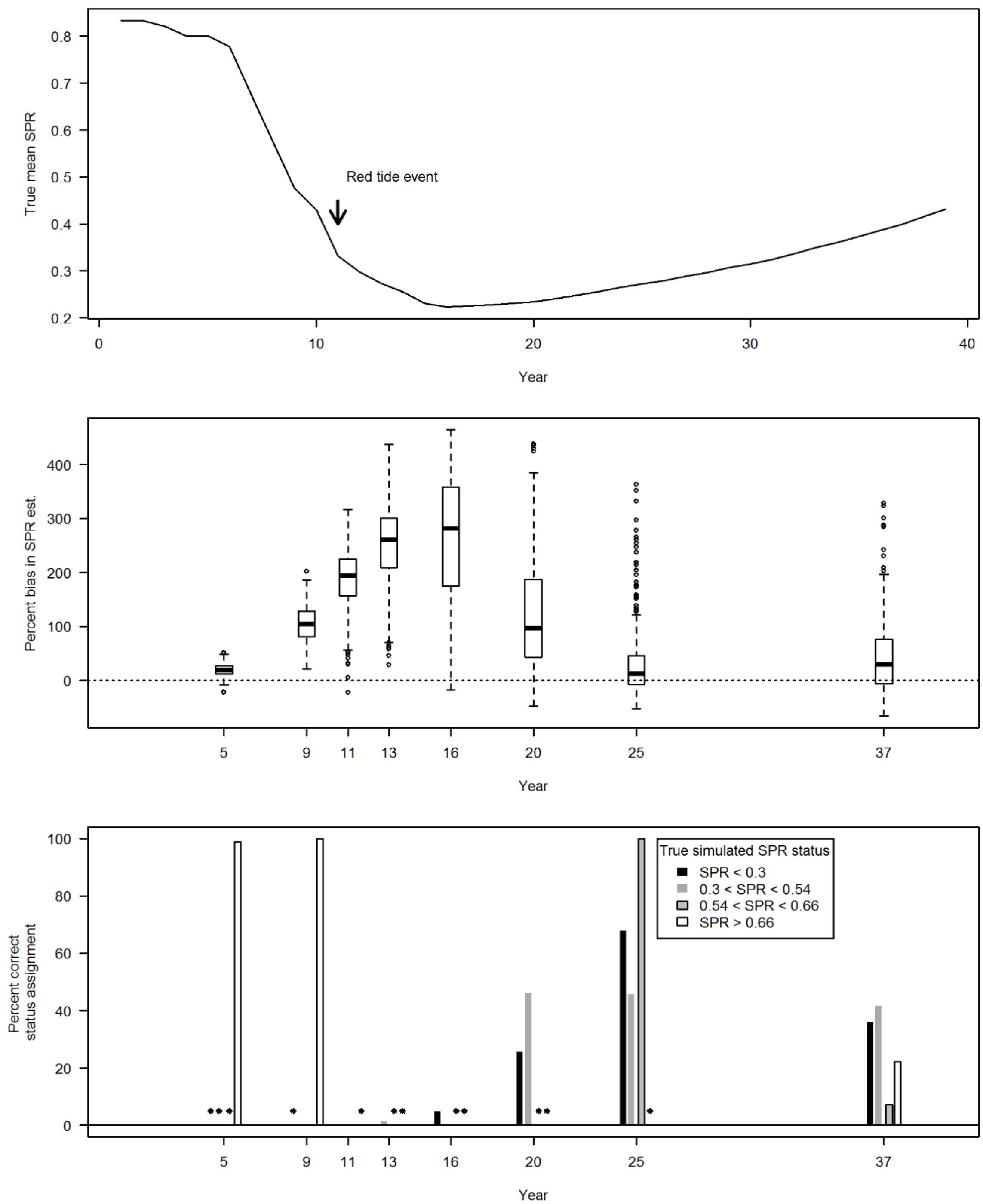


Figure D4. Summary of SPR estimation reliability under historically declining abundance. Upper panel is average SPR trend in 100 simulation runs, middle panel is percent bias boxplots in select years of simulation runs, and lower panel is the percent of instances of SPR estimates being correctly assigned to a status category. Asterisks indicate no true simulated instances of a status category.

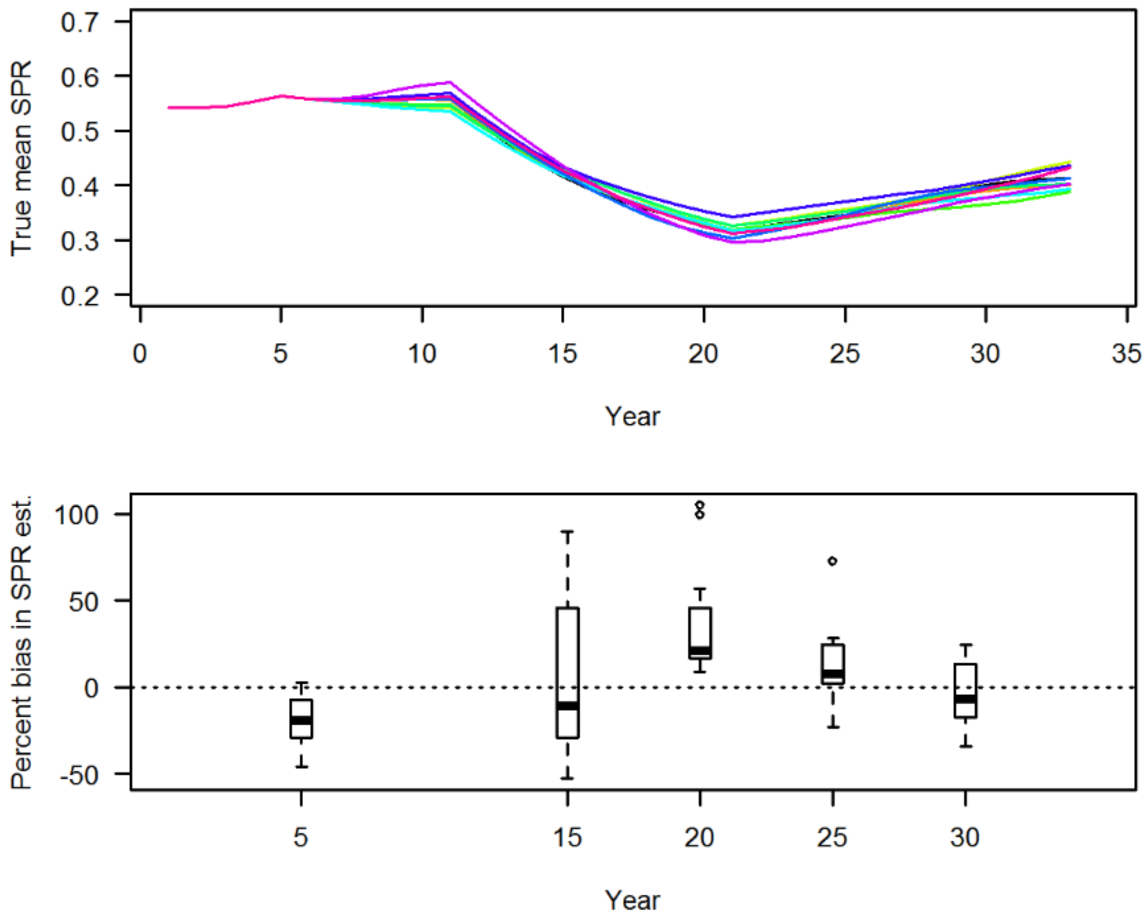


Figure D5. Upper panel shows 10 simulated stock trends that reflect increased natural mortality between years 11 and 20. The lower panel shows the corresponding bias in SPR estimation via the LB-SPR fitting method at years 5, 10, 20, 25, and 30.

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Mendocino County Fish & Game Commission
860 North Bush Street, Ukiah, CA 95482
https://www.mendocinocounty.org/government/planning-building-services/fish-game

November 14th, 2017

Mr. Eric Sklar, President
California Fish and Game Commission
1416 Ninth Street, Room 1320
Sacramento, CA 95814

Dear President Sklar,

The Mendocino Fish and Game Commission has been closely following the red abalone fishery since the decline of stocks was noticed by the Department and Fish and Wildlife and reductions of the daily bag limit and annual limits began. Abalone fishing represents a unique culture along the North Coast and a tradition that is cherished by locals and visitors alike. We fully understand that this long-held custom depends on a well-managed, healthy local ecosystem. Based upon our understanding and numerous conversations with local abalone divers, business owners, representatives of the Recreational Abalone Advisory Committee (RAAC), and various non-profits, the Mendocino Fish and Game would like to recommend the following for the new management framework for red abalone.

- Consider data streams and management approaches that utilize the best available science. Length data, for example, has shown to be an invaluable management tool for invertebrate fisheries around the world. Collaboration with a diverse array of stakeholders, including recreational fisherman, non-profits and academic researchers is also encouraged and aligns with the California Marine Life Management Act which also supports the use of the best available science.
- Utilize the best management practices and data collection strategies that can achieve better outcomes at significant financial savings. Citizen scientists already collect length information through existing surveys and new technologies are in development that can allow harvesters to collect length data with the level of precision necessary to inform management decisions. Both of these strategies may represent significant cost savings over more traditional data collection programs.

The Mendocino Fish and Game Commission is committed to these recommendations and has taken an active role in supporting the science around red abalone management by funding projects like Reef Check California to collect length and density data on red abalone along the Mendocino coast. The Mendocino Fish and Game Commission would like to encourage the use of the best available science that utilize multiple data streams that are cost effective and facilitate stakeholder engagement.

Thank you for your time

Randy Vann
Chair

Anna Neumann
Co-Chair

Mendocino Fish and Game Commissioners

Norm Brown *Patrick Ford* *Anna Neumann* *Randy Vann*
Michael Kura *Patty Madigan* *RedHawk Pallesen*

November 22, 2017

California Fish & Game Commission
1416 Ninth Street
Sacramento, CA 95814

RE: Red Abalone Fishery Management Plan

Dear Commissioners,

We are writing to you as leaders in the marine science community to request that the Commission ensure the best available science is used to guide the development of the fishery management plan for sustainable management of the red abalone fishery.

We encourage the Commission to consider two things when reviewing the Red Abalone Fishery Management Plan:

1) All proposed harvest control rules submitted to the Commission, including the ones proposed by external stakeholders, and CDFW staff biologists, should be subjected to a peer reviewed process by independent scientists. All scientific rationale, specifications of the approach and intended use should be made public prior to approval of any one approach.

2) Management Strategy Evaluation (MSE) is a formal process used to objectively compare alternative harvest control rules through computer simulation. MSE is the standard-bearer for development and testing of harvest control rules and should be used in the peer review process to ensure the highest level of scrutiny and objective analysis of tradeoffs in the fishery.

Thank you for your consideration.

Sincerely,

Jono Wilson, PhD, The Nature Conservancy and UCSB
Bill Harford, PhD, University of Miami
Steve Gaines, PhD, Dean Bren School of Environmental Science & Management, UCSB
Jeremy Prince, PhD, Biospherics, Murdoch University, Australia
Lyall Bellquist, PhD, The Nature Conservancy & Scripps Institute of Oceanography, UCSD
Stuart Sandin, PhD, Director at the Center for Marine Biodiversity and Conservation, UCSD
Hunter Lenihan, PhD, Professor Bren School of Environmental Science & Management, UCSB