Bull Mar Sci. 92(4):423–445. 2016
https://doi.org/10.5343/bms.2016.1025

research paper

Management strategy evaluation of a multi-indicator adaptive framework for data-limited fisheries management

WJ Harford [1*]
T Gedamke [2]
EA Babcock [3]
R Carcamo [4]
G McDonald [5]
JR Wilson [6]

[1] *Cooperative Institute of Marine and Atmospheric Studies, Rosenstiel School of Marine & Atmospheric Science, University of Miami, 4600 Rickenbacker Causeway, Miami, Florida 33149.*

[2] *MER Consultants, 5521 SE Nassau Terr., Stuart, Florida 34997.*

[3] *Department of Marine Biology and Ecology, Rosenstiel School of Marine & Atmospheric, Science, University of Miami, 4600 Rickenbacker Causeway, Miami, Florida 33149.*

[4] *Belize Fisheries Department, Coastal Zone Multi- Complex Building, Princess Margaret Drive, PO Box 148, Belize City, Belize.*

[5] *Sustainable Fisheries Group, Bren School of Environmental Science & Management, University of California, 2400 Bren Hall, Santa Barbara, California 93106.*

[6] *The Nature Conservancy, Bren School of Environmental Science & Management, University of California, 3021 Bren Hall, Santa Barbara, California 93106.*

** Corresponding author email: <wharford@rsmas.miami.edu>.*

Date Submitted: 24 February, 2016.
Date Accepted: 1 August, 2016.
Available Online: 12 September, 2016.

ABSTRACT.—In data-limited fisheries, making informed management decisions based on scientific advice is challenging. Here, we evaluate a multi-indicator adaptive management framework (AMF) that allows dynamic responses to changing environmental, socioeconomic, and fishing conditions. Using stakeholder-defined goals as a foundation for specifying performance metrics, we employ management strategy evaluation (MSE) to explore the performance of the AMF relative to prescriptive alternatives that are sometimes used in data-limited situations. We conduct simulations involving the two most economically-important fisheries in Belize, spiny lobster, *Panulirus argus* (Latreille, 1804), and queen conch, *Strombus gigas* (Linnaeus, 1758). Spiny lobster fishery simulations demonstrate that when relatively stable catches have historically persisted, an AMF can help to ensure that stable catches continue to persist into the foreseeable future when faced with factors such as increased entry to the fishery or environmentally-induced recruitment fluctuations. The queen conch fishery simulations demonstrate that optimizing economic performance is complicated without stock status indicators and depends greatly upon the current, yet typically unknown, state of the resource. Since our indicator-based approach could not provide direct information about resource status in relation to management reference points such as maximum sustainable yield, economic objectives could not be achieved. Nevertheless, implementing the AMF served as a beneficial control against stock collapse and could function well as an interim fishery policy during which sufficient fishery data could be collected to inform population modeling and quantitative stock assessment.

Fishery management decisions aimed at achieving long-term yields are often informed by quantitative stock assessments (Mace 1994, Walters and Martell 2004). However, >80% of global catches occur in fisheries that lack the necessary data, resources, and infrastructure to conduct such assessments (Costello et al. 2012). There are a variety of data-limited methods that enable quantitative metrics of fishery status to be compared against management reference points. For instance, total mortality estimates can be made from length frequency data and compared to per-recruit-based fishing mortality reference points (Ault et al. 2005, Gedamke and Hoenig 2006, Wayte and Klaer 2010, Hordyk et al. 2014). Simplified models of population dynamics serve a similar purpose (MacCall 2009, Dick and MacCall 2011, Martell and Froese 2012). However, underlying many data-limited approaches is an assumed mathematical model of fish population dynamics, from which data-limited metrics are derived. While it is often impractical to expect these underlying modeling assumptions to be vetted prior to application in data-limited circumstances, inaccurate metrics can be produced when implicit assumptions are violated (Carruthers et al. 2014, Hordyk et al. 2015).

As an alternative, indicator-based approaches can be used to make relative adjustments to total allowable catches (TACs) in data-limited situations. Indicator-based approaches generally do not depend upon estimates of stock abundance that are typically obtained from stock assessment. Thus, exploitation is not controlled by deriving total allowable catches (TACs) from an estimate of stock abundance and a target exploitation rate, as may be the case where stock assessments are performed. Instead, indicator-based approaches use harvest control rules (HCRs) to provide guidance on future exploitation through relative adjustments to previous TACs (Apostolaki and Hillary 2009). In the context of indicator-based fisheries management, a HCR is a pre-determined process that connects measured values of various indicators to regulatory tactics for controlling catches. Indicator-based HCRs have been introduced to avoid problems associated with uncertainty in results of stock assessments and in instances where the reliability of catch histories has been called into question (Hilborn et al. 2002, Apostolaki and Hillary 2009, Mesnil et al. 2009). The tractability of indicator-based HCRs has generated interest in comparisons against other approaches that rely on more complex stock assessment procedures (Geromont and Butterworth 2015a).

Indicator-based HCRs have been developed for North Atlantic and Australian fisheries (Pomarede et al. 2010, Little et al. 2011, Cook 2013) and have been proposed for coastal Pacific fishery management in conjunction with the use of marine reserves (Wilson et al. 2010, Babcock and MacCall 2011, McGilliard et al. 2011). But our interest in indicator-based approaches stems principally from their modest data requirements (Carruthers et al. 2015, Geromont and Butterworth 2015b), and from their potential as flexible and adaptive fishery controls for stocks that may otherwise not be subject to quantitative stock assessment. In the present study, we present a simulated management strategy evaluation of an indicator-based approach aimed at addressing management concerns about increased entry to fisheries that have historically produced stable catches without reliance on TACs. Our simulations are representative of the spiny lobster, *Panulirus argus* (Latreille, 1804), and queen conch, *Strombus gigas* (Linnaeus, 1758), fisheries of Belize and reflect the ongoing need for indicator-based approaches for management of tropical fisheries, and in particular, for invertebrate fisheries that have experienced increased fishing effort in recent decades (FAO 2001, Anderson et al. 2011).

The Belize Fisheries Department, which is recognized as a global leader in marine conservation, along with its non-governmental partners, is exploring adaptive decision-making that draws upon decades of research, managed access programs, and indicator-based HCRs. Expert consensus in identifying suites of indicators of stock trajectories has taken place in this region; however, practical management concerns have emerged as to how to develop HCRs that rely directly on indicator-based data inputs. Furthermore, HCRs are needed that achieve management objectives under circumstances where stock productivity is uncertain, catch histories do not exist, or where environmental conditions and fisher behavior are highly variable. Here, we report on the process of developing HCRs that link indicators to the recursive adjustment of TACs.

HCRs were evaluated through simulated management strategy evaluation (MSE). MSE simulates connections across an entire management system (Hertz and Thomas 1983, Sainsbury et al. 2000, Punt et al. 2014). A management system consists of an operating model that describes stock dynamics and a management strategy that describes (1) information collection, (2) scientific analysis or calculations involving indicators, and (3) a HCR. Simulated implementation of management tactics is also necessary, which can involve simulation of implementation error to evaluate implementation effects on HCR performance (Punt et al. 2014). Adjusting fishery tactics affects stock dynamics, and stock dynamics are monitored through indicator variables. Thus, MSE simulates a closed-loop feedback cycle of management decisions that can be simulated over various time horizons. This approach is useful for conveying trade-offs in decision-making to fishery managers because HCR performance is evaluated in terms of whether fishery management objectives are expected to be achieved. We conducted simulations involving the two most economically important fisheries in Belize, spiny lobster and queen conch. The spiny lobster fishery has historically maintained stable catches and was simulated to provide insights into whether indicator-based HCRs would inadvertently introduce catch reductions in circumstances where they were perhaps unnecessary. The queen conch fishery has had historically stable catches, but in recent decades, increased catches have concerned resource managers about continued resource sustainability. Our evaluation of HCRs focused on addressing (1) management concerns about data quantity and reliability and whether multi-indicator HCRs could mitigate these concerns, (2) the robustness of HCR performance in relation to key ecological uncertainties about life history and historical and current levels of stock depletion, and (3) whether HCRs could help to avoid undesirable resource states when stocks were subject to environmentally-driven productivity declines or subjected to increasing fishing effort through time.

Methods

Overview of Spiny Lobster and Queen Conch Fisheries.—The Belize spiny lobster fishery occurs exclusively by free diving and is currently regulated by a fishing season (from June 15 to February 14 of the following year), a size limit [carapace length 3 in (76 mm) or tail weight 4 oz (113 g)], a ban on the use of scuba, gear restrictions, and license limitation (Gongora 2010). Fishery selectivity is thought to

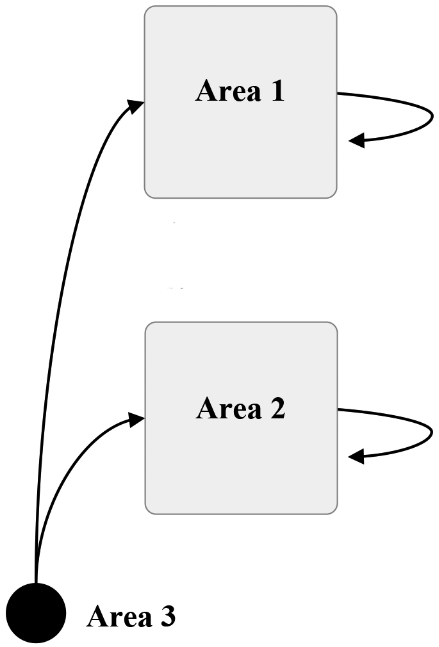

Figure 1. Conceptual representation of recruitment dispersal. Simulated spatial stock structure reflected the two major fishing areas in Belize (Area 1 and Area 2). Area 3 served as a constant source of spiny lobster recruitment from locations outside of Belize.

follow a dome-shaped relationship described in Babcock et al. (2014) with a minimum harvest length of 3 in (76 mm) carapace length. Temporal patterns of monthly fishing effort from commercial logbooks at Glover's Reef suggest that fishing effort (boat-days) is highest at the beginning of the season, declines continuously through the season, and experiences a slight increase in the final 2 mo. This temporal pattern in fishing effort is also reported for the Port Honduras spiny lobster fishery (Babcock et al. 2014).

The queen conch fishery occurs by free diving at depths <18 m. The fishing season occurs between October and June, with a seasonal closure in July, August, and September. The fishery is regulated by a size limit on queen conch siphon length and by meat weight. The meat weight of 78 g (100% clean weight) is the minimum legal harvest weight, and was specified as such in our simulations. Without additional information about fishery selectivity, the minimum legal capture weight was used to define knife-edge selectivity in our queen conch simulations.

Operating Model.—A spatially explicit operating model was constructed as a simulated representation of spiny lobster and queen conch stock dynamics. Spatial stock structure consisted of modeling northern Belize (area 1) and southern Belize (area 2) as separate stock components to reflect the two major fishing areas in the country (Fig. 1). A third stock component, known as area 3, was used to represent spiny lobster recruitment contributions to areas 1 and 2 that were attributed to sources occurring outside of Belize. The stock dynamics of area 3 were not modeled explicitly; rather, area 3 was considered to be a constant source of spiny lobster recruitment. Recruitment that was external to areas 1 and 2 was always specified to originate from area 3. No recruitment dispersal occurred between areas 1 and 2, and no movement of adult lobster was simulated. This spatial representation was constructed because of the high uncertainty that surrounds contributions of localized vs long-distance dispersal of larval spiny lobster (Ehrhardt 2005, Butler et al. 2011, Truelove et al. 2012, Kough et al. 2013). Despite this uncertainty, fishery management decisions are required at national and international scales (FAO 2001, Gongora 2010, Babcock et al. 2013). Consequently, this simulated spatial structure enabled exploration of the sensitivity of spiny lobster HCR performance to scenarios about dispersal of recruits. We did not examine spatial dynamics of queen conch and specified 100% self-recruitment to areas 1 and 2, and no external recruitment input from area 3. Queen conch instead served as a stark contrast to spiny lobster in terms of exploitation history, which has displayed steady increases in catches since 1989, in comparison with the relative stability of spiny lobster catches since 1999 (Gongora 2010, 2012).

The temporal dynamics of stocks in areas 1 and 2 were calculated using age-structured cohort equations, operating on a monthly time step (Table 1). Within a monthly time step, growth and spawning occurred at the beginning of the month, followed by instantaneous rates of natural mortality and fishing mortality (Table 1). For spiny lobster, we simulated recruitment of cohorts to the fishery at 76 mm, which also coincides with the length at maturity (FAO 2001). Thus, we simulated adult stocks of spiny lobster that were assumed 50% female at all sizes, and which were assumed to have a longevity of 12 yrs in the adult phase, based upon a natural mortality rate of 0.34 yr^{-1} (FAO 2001, Gongora 2010). Recruitment consisted of first pooling the self-recruiting fraction of locally produced recruits with recruits arriving from area 3, and then applying density-dependent mortality. Peak spawning of spiny lobster occurs throughout the Caribbean in spring, which approximately corresponds to the Belize fishery closure (Villegas et al. 1982, Chubb 1994, FAO 2001, Cruz and Bertelsen 2008). Thus, total recruits of spiny lobster in year y are calculated from February spawning biomass in year $y - 2$, and density-dependent mortality is applied as a function of spawning biomass. Ralston and O'Farrell (2008) present Beverton-Holt stock-recruitment functions with alternative assumptions about the life stages in which density-dependent mortality operates. Our simulations are similar to their post-dispersal density dependence model and includes a single annual log-normally distributed recruitment deviate that is applied to both areas (Ralston and O'Farrell 2008). Temporal distribution of recruits occurred in February, March, April, and May in the quantities of 10%, 20%, 50%, and 20% of the total recruits, respectively. This pattern approximates observations that peak recruitment to the fishery commonly occurs over a protracted spring period (Villegas et al. 1982, Chubb 1994, FAO 2001, Cruz and Bertelsen 2008).

An age-structured simulation was similarly constructed for queen conch, except that growth was calculated using a relationship between age and clean meat weight for the south Caribbean region (Table 1; Ehrhardt and Valle-Esquivel 2008). Queen conch were simulated to spawn in July and recruited to the fishery at 78 g (100% clean weight), which corresponds to fishery entry in their second year, during the months of July (33%), August (33%), and September (34%). Natural mortality was specified as a decreasing function of age, which corresponded to an approximate longevity of 20 yrs after recruitment (Table 1; Ehrhardt and Valle-Esquivel 2008). Since conch

Table 1. Processes and parameters of simulated stock dynamics for spiny lobster (*Panulirus argus*) and queen conch (*Stombus gigas*) off Belize.

Process	Parameters	Description
Time and area		
Area	c	Areas used in spatial configuration
Time	t, a	Time step in months, age in years
Life history		L_1 =76 mm, $L_{a+t/12} = La + (L_{inf} - L_a)(1 - \exp(-k/12))$
Lobster length (mm carapace)	$L_{\text{inf}} = 183$, $k = 0.24\ \text{yr}^{-1}$	$W_L^{tail} = \alpha L^{\beta}(2.2046\ \text{lbs/kg})$
Lobster weight (lbs)	$\alpha = 0.0046$, $\beta = 2.630$	
Lobster mortality	$M = 0.34\ \text{yr}^{-1}$	Constant M for all ages
Conch weight (100% clean g)	$W_{\text{inf}} = 240.8$, $r = 0.691$	$W_a^{clean} = W_{\text{inf}} / W_{\text{inf}}^{\exp(-ra)}$
Conch weight (whole lbs)	$\alpha = 3.69$, $\beta = 0.581$	$W_a^{whole} = (W_a^{clean} + \alpha)/\beta(0.00220462\ \text{lbs/g})$
Conch mortality	$c = 2.048$, $d = 1.108$	$M_a = ca^{-d}/12$
Cohort equations		
Survival	S	$S_{a,t} = \exp(-M_a - F_t Sel_a)$, F is fishing mortality
Cohort abundance	N	$N_{a+1,t+1} = N_{a,t} S_{a,t}$
Biomass (lbs)	B	$B_{a,t} = N_{a,t} W_a$
Catch (lbs)	C	$C_{t,a} = F_t Sel_a / (F_t Sel_a + M_a) N_{a,t} (1 - \exp(-M - F_t Sel_a)) W_a$ F is fishing mortality, Sel is selectivity at age
Stock-recruitment		
Beverton–Holt	$h = 0.8$, $\sigma_R = 0.2$, ε_t ,	h is steepness, σ_R is recruitment variation, ε_t~Norm(0, σ_R), R_0 is unfished recruits, B_0 is unfished spawning biomass, w is fraction self recruiting.
$R_{c,y} = \left(\frac{0.8 R_c^0 h}{0.2 B_c^0 (1-h) + (h-0.2) B_{c,y-2}^S} \right) (w_c B_{c,y-2}^S + B_3^S) \exp(\varepsilon_t - \sigma_R^2/2)$		
Spawning biomass	B^S,	$B^S_{c,a,t} = B_{c,a,t} \times probMat_a \times probFemale_a$

vary regionally in their growth characteristics, we specified age at maturation of 4 yrs (50% female at all sizes) and later explored an alternative maturation age of 6 yrs in the sensitivity analysis (Appeldoorn 1988, Gongora 2005, Ehrhardt and Valle-Esquivel 2008).

Simulation Design.—In simulation design, a principal concern was specification of historical stock dynamics prior to implementing a HCR. While actual catch histories were available for spiny lobster and queen conch, historical biomass trajectories, fishery effort trends, and stock depletion were less well established. The Belize Fisheries Department provided spiny lobster and queen conch catches that were reported from fishery cooperatives (Gongora 2010). Because the fishing cooperatives

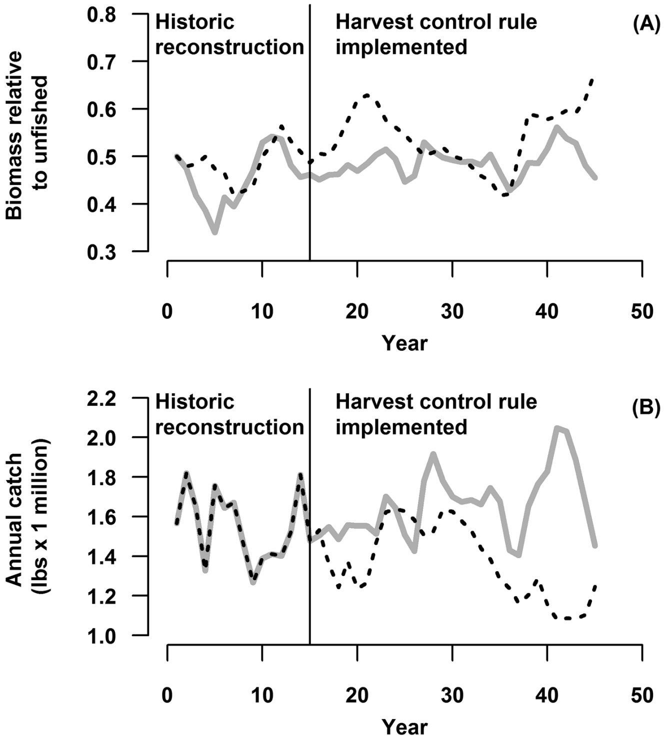

Figure 2. Example of simulated stock dynamics for spiny lobster showing (A) reconstruction of biomass during the historical time period and (B) reproduction of actual observed catches during the historic time period prior to implementation of a simulated harvest control rule. Vertical lines indicate transition from historical time period to time period where a simulated harvest control rule was implemented; time series (thick solid lines and dashed lines) are two different examples of simulation runs.

process all conch and lobster that are exported from Belize, and the vast majority of the catch is believed to be exported, the cooperative data are thought to provide the most accurate record of total catches that is available. Historical biomass reconstructions were initiated by calculating an equilibrium age structure at an assumed level of biomass depletion in the initial simulation year. The spiny lobster operating model was initialized for 1998, using equilibrium age structure that conformed to both (1) an assumed level of depletion and (2) the mean catch of 1,537,182 lbs (698,719 kg) whole weight calculated from the observed catches that occurred between 1999 and 2013. Each simulated stock area was specified to contribute 50% to the catch. The queen conch operating model was initialized for 1977, using equilibrium age structure that conformed to both (1) an assumed level of depletion and (2) the mean catch of 667,652 lbs (303,478 kg) whole weight, which was calculated as the average catch during the relatively stable 20-yr period between 1978 and 1997. Each simulated queen conch stock area was specified to contribute 50% to the catch.

After initializing each stock, monthly catches were used to drive the model forward between the initial year and 2013; we refer to this time period as a historical reconstruction. This time period was 1999 to 2013 for spiny lobster and 1978 to 2013 for queen conch (Fig. 2). Annual catches were divided into monthly catches using the proportion of monthly catch totals reported in commercial logbooks from Glover's Reef in 2011 and using the National Queen Conch Quota Disbursement Schedule for 2012 (Gongora 2012). Noting that recruitment was simulated as a stochastic process, each simulation run produced a somewhat unique reconstruction while ensuring observed catches were reproduced (Fig. 2). In atypical instances where stock collapse occurred during the historical period, simulation runs were considered biologically implausible and were removed from the analysis. In reconstructing observed catches, fishing effort associated with the catch was a derived quantity. Fishing effort derived during reconstruction was used to drive harvests during the forward-looking time period in which HCRs were implemented.

Given our uncertainty about reconstruction of spiny lobster and queen conch biomass dynamics, we simulated base-case operating models representing different scenarios about: (1) initial biomass depletion levels used in historical reconstructions, (2) the future intensity of fishery effort utilized in the forward-looking time period in which HCRs were implemented, and (3) environmentally-driven changes in production of recruits during the forward-looking time period. Levels of initial spawning stock biomass (SSB) as a fraction of the unfished state were 0.2, 0.5, 0.8. Future intensity of fishery effort was held constant at the 2013 derived effort level, and alternatively, was simulated as a 3% annual increase to reflect modest fishery expansion. Our simulated effort creep of 3% is consistent with reported effort trends in Belize, although license limitation programs have recently been introduced at Glover's Reef Marine Reserve (since 2011) and Port Honduras Marine Reserve (since 2012) (Gongora 2010). Levels of environmentally-driven recruitment variation were specified as stochastic recruitment (using the standard assumption of lognormal recruitment deviations), and alternatively, as stochastic recruitment coupled with a systematic reduction of 30% every sixth and seventh year to coarsely represent an El Niño event. For simplicity, in each base-case operating model that we specified, each stock area had 100% self-recruitment (0% external recruitment input). We later examined alternative spatial assumptions regarding recruitment dispersal in the sensitivity analysis.

Harvest Control Rules (HCRs).—We evaluated four HCRs for spiny lobster. A status quo HCR that reflected the current regulatory size limit and seasonal closure was simulated (i.e., a status quo HCR), as well as two prescriptive (non-adaptive) HCRs that increased minimum harvest size from 76 to 85 mm carapace length or reduced fishing season length from 8 to 6 mo. These three HCRs were not constrained by a TAC and instead catches were determined only by the intensity of fishing effort (i.e., effort specified in relation to the 2013 effort level). We compared these prescriptive HCRs to an adaptive management framework (AMF) that was based on the idea that informative indicators would enable an in-season TAC adjustment. Because the current capacity of the fishing fleet was driven by intensity of fishing effort, HCRs that implemented TACs also specified fishery closure to occur in the month when the TAC was achieved. If the TAC was not achieved, closure occurred as usual at the end of the fishing season (i.e., spiny lobster: February 14; queen conch: July 1). Since fishery closure occurred when the TAC was achieved, our analysis did not address implementation uncertainty of TACs. For queen conch, we compared two HCRs: the status quo HCR and the AMF HCR.

The specificity of indicator inputs to the AMF HCR reflected actual types of monitoring data associated with spiny lobster and queen conch. For spiny lobster, indicators were catches in the previous year, average length in the catch in the previous year, and fishery catch-per-unit-effort (CPUE) during the first 2 mo of the current fishing season. Declines in catch trends triggered TAC reduction and increased catch trends triggered TAC increases. The catch indicator worked to protect the stock against recruitment failure, but would reward catch increases (whether they were sustainable or not) with TAC increases. Average length reflects size-frequency distribution in the catch and exploitation status of a stock because as rates of fishing mortality increase, fewer individuals reach larger sizes (Beverton and Holt 1957, Gedamke and Hoenig 2006). Declining average length trends in the catch triggered TAC reductions and increasing average length triggered TAC increases. Average length served to maintain stable biomass through time and reduce TACs if exploitation rates increased. However, anomalously large recruitment events reduce average length because many small individuals enter the stock, producing a counter intuitive reduction to TAC. Fishery CPUE was simulated to be proportional to exploitable stock biomass, thus CPUE increases triggered TAC increases and vice versa. For queen conch, indicators were catch, CPUE, and a pre-season survey of mature conch density. The density survey tracked mature invertebrate abundance, thus higher survey densities triggered TAC increases and lower survey densities triggered TAC decreases.

To implement the indicator-based AMF HCR, the following algorithm was constructed:

1. A set of measured indicators were reported.
2. A set of indicator reference conditions were used to determine whether relative changes to the state of the stock have taken place. Reference conditions for spiny lobster were calculated as the means and standard deviations of the indicators between 1998 and 2013. Reference conditions for queen conch were calculated for the period of stable catches between 1978 and 1997.
3. TAC adjustment was made in-season following the second month of each fishing season. The HCR determined if each indicator exceeds an upper reference threshold $I > (I_{ref} + SD\ (I_{ref}))$ or fell below a lower reference threshold $I < (I_{ref} + SD\ (I_{ref}))$, where SD is the reference standard deviation of the indicator. The maximum TAC adjustment as a percentage of the previous year's TAC was specified a priori. For example, if up to 10% annual change was permitted, each indicator contributed in part to this maximum. Indicators that denoted an increase would contribute $1/3 \times 10/100$ to the adjustment, while those denoting a decrease would contribute $-1/3 \times 10/100$, and zero adjustment otherwise. The total adjustment as a TAC multiplier was calculated as one plus the sum of all indicator contributions. As an additional condition, TACs were prevented from being reduced below 0.5 times, or exceeding 1.5 times the reference mean catch.

In evaluating the AMF harvest control rule, we first considered multi-indicator performance when indicators were reported without error. Performance of multi-indicator HCRs were simulated to allow for up to 10% or 30% annual TAC change. We then evaluated AMF HCR performance under imprecision in data collection. In this case, catches were still reported without error, but mean length in the catch was estimated by randomly sampling 10% of the catch and relative biomass or abundance indices were observed with constant coefficients of variation (CV) of 40%. Index CVs were consistent with observed error rates in fish population surveys and values assumed in other simulation studies (Patterson 1998, Karnauskas et al. 2011, Smith et al. 2011, McCauley et al. 2012, Zhang 2013).

Performance Measures.—We repeated simulation runs for each operating model configuration 500 times and calculated five performance measures. The first was the probability of stock collapse at the end of the 30-yr MSE period. We determined whether the mean spawning biomass in the final 3 yrs of the forward-looking projections was <10% of the "true" unfished spawning biomass. The fraction of times this condition occurred represented the probability of stock collapse. The second was biomass stability and was calculated as the ratio of spawning biomass at the end of the forward-looking projections to the spawning biomass at the start of the forwarding-looking projections (using 3-yr means). Biomass stability near 1 indicates similar stock size at the beginning and end of the forward-looking period, while values <1 indicate biomass declines. The third and fourth metrics were the sum total value of catches across each 30-yr forward projection period and mean catch at the end of the forward-looking period, respectively. Catch value in BZ$ was calculated by determining the processed weight of the catch (lobster: tail weight in lbs; queen conch: 100% clean meat weight) and multiplying by current fisher's sale prices. The fifth was the inter-annual coefficient of variation in the catch, which reflects year-to-year catch stability.

Sensitivity Analysis.—In the sensitivity analysis, we investigated the effects of recruitment dispersal on HCR performance. Thus, we simulated 50% self-recruitment and 10% self-recruitment scenarios, and compared these scenarios to the corresponding base-case operating model that specified 100% self-recruitment. Sensitivity of HCR performance to aspects of spiny lobster and queen conch life history were also explored. For stock-recruitment steepness, we compared HCR performance for spiny lobster when steepness was modified to 0.5 or 0.97 from the base-case of 0.8. We also evaluated sensitivity of HCR performance to queen conch age at maturity. Since queen conch vary regionally in their growth characteristics, we modified the base-model specification of maturity at age 4 to an age at maturity of 6 yrs.

Results

Base-case Operating Models.—Throughout this results section, model outcomes for spiny lobster are presented for base-case scenarios involving initial SSB/SSB unfished of 0.2 and 0.5, as results for SSB/SSB unfished 0.5 and 0.8 were qualitatively similar. Historical reconstruction suggested that queen conch biomass declined through the simulated historical time period, and thus, specifying initial SSB/SSB unfished of 0.2, led to very frequent stock collapse before the end of the historical period. It therefore seemed biologically unreasonable to assume that the stock could have been at such a low initial state in 1977 and we only present results for queen conch involving initial SSB/SSB unfished of 0.5 and 0.8.

We begin by reporting AMF HCR performance relative to the status quo and to prescriptive HCRs when indicators were reported without error. For spiny lobster, simulating constant fishing effort into the forward-looking period produced biomass

Table 2. Spiny lobster (*Panulirus argus*) performance measures for multi-indicator adaptive management framework (AMF) when indicators are reported with and without observation error. Simulations initialized at spawning stock biomass (SSB)/SSB unfished of 0.2. Catches in millions BZ$, CV is coefficient of variation. Mean values are reported with standard errors in parentheses. TAC is total allowable catch.

Management framework	Probability of collapse	Biomass stability	Total catch	End-state catch	Catch CV
Without observation error					
Constant effort scenario					
Status quo (no TAC)	0.16	0.91 (0.25)	275 (41)	9.0 (1.7)	0.12
Increased size at harvest (no TAC)	0.05	1.31 (0.22)	299 (24)	10.2 (1.3)	0.12
Decreased fishing season (no TAC)	0.09	1.15 (0.24)	276 (29)	9.3 (1.4)	0.10
AMF (10% max TAC adjustment)	0.03	1.12 (0.29)	282 (37)	9.6 (1.7)	0.12
AMF (30% max TAC adjustment)	0.03	1.15 (0.23)	286 (22)	9.6 (1.3)	0.13
Effort creep scenario					
Status quo (no TAC)	0.63	0.33 (0.17)	260 (62)	7.0 (3.1)	0.22
Increased size at harvest (no TAC)	0.27	0.66 (0.16)	312 (37)	10.1 (2.1)	0.14
Decreased fishing season (no TAC)	0.40	0.48 (0.19)	278 (49)	8.5 (2.7)	0.16
AMF (10% max TAC adjustment)	0.24	0.66 (0.22)	280 (52)	8.9 (2.4)	0.16
AMF (30% max TAC adjustment)	0.19	0.73 (0.19)	287 (31)	9.2 (1.9)	0.14
Recruitment decline scenario					
Status quo (no TAC)	0.28	0.59 (0.19)	215 (36)	5.3 (1.3)	0.29
Increased size at harvest (no TAC)	0.18	0.83 (0.15)	233 (21)	6.1 (0.9)	0.25
Decreased fishing season (no TAC)	0.20	0.70 (0.18)	216 (24)	5.6 (1.0)	0.24
AMF (10% max TAC adjustment)	0.09	0.92 (0.27)	213 (33)	5.7 (1.2)	0.24
AMF (30% max TAC adjustment)	0.06	1.03 (0.23)	214 (23)	5.9 (1.1)	0.23
With observation error					
Effort creep scenario					
AMF (10% max TAC adjustment)	0.22	0.65 (0.21)	288 (38)	9.2 (1.9)	0.12
AMF (30% max TAC adjustment)	0.19	0.68 (0.20)	287 (34)	8.9 (1.9)	0.14
Recruitment decline scenario					
AMF (10% max TAC adjustment)	0.09	0.93 (0.27)	213 (33)	5.7 (1.3)	0.24
AMF (30% max TAC adjustment)	0.05	1.04 (0.20)	216 (18)	5.9 (0.7)	0.21

and catches that remained relatively constant when the AMF rule was used, suggesting that this HCR did not dramatically modify catches when there was little cause to do so (Table 2). Not surprisingly, a prescriptive increase in minimum harvest length from 76 mm to 85 mm CL (while maintaining constant fishing effort) produced long-term increases in SSB (Table 2). Introducing effort creep or recruitment declines, both of which act to modify resource state, demonstrated the benefits of the AMF rule. The AMF rule fared better at avoiding biomass declines than the status quo, which fared poorly during scenarios of effort creep and recruitment decline (Fig. 3). Also, the simulated historical stability of biomass trends for spiny lobster is continued using the AMF HCR under perturbations to fishing effort or stock productivity, although there is considerable overlap in performance with the prescriptive HCRs (Fig. 4). Results for the effort creep scenario are encouraging as biomass stability can be retained using indicator-based HCRs (Fig. 4), and similar results were found for the scenario of periodic recruitment decline. Achieving biomass stability under effort increases and periodic recruitment declines came at some expense to catch value, with the increased size-at-harvest HCR producing the highest long-term

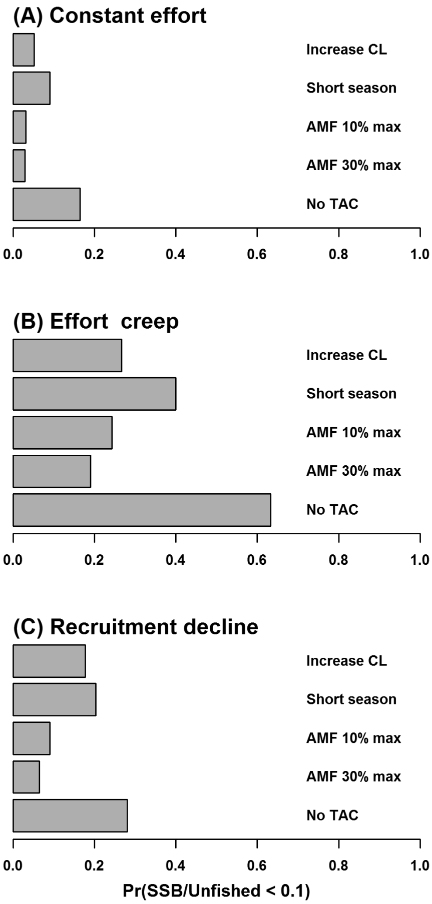

Figure 3. Probability of spiny lobster stock collapse (Pr(SSB/SSBunfished < 0.1)) in (A) base-case scenarios of constant effort, (B) effort creep at 3% yr^{-1}, and (C) environmentally-driven reduction in recruitment. Simulations initialized at SSB/SSBunfished of 0.2, CL is carapace length, AMF is adaptive management framework, SSB is spawning stock biomass, TAC is total allowable catch.

catches and the AMF HCR leading to catch reductions during the forward-looking MSE phase (Fig. 4).

Given the increasing trend in queen conch catches between 1978 and 2013, it was not surprising that maintaining the 2013 effort levels or increasing this effort level as the simulations entered the forward-looking MSE period led to high probability of stock collapse (Table 3). When initial SSB/SSB unfished was specified at 0.5, queen conch biomass declined, on average, to 0.3 SSB/SSB unfished by the start of the forward-looking MSE period. During the forward-looking MSE period, the probability of collapse was >0.90 across effort creep and recruitment decline scenarios for status quo management (Table 3). Probability of collapse was reduced using the AMF HCR, with probabilities <0.6 for the constant effort scenario and the periodic recruitment decline scenario, and a probability <0.85 for the effort creep scenario (Table 3). Queen conch simulations were also particularly instructive about the dependency of future catch value on the specified initial level of biomass depletion. This means

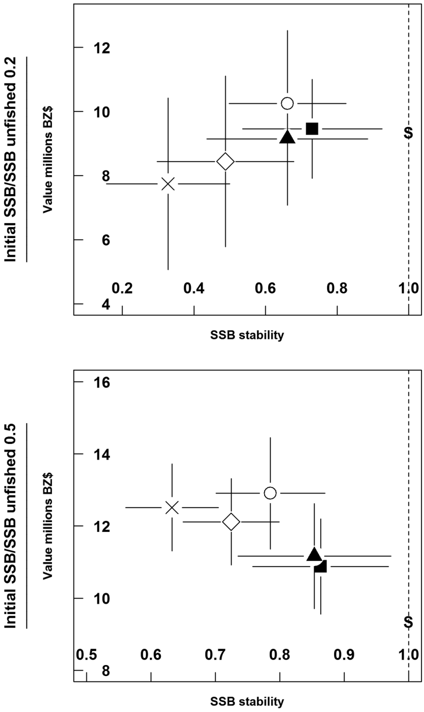

Figure 4. Spiny lobster spawning stock biomass (SSB) stability and end-state catch value BZ$ under 3% annual effort creep during the forward-looking management strategy evaluation (MSE) period. S is the resource state just prior to the forward-looking MSE time period, × is the status quo case, ■ is TAC 30% max, ▲ is total allowable catch (TAC) 10% max, ◊ is shortened season, ○ is increased minimum harvest size. Error bars are ± 1 standard deviation.

that after a historical reconstruction, if the 2013 stock size remained larger than the biomass expected to produce maximum sustainable yield (MSY), then increased fishing effort would produce increased long-term catches. This trend was common for conch simulations initialized at 0.8 SSB/SSB unfished, as reduction of stock biomass via status quo management led to higher catches, whereas the more conservative AMF rule worked to maintain historically lower catches (Fig. 5). If, however, the 2013 stock size was smaller than the biomass expected to produce MSY, increased effort would further reduce stock size and would lead to poor long-term catches, as was commonly the case for simulations initialized at 0.5 SSB/SSB unfished (Fig. 5). This result is intuitive and reflects the inability of the indicator approach to provide any direct information about MSY. In the instance where long-term biomass trends were already well below the "true" biomass level that would produce MSY, the AMF rule helped to better maintain catches and avoid stock collapse relative to the status quo HCR, although probability of stock collapse remained quite high regardless of HCR formulation (Table 3).

For both spiny lobster and queen conch, we also simulated the separate implementation of each indicator used in the AMF (Tables 4, 5). The results of simulating the separate performance of each indicator without observation error served as a cautionary example of some subtleties of using catch and mean length as indicators of stock trajectory. As expected, increases in fishing effort via the effort creep scenario

Table 3. Queen conch (*Stombus gigas*) performance measures for multi-indicator adaptive management framework (AMF) when indicators are reported with and without observation error. Simulations initialized at spawning stock biomass (SSB)/SSB unfished of 0.5. Catches in millions BZ$, CV is coefficient of variation. Mean values are reported with standard errors in parentheses. TAC is total allowable catch.

Management framework	Probability of collapse	Biomass stability	Total catch	End-state catch	Catch CV
Without observation error					
Constant effort scenario					
Status quo (no TAC)	0.98	0.13 (0.10)	105 (31)	2.2 (1.3)	0.52
AMF (10% max TAC adjustment)	0.20	0.79 (0.36)	126 (27)	4.1 (1.6)	0.24
AMF (30% max TAC adjustment)	0.08	0.93 (0.16)	138 (10)	4.8 (0.5)	0.12
Effort creep scenario					
Status quo (no TAC)	1.0	0.01 (0.02)	85 (26)	0.5 (0.6)	0.85
AMF (10% max TAC adjustment)	0.84	0.28 (0.17)	127 (36)	3.5 (1.9)	0.32
AMF (30% max TAC adjustment)	0.84	0.30 (0.13)	137 (20)	4.0 (1.1)	0.15
Recruitment decline scenario					
Status quo (no TAC)	0.99	0.07 (0.06)	81 (22)	1.0 (0.7)	0.80
AMF (10% max TAC adjustment)	0.58	0.36 (0.30)	91 (23)	1.8 (1.2)	0.52
AMF (30% max TAC adjustment)	0.37	0.61 (0.18)	106 (12)	2.8 (0.5)	0.27
With observation error					
Effort creep scenario					
AMF (10% max TAC adjustment)	0.92	0.17 (0.17)	112 (37)	2.3 (2.0)	0.48
AMF (30% max TAC adjustment)	0.86	0.30 (0.12)	134 (22)	3.9 (1.2)	0.19
Recruitment decline scenario					
AMF (10% max TAC adjustment)	0.70	0.26 (0.25)	88 (22)	1.4 (1.0)	0.61
AMF (30% max TAC adjustment)	0.35	0.59 (0.20)	104 (15)	2.7 (0.7)	0.34

resulted in higher catches, which were rewarded with higher TACs when catch alone was used as an indicator in isolation. This scenario led to high probability of stock collapse and destabilized the spiny lobster stock (Table 4). These negative performance trajectories were more dramatic for queen conch (Table 5). In the periodic recruitment decline scenario, the shortcomings of using mean length for spiny lobster TAC adjustments were also pronounced (Table 4). Increased probability of stock collapse and greater instability occurred in this instance because recruitment fluctuations produce counter intuitive changes in TAC adjustments when mean length alone was used in adjusting TACs.

We next returned to the simulation of multi-indicator AMF control rules when indicators were reported to the HCRs with observation error. Observation error was introduced to indicators by estimating mean length in the catch by sampling 10% of the catch and by introducing a 40% CV on observations of biomass indices. In comparing multi-indicator AMF HCR performance when simulated with and without observation error, we observed reasonable consistency in HCR performance (Tables 2, 3). In further examining the performance of the multi-indicator AMF, we contrasted its performance against that of using CPUE in a single-indicator approach when both were subject to observation error. Noting that CPUE is proportional to biomass in our simulations, it is not surprising that it was the best performing single indicator across all operating model scenarios, and thus, was used in contrasts with the multi-indicator AMF. Beginning with the recruitment decline scenario, the spiny

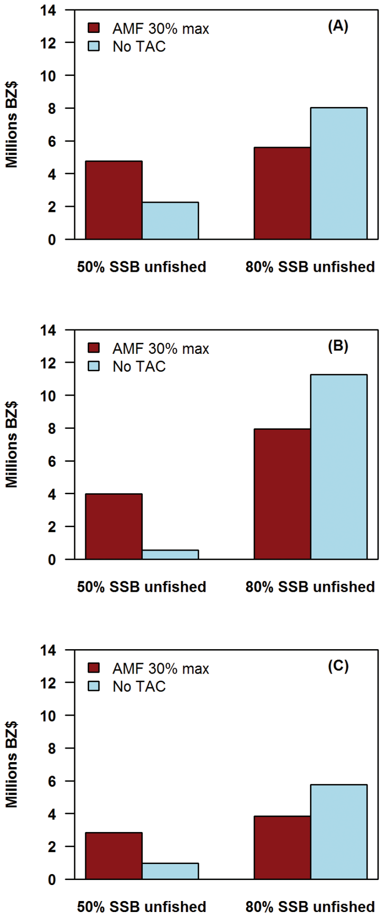

Figure 5. End-state queen conch fishery value (millions BZ$) for base-case scenarios of 0.5 SSB/SSB unfished and 0.8 SSB/SSB unfished initial conditions. Compared are the status quo harvest control rule and adaptive management framework harvest control rule [with 30% max annual total allowable catch (TAC) change]. Summaries are provided for scenarios of (A) constant effort, (B) effort creep at 3% yr^{-1}, and (C) recruitment decline. SSB is spawning stock biomass.

lobster multi-indicator AMF performed similarly or fared better than CPUE alone for most performance metrics (Tables 2, 4). Under the effort creep scenario, CPUE alone fared better than the multi-indicator AMF and we expect that this result occurred because of the influence of the catch indicator producing undesirable TAC increases (or hindering TAC reductions) as fishing effort increased (Tables 2, 4). For queen conch, interpreting the multi-indicator AMF comparison to single-indicators of relative biomass (survey density or CPUE) was more complex and required accounting for instability of biomass trajectories at the beginning of the forward-looking MSE period. First, note that the multi-indicator AMF 30% max TAC adjustment performed better across most scenarios than its 10% max TAC adjustment counterpart (Table 3). The reason for this result is that as declining queen conch biomass trajectories entered the forward-looking MSE period, recursive 10% TAC reductions may have been inadequate in some instances to stop continued biomass declines,

Table 4. Spiny lobster (*Panulirus argus*) performance measures of adaptive management framework when indicators were each applied separately in adjusting total allowable catch up to 10% annually. Simulations were initialized at spawning stock biomass (SSB)/SSB unfished of 0.2 Catches in millions BZ$, CV is coefficient of variation, CPUE is fishery catch per unit effort. Mean values are reported with standard errors in parentheses.

Indicator	Probability of collapse	Biomass stability	Total catch	End-state catch	Catch CV
Without observation error					
Effort creep scenario					
Catch	0.38	0.60 (0.27)	278 (48)	8.8 (2.6)	0.16
CPUE	0.13	0.76 (0.19)	286 (37)	9.4 (1.9)	0.14
Mean length in catch	0.17	0.70 (0.21)	286 (42)	9.2 (2.0)	0.13
Recruitment decline scenario					
Catch	0.08	1.04 (0.31)	204 (31)	5.6 (1.3)	0.25
CPUE	0.07	0.89 (0.21)	216 (29)	6.0 (1.2)	0.24
Mean length in catch	0.17	0.69 (0.19)	217 (30)	5.7 (1.2)	0.23
With observation error					
Effort creep scenario					
CPUE	0.24	0.63 (0.23)	282 (49)	8.9 (2.5)	0.14
Mean length in catch	0.18	0.69 (0.22)	285 (43)	9.1 (2.2)	0.13
Recruitment decline scenario					
CPUE	0.13	0.81 (0.27)	213 (35)	5.6 (1.4)	0.25
Mean length in catch	0.20	0.68 (0.21)	216 (33)	5.6 (1.3)	0.24

whereas 30% TAC reductions had improved performance (Table 3). Second, the use of catch in the multi-indicator AMF probably produced TAC increases (or hindered TAC reductions), thus lowering performance of the multi-indicator AMF relative to CPUE or density alone (Tables 3, 5). Thus, in the case of queen conch dynamics using the relative biomass indicator alone offered better performance than the multi-indicator AMF, although the magnitude of TAC adjustments remains a critical issue in queen conch AMF performance.

Sensitivity Analysis.—In the sensitivity analysis, we modified assumptions about external recruitment to include the effects of 50% self-recruitment, and 10% self-recruitment on HCR performance. In some instances, the post-dispersal recruitment process produced very strong compensatory responses, which should be interpreted with caution. Strong compensatory responses occurred when local spawning stock was greatly depleted, but where external sources of recruitment remained relatively large. This combination of high recruit survival rate coupled with large influx of recruits from area 3, sometimes produced highly unstable dynamics. Fortunately, for both spiny lobster and queen conch, biomass stability was more sensitive to overall biomass declines caused by fishing effort increases or recruitment declines than it was to instability in stock-recruitment dynamics. Across levels of self-recruitment, stability remained highest for the AMF rule, relative to prescriptive alternatives. A notable effect of high quantities of external recruits was on long-term fishery value. Because local stock resiliency was raised with higher external inputs of recruits, higher catches could be sustained without dramatic biomass declines.

Performance sensitivity to stock-recruitment steepness was investigated by modifying the base-case specification of 0.8 for spiny lobster to 0.5 and 0.97. For status quo management, model outcomes were affected by steepness, as decreased steepness

Table 5. Queen conch (*Stombus gigas*) performance measures of adaptive management framework when indicators were each applied separately in adjusting total allowable catch up to 10% annually. Simulations were initialized at spawning stock biomass (SSB)/SSB unfished of 0.5. Catches in millions BZ$, CV is coefficient of variation, CPUE is fishery catch per unit effort. Mean values are reported with standard errors in parentheses.

Indicator	Probability of collapse	Biomass stability	Total catch	End-state catch	Catch CV
Without observation error					
Effort creep scenario					
Catch	0.99	0.02 (0.04)	99 (32)	0.8 (1.0)	0.68
CPUE	0.82	0.32 (0.13)	138 (20)	4.1 (1.1)	0.15
Survey density	0.82	0.32 (0.12)	138 (22)	4.1 (1.2)	0.17
Recruitment decline scenario					
Catch	1.00	0.08 (0.07)	84 (23)	1.0 (0.7)	0.69
CPUE	0.35	0.60 (0.21)	104 (16)	2.8 (0.8)	0.30
Survey density	0.35	0.60 (0.21)	105 (15)	2.8 (0.7)	0.29
With observation error					
Effort creep scenario					
CPUE	0.84	0.33 (0.12)	139 (19)	4.1 (1.0)	0.15
Survey density	0.82	0.31 (0.14)	135 (25)	3.9 (1.3)	0.19
Recruitment decline scenario					
CPUE	0.38	0.58 (0.21)	104 (16)	2.7 (0.7)	0.31
Survey density	0.39	0.53 (0.26)	100 (20)	2.4 (1.0)	0.38

reduced stock resiliency and consequently affected the end-value of the fishery (Fig. 6). Comparatively, the multi-indicator AMF rule was reasonably insensitive to steepness in terms of preserving biomass stability, reducing probability of collapse, and maintaining fishery value (Fig. 6). In the queen conch operating model, we assumed a constant relationship between age and clean meat weight for the south Caribbean region. This age-weight relationship indicated that queen conch entered the fishery in their second year. We specified age at maturation of 4 yrs in the base-case operating model and explored an alternative maturation age of 6 yrs in the sensitivity analysis. In the case of status quo management, probability of collapse was not noticeably reduced by increasing maturation age to 6 yrs. This effect was particularly acute for the effort creep scenario, as fishing effort increased through the forward-looking MSE period (Fig. 7). When the multi-indicator AMF rule was introduced, reasonably similar levels of biomass stability and fishery value were preserved by the control rule. This result suggests that the AMF rule was reasonably robust to uncertainty about maturation for the range of ages that we considered.

Discussion

When data-limited fisheries are managed with little scientific input, poor social and economic outcomes can sometimes result for communities that are dependent on fishing (Worm et al. 2009, Costello et al. 2012). Across all the simulations that we conducted, AMF HCRs (those that annually adjust a TAC) tended to outperform status quo and prescriptive strategies (including increased harvestable size limit and decreased season length) in maintaining biomass stability through time and decreasing the risk of stock collapse. This result occurred not only for scenarios when

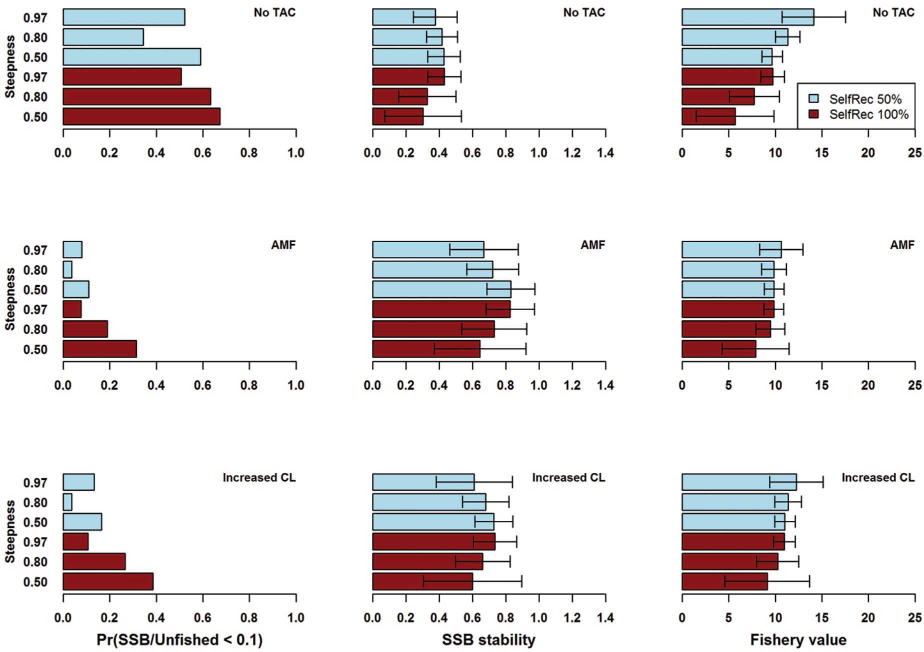

Figure 6. Sensitivity of control rule performance to assumptions about spiny lobster stock-recruitment steepness. Base-case steepness of 0.8 was compared to assumptions of 0.5 and 0.97 in the scenario of effort creep at 3% yr^{-1}. The base-case scenario of initial conditions of SSB/SSB unfished of 0.2 are shown. Rows of plots are harvest control rules [status quo, Adaptive management framework (AMF) with 30% max annual total allowable catch (TAC) change, and Increased carapace length (CL) to 85 mm] and columns are performance metrics [probability of collapse, standing stock biomass (SSB) stability, and Fishery value of processed catch in millions of $BZ]. Error bars are ± 1 standard deviation.

effort stayed constant through time, but perhaps more importantly, also in the scenario of effort creep at 3% yr^{-1} and for environmentally-driven periodic reduction in recruitment. Thus, TACs implemented through indicator-based HCRs appear to offer improved biomass stability and decreased risk of stock collapse relative to circumstances where total catches remain unregulated. As in any management planning process, tradeoffs exist between the HCRs we evaluated. While AMF HCRs performed better in terms of maintaining biomass stability and decreasing the risk of stock collapse, they generally were more conservative than prescriptive control rules in terms of long-term fishery catches.

Our analysis produced three main conclusions about the use of indicator-based approaches to making TAC adjustments. The first conclusion was that management strategy performance can be sensitive to historical stock trajectories entering the time period when a HCR is implemented, and some care is needed in considering plausible historical stock trajectories in MSE design. Our spiny lobster fishery simulations demonstrated that when relatively stable catches have historically persisted, adaptive HCRs can be introduced that help to ensure that these catches can continue into the foreseeable future. That is, an indicator-based AMF can be used to guard against several factors, like increased entry to the fishery or environmentally caused recruitment fluctuations in fisheries that are otherwise relatively stable. Our

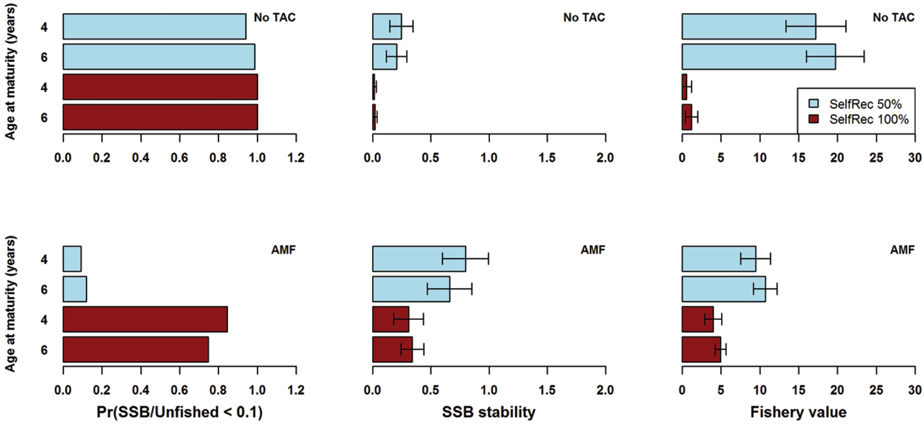

Figure 7. Sensitivity of control rule performance to assumptions about conch age at maturity. Base-case age 4 maturity was compared to age 6 maturity in the scenario of effort creep at 3% yr^{-1}. Simulations initialized at SSB/SSB unfished of 0.5. Rows of plots are harvest control rules [status quo, adaptive management framework (AMF) with 30% max annual total allowable catch (TAC) change] and columns are performance metrics (Probability of collapse, SSB stability, and Fishery value of processed catch in millions of $BZ). Error bars are ± 1 standard deviation. SSB is spawning stock biomass.

simulations did not evaluate regime shifts, and management strategy performance could be substantially poorer under these circumstances (Vert-pre et al. 2013). The simulated declining trajectories of the queen conch stocks illuminated subtler aspects of AMF HCR design, including the possibility that stock declines coupled with environmentally-induced recruitment declines require consideration of the strength of management interventions (i.e., 10% TAC reductions vs 30% TAC reductions).

The second conclusion was that performance of indicator-based management strategies was sensitive to the state of stock depletion corresponding to specified reference conditions. This conclusion was pronounced in queen conch simulations, which demonstrated that optimizing economic performance depended greatly on depletion status. Perhaps problematically, actual reference conditions used to implement indicator-based approaches can rarely be chosen based on actual depletion status, but can be chosen to reflect other conditions like maintaining current catch rates (Hilborn et al. 2002). In simulating an indicator-based AMF, this strategy did not attempt to direct stock dynamics toward the biomass associated with MSY, but importantly, the AMF did serve as a beneficial control against stock collapse. It is clear then that continued long-term use of indicator-based approaches influence the types of management objectives that can be achieved, but conversely, mandated management objectives may influence the long-term viability of indicator-based management approaches. But where data-limitations currently persist, indicator-based HCRs may well support interim fishery policies while alternative policies and monitoring programs are developed, or until sufficiently long time series accumulate that can be used to estimate target or limit reference points via quantitative stock assessment (Caddy and McGarvey 1996, Quinn and Deriso 1999). Queen conch simulations revealed a trade-off between the availability of information for decision-making and the optimality of those decisions. This means that indicator-based management helped to protect spawning biomass in some circumstances, but gaining additional monitoring information that could lead to MSY estimation (or other management reference points) could potentially produce improved catches.

The third conclusion was that the multi-indicator aspect of the AMF HCR reasonably mitigated the influence of observation error on TAC adjustments under the conditions that we simulated. This finding was informative because it demonstrated that when observation errors occur independently between indicators (i.e., are not correlated) that a multi-indicator approach can potentially perform well and can do so without allowing noisy indices to inadvertently influence TAC adjustments. Further, we used a buffer of 1 standard deviation in determining whether indicator values exceeded or fell below reference thresholds, which appeared to be sufficient to prevent erroneous TAC adjustments from being repeatedly implemented. It appears, however, that performance of the AMF HCR was largely driven by relative biomass indices, and this metric should not be undervalued for use in indicator-based HCRs (Geromont and Butterworth 2015b, Jardim et al. 2015, Harford and Babcock 2016).

Our MSE was constructed to provide a first-order evaluation of the multi-indicator adaptive management framework being developed in collaboration with the Belize Fisheries Department. Our performance analysis is only one aspect of the broader stakeholder driven processes associated with fishery policy development (Dowling et al. 2015). In addition, we view MSE as a decision support tool that best fits within a broader and recursive process of consultation with managers and stakeholders. Accordingly, several challenges remain to be addressed through simulated MSE. Operating model development could focus on spatial and temporal fishing patterns, changes in gear types or selectivity, recruitment pulses and shifting baselines in stock productivity, and variability in somatic growth rates. Design of HCRs could focus on refining the reference conditions representing "acceptable" catch levels, examining indicator weightings (perhaps based upon index precision), changing the frequency of TAC adjustments (including setting TACs for several years at a time), hyperstability in CPUE, addressing practical impediments to making timely in-season TAC adjustments, and confronting implementation error, catch compliance, and catch reporting accuracy. Consultation with the Belize Fisheries Department and Belize fisheries experts continues as a means to seek improvement of this management framework.

Acknowledgments

We thank the Belize Fisheries Department for their support of this work. Financial support was provided by The Nature Conservancy. E Babcock's work was supported in part by the Wildlife Conservation Society. This manuscript was greatly improved thanks to the constructive advice of three anonymous reviewers.

Literature Cited

Anderson SC, Mills Flemming J, Watson R, Lotze HK. 2011. Rapid global expansion of invertebrate fisheries: trends, drivers, and ecosystem effects. PLoS One. 6:e14735. http://dx.doi.org/10.1371/journal.pone.0014735

Apostolaki P, Hillary R. 2009. Harvest control rules in the context of fishery-independent management of fish stocks. Aquat Living Resour. 22:217–224. http://dx.doi.org/10.1051/alr/2009022

Appeldoorn RS. 1988. Age determination, growth, mortality and age of first reproduction in adult queen conch, *Strombus gigas* L., off Puerto Rico. Fish Res. 6:363–378. http://dx.doi.org/10.1016/0165-7836(88)90005-7

Ault JS, Smith SG, Bohnsack JA. 2005. Evaluation of average length as an estimator of exploitation status for the Florida coral-reef fish community. ICES J Mar Sci. 62:417–423. http://dx.doi.org/10.1016/j.icesjms.2004.12.001

Babcock EA, Harford WJ, Coleman R. 2013. Updated depletion analysis of spiny lobster (*Panulirus argus*) at Glover's Reef Marine Reserve, for the 2011–2012 and 2012–2013 lobster seasons. Wildlife Conservation Society, Belize City.

Babcock EA, Harford WJ, Coleman R, Gibson J, Maaz J, Foley JR, Gongora M. 2014. Bayesian depletion model estimates of spiny lobster abundance at two marine protected areas in Belize with or without in-season recruitment. ICES J Mar Sci. Article fsu226. http://dx.doi.org/10.1093/icesjms/fsu226

Babcock EA, MacCall AD. 2011. How useful is the ratio of fish density outside versus inside no-take marine reserves as a metric for fishery management control rules? Can J Fish Aquat Sci. 68:343–359. http://dx.doi.org/10.1139/F10-146

Beverton RJH, Holt SJ. 1957. On the dynamics of exploited fish populations. London UK: Chapman and Hall.

Butler MJI, Paris CB, Goldstein JS, Matsuda H, Cowen RK. 2011. Behavior constrains the dispersal of long-lived spiny lobster larvae. Mar Ecol Prog Ser. 422:223–237. http://dx.doi.org/10.3354/meps08878

Caddy JF, McGarvey R. 1996. Targets or limits for management of fisheries? N Am J Fish Manage. 16:479–487. http://dx.doi.org/10.1577/1548-8675(1996)016<0479:TOLFMO>2.3.CO;2

Carruthers TR, Kell LT, Butterworth DDS, Maunder MN, Geromont HF, Walters C, McAllister MK, Hillary R, Levontin P, et al. 2015. Performance review of simple management procedures. ICES J Mar Sci. Article fsv212. http://dx.doi.org/10.1093/icesjms/fsv212

Carruthers TR, Punt AE, Walters CJ, MacCall A, McAllister MK, Dick EJ, Cope J. 2014. Evaluating methods for setting catch limits in data-limited fisheries. Fish Res. 153:48–68. http://dx.doi.org/10.1016/j.fishres.2013.12.014

Chubb CF. 1994. Reproductive biology: issues for management. *In:* Phillips BF, Cobb JS, Kittaka J, editors. Spiny lobster management. Cambridge, MA: Blackwell Scientific Publications. p. 181–212.

Cook RM. 2013. A fish stock assessment model using survey data when estimates of catch are unreliable. Fish Res. 143:1–11. http://dx.doi.org/10.1016/j.fishres.2013.01.003

Costello C, Ovando D, Hilborn R, Gaines SD, Deschenes O, Lester SE. 2012. Status and solutions for the world's unassessed fisheries. Science. 338:517–520. http://dx.doi.org/10.1126/science.1223389

Cruz R, Bertelsen RD. 2008. The spiny lobster (*Panulirus argus*) in the wider Caribbean: a review of life cycle dynamics and implications for responsible fisheries management. Proceedings of the 61st Gulf and Caribbean Fisheries Institute. 61:433–446.

Dick EJ, MacCall AD. 2011. Depletion-based stock reduction analysis: a catch-based method for determining sustainable yields for data-poor fish stocks. Fish Res. 110:331–341. http://dx.doi.org/10.1016/j.fishres.2011.05.007

Dowling NA, Dichmont CM, Haddon M, Smith DC, Smith ADM, Sainsbury K. 2015. Guidelines for developing formal harvest strategies for data-poor species and fisheries. Fish Res. 171:130–140. http://dx.doi.org/10.1016/j.fishres.2014.09.013

Ehrhardt NM. 2005. Population dynamic characteristics and sustainability mechanisms in key western central Atlantic spiny lobster, *Panulirus Argus*, fisheries. Bull Mar Sci. 76:501–526.

Ehrhardt NM, Valle-Esquivel M. 2008. Conch (*Strombus gigas*) stock assessment manual. Caribbean Fishery Management Council.

FAO. 2001. Report on the FAO/DANIDA/CFRAMP/WECAFC regional workshops on the assessment of the Caribbean spiny lobster (*Panulirus argus*). FAO Report No. 619.

Gedamke T, Hoenig JM. 2006. Estimating mortality from mean length data in nonequilibrium situations, with application to the assessment of goosefish. Trans Am Fish Soc. 135:476–487. http://dx.doi.org/10.1577/T05-153.1

Geromont HF, Butterworth DS. 2015a. Complex assessments or simple management procedures for efficient fisheries management: a comparative study. ICES J Mar Sci. 72:262–274. http://dx.doi.org/10.1093/icesjms/fsu017

Geromont HF, Butterworth DS. 2015b. Generic management procedures for data-poor fisheries: forecasting with few data. ICES J Mar Sci. 72:251–261. http://dx.doi.org/10.1093/icesjms/fst232

Gongora M. 2005. Preliminary analysis of growth of queen conch, *Strombus gigas*, in San Pedro, Belize. Proceedings of the 47th Gulf and Caribbean Fisheries Institute. 824–834.

Gongora M. 2010. Assessment of the spiny lobster (*Panulirus argus*) of Belize based on fishery-dependent data. United Nations University Fisheries Training Programme, Iceland [final project]. Available from: http://www.unuftp.is/static/fellows/document/mauro09prf.pdf

Gongora M. 2012. Belize National Conch Report 2012. Belize Ministry of Forestry & Sustainable Development, Belize Fisheries Department, Capture Fisheries Unit. Belize City, Belize.

Harford WJ, Babcock EA. 2016. Aligning monitoring design with fishery decision-making: examples of management strategy evaluation for reef-associated fisheries. Aquat Living Resour. 29(2):205. http://dx.doi.org/10.1051/alr/2016018

Hertz DB, Thomas H. 1983. Risk analysis and its applications. New York: Wiley.

Hilborn R, Parma A, Maunder M. 2002. Exploitation rate reference points for west coast rockfish: are they robust and are there better alternatives? N Am J Fish Manage. 22:365–375. http://dx.doi.org/10.1577/1548-8675(2002)022<0365:ERRPFW>2.0.CO;2

Hordyk A, Ono K, Valencia S, Loneragan N, Prince J. 2014. A novel length-based empirical estimation method of spawning potential ratio (SPR), and tests of its performance, for small-scale, data-poor fisheries. ICES J Mar Sci. Article fsu004. http://dx.doi.org/10.1093/icesjms/fsu004

Hordyk AR, Loneragan NR, Prince JD. 2015. An evaluation of an iterative harvest strategy for data-poor fisheries using the length-based spawning potential ratio assessment methodology. Fish Res. 171:20–32. http://dx.doi.org/10.1016/j.fishres.2014.12.018

Jardim E, Azevedo M, Brites NM. 2015. Harvest control rules for data limited stocks using length-based reference points and survey biomass indices. Fish Res. 171:12–19. http://dx.doi.org/10.1016/j.fishres.2014.11.013

Karnauskas M, McClellan DB, Wiener JW, Miller MW, Babcock EA. 2011. Inferring trends in a small-scale, data-limited tropical fishery based on fishery-independent data. Fish Res. 111:40–52. http://dx.doi.org/10.1016/j.fishres.2011.06.010

Kough AS, Paris CB, Butler MJ IV. 2013. Larval connectivity and the international management of fisheries. PLoS One. 8:e64970. http://dx.doi.org/10.1371/journal.pone.0064970

Little LR, Wayte SE, Tuck GN, Smith ADM, Klaer N, Haddon M, Punt AE, Thomson R, Day J, Fuller M. 2011. Development and evaluation of a cpue-based harvest control rule for the southern and eastern scalefish and shark fishery of Australia. ICES J Mar Sci. 68:1699–1705. http://dx.doi.org/10.1093/icesjms/fsr019

MacCall AD. 2009. Depletion-corrected average catch: a simple formula for estimating sustainable yields in data-poor situations. ICES J Mar Sci. 66:2267–2271. http://dx.doi.org/10.1093/icesjms/fsp209

Mace PM. 1994. Relationships between common biological reference points used as thresholds and targets of fisheries management strategies. Can J Fish Aquat Sci. 51:110–122. http://dx.doi.org/10.1139/f94-013

Martell S, Froese R. 2012. A simple method for estimating MSY from catch and resilience. Fish Fish. http://dx.doi.org/10.1111/j.1467-2979.2012.00485.x

McCauley DJ, McLean KA, Bauer J, Young HS, Micheli F. 2012. Evaluating the performance of methods for estimating the abundance of rapidly declining coastal shark populations. Ecol Appl. 22:385–392. http://dx.doi.org/10.1890/11-1059.1

McGilliard CR, Hilborn R, MacCall A, Punt AE, Field JC. 2011. Can information from marine protected areas be used to inform control-rule-based management of small-scale, data-poor stocks? ICES J Mar Sci. 68:201–211. http://dx.doi.org/10.1093/icesjms/fsq151

Mesnil B, Cotter J, Fryer RJ, Needle CL, Trenkel VM. 2009. A review of fishery-independent assessment models, and initial evaluation based on simulated data. Aquat Living Resour. 22:207–216. http://dx.doi.org/10.1051/alr/2009003

Patterson KR. 1998. Assessing fish stocks when catches are misreported: model, simulation tests, and application to cod, haddock, and whiting in the ICES area. ICES J Mar Sci. 55:878–891. http://dx.doi.org/10.1006/jmsc.1998.0351

Pomarede M, Hillary R, Ibaibarriaga L, Bogaards J, Apostolaki P. 2010. Evaluating the performance of survey-based operational management procedures. Aquat Living Resour. 23:77–94. http://dx.doi.org/10.1051/alr/2010005

Punt AE, Butterworth DS, de Moor CL, De Oliveira JAA, Haddon M. 2014. Management strategy evaluation: best practices. Fish Fish. 17(2):303–334. http://dx.doi.org/10.1111/faf.12104

Quinn TJI, Deriso RB. 1999. Quantitative fish dynamics. New York, USA: Oxford University Press.

Ralston S, O'Farrell MR. 2008. Spatial variation in fishing intensity and its effects on yield. Can J Fish Aquat Sci. 65:588–599. http://dx.doi.org/10.1139/f07-174

Sainsbury K, Punt AE, Smith ADM. 2000. Design of operational management strategies for achieving fishery ecosystem objectives. ICES J Mar Sci. 57:731–741.

Smith SG, Ault JS, Bohnsack JA, Harper DE, Luo J, McClellan DB. 2011. Multispecies survey design for assessing reef-fish stocks, spatially-explicit management performance, and ecosystem condition. Fish Res. 109:25–41. http://dx.doi.org/10.1016/j.fishres.2011.01.012

Truelove NK, Burdfield-Steel E, Griffiths S, Ley-Cooper K, Preziosi R, Butler MJI, Behringer DC, Box S, Canty S. 2012. Genetic connectivity of Caribbean spiny lobster (*Panulirus argus* in Belize. Proceedings of the 64th Annual Gulf and Caribbean Fisheries Institute. Puerto Morelos Mexico 463–467.

Vert-pre KA, Amoroso RO, Jensen OP, Hilborn R. 2013. Frequency and intensity of productivity regime shifts in marine fish stocks. Proc Natl Acad Sci USA. 110:1779–1784. http://dx.doi.org/10.1073/pnas.1214879110

Villegas L, Jones AC, Labisky RF. 1982. Management strategies for the spiny lobster resources in the western central atlantic: a cooperative approach. N Am J Fish Manage. 2:216–223. http://dx.doi.org/10.1577/1548-8659(1982)2<216:MSFTSL>2.0.CO;2

Walters CJ, Martell SJD. 2004. Fisheries ecology and management. USA: Princeton University Press.

Wayte SE, Klaer NL. 2010. An effective harvest strategy using improved catch-curves. Fish Res. 106:310–320. http://dx.doi.org/10.1016/j.fishres.2010.08.012

Wilson JR, Prince JD, Lenihan HS. 2010. A management strategy for sedentary nearshore species that uses marine protected areas as a reference. Mar Coast Fish. 2:14–27. http://dx.doi.org/10.1577/C08-026.1

Worm B, Hilborn R, Baum JK, Branch TA, Collie JS, Costello C, Fogarty MJ, Fulton EA, Hutchings JA, Jennings S, et al. 2009. Rebuilding global fisheries. Science. 325:578–585. http://dx.doi.org/10.1126/science.1173146

Zhang Z. 2013. Evaluation of logistic surplus production model through simulations. Fish Res. 140:36–45. http://dx.doi.org/10.1016/j.fishres.2012.12.003