Management strategy evaluation of United States Caribbean yellowtail snapper (Ocyurus chrysurus): Advancing management advice for United States Caribbean fish stocks

Matt Damiano[1,2]*, Matt Zink[1], Adyan Rios[3], Kevin McCarthy[3], Cassidy Peterson[2]

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Authors: Matt Damiano[1,2]*, Matt Zink[1], Adyan Rios[3], Kevin McCarthy[3], Cassidy Peterson[2]

[1]Division of Marine Fisheries, North Carolina Department of Environmental Quality, Morehead City, NC, USA

[2]Southeast Fisheries Science Center, National Marine Fisheries Service, Beaufort, NC, USA

[3]Southeast Fisheries Science Center, National Marine Fisheries Service, Miami, FL, USA

*Corresponding author, matt.damiano@deq.nc.gov

Structured Abstract

Objective

Uncertainty stemming from data limitations in the U.S. Caribbean fisheries management system have historically precluded the use of conventional integrated stock assessment to generate model-based management advice. During 2015-2016, the NOAA Southeast Fisheries Science Center conducted a data-limited management strategy evaluation (MSE) for four US Caribbean fish stocks, including yellowtail snapper (*Ocyurus crysurus*). Although index-based management procedures (MP) showed broad promise for managing data-limited stocks, the results were not used to generate management advice. US Caribbean data streams have grown over the past decade, potentially enabling the estimation of model-based reference points. Whether this approach satisfies management objectives in the long-term remains unknown, and most stocks managed by the Caribbean Fishery Management Council remain data limited. Therefore, the goal of this study was to evaluate, using MSE, the performance past, present and index-based MPs against key fishery management objectives and a range of uncertainty for the data-limited US Caribbean yellowtail snapper stock.

Methods

We conducted a size-structured MSE for US Caribbean yellowtail snapper as a case study to test the long-term performance of model-based, catch-averaging, market-driven, and index-based MPs. We tested MPs against a range of uncertainty in recruitment dynamics and provided measures of relative risk of the stock experiencing overfishing or becoming overfished 30 years into the future.

Results

Model- and index-based MPs performed comparably in the long-term with low risk of overfishing or being overfished. The catch-averaging-based MP performed worst by exhibiting the greatest risk of overfishing and of being overfished.

Conclusion

Model-based advice is appropriate for stocks with sufficient data, while data-limited MPs such as index-based methods remain a viable path forward to managing data-limited stocks in the US Caribbean.

Lay Summary

We determined, using simulation-testing, that management advice based on a stock assessment model or a survey index of relative abundance result in a low risk of overfishing the stock or an overfished state for US Caribbean yellowtail snapper in the long-term. Yellowtail snapper, like most of the stocks managed by the Caribbean Fishery Management Council, is data-limited. Therefore, we conclude that index-based management procedures remain a viable alternative to stock assessment models for generating management advice, especially when data limitations create substantial uncertainty.

Introduction

The United States (US) Caribbean fisheries management system is comprised of three island platforms: Puerto Rico (PR), St. Thomas and St. John (STTJ), and St. Croix. Federal fisheries management is overseen by the Caribbean Fishery Management Council (CFMC) and fisheries are managed according to recently adopted island platform-specific fishery management plans (FMP) (Crabtree 2019a, 2019b, 2019c). Fisheries management in the US Caribbean is characterized by high uncertainty, largely stemming from data limitations. These data limitations include a general lack of information on removals, i.e., landings, and effort information from recreational sectors (Goedeke et al. 2016), sporadic gaps in fishery-dependent sampling (Godwin et al. 2024), and few fishery-independent data streams limited in space and/or time (Grove et al. 2021, Cruz Motta 2024).

Historically, these data limitations have prevented the application of both integrated age-structured stock assessment models in the region, as well as data-limited empirical approaches, with most stocks managed using a constant catch harvest control rule (HCR) (Sagarese et al. 2018). As more fishery-dependent data and some fishery-independent survey data have become available over the past decade, the Southeast Fisheries Science Center (SEFSC) of the National Marine Fisheries Service identified four federally managed candidates for stock assessment via a systematic review of data streams (SEDAR 2016, Sagarese et al. 2018) and a synthesis of life history information (Stevens et al. 2019). Integrated statistical catch-at-age modelsusing the Stock Synthesis modeling platform (Methot & Wetzel 2013), have been applied to four identified US Caribbean stocks, two of which include queen triggerfish (*Balistes vetula*) and spiny lobster (*Panulirus argus*) (SEDAR 2019, 2022a, 2022b). However, the CFMC has adopted island-based fisheries management, regardless of stock structure (Kough et al. 2013, Antoni 2017, Saillant et al. 2022, Shervette and Rivera-Hernandez 2022), with separate assessments required for each island platform. Island-based fisheries management creates additional data limitations: for example, sample sizes for size composition information are reduced by dividing data for a given stock by island platform.

Stock assessments for US Caribbean spiny lobster and queen triggerfish have produced estimated fishing mortality (*F*)-based biological reference points using spawning potential ratio

(SPR)-based proxies, which are used to set catch targets. Stock status, however, was not estimable by island platform (SEDAR 2019, 2022a, 2022b). Stock assessments assumed the null stock-recruitment relationship (Brooks 2024) to model each island platform's individuals as an open population. Therefore, individual model results by island platform did not allow for conclusions at the population level. Development of integrated statistical catch-at-age assessment models enabled a shift from management via constant catch to model-based catch advice (Cope 2024) using a threshold HCR. For the other two identified stocks, US Caribbean yellowtail snapper (*Ocyurus chrysurus*) and stoplight parrotfish (*Sparisoma viride*), data limitations and few estimable parameters precluded estimation of either *F* or biomass-based reference points using a statistical catch-at-age model (SEDAR 2025a, 2025b). The effects of data limitations and model uncertainty have largely been explored through sensitivity runs and model diagnostics. analyses (SEDAR 2025a, 2025b, 2025c, 2025d, 2025e). However, the extent to which these uncertainties affect the long-term performance of model-based catch advice remains unknown.

When uncertainty threatens the integrity of the current or proposed management approach, a management strategy evaluation (MSE) is justifiable (Walter et al. 2023). MSE is a closed-loop simulation framework that seeks to model the entire socio-ecological management system, is designed to stress-test alternate MPs against a range of uncertainties, and can evaluate MP performance against a set of pre-defined objectives (Butterworth and Punt 1999, Punt et al. 2016). MSE ideally involves regular stakeholder input to define and refine fisheries management objectives before and during simulation-testing, and iteratively engage with MSE outputs, as MPs are tuned to meet objectives and identify tradeoffs (Punt et al. 2016). However, MSE can require a large time commitment (years) from stakeholders and scientific staff, often requiring substantial financial investment in the process. In lieu of such a "full" MSE process, intermediate or "desk" MSEs can be conducted as a simulation exercise with limited or no stakeholder engagement (Damiano et al. 2022, Walter et al. 2023). Desk MSEs should be used when management objectives are already known to reduce stakeholder fatigue and more appropriately utilize available resources given the research question (Walter et al. 2023).

Prior to the pursuit of stock assessment using statistical catch-at-age models, a desk MSE was conducted during SEDAR 46 using the DLMtool R package (Carruthers and Hordyk 2018) for US Caribbean queen triggerfish, spiny lobster, yellowtail snapper, and stoplight parrotfish to address whether adaptive data-limited MPs could outperform the constant catch HCR (SEDAR 2016, Sagarese et al. 2018). Sagarese et al. (2018) conditioned the simulation on available data and tested a broad array of generic data-limited MPs that use empirical stock indicators, e.g., catch-per-unit-effort or an index of relative abundance (Geromont and Butterworth 2015). The analysts broadly concluded that empirical MPs, such as those based on an index target, outperformed the constant catch MP by achieving comparable yields while protecting a larger proportion of the spawning stock (SEDAR 2016, Sagarese et al. 2018). Therefore, empirical MPs could be a viable approach for management given data limitations and system uncertainty in the US Caribbean (SEDAR 2016, Sagarese et al. 2018). Ultimately, the results of the MSE were not recommended for use in management due to a lack of MP tuning, a topic we return to in the Discussion.

The CFMC is responsible for managing 179 fish species, the most of any of the eight fishery management councils, and most of these stocks are data-limited (Sagarese et al. 2018). Data-limitations continue to hinder efforts toward implementation of integrated statistical catch-at-age models (SEDAR 2025a, 2025b), and the ability of recent model-based management to achieve legally mandated and stakeholder defined management goals is unknown. These caveats have recently generated strong interest in exploring management approaches for the US Caribbean alternative to traditional stock assessments. Current efforts prioritize reevaluating all available datasets to identify applicable data-limited methods and streamlined approaches that provide more timely management guidance (CFMC SSC, personal comm.). Furthermore, the CFMC has expressed concern about the potential effects of nonstationary recruitment, as seen in the Southeast United States Atlantic (Wade et al. 2023, Shertzer et al. *in prep*.), on the population dynamics of federally managed reef fish stocks in the region (CFMC, personal comm.).

Therefore, the questions remain as to what MPs are a suitable path forward for the US Caribbean's data-limited stocks, or those for which data is more plentiful, but stock assessment has not been able to produce reference points for management. To address these questions, we conducted a desk MSE for US Caribbean yellowtail snapper. The objectives of this study were to: evaluate past and current status quo MPs, model-based MPs, an index-based empirical MP, and market-driven fishing effort over a range of recruitment uncertainty; identify tradeoffs between MPs where they may occur; and evaluate the relative long-term risk associated with each MP at the US Caribbean scale.

Methods

Operating models

The MSE was conducted using the size-structured framework described in Damiano et al. (2024), in which operating models (OMs) simulated size-structured population dynamics for PR and STTJ yellowtail snapper during 2012-2023. Stock assessments were recently conducted for the PR and STTJ island platforms using Stock Synthesis (SEDAR 2025a, 2025b). The focus of this study was on the performance of MPs at the US Caribbean (e.g., population-wide) scale, so we used an areas-as-fleets approach, where each fleet corresponds to an island platform and corresponding differences in availability of yellowtail snapper by island platform were modeled as a function of fleet selectivity (Hurtado-Ferro et al. 2014). OMs were not conditioned on true data; they were simulated using the parameters obtained from the 2025 stock assessments for PR (SEDAR 2025a) and STTJ (SEDAR 2025b). The 2012-2023 time period was selected as the historical period for the MSE based on the number of years for which data were available from both PR and STTJ island platforms (2012-2022), plus a one-year of projected fishing mortality (2023).

We used 16 size bins at three-centimeter increments from 3-48 cm fork length to be consistent with the length composition from each stock assessment (SEDAR 2025a, 2025b). The initial size composition of the population was assumed to decline exponentially from the smallest size bin (3 cm). Distribution of recruits by size bin was assumed to follow a similar pattern with 50% distributed to the minimum size bin (3 cm) and none beyond the 15-cm bin for general consistency with SEDAR 84 (2025a, 2025b). Abundance-at-size for each year was calculated as a function of abundance-at-size that survived total mortality and grew, and new fish recruited to the stock during the previous year. Recruitment was modeled using the null (“mean”) recruitment model (Brooks 2024) with lognormally distributed annual deviations. Growth was modeled using a growth transition matrix (Chen et al. 2003, Cao et al. 2017). Mortality was assumed to occur instantaneously throughout the year. Natural mortality (M) was assumed constant and time-invariant, and we provided a matrix of estimated F values by fleet from the PR and STTJ stock assessments. Fishery selectivity was assumed asymptotic for the PR and STTJ “fleets” and parameterized using values from each stock assessment. Catch was modeled using the Baranov catch equation (Sharov 2021). We assumed a 50-50 sex ratio, and spawning stock biomass was a function of female abundance, asymptotic maturity, and fecundity (number of eggs).

We modeled a single fishery-independent survey based on the National Coral Reef Monitoring Program (NCRMP) Reef Visual Census (RVC), which provides an annual design-based index of relative abundance for PR and STTJ during 2012-2015 and then every other year during 2016 onward (Grove et al. 2021). The RVC substantially expanded its spatial coverage from 2016 onward (Grove et al. 2021), and US Caribbean stock assessments are typically fit to RVC data beginning in 2016 (SEDAR 2022a, 2022b, 2025a, 2025b). OM-simulated data cannot accommodate missing years (Damiano et al. 2024). Therefore, we assumed an uninterrupted time series during 2012-2023 for the RVC under the assumption that data during 2012-2015 could be combined over space and time with data from 2016 onward using a survey data combination method similar to O'Leary et al. (2022). Additional details concerning the population dynamics functions are described in the supplementary material of Damiano et al. (2024). We assumed a double-logistic dome-shaped selectivity for the survey as the RVC is limited by depth constraints and does not detect the largest size classes of yellowtail snapper that appear in the fisheries (SEDAR 2025a, 2025b).

We constructed three reference OMs characterized by unique recruitment conditions. Each OM was projected forward for 30 years with a five-year management cycle. The mean recruitment, *R0*, was projected at the historical average ("average"), half of the historical average ("low"), or using a vector of pre-defined random values of *R0* to represent nonstationary fluctuations in the average condition ("nonstationary") (Table 1). Robustness testing was conducted via six OMs to explore the effects of uncertainty in size-structured OM assumptions and to examine the effect of alternate life history parameters to which the stock assessments were highly sensitive (SEDAR 2025a, 2025b). Effects of these potential sources of uncertainty can potentially be used to determine exceptional circumstances, i.e., circumstances that cause management action to deviate from or revise the MP (de Moor et al. 2022, Walter et al. 2023). Specifically, we explored the effects of alternative settings related to the initial size composition, where a larger relative proportion of fish (50%) is assigned to the 12-cm and 15-cm bins; the distribution of recruits by size bin, where all recruitment is assigned to the 3-cm and 6-cm bins; and an alternate, positive degree of correlation between von Bertalanffy growth parameters. We also examined the effects of alternative parameter values for the growth transition matrix: the von Bertalanffy growth parameters, asymptotic average length L_∞ and Brody growth coefficient K, and the correlation between the two, rho; and a higher rate of M (Table 1). Average recruitment conditions were assumed for all robustness grid OMs.

Estimation model

The size-structured MSE estimation model (EM) is a size-structured stock assessment model (Cao et al. 2017) written in AD Model Builder software (Fournier et al. 2012). The size-structured EM is a forward-projecting statistical catch-at-size model that is functionally similar to Stock Synthesis and other statistical catch-at-age stock assessment models; the key difference is that growth is quantified using a growth transition matrix to model discrete changes in growth potentially to any larger size bin depending on the life history of the stock (as opposed to growing from an X-year old fish to a X+1-year old fish) (Chen et al. 2003, Cao et al. 2017). Although initially designed for an invertebrate stock (Cao et al. 2017), the model has since been employed in stock assessment (North Carolina Division of Marine Fisheries 2022) and MSE (Damiano et al. 2024) for finfish stocks. EM functions are described in detail in Cao et al.

(2017). The EM is fit to historical and projected data to estimate a time series of F and F-based reference points that were used to form the basis of the HCR applied within each MP. During each stock assessment interval, the following parameters were estimated: annual recruitment deviations, annual F deviations by fleet, initial F, fleet selectivity, survey selectivity, and survey catchability.

Management procedures

We tested model-based and empirical MPs (Table 2). Model-based MPs used EM-based estimates of spawning potential ratio (SPR) F maximum sustainable yield (MSY) proxies to define management recommended fishing effort. Empirical MPs tested included index-based control rules and constant average catch. Additionally, we explored a model-based MP in which a random walk was simulated to approximate fluctuations in market demand (Table 2). All MPs were F-based; the MP-recommended F was directly applied within the OM for each year of the management cycle, rather than estimating total allowable catch, i.e., landings, as would occur in practice. This is a simplifying assumption that may underestimate associated uncertainty in MP performance.

Each model-based MP consisted of the EM and an HCR. The same EM was used for each of the three model-based MPs tested. The first MP is defined by an HCR that fishes the stock at a constant rate that will reduce SPR to 30%, F_{30} ("*F30*"). The second HCR fishes the stock at a constant rate of 75% of F_{30} ("*75% F30*"). The third HCR approximates the threshold HCR commonly applied to Southeast US federal marine fisheries, including those in the US Caribbean, which fishes the stock at a constant rate (F_{30}), but introduces a biomass threshold that, if SSB drops below the threshold, the stock is considered overfished and fishing stops until the next stock assessment ("*F30 with B-thresh*"). The overfished threshold was defined as the average SSB during the historic period, because stock status and a minimum stock size threshold could not be estimated in the stock assessments (SEDAR 2025a, 2025b).

The fourth MP scales the projected rate of F using a modified version of the generic *iTarget* MP, described in Geromont and Butterworth (2015); the algorithm produces a target rate of F, F_{targ}, that scales the terminal estimate of apical F, F_{apex}, using the index of relative abundance:

$$F_{targ} = F_{apex} * \left[1 + \left(\frac{I_{rec} - I_{ref}}{I_{targ} - I_{ref}}\right)\right] \text{ if } I_{rec} \geq I_{ref} \qquad (1),$$

or,

$$F_{targ} = F_{apex} * \left[\frac{I_{rec}}{I_{ref}}\right]^2 \text{ if } I_{rec} < I_{ref} \qquad (2),$$

where I_{rec} represents the average of the last five years of relative abundance; I_{ref} represents 80% of average relative abundance during the historic period, and I_{targ} is the target level of relative abundance, which we assumed was the average relative abundance during the historic period ("*iTarget*"). We omitted the 0.5 scalar from Equations 1 and 2 (Geromont and Butterworth 2015) and chose the values of I_{ref} and I_{targ} such that the MP would target an intermediate level of abundance that was achieved during the historic period. This MP is also the closest approximation to the index target MP tested by Sagarese et al. (2018).

The fifth MP fishes the stock at a constant rate of F based on the average total F achieved during 2017-2020 to approximate the constant catch HCR from Sagarese et al. (2018) ("*Catch* *avg*"). The sixth MP assumes that local market conditions dictate the magnitude of fishing effort, as is common in US Caribbean fisheries (Agar et al. 2024, Karnauskas et al. 2024); this MP modifies the model-based F_{30} each assessment cycle using a simple random walk function to simulate fluctuations in market demand ("*Random walk F*"):

$$F_{y+1} = F_y + \alpha, \quad (3),$$

where projected F is a function of F in the previous year (y) plus the normally distributed drift parameter α, with a mean of 0 and variance of 0.08 to achieve variability in landings consistent with SEDAR 84 (2025a, 2025b). Essentially, in the *Random walk F* MP, management advice is heeded but not strictly adhered to.

Study design

All MPs were simulation-tested over the reference grid resulting in 18 unique OM-MP combinations. Only the *F30* MP was simulation-tested over the robustness grid, therefore the total OM-MP combinations tested in this study was 24. Management implementation errors were included during projections through uncertainty in allocation proportions. A vector of allocation proportions by fleet was drawn from a normal distribution using the mean and standard deviations of F that each fleet was responsible for during the previous 10 years and applied to MP-recommended Fs for each year of the management cycle (Damiano et al. 2024); this allows fleets to fish near but not precisely at hypothetical allocations.

Observation error was applied to the OM-simulated landings and index of abundance values to generate observed values that were input into the EM. We applied a coefficient of variation (CV) of 0.05 to landings, consistent with the PR and STTJ stock assessments (SEDAR 2025a, 2025b). We applied a CV of 0.35 for the index of relative abundance and assumed an annual effective sample size of 50 fish for both fishery-dependent and independent length compositions to approximate the relatively low number of fishery-dependent samples (SEDAR 2025a, 2025b).

Model sampling error was included by simulating 200 iterations of each OM and MP. Process error was included in all simulations using randomly generated lognormal deviations in mean recruitment during projections. Stochastic deviations in mean recruitment were saved from the first 200 iterations and applied during all other MP simulation-testing to ensure a comparable study design. Any EM fits to OM and projection data that did not converge were removed and the model was re-run such that summarized data represented only convergent models. In other words, if the model failed, the iteration was rejected and the model was re-run using the same data until a convergent model was obtained. No post-hoc statistical tests were conducted on results.

Objectives and performance metrics

For the purposes of this desk MSE, we assumed management objectives were known. Consistent with legally mandated objectives in US federal fisheries management (Walter et al. 2023), we rely on two primary objectives for the purposes of interpretation and trade-off analyses: 1) prevent overfished status and 2) prevent overfishing. These are the same two objectives that were assumed by Sagarese et al. (2018). We relied on estimates of SSB in number of eggs and rates of F to analyze the effects of each MP on the population dynamics. We also provide estimates of recruits, population abundance, and landings in 1000s of fish for further interpretation of MSE results. We summarized these results by taking the median of projections over all 200 iterations and providing the 10^{th} and 90^{th} quantiles to quantify variation across iterations.

To measure the performance of each MP with respect to the two primary objectives, we calculated the number of iterations in which the projected rate of *F* exceeded the maximum fishing mortality threshold (MFMT) at any point in the projection period. MFMT was assumed to be equal to the average total *F* during the historic period. We also calculated the number of iterations in which the projected SSB decreased below the minimum stock size threshold (MSST) at any year in the projection period, where MSST was assumed to be equal to the average SSB during the historic period. These assumptions were necessary due to the inability to obtain stock-wide values of MFMT or MSST from the recent stock assessments (SEDAR 2025d, 2025e).

Results

EM fits to OM and projected data were generally stable with a convergence rate of >99% for MPs tested across reference and robustness grids. The population dynamics of the historic period were defined by higher recruitment at the beginning of the time series followed by a steep decline. This led to a lagged peak in abundance and corresponding peak in SSB followed by a decline to approximately the MSST (Figure 1). Estimated rates of *F* for PR and STTJ produced correspondingly high and low landings during periods of high and low abundance (Figure 1).

Under average recruitment conditions, median recruitment was maintained at an intermediate-to-low level with large variability across iterations (Figure 1). MPs performed similarly with respect to median abundance under average recruitment conditions (Figure 1). *75% F30* achieved the highest median SSB, followed by *F30* (Figure 1). *F30 with B-thresh* achieved a notably higher SSB during the first five years of projections but declined to a median SSB comparable with *F30* afterward (Figure 1). *iTarget* initially achieved a median SSB comparable with *75% F30* during the first 15 years of projections but then declined to a median SSB comparable to what was achieved by the *Random walk F*, which maintained an SSB lower than *F30* throughout the projection period (Figure 1). *Catch avg* achieved the lowest median SSB, dropping below the MSST several times (Figure 1). Conversely, *Catch avg* achieved the highest landings in both PR and STTJ (Figure 1). *F30 with B-thresh* activated the biomass threshold trigger because the historic period SSB dropped below the MSST in the terminal year (2023); in the next projection cycle, the closure created a small increase in median landings greater than or comparable to *Catch avg* in the two years that followed; the initial peak can be seen in SSB over that same five-year period (Figures 1 and 2). The other MPs performed comparably with respect to landings, achieving intermediate catch relative to the historic period (Figure 1).

Under low recruitment conditions, the projected dynamics were generally similar to those under average recruitment conditions (Figure 2). The *iTarget* MP achieved the largest median SSB, which increased continuously throughout the projections as landings declined with each stock assessment cycle (Figure 2). These results indicated that while recruitment remained low, I_{rec} could never be greater than I_{ref} (Supplemental Material section 1). Consequently, F would be scaled down with each assessment cycle, leading to higher spawning stock biomass. The other MPs performed comparably with respect to landings, achieving lower catches relative to the historic period (Figure 2). However, the relative performance of each MP shifted in terms of island-based landings when compared to the average recruitment scenario.

Under nonstationary recruitment conditions, changes to the average recruitment each projection cycle resulted in similar oscillations in abundance and SSB (Figure 3). Only the *Random walk F* and *Catch avg* MPs resulted in median SSB dropping below the MSST (Figure 3). MPs produced similar patterns in landings for both PR and STTJ (Figure 3). Apart from *F30 with B-thresh*, there was generally little difference in the magnitude of landings among MPs, but magnitude of landings oscillated with changes in the average recruitment each projection cycle (Figure 3). Relative ranking of MPs by landings shifted under nonstationary recruitment scenario compared to average recruitment.

The nested box and violin plots synthesized and further illustrated the range of possible outcomes with respect to SSB and landings by MP. *75% F30* consistently achieved the highest SSB across 200 iterations of the terminal year in the final five-year projection, regardless of recruitment conditions, except for *iTarget* in the low recruitment scenario (Figure 4). *F30 with B-thresh* could achieve higher SSB under average recruitment conditions (Figure 4), but this was enabled by the fishery closure during the first projection cycle (Figure 1). *Random walk F* and *Catch avg* consistently resulted in the lowest SSB, and at comparable levels, regardless of recruitment condition (Figure 4). *Catch avg* and *Random walk F* MPs produced the highest level of landings over the smallest spread, followed by *F30* and *75% F30* (Figure 4). *F30 w/ B-thresh* and *iTarget* had the largest spread of possible landings, which was to be expected given each MP's design, i.e., shutting the fishery down after an overfished state, and scaling *F* to achieve a target level of abundance, respectively (Figure 4). As with SSB, *F30 with B-thresh* could technically achieve a high level of landings under average and nonstationary recruitment conditions, but this was also likely driven by the subsequent bump in SSB achieved by the fishery closure that occurred during the first projection cycle (Figures 1, 3).

Recall that MFMT and MSST are assumed to equal historical average *F* and SSB. Regardless of recruitment conditions, *F30, 75% F30*, and *F30 with B-thresh* MPs resulted in the stock being in an overfished condition less than five percent of the time (i.e., < 5% over all 200 iterations of the 30-year projection period), with zero probability of experiencing overfishing (Tables 3-4). Under low recruitment conditions, no MP resulted in a probability of experiencing overfishing exceeding 1% (Table 4); however, this was likely a function of landings being maintained at low levels (Figure 4). The stock was overfished and experiencing overfishing under the *iTarget* MP approximately 18-20% of the time under average and nonstationary recruitment conditions (Tables 3-4). The *Catch avg* MP resulted in the stock being overfished approximately 45% of the time under average and nonstationary recruitment conditions, and 12.1% under low recruitment conditions (Table 3). The *Random walk F* MP resulted in the stock being overfished 24.5% of the time under average and nonstationary recruitment conditions, and 4.9% of the time under low recruitment conditions (Table 3). The probability of overfishing for *Catch avg* and *Random walk F* MPs were relatively high by comparison (Table 4).

Only the *F30* MP was simulation-tested over the robustness grid (Table 1). The alternative initial abundance composition, recruitment distribution, and alternate correlation parameter for von Bertalanffy growth parameters did not result in substantially different median estimates of population dynamics quantities (Figure 5). The higher rate of *M* resulted in large reductions in abundance, SSB, and landings in PR (Figure 5). The alternate values of L_∞ and *K* resulted in lower SSB but not abundance, and the alternate value of *K* resulted in lower PR catch (Figure 5). The magnitude of STTJ landings was comparable across the robustness grid (Figure 5).

Discussion

We conducted a desk MSE for US Caribbean yellowtail snapper by simulation-testing six model-based and empirical MPs over a range of recruitment uncertainty and against the two primary objectives of US federal fisheries management. Most model-based MPs were robust to recruitment uncertainty with minimal risk of overfishing or overfished status. Model-based MPs such as *F30* and *75% F30* were notably robust to the nonstationary recruitment scenario, consistent with Shertzer et al.'s conclusions that $F_{\%}$ SPR proxies are robust to various forms of recruitment nonstationarity for Southeast US Atlantic snapper-grouper stocks (*in prep*). The *Catch avg* MP performed worst with respect to the probabilities of overfishing and of being overfished, which, provided that F_{30} is a reasonable proxy for F_{MSY}, demonstrates the overall improvement of model-based reference points over the status quo constant catch HCR. The relatively small effect of alternative growth parameters demonstrated by the robustness grid further support the general robustness of $F_{\%}$ SPR proxies to nonstationarity in underlying biological processes for snapper-grouper species (Shertzer et al. 2024). However, managing with $F_{\%}$ SPR targets is less straightforward in practice, because we cannot practically manage fishing mortality rate; instead, management advice is translated into annual catch limits, which are then imperfectly implemented and measured. Rate-based control rules can, however, technically be achieved in data-limited situations through input (effort) controls (Macpherson et al. 2022).

No stock assessment in the US Caribbean to date has resulted in the successful estimation of stock status (SEDAR 2016, 2019, 2022a, 2022b, 2025a, 2025b, 2025c, 2025d, 2025e), which we note is largely due to the nature of island-based management. However, we demonstrated that model-based MPs using $F_{\%}$ SPR proxies generally avoid overfished status by focusing on preventing overfishing, i.e., what fisheries management hypothetically controls (Shertzer et al. *in* *prep or in review*). Although the SSB limit used in the *F30 with B-thresh* MP was somewhat arbitrary, Damiano et al. (2024) similarly demonstrated that $F_{\%}$ SPR proxies achieve levels of SSB above the true MSST by targeting a specific level of effort, i.e., *F* to meet management objectives. The performance of the *F30 with B-thresh* MP suggested that fishery closures could result in sizeable short-term increases in landings, but generally, the long-term performance does not differ from fishing at F_{30} without a biomass threshold. Therefore, fishing at a more conservative $F_{\%}$ SPR proxy instead of closing the fishery may prevent short-term economic impacts to fishermen, even if the stock is briefly in an overfished condition or experiencing weak recruitment in the long-term. Although we did not test such an MP in this study, another alternative would be a ramped threshold HCR where *F* is gradually reduced at low biomass levels.

Reporting and compliance in the US Caribbean remain highly uncertain (Sagarese et al. 2018). To that effect, the *Random walk F* MP was meant to represent the true status quo in which management advice is recognized, but market conditions ultimately dictate the extent of fishing effort. In this sense, this model-based MP is essentially another form of implementation error meant to model the economic reality of the region, in contrast to the *F30* MP which represents stricter adherence to the model-based management advice provided by the stock assessment. Our results suggest that, insofar as they are approximated, allowing market conditions to dictate fishing effort results in higher probabilities of overfishing and of the stock being overfished. Without additional monitoring coupled with increased enforcement, this status quo is likely to persist, and with it, more risk than the model- or index-based MPs.

The performance of the *iTarget* MP was comparable to the index target MP tested during SEDAR 46 (2016) by Sagarese et al. (2018): landings and SSB were maintained at levels similar to the *75% F30* MP with some risk of overfishing and overfished status under average and nonstationary recruitment conditions. The *iTarget* MP did not perform well under low recruitment conditions, achieving low landings, and unrealistically high SSB. Although these results can be explained by the mechanics of our definition of the iTarget algorithm, adverse yield performance of *iTarget* under low recruitment contrasts with findings from the South Atlantic US (Peterson et al. 2025). Sagarese et al. (2018) noted that empirical MPs must be tuned for optimal performance in the US Caribbean, and we recommend that future MSE in the US Caribbean, particularly those that involve stakeholders, should give this consideration. MP tuning is highly computationally demanding (which is why it was not conducted in the current study) but has the potential to increase MP flexibility and ensures desirable MP performance across the reference OM grid (Rademeyer et al. 2007). Should periods of low recruitment persist, a conservative $F_{\%}$ SPR proxy may achieve a better balance between yield and SSB, whether reference points are dynamic to reflect changes in recruitment (Shertzer et al *in prep*) or static (this study). Moreover, based on these results, extended periods of low recruitment would constitute exceptional circumstances for *iTarget* applied to yellowtail snapper in practice.. Breaching exceptional circumstances in this way would likely trigger a revisiting of the parameterization (e.g., what years define the reference period) and choice of empirical MP. Our results were consistent with those of Sagarese et al. (2018) in that the *iTarget* MP outperformed our constant catch MP, *Catch-averaging*, with respect to relative risk of overfishing and overfished status. Therefore, we re-iterate Sagarese et al's (2018) conclusions that empirical MPs are a viable alternative in the US Caribbean management system if a traditional stock assessment is not feasible.

We made several simplifying assumptions to conduct this MSE. In reality, STTJ yellowtail snapper landings are approximately 10% of PR's (SEDAR 2025a, 2025b). Therefore, using assessment estimates of F to generate landings for STTJ during the historical period, and by extension, during projections, resulted in unrealistically high landings for STTJ. However, this study was less concerned with precise magnitude of landings by island, and focused more on the relative magnitude of landings across the MPs tested. In the absence of status determination criteria from the stock assessment, we used the historic period average SSB to represent the MSST. This average was numerically equivalent to 0.5 of the long-term SSB achieved by the *F30* MP under average recruitment conditions. Therefore, it was not inconsistent with an MSST of ~$0.5B_{MSY}$ or its proxy that is the minimum biomass threshold legally allowable in US fisheries management (Methot et al. 2025). We made a similar assumption with F, assuming that the historic average F, approximately two times the rate of F_{30} under average recruitment conditions, was a reasonable proxy for the MFMT. In reality, these limits will not be static, i.e., they will be influenced by recruitment conditions as reference points change. Therefore, while still informative in a relative sense, some caution is necessary when interpreting the probabilities of overfished and overfishing in Tables 3 and 4. There is, however, increasing evidence that SPR-based proxies such as those used in several of the MPs tested in this study are robust to a host of different recruitment dynamics (Shertzer et al., *in prep*). Finally, we assumed that all MPs could take effect immediately following the results of each assessment cycle. Implementation of new management is rarely, if ever, instantaneous in this way.

We also used an areas-as-fleets approach (Hurtado-Ferro et al. 2014), which precludes the ability to model localized depletion, or the effects of management at the island-platform scale. However, this is not necessarily problematic for the following reasons: management advice generated by stock assessments for each island platform tends to be broadly consistent (SEDAR 2019, SEDAR 2022a, 2022b); EM fits were highly stable given a relatively short time series; and each island platform's unit stock is likely a part of a panmictic population (Davis 2025). Indeed, our results suggest that more data pooled across island platforms increased information content of the existing data streams and improved model stability; because we did not condition the OM on real data, we fit an area-as-fleets configuration of the size-structured model to data from SEDAR 84 during 2012-2022, and determined that this is demonstrably true (Supplemental Material, section 2). Moreover, the model-based MP performance observed herein was based on a single, spatially aggregated EM. To achieve these management results in the current system, we would need to duplicate efforts to generate island-based assessments to produce stock status and a spatially aggregated EM for the purposes of providing management advice. Therefore, island platform-specific stock assessments are likely not an ideal approach to quantifying the population dynamics and administering management advice for stocks in the US Caribbean, and an areas-as-fleets approach to stock assessment may be more appropriate. We note that this conclusion is partly conditional on the RVC index of relative abundance having enough years of data to inform population trend and recruitment over time, but index estimation during missing years and across island platforms is feasible using a spatiotemporal modeling framework such as sdmTMB (Anderson et al. 2025) (Supplemental Material section 3).

MSE is a powerful tool for evaluating tradeoffs between MPs under a range of conditions against stakeholder objectives (Damiano et al. 2024). Our untuned *iTarget* MP was a simple example designed to be a proof of concept specifically for comparison with model-based MPs derived from EM fits to data. We recommend that future MSEs in the US Caribbean explore other data-limited empirical MPs such as *iSlope* (Geromont and Butterworth 2015, Carruthers and Hordyk 2018, *sensu* Sagarese et al. 2018) and more thorough tuning. During SEDAR 46, the lack of tuning the empirical MPs likely derailed their potential use for management because the "off-the-shelf" generic MPs assumed depleted stock conditions and resulted in relatively low catches. We demonstrated that model-based and empirical MPs have similar potential to achieve the primary objectives of US federal fisheries management. However, only two of 179 stocks managed in the US Caribbean have enough data to support integrated stock assessment models capable of producing model-based catch advice. The RVC generates design-based indices of relative abundance for many US Caribbean reef fish stocks (Grove et al. 2021). Recent data provision improvements within the Caribbean have also allowed the development of standardized catch-per-unit-effort indices from fisheries logbook data. Therefore, empirical index-based MPs such as *iTarget*, or a similar index-based interim MP approach (Huyhn et al. 2020) have greater potential to respond to changes in population dynamics for those stocks that are likely to remain data-limited. Furthermore, a fully integrated, stakeholder-driven MSE has yet to be conducted in the US Caribbean, and stakeholder confidence in the stock assessment process and the management advice it generates is notably weak in the US Caribbean (CFMC staff, personal comm.). Therefore, we recommend that sufficient lead time be devoted to socializing MSE with the CFMC and its SSC, and that future MSE in the region seek to integrate stakeholder feedback and participation in the process. Socialization of MSE would be an important step toward operational MSE in the US Caribbean (Peterson et al., in prep).

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Table 1. Operating model (OM) reference and robustness grids.

Grid	Reference	Robustness
	Average recruitment	Alternative initial population size composition
	Low recruitment	Alternative size distribution of recruitment
	Nonstationary recruitment	Growth transition matrix rho parameter = 0.4
		Growth transition matrix Linf parameter = 38 (mm)
		Growth transition matrix K parameter = 0.15
		Natural mortality = 0.3

Table 2. Management procedure (MP) names and descriptions.

MP	Description
F30	Stock is fished at F_{30}
75% F30	Stock is fished at 75 percent of F_{30}
F30 with B-thresh	Stock is fished at F_{30}; if spawning stock biomass is reduced below the MSST, fishing stops until the next stock assessment is completed
iTarget	Stock is fished at a projected rate of F based on the historical mean and adjusted using a version of the *iTarget* formula tuned to the index of relative abundance (see Equations 1 and 2)
Catch avg	Stock is fished at the average rate of F achieved during 2017-2020
Random walk F	Stock is fished at a rate of F determined by a random walk

Table 3. Probability that the stock falls into an overfished status at any point in the 30-year projection period across 200 iterations for each management procedure (MP). Results are organized by recruitment scenario (top) and management procedure (left). Overfished status is defined as spawning stock biomass (SSB) dropping below the minimum stock size threshold (MSST), which is assumed to equal the average SSB during the historic period (2012-2023).

MP	**Average recruitment**	**Low recruitment**	**Nonstationary recruitment**
F30	4.7%	0.0%	5.1%
75% F30	3.3%	0.0%	2.3%
F30 with B-thresh	1.6%	0.0%	2.6%
iTarget	18.2%	0.02%	20.4%
Catch-averaging	44.4%	12.1%	47.1%
Random walk F	24.5%	4.9%	24.5%

Table 4. Probability that the stock experiences overfishing at any point in the 30-year projection period across 200 iterations for each management procedure (MP). Results are organized by recruitment scenario (top) and management procedure (left). Overfishing is defined as fishing mortality (F) exceeding the maximum fishing mortality threshold (MFMT), which is assumed to equal the average F during the historic period (2012-2023).

MP	**Average recruitment**	**Low recruitment**	**Nonstationary recruitment**
F30	0.0%	0.0%	0.0%
75% F30	0.0%	0.0%	0.0%
F30 with B-thresh	0.0%	0.0%	0.0%
iTarget	18.6%	0.0%	20.2%
Catch-averaging	41.4%	0.0%	35.0%
Random walk F	16.4%	1.0%	16.4%

Figure 1 MP performance under average recruitment conditions. Solid dotted lines represent the median estimate of recruitment (R, top-left) and abundance (N, top-middle) in thousands of fish, spawning stock biomass (SSB, top-right) in millions of eggs with the black line representing the minimum stock size threshold, and estimated median landings (catches) in thousands of fish for Puerto Rico (bottom-left) and St. Thomas/St. John (bottom-middle) for each MP. The dashed colored lines represent the 10^{th} and 90^{th} quantiles of the 200 iterations of each operating model (OM).

Figure 2 MP performance under low recruitment conditions. Solid dotted lines represent the median estimate of recruitment (R, top-left) and abundance (N, top-middle) in thousands of fish, spawning stock biomass (SSB, top-right) in millions of eggs with the black line representing the minimum stock size threshold, and estimated median landings (catches) in thousands of fish for Puerto Rico (bottom-left) and St. Thomas/St. John (bottom-middle) for each MP. The dashed colored lines represent the 10^{th} and 90^{th} quantiles of the 200 iterations of each operating model (OM).

Figure 3 MP performance under nonstationary mean recruitment conditions. Solid dotted lines represent the median estimate of recruitment (R, top-left) and abundance (N, top-middle) in thousands of fish, spawning stock biomass (SSB, top-right) in millions of eggs with the black line representing the minimum stock size threshold, and estimated median landings (catches) in thousands of fish for Puerto Rico (bottom-left) and St. Thomas/St. John (bottom-middle) for each MP. The dashed colored lines represent the 10^{th} and 90^{th} quantiles of the 200 iterations of each operating model (OM).

Figure 4 Spawning stock biomass (SSB) in millions of eggs (top), Puerto Rico (middle) and St. Thomas/St. John (bottom) landings in thousands of fish over 200 iterations of the final year in the terminal five-year projection achieved under each MP (x-axis) by recruitment conditions: average (red), low (green), and nonstationary mean (blue). Violins represent the total distribution of SSB and landings by island platform over 200 iterations while boxes represent the distribution's median and tails by recruitment condition.

Figure 5 *F30* MP performance across the robustness model grid by operating model (OM) under average recruitment conditions. Solid dotted lines represent the median estimate of recruitment (R, top-left) and abundance (N, top-middle) in thousands of fish, spawning stock biomass (SSB, top-right) in millions of eggs with the black line representing the minimum stock size threshold, and estimated median landings (catches) in thousands of fish for Puerto Rico (bottom-left) and St. Thomas/St. John (bottom-middle) for each robustness operating model (OM; defined in Table 1). The dashed colored lines represent the 10^{th} and 90^{th} quantiles of the 200 iterations of each OM. The green dotted line represents the *F30* MP with no changes to OM parameters and is for comparison.

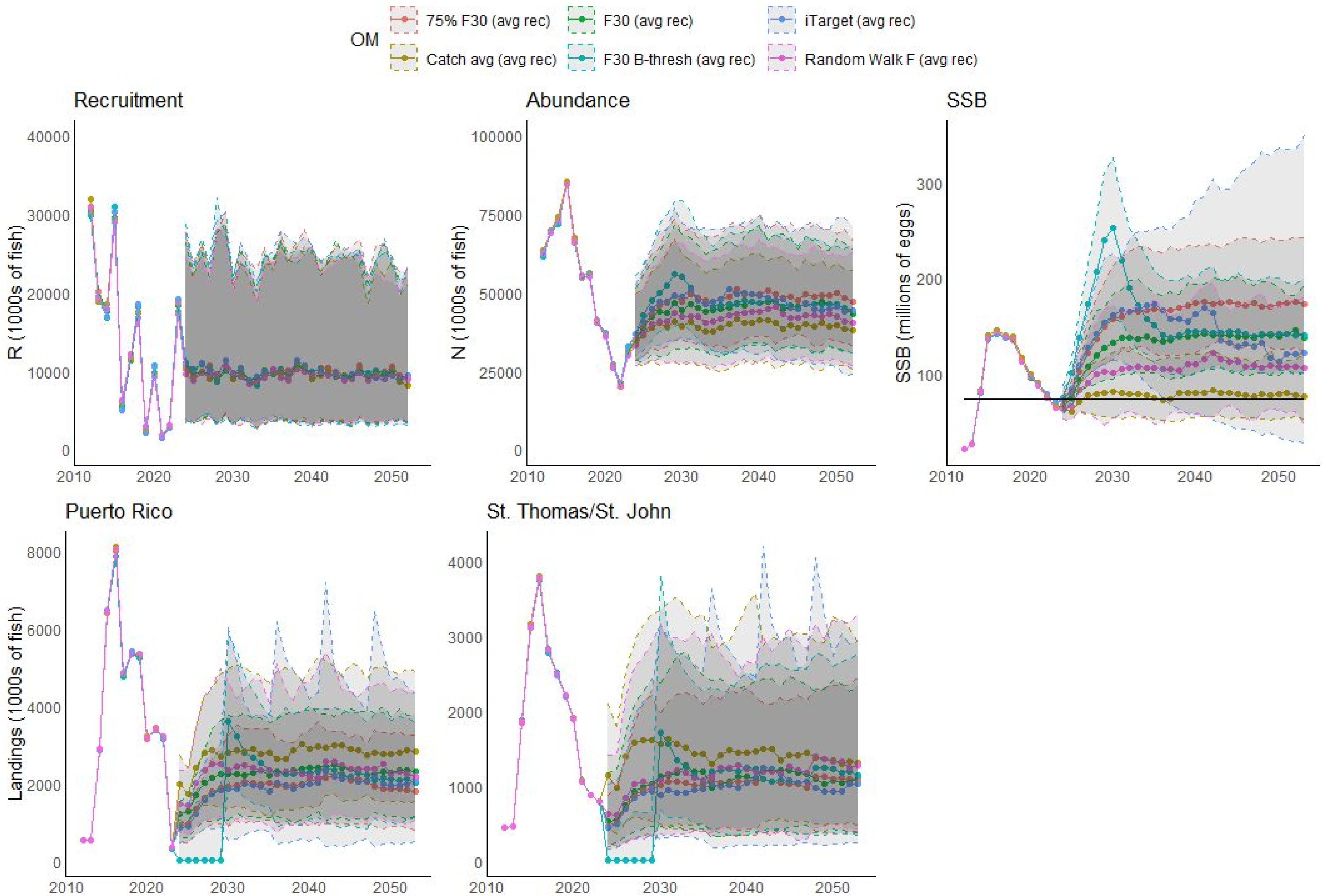
OM
75% F30 (avg rec)
F30 (avg rec)
iTarget (avg rec)
Catch avg (avg rec)
F30 B-thresh (avg rec)
Random Walk F (avg rec)
Recruitment
R (1000s of fish)
Abundance
N (1000s of fish)
SSB
SSB (millions of eggs)
Puerto Rico
Landings (1000s of fish)
St. Thomas/St. John

Figure 1

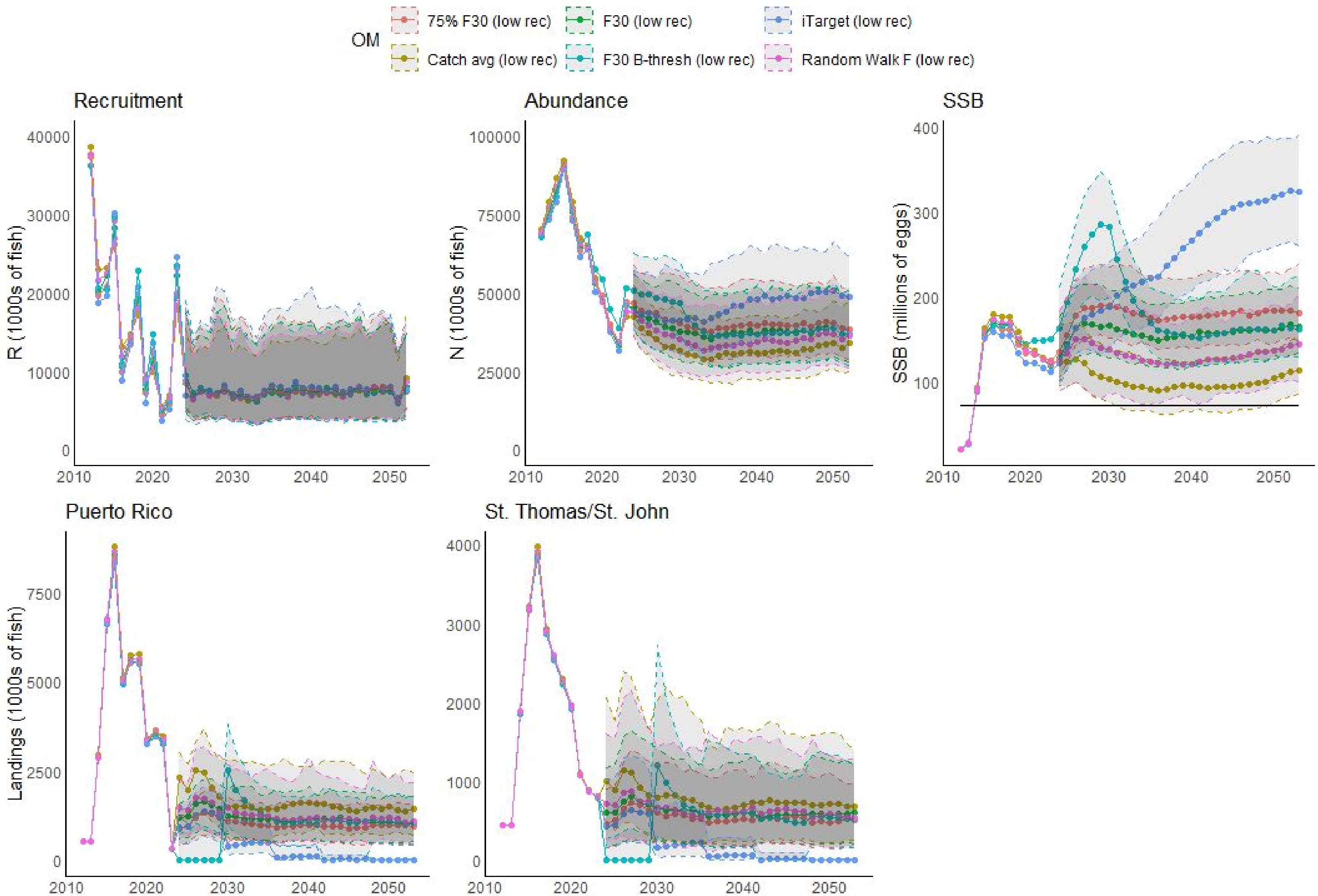
OM
75% F30 (low rec)
F30 (low rec)
iTarget (low rec)
Catch avg (low rec)
F30 B-thresh (low rec)
Random Walk F (low rec)
Recruitment
R (1000s of fish)
Abundance
N (1000s of fish)
SSB
SSB (millions of eggs)
Puerto Rico
Landings (1000s of fish)
St. Thomas/St. John

Figure 2

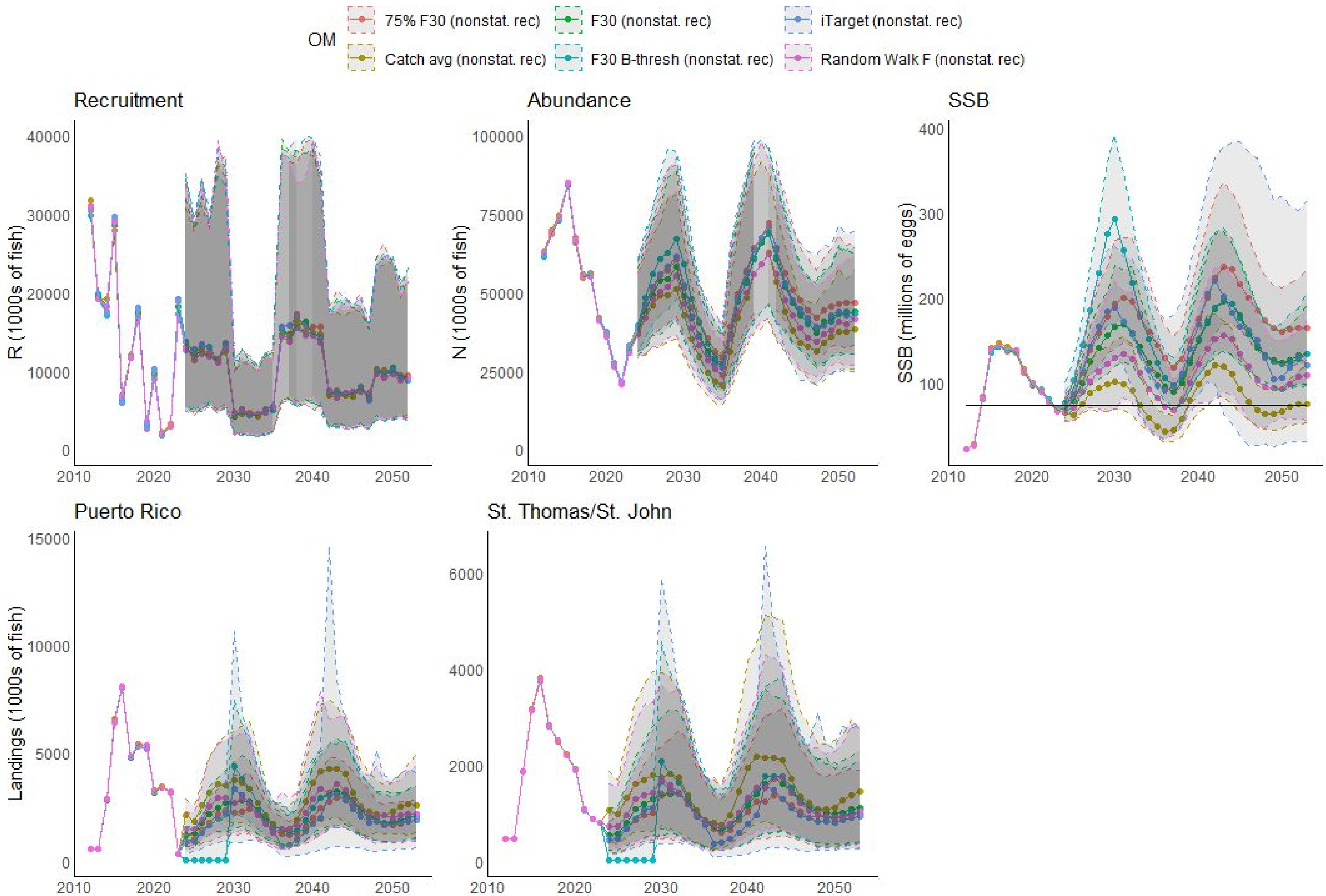
OM
75% F30 (nonstat. rec)
F30 (nonstat. rec)
iTarget (nonstat. rec)
Catch avg (nonstat. rec)
F30 B-thresh (nonstat. rec)
Random Walk F (nonstat. rec)
Recruitment
R (1000s of fish)
Abundance
N (1000s of fish)
SSB
SSB (millions of eggs)
Puerto Rico
Landings (1000s of fish)
St. Thomas/St. John
2010
2020
2030
2040
2050

Figure 3

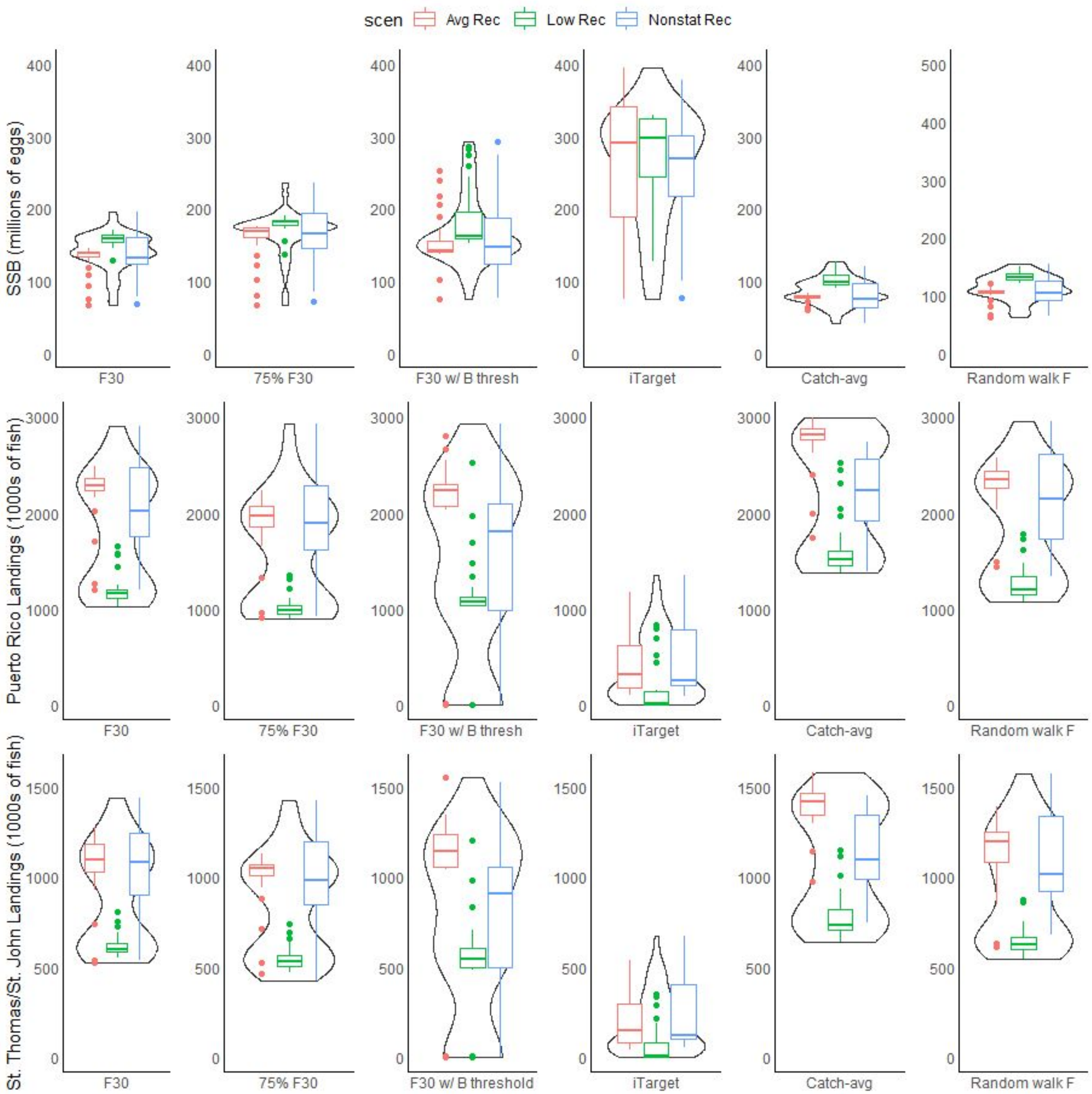
scen
Avg Rec
Low Rec
Nonstat Rec
SSB (millions of eggs)
Puerto Rico Landings (1000s of fish)
St. Thomas/St. John Landings (1000s of fish)
F30
75% F30
F30 w/ B thresh
F30 w/ B threshold
iTarget
Catch-avg
Random walk F

Figure 4

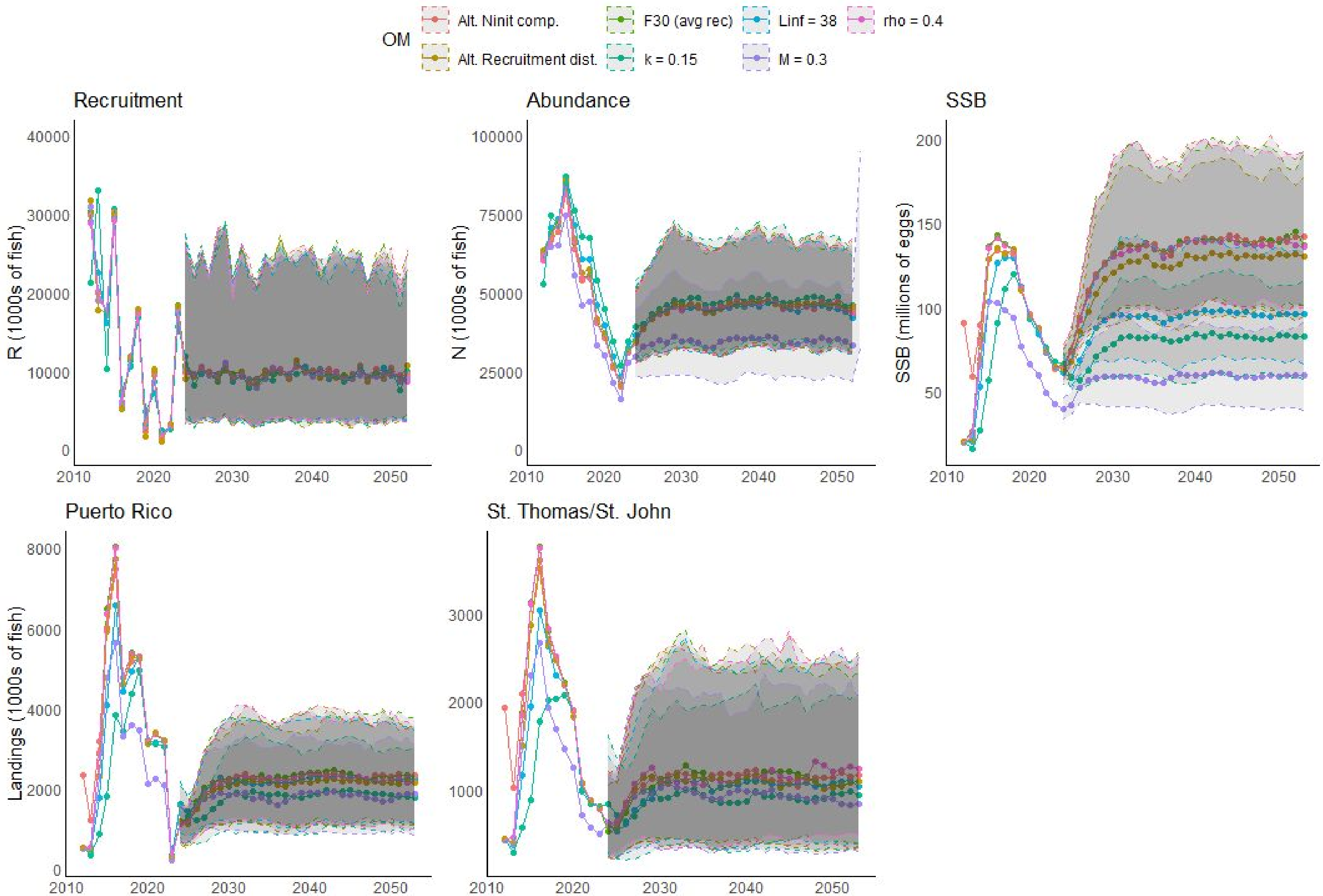
OM
Alt. Ninit comp.
Alt. Recruitment dist.
F30 (avg rec)
k = 0.15
Linf = 38
M = 0.3
rho = 0.4
Recruitment
R (1000s of fish)
Abundance
N (1000s of fish)
SSB
SSB (millions of eggs)
Puerto Rico
Landings (1000s of fish)
St. Thomas/St. John

Figure 5

Supplemental Material

Section 1. *iTarget* management procedure under low recruitment conditions

Figure 1 illustrates that the most recent five-year average of the survey index of relative abundance during projections could never equal the reference level of the index under low recruitment conditions, thereby resulting in reduced fishing mortality with each assessment cycle.

Section 2. Areas-as-fleets stock assessment using the size structured assessment model

For proof of concept, we fit the size structured stock assessment model (Cao et al. 2017) to commercial landings and length composition data during 2012-2022 from Puerto Rico (PR) and Saint Thomas/Saint John (STTJ), which were treated as separate fleets. Although data on yellowtail snapper density are available from the National Coral Reef Monitoring Program during 2001-2013, the survey methodology has changed considerably (Grove et al. 2021), and only RVC data during 2013 and onward were used in the stock assessments for PR and STTJ yellowtail snapper (SEDAR 2025a, 2025b). Additionally, data were not collected by the RVC during 2012, 2018, 2020, and 2022. The size structured assessment model requires the same temporal dimensions in both the fishery-dependent and independent model files (Jie Cao, North Carolina State University, personal comm.). Therefore, we calculated an average based on temporal neighbor values to approximate a model-based estimate of the index value over missing years, e.g., 2012 was calculated from an average of 2013-2014, 2018 from an average of 2017 and 2019, and 2022 from an average of 2020-2021. This was a practical solution to serve in lieu of a continuous time series of model-based indices of relative abundance during 2012-2022. See Section 3 for proof of concept.

For consistency with SEDAR 84, we used the same range of size bins: 3-57 centimeters (cm) in increments of 3 cm and estimated a similar suite of assessment model parameters (SEDAR 2025a, 2025b). We estimated initial and annual fishing mortality for the PR and STTJ fleets. These fleets were initialized with the same pattern of logistic selectivity, but both selectivities were estimated to model differences in availability of yellowtail snapper to each island platform (Hurtado-Ferro et al. 2014). We initialized the survey selectivity with a double-logistic pattern to capture the dome shape of the RVC for yellowtail snapper (SEDAR 2025a, 2025b), and estimated all the selectivity parameters. The catchability coefficient of the survey index was also estimated. We estimated mean recruitment, $R0$, and annual recruitment deviations. We estimated the initial composition of abundance-at-size, and the size bins to which new fish recruit: these are parameter estimation options that are unique to the size structured assessment model (Cao et al. 2017). Fixed life history parameters such as natural mortality, length-weight and maturity, and von Bertalanffy growth parameters used to calculate the growth transition matrix were borrowed directly from SEDAR 84 (SEDAR 2025a, 2025b).

We experimented with several configurations of the model. Once we reduced the coefficient of variation for the survey index to 0.05, forcing the model to more closely fit the survey index, the model converged with a reasonably low gradient (<0.01) and an inverted Hessian. We provide the following model results below: model fits to landings by island platform and the survey index (Figure 2); model fits to commercial length compositions by island platform (Figures 3-4); model fits to survey length compositions (Figure 5); estimates of fleet and survey selectivity (Figure 6); model estimated annual recruitment, abundance, fishing mortality, and spawning stock biomass (SSB) (Figure 7); and model estimates of numbers at size over time (Figure 8). We did not conduct any stock assessment diagnostics, e.g., likelihood profiling, jitter, or retrospective analysis as this was a proof-of-concept exercise.

Section 3. Spatiotemporal standardization model

We fitted a delta-lognormal generalized linear mixed model in sdmTMB (Anderson et al. 2025) to RVC data during 2016, 2017, 2019, 2021, and 2023 to demonstrate that a spatiotemporal modeling framework can combine the RVC data across island platforms while estimating values for missing years of data. Results include a heatmap of estimated density over space (Figure 9) and an estimated index of relative abundance with standard errors (Figure 10). We tested a single Tweedie-distributed linear predictor and a delta-gamma model, but the delta-lognormal model resulted in the best model diagnostics (Figure 11), which we tested using simulated DHARMa residuals (Hartig 2024). We note that the 2023 data were not available during the SEDAR 84 assessments and were obtained directly from NCRMP.

For the delta-lognormal model, we removed five data points collected during 2023 on the north coast of PR so that the prediction grid would not extrapolate estimated density across the mainland of PR; this occurred whenever those five data points were included during model fitting. Extrapolation of density across land masses occurred for all islands excluding PR because RVC data were collected along entire coastlines. While a barrier model could address this issue (Jie Cao, North Carolina State University, personal comm.), the size of the island land masses relative to the data points mapped within the spatial mesh are likely too small to bias density estimates (Figure 12).

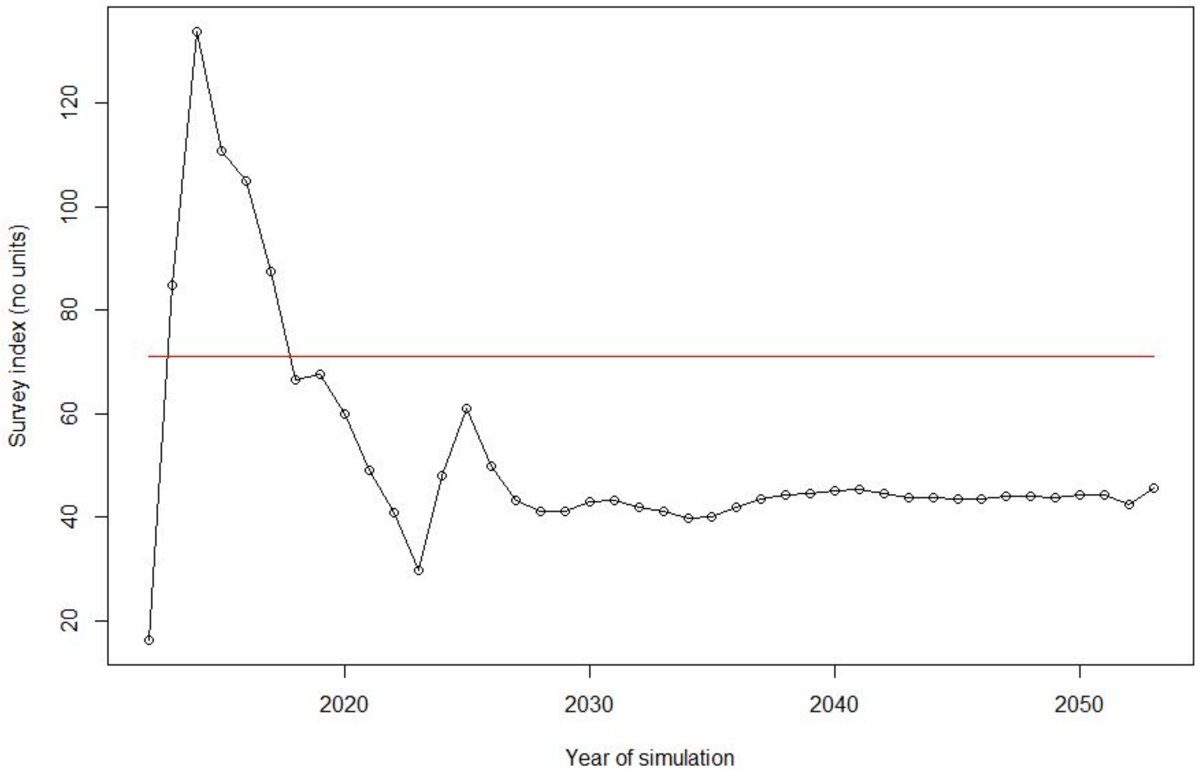

Figure 1. Mean estimate of the survey index of relative abundance (dotted black line) over 200 iterations of the *iTarget* management procedure applied under low recruitment conditions. The red line represents the mean of the historical period.

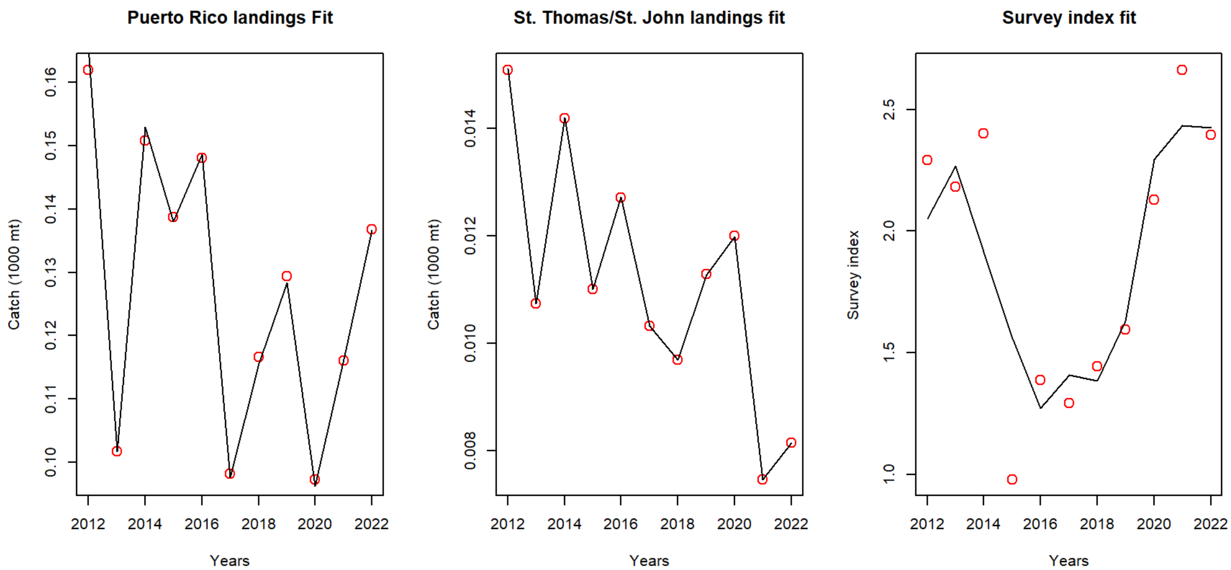

Figure 2. Areas-as-fleets stock assessment model fits to Puerto Rico landings (left), St. Thomas/St. John landings (center) and the National Coral Reef Monitoring Program Reef Visual Census (right) during 2012-2022 for US Caribbean yellowtail snapper. Open red dots represent observed data, and solid black lines represent assessment model predictions.

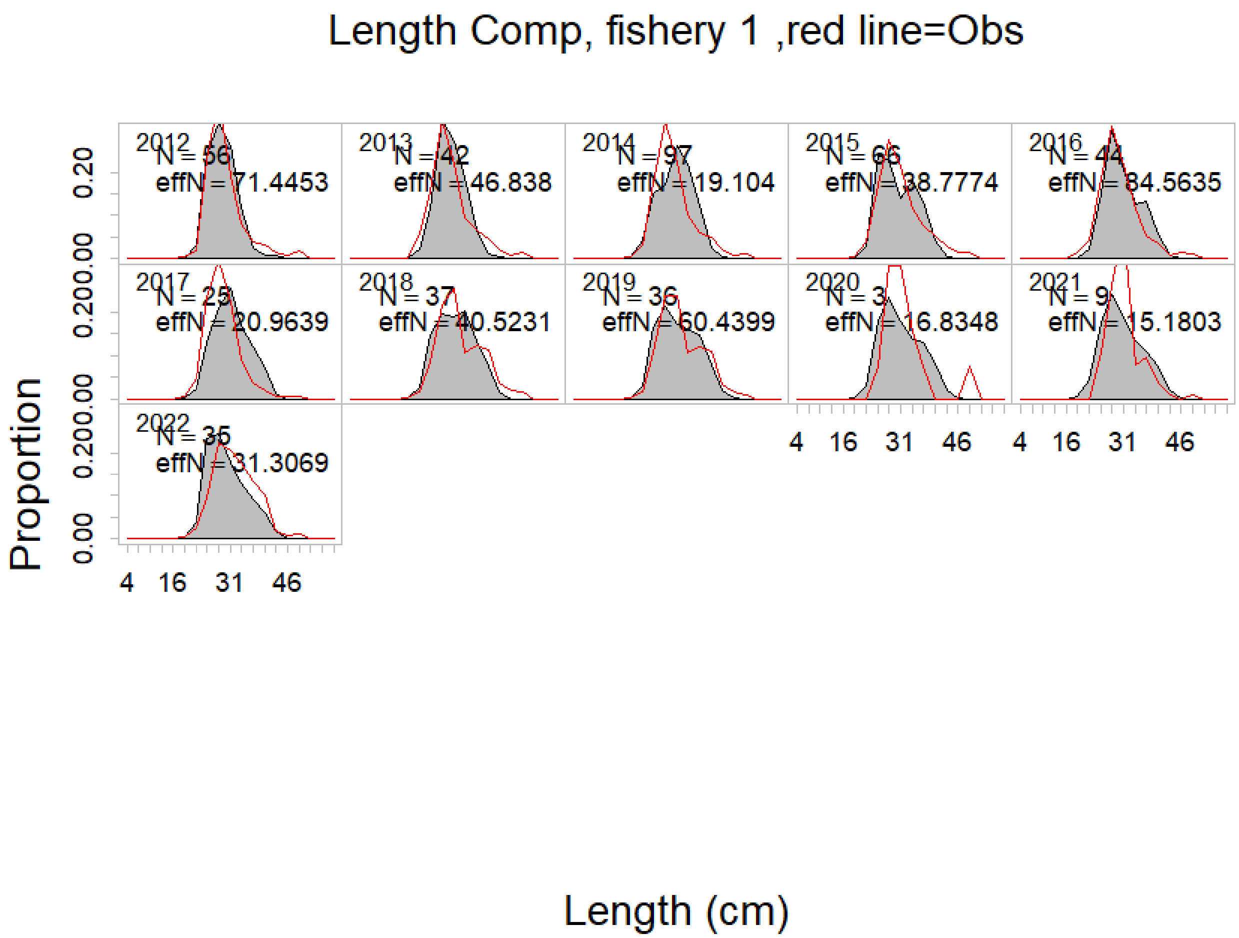

Figure 3. Areas-as-fleets stock assessment model fits to Puerto Rico ("fishery 1") length compositions in centimeters (cm) during 2012-2022 for US Caribbean yellowtail snapper. Grey mass outlined with solid black lines represent observed data, and solid red lines represent assessment model predictions. X-axis represents size bin midpoints and y-axis represents proportion of fish within size bins. N refers to observed sample size and effN refers to estimated effective sample size in number of trips. Figure generated using pre-built functions from Cao et al. (2017).

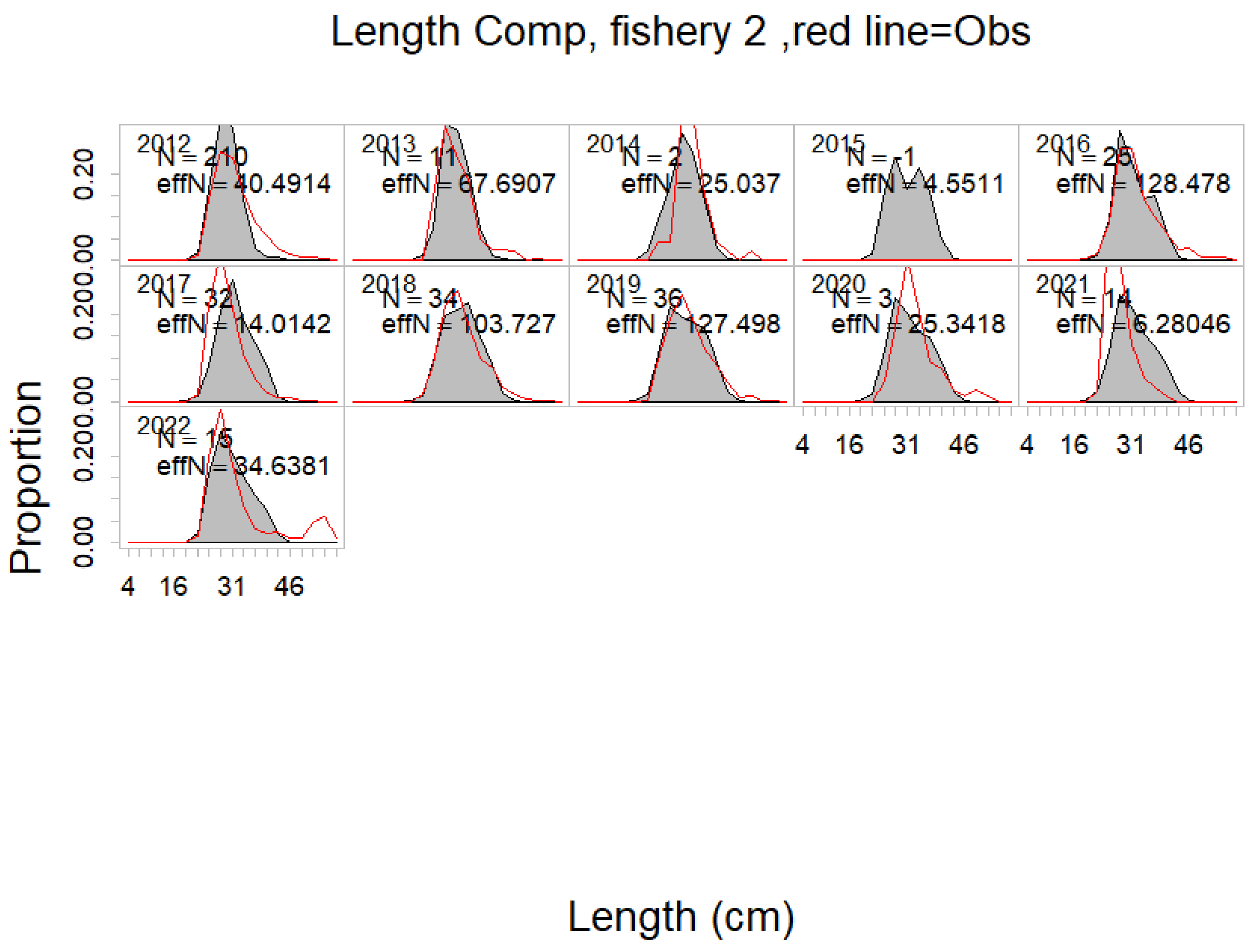

Figure 4. Areas-as-fleets stock assessment model fits to St. Thomas/St. John ("fishery 2") length compositions in centimeters (cm) during 2012-2022 for US Caribbean yellowtail snapper. Grey mass outlined with solid black lines represent observed data, and solid red lines represent assessment model predictions. X-axis represents size bin midpoints and y-axis represents proportion of fish within size bins. N refers to observed sample size and effN refers to estimated effective sample size. N equal to -1 indicates missing data. Figure generated using pre-built functions from Cao et al. (2017).

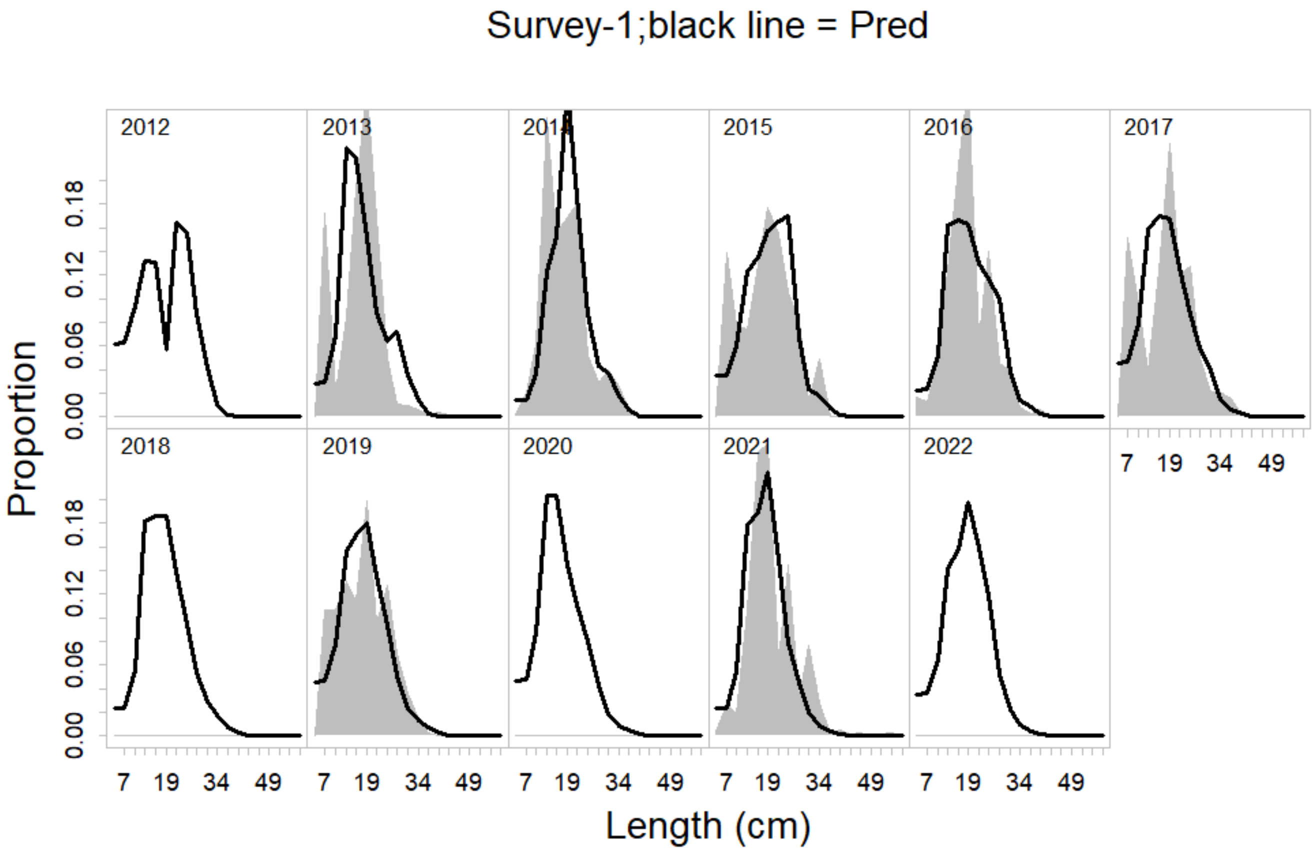

Figure 5. Areas-as-fleets stock assessment model fits to the National Coral Reef Monitoring Program ("survey 1") length compositions in centimeters (cm) during 2012-2022 for US Caribbean yellowtail snapper. Grey mass represents observed data, and solid black lines represent assessment model predictions. X-axis represents size bin midpoints and y-axis represents proportion of fish within size bins. Figure generated using pre-built functions from Cao et al. (2017).

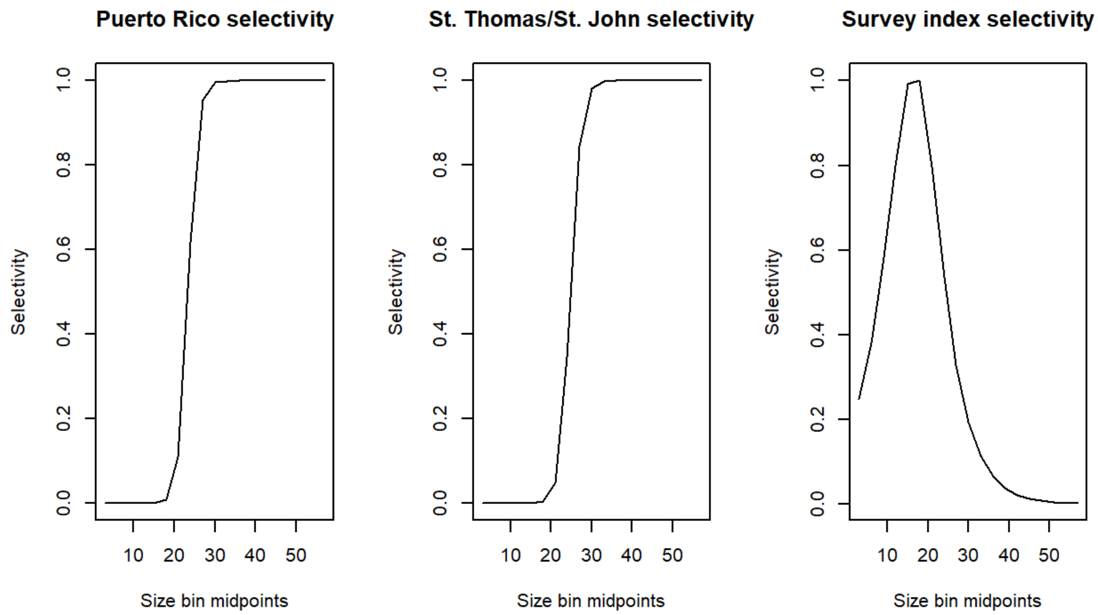

Figure 6. Estimated selectivity patterns for the Puerto Rico “fleet” (left), the St. Thomas/St. John “fleet” (center), and survey index (right) from the areas-as-fleets stock assessment model for US Caribbean yellowtail snapper.

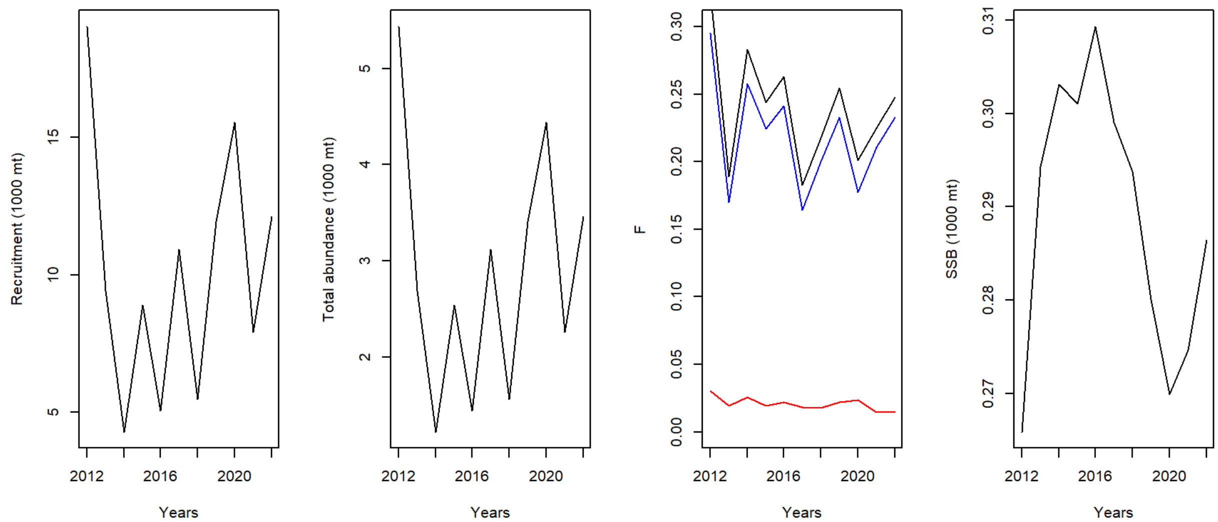

Figure 7. Estimated recruitment (left) and abundance (left-center) in 1000s of metric tons (mt), estimated fishing mortality (right-center) for the Puerto Rico "fleet" (blue), St. Thomas/St. John "fleet" (red) and total (black), and estimated spawning stock biomass (SSB) in 1000s of mt from the areas-as-fleets stock assessment model for US Caribbean yellowtail snapper.

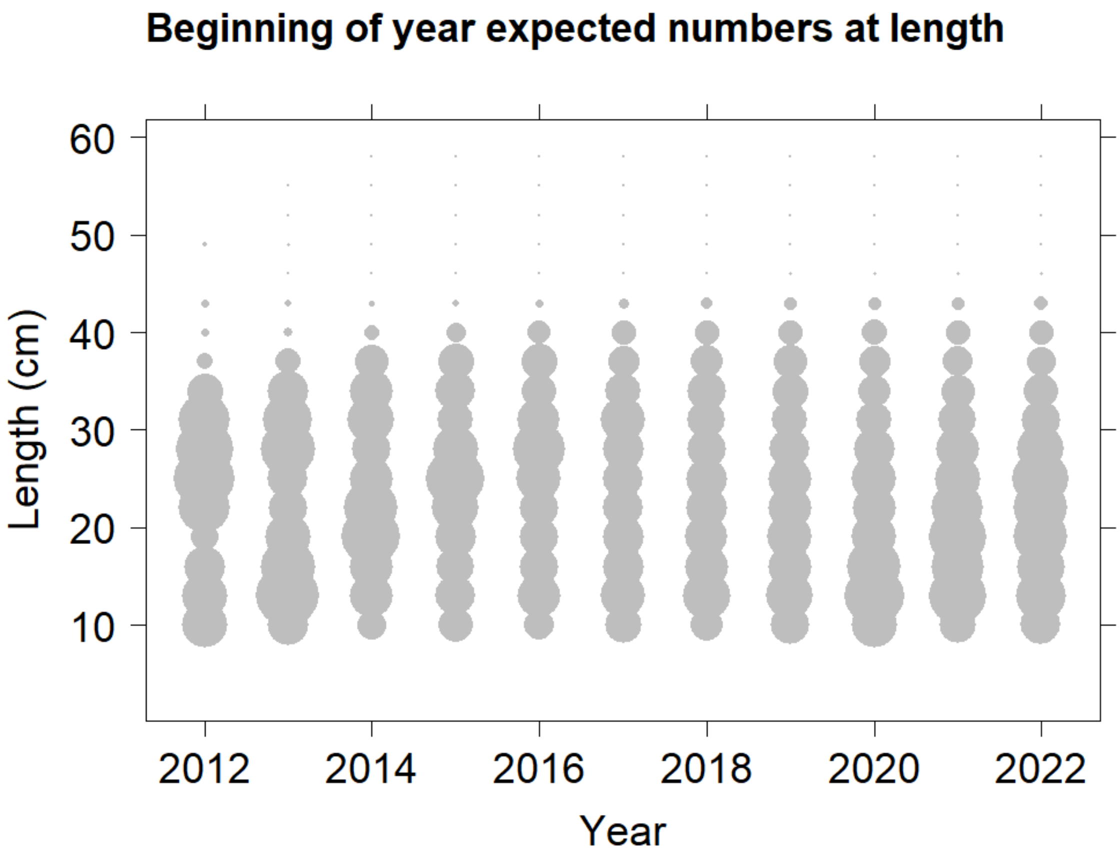

Figure 8. Estimated yellowtail snapper numbers at length (by size bin) in centimeters (cm) from the areas-as-fleets stock assessment model.

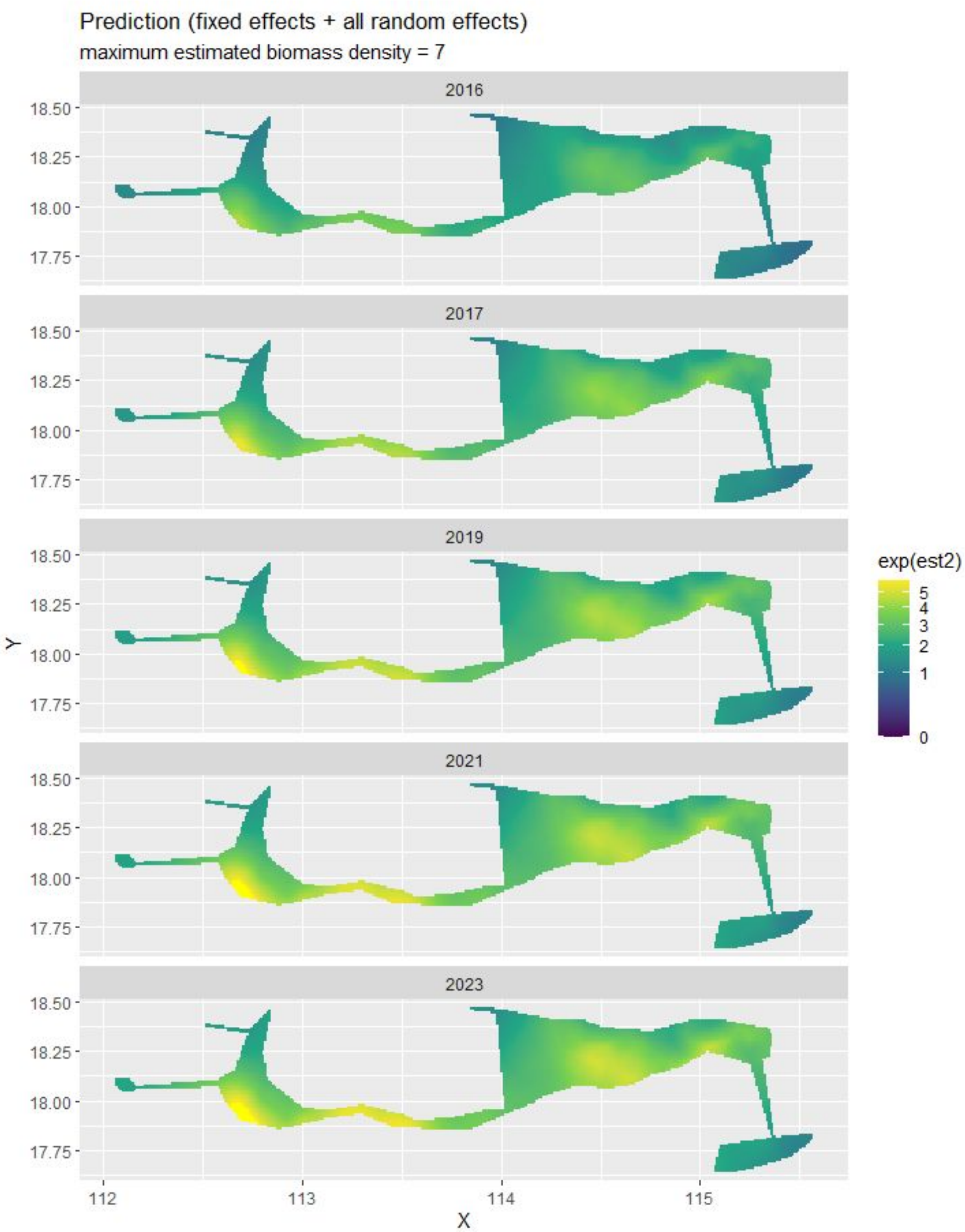

Figure 9. Estimated US Caribbean yellowtail snapper density during 2016, 2017, 2019, 2021, and 2023 over space and time. X-axis is longitude and y-axis is latitude in degrees.

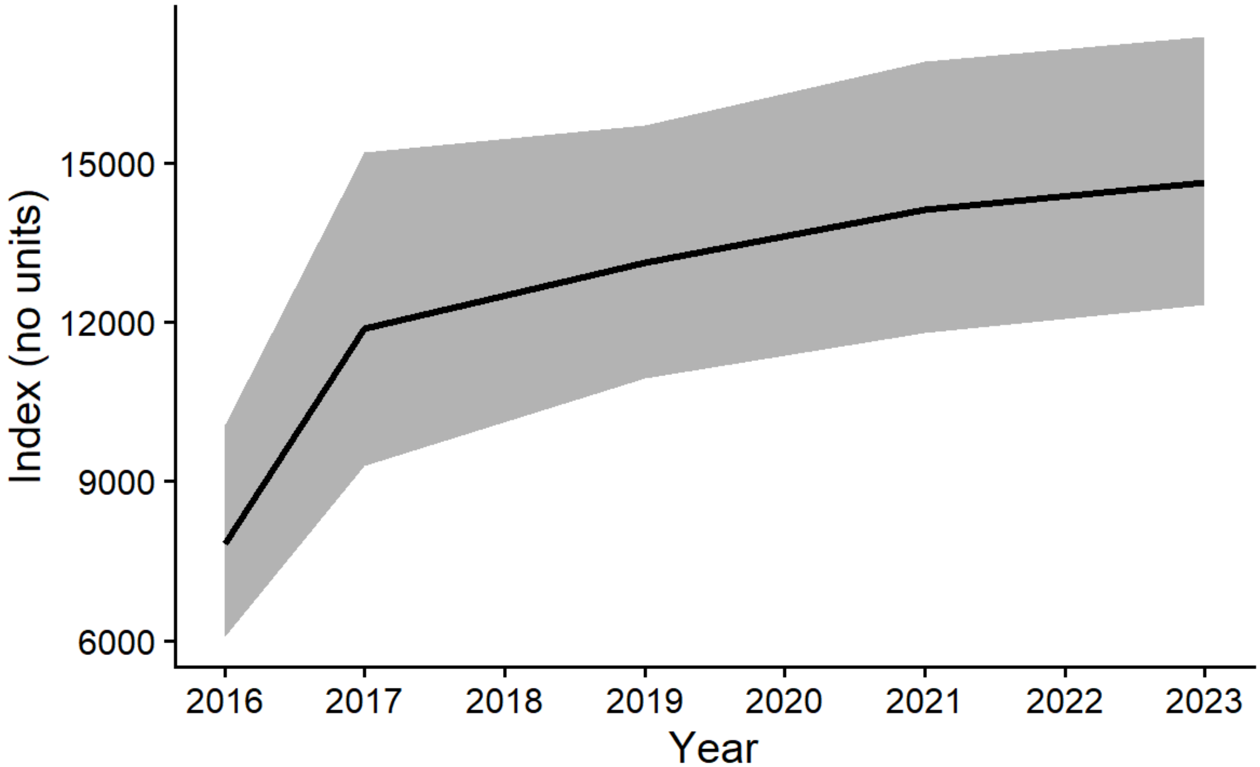

Figure 10. Estimated index of relative abundance for US Caribbean yellowtail snapper.

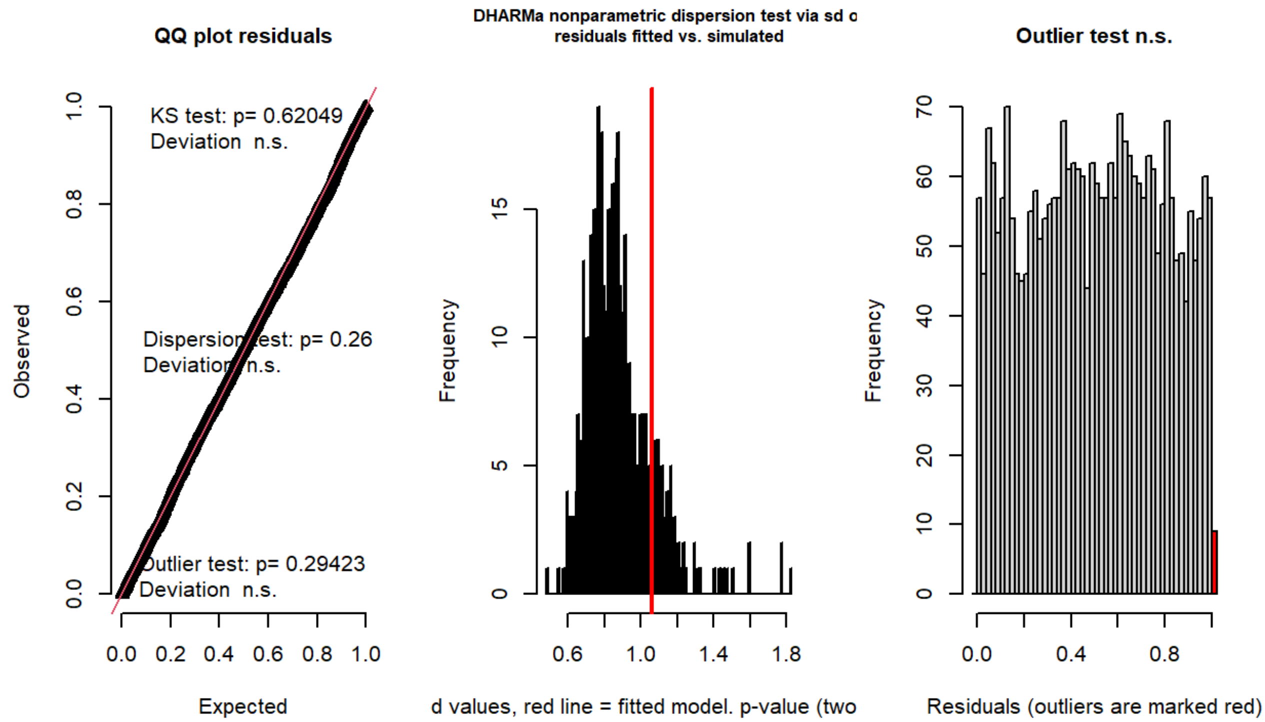

Figure 11. Simulated DHARMa residuals for the delta-lognormal generalized linear mixed model fit using sdmTMB.

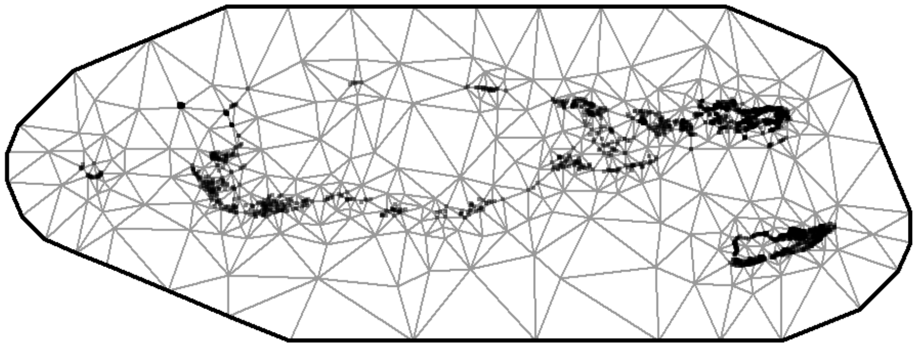

Figure 12. Spatial mesh constructed for fitting sdmTMB to US Caribbean yellowtail snapper densities obtained from the National Coral Reef Monitoring Program Reef Visual Census.

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