

Optimizing Fishing Survey Sampling Effort for Hawaiian 'Ōpakapaka Stock Assessments

Megumi Oshima, Marc Nadon, John Syslo, Hongguang Ma, and Felipe Carvalho

NOAA Technical Memorandum NMFS-PIFSC-193
U.S. Department of Commerce
National Oceanic and Atmospheric Administration
National Marine Fisheries Service
Pacific Islands Fisheries Science Center
November 2026

Optimizing Fishing Survey Sampling Effort for Hawaiian 'Ōpakapaka Stock Assessments

Megumi Oshima, Marc Nadon, John Syslo, Hongguang Ma, and Felipe Carvalho

Pacific Islands Fisheries Science Center
National Marine Fisheries Service
1845 Wasp Boulevard
Honolulu, HI 96818

NOAA Technical Memorandum NMFS-PIFSC-193
November 2026

U.S. Department of Commerce
National Oceanic and Atmospheric Administration
National Marine Fisheries Service
Pacific Islands Fisheries Science Center

Acknowledgements

We would like to thank the Bottomfish Fishery-Independent Survey (BFISH) team for collecting and managing the survey data that supported this work. We also acknowledge the fishers whose fishing expertise informed the underlying stock assesment model for the ‘ōpakapaka stock. We would also like to thank Leonardo Durante for his technical review.

Cover drawing: Hawaiian 'Ōpakapaka *(Pristipomoides filamentosus)* . Drawing credit: Hawai'i Division of Aquatic Resources. Artist: Les Hata.

Edited by Revere Wood.

To develop the simulation code, analyze datasets, and create final tables and figures, R scripts were generated using GitHub Copilot and Claude 3.5 Sonnet. All AI-generated code was manually audited, debugged, and verified prior to execution. During the preparation of this manuscript, the author used Claude 3.5 Sonnet to refine the grammar, structure, and academic tone of the literature review. After using this tool, the author critically reviewed, edited, and modified the suggested text. The author takes full responsibility for the final contents and accuracy of this publication.

Recommended citation

Oshima, M., Nadon, M., Syslo, J., Ma, H., & Carvalho, F. (2026). *Optimizing Fishing Survey Sampling Effort for Hawaiian 'Ōpakapaka Stock Assessments* (Technical Memorandum Series, TM-PIFSC-193). Pacific Islands Fisheries Science Center.

Copies of this report are available from

Pacific Islands Fisheries Science Center
National Marine Fisheries Service
National Oceanic and Atmospheric Administration
1845 Wasp Boulevard, Building #176
Honolulu, Hawai‘i 96818

Or online at

https://repository.library.noaa.gov/

Table of contents

List of Figures ii

List of Tables iii

Executive Summary iv

Introduction 1

Methods 3
- Simulation Approach 3
- Operating Model 3
- Scenarios 10
- Estimation Model 11
- Performance Indices 12

Results 13
- Effort Scenarios 13
- Effect of Survey Selectivity 20

Discussion 22

Literature Cited 26

List of Figures

Figure 1. 100 unique time series of fishing mortality for the commercial (green lines) and non-commercial (orange lines) fisheries used for each iteration. 4

Figure 2. Log recruitment deviations for one iteration over the simulation time period. Recruitment deviations in the historical period (1949-2023, grey shaded area and grey line) were the same for both recruitment conditions, but after 2023 they diverged. The normal (purple line) condition assumed recruitment pattens from the historical period continued into the future. The poor recruitment scenario (green line) assumed there was a 10 year period of declining recruitment, followed by a constant reduced recruitment (compared to the normal). 6

Figure 3. Selectivity functions used for the commercial (green line), non-commercial (orange line), and survey (purple line). 7

Figure 4. Data generated by the operating model and used by estimation models with (a) and without (b) the survey. Point size indicates relative data amount; colors denote commercial (green), non-commercial (orange), and BFISH survey (purple) data. 9

Figure 5. Time series of median (solid line) and 95% quantile (band) relative error of spawing stock biomass for the high (HSE), intermediate (ISE), low (LSE), extra low (XLSE), and no survey effort (NSE) scenarios under both the normal and poor recruitment conditions. . . . 14

Figure 6. Time series of median (solid line) and 95% interval (band) relative error of fishing mortality for the high (HSE), intermediate (ISE), low (LSE), extra low (XLSE), and no survey effort (NSE) scenarios under both the normal and poor recruitment conditions. 15

Figure 7. Time series of median (solid line) and 95% interval (band) relative error of age-0 recruitment for the high (HSE), intermediate (ISE), low (LSE), extra low (XLSE), and no survey effort (NSE) scenarios under both the normal and poor recruitment conditions. 16

Figure 8. Distribution of relative error for the terminal year stock status (SSB/SSB_{MSST}) and terminal year fishing status (F/F_{MSY}). 18

Figure 9. Median relative error of terminal year spawning stock biomass for the high (HSE), intermediate (ISE), and low (LSE) scenarios with dome-shaped (red bars), logistic selectivity (blue bars), and logistic selectivity with an informative prior on q (green bar). 20

List of Tables

Table 1. The observational error used to sample data from the OM for high survey effort (HSE), intermediate survey effort (ISE), low survey effort (LSE), extra low survey effort (XLSE), and no survey effort (NSE) for effort-based scenarios and selectivity-based scenarios. For each survey effort, the number of sampling grids (Grids) that effort would translate to, the resulting index of abundance CV, and effective sample size (effN) for length composition data are shown. All effort-based and selectivity-based scenarios were tested under both normal and poor recruitment conditions. 10

Table 2. Median relative error and standard deviation of relative error in the terminal year for spawning biomass, fishing mortality, and recruitment by scenario. 17

Table 3. Median relative error and standard deviation of relative error in the terminal year for SSB/SSB_{MSST} and F/F_{MSY} by scenario. 19

Table 4. Probability that reference points SSB/SSB_{MSST} and F/F_{MSY} are above or below 10% from the true value for each scenario. 19

Table 5. Median relative error of terminal year spawning biomass and standard deviation for selectivity scenarios under normal and poor recruitment conditions. 21

Executive Summary

‘Ōpakapaka, (*Pristipomoides filamentosus*), is one of Hawai‘i’s most culturally signifi-cant species and is a member of the Deep 7 bottomfish complex, a group of six deep-water snapper and one grouper. The Deep 7 complex is currently assessed with a sin-gle surplus production model, however, since ‘ōpakapaka comprises over 50% of the commercial catch of Deep 7 and is one of the few species with enough data for an age-structured, integrated model, a single-species model has been developed to evaluate the possibility of a single-species assessment. One key source of information for the Deep 7 complex assessment model, as well as for the ‘ōpakapaka single-species model, is the Bottomfish Fishery-Independent Survey in Hawai‘i (BFISH), which provides in-dex of abundance and length composition data. The BFISH is an annual survey con-ducted around the main Hawaiian islands since 2016 that specifically targets deep-water snapper and grouper. The sampling design historically integrated two gear types, a re-mote stereo-video camera system and a hook-and-line research fishing. However, in response to operational and financial constraints, the camera gear was removed from the survey and it now relies solely on research fishing. The number of grids the BFISH surveys in a given year has fluctuated depending on funding and logistical constraints. Because the number of sampled grids directly impacts the uncertainty of the abundance indices, it is important to evaluate alternative sampling strategies to understand the re-lationship between number of grids sampled and the impact on key model outputs used in management of the fishery. We wanted to evaluate whether we could optimize the fishery-independent survey for ‘ōpakapaka by first looking at the effect of varying lev-els of survey effort on the model’s ability to estimate key stock quantities under periods of normal or poor recruitment. Second, we wanted to evaluate the impact of alternative gear type (and the resulting selectivity) on the assessment model performance, particu-larly under poor recruitment conditions.

We simulated 100 operating model/estimation model pairs for 17 scenarios to test the impact of different survey efforts and gear configurations on the ‘ōpakapaka single-species model under both normal future recruitment conditions and poor fu-ture recruitment conditions. For the poor recruitment condition, we simulated a 40% sustained decline in mean recruitment for 25 years, whereas the normal conditions assumed the same recruitment patterns continued in the future. We tested five survey effort scenarios: high (HSE), intermediate (ISE), low (LSE), extra low (XLSE), and none (NSE) (fishery-dependent data only) under both normal and poor recruitment conditions. We also tested a change in selectivity (from dome-shaped to logistic) for HSE, ISE, and LSE efforts under both recruitment conditions. To compare bias and precision of each scenario, we calculated median relative error for spawning stock biomass, fishing mortality, age-0 recruitment, and reference points (SSB/SSB_{MSST} and F/F_{MSY}).

We found that under normal recruitment conditions, all sampling scenarios performed similarly well, with precision decreasing slightly as survey effort decreased. Under poor recruitment conditions, we found that bias increased and precision decreased as survey effort decreased. Additionally, the scenario with no survey effort (NSE) highlighted the dangers of relying only on fishery-dependent data. Key management reference points were estimated fairly well by the model at all survey efforts, but precision degraded as effort decreased. We found that under poor recruitment, the majority of models were unable to recover the true reference point values and that terminal year SSB/SSB_{MSST} was overestimated over 50% of the time for all effort scenarios.

We also found that changing the research fishing gear configuration from dome-shaped to logistic had an interesting effect on model performance. Looking at terminal year SSB specifically, under normal recruitment conditions, logistic selectivity performed worse than dome-shaped selectivity for all survey efforts. However, under the poor recruitment scenario, logistic selectivity slightly improved estimation for HSE compared to dome-shaped selectivity, but for ISE and LSE, the relative error for SSB was higher for logistic selectivity than dome-shaped. Additionally, if an informative prior was given for catchability, the model performed much better under intermediate survey effort.

The results of this simulation highlight the importance of maintaining adequate survey effort; we suggest maintaining effort levels high enough to keep the index CV between 15-18% for more reliable stock assessment estimates. And particularly, in times of poor recruitment, increased monitoring should be considered. Additionally, any changes to gear configuration may result in unexpected modelling difficulties and adequate research should be done to understand how new gear configurations impact catchability.

Introduction

The ‘ōpakapaka (*Pristipomoides filamentosus*), represents one of Hawaii’s most culturally and economically significant deep-water bottomfish species. ‘Ōpakapaka supports both vital commercial and non-commercial fisheries that are deeply embedded in Hawaiian culture and food security, comprising over 50% of the total Deep 7 bottomfish catch and generating close to $1 million annually in commercial value (Luers, DeMartini, and Humphreys 2017). ‘Ōpakapaka is a slow-growing, long-lived snapper species that can live up to 43 years of age (Andrews et al. 2012) and inhabits depths of 100–400 meters around the Main Hawaiian Islands (Luers, DeMartini, and Humphreys 2017). The species is currently managed under the Western Pacific Regional Fishery Management Council’s Hawaii Fishery Ecosystem Plan as part of the Deep 7 bottomfish complex (WPRFMC 2009).

The current stock assessment model for the Deep 7 complex in the main Hawaiian islands combines all seven species together in a surplus production model that relies on combined catch and index of abundance data (Syslo et al. 2024). A single-species model for ‘ōpakapaka has been developed for research and to support the Deep 7 assessment, but it has not been used for management (Syslo et al. 2024). The dominance of ‘ōpakapaka in the fishery means that it is one of the few species out of the seven that can be assessed with an integrated, single-species model. One of the benefits of transitioning to an integrated model is that it allows for the incorporation of more data such as length or age compositions and species-specific life-history information. However, collecting the information that goes into an integrated assessment can be resource- and time-intensive. For example, fishery-independent surveys can provide high-quality, nonbiased data that reflect the true population dynamics of targeted species, however, they can be expensive to conduct annually. Surveys require sufficient effort to produce quality data that informs stock assessment models. Therefore, it is important to optimize surveys to provide the most informative data while also balancing the costs and time required.

The Bottomfish Fishery-Independent Survey in Hawai’i (BFISH) utilizes a stratified-random sampling design to estimate the abundance of the Deep 7 bottomfish complex, including ‘ōpakapaka, across the main Hawaiian Islands. Since its inception in 2016, the survey had historically integrated two sampling modalities: remote stereo-video camera systems and hook-and-line research fishing. However, in response to evolving operational and financial constraints, the survey transitioned to a single-gear approach in 2025, relying exclusively on research fishing. Sampling is conducted within 500 x 500 m Primary Sampling Unit (PSU) grids distributed across 24 distinct strata. A standard research fishing sample consists of 30 minutes of active fishing within a PSU using two

four-hook lines baited with squid and fish (Richards 2025). This method provides critical species-level identification, fork-length measurements, and life-history data. Historically, camera deployments complemented this data, with PSU-level metrics derived from the average of two 15-minute deployments (Richards 2025). The camera and research fishing data are synthesized into joint and separate indices of relative abundance to inform population trends within the Deep 7 stock assessment framework (Ducharme-Barth, N. 2023).

One well-documented limitation that can arise in surveys using hook-and-line gear is the gear selectivity which can cause larger, older individuals to be under-represented in catch due to gear saturation, hook size, and avoidance behavior, producing a dome-shaped selectivity pattern relative to the true population age/size structure (Hommik et al. 2020; Hutchings 2009; Garner et al. 2014). While camera-based indices previously offered a partial check on this limitation by sampling size structure differently, the 2025 transition to a single-gear, research-fishing-only design means the survey's selectivity pattern is now determined entirely by hook-and-line gear. This raises the question of whether modifying gear configuration to produce a more asymptotic (logistic) selectivity pattern, sampling proportionally more of the older/larger portion of the population, could improve the survey's contribution to stock assessment, independent of any change in sampling effort.

The scale of the BFISH survey has fluctuated over time due to logistical and budgetary shifts. Because the total number of sampled grids directly influences the precision of survey-derived indices, it is essential to quantify the relationship between sampling intensity and the reliability of stock assessment outputs. Furthermore, as environmental conditions shift and resource constraints persist, evaluating the implications of alternative sampling designs is necessary to optimize survey efficiency and ensure the long-term stability of management advice.

The objective of this project was to evaluate whether we can optimize an operational fishery-independent survey for ʻōpakapaka in the main Hawaiian Islands. We addressed two related questions: first, the effect of varying levels of survey effort on the ability to estimate key stock quantities, such as spawning stock biomass, fishing mortality, and management reference points, evaluated under two future recruitment conditions; and second, whether altering research fishing gear configuration to produce logistic rather than dome-shaped selectivity affects assessment performance, evaluated under both recruitment conditions.

Methods

Simulation Approach

We tested the impact of varying sampling efforts of a fishery-independent survey by simulating abundance trends and data for ʻōpakapaka in the main Hawaiian islands given appropriate process and observational error. We fitted the simulated data to an age-structured catch-at-age model and estimated spawning stock biomass, fishing mortality, and management reference points (Syslo et al. 2024). Both the operating model (OM) and estimation model (EM) were built in Stock Synthesis (Methot and Wetzel 2013) (SS3) and the simulation-estimation process was implemented using *ss3sim* (Anderson et al. 2014; Johnson et al. 2024) in the R statistical software environment (R Core Team 2024). In total, 1,400 iterations (100 iterations per scenario) were run using the Open Science Grid OSG (2015). Each iteration involved (1) generating the population dynamics from the OM, with the given F and recruitment deviations time series, (2) sampling data from the OM with observational error, and (3) fitting those data in an EM. For each iteration, estimated quantities of interest were compared to the "true" values as calculated by the OM. All code for the analysis is available in the GitHub repository.

Operating Model

The operating model was a single-species, single-sex, age-structured model conditioned on ʻōpakapaka life history parameters and historical fishery data from the Deep 7 complex. Historical data included 75 years of catch, CPUE, and size data from commercial and non-commercial fisheries, plus seven years of abundance indices and length composition data from the BFISH survey. The OM simulated population dynamics and generated abundance indices and compositional data for 100 years. Fishing mortality time series were generated based on historical patterns: low values at fishery inception, increasing through the 1970s and remaining high until the late 1990s, then declining in the early 2000s and stabilizing through the end of the time series (Figure 1). Annual fishing mortality values included stochastic variability (standard deviation of 0.002) to introduce realistic variation between iterations. Following the most recent Deep 7 benchmark stock assessment, we applied time-varying ratios for non-commercial catch: 1.94 from 1948-2003 and 1.09 for 2004-2049 (Syslo et al. 2024).

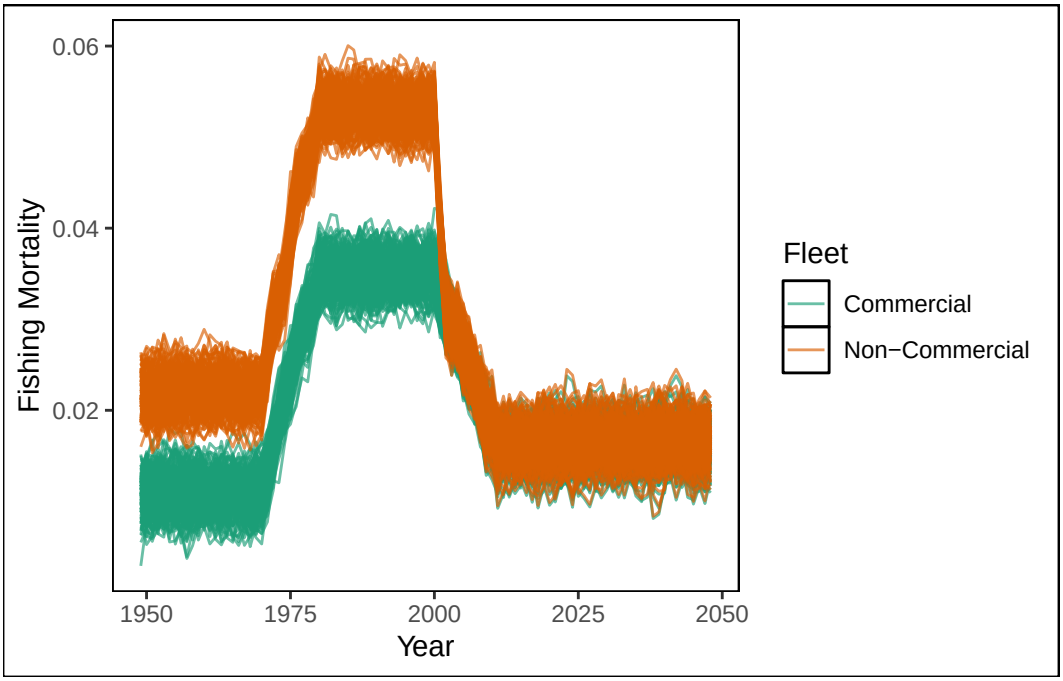

Figure 1. 100 unique time series of fishing mortality for the commercial (green lines) and non-commercial (orange lines) fisheries used for each iteration.

Recruitment Deviations

The simulation framework was structured to evaluate estimation model performance under varying future conditions. The first 75 years of the 100-year simulation represented the historical period with known data patterns, while the final 25 years constituted the "future years" designed to test the robustness of the estimation model against potential changes in recruitment dynamics. Two distinct recruitment scenarios were implemented for these future years to bracket plausible recruitment conditions: (1) a "normal" recruitment scenario that maintained historical mean recruitment levels with no systematic change over time, and (2) a "poor recruitment" scenario that imposed a 40% decline in mean recruitment relative to historical levels. This approach allowed us to assess whether survey sampling intensity affects the estimation model's ability to detect and respond to recruitment shifts that could significantly impact stock productivity and sustainable harvest levels. A total of 200 recruitment deviation time series were generated, 100 were independent, bias-corrected log-normal random deviates with a standard deviation (σ_R) of 0.52 for the entire 100 years, and the remaining 100 were the same for the first 75 years and then the last 25 years were calculated to drive a decline in recruitment.

The baseline recruitment level was established using the mean recruitment from the

most recent 15-year period (280,000 individuals), representing contemporary recruitment conditions prior to the simulated decline.

The declining recruitment scenario was structured as a two-phase process spanning 25 years. Phase 1 comprised a 10-year transition period characterized by a smooth exponential decline from baseline recruitment. The annual proportional rate of change (*r*) was calculated as:

$$r = M_{\text{target}}^{\frac{1}{10}} - 1$$

where M_{target} represents the recruitment multiplier at year 10 relative to baseline. Because recruitment remains above the reduced state during the 10-year transition phase and varies non-linearly with spawning biomass, M_{target} was iteratively solved to achieve an overall 40% reduction in long-term mean expected recruitment (60% of baseline). This yielded $M_{\text{target}} = 0.62$, corresponding to an annual decline rate of $r \approx -4.67\%$. Phase 2 maintained recruitment at $M_{\text{target}} = 0.62$ for the remaining 15 years, simulating a persistent regime shift to lower productivity.

Annual recruitment multipliers (M_t) across both phases were calculated as:

$$M_t = \begin{cases} (1+r)^t, & 1 \leq t \leq 10 \\ M_{\text{target}}, & 11 \leq t \leq 25 \end{cases}$$

Projected deterministic recruitment values ($R_t = \bar{R} \cdot M_t$) were converted to recruitment deviations in log-space to maintain consistency with stock assessment model parameterization:

$$\delta_t = \ln\left(\frac{R_t}{\bar{R}}\right)$$

where $\bar{R}$ is the baseline mean recruitment (279.67). No bias-correction term was applied at this step because δ_t is a deterministic quantity, not a random draw, so there is no log-normal inflation to correct for.

To incorporate realistic recruitment variability around the deterministic decline trend, we generated 100 Monte Carlo iterations of the low-recruitment time series. For each iteration i, final recruitment deviations ($\delta_{t,i}$) were calculated by adding random process noise ($\varepsilon_{t,i}$), bias-corrected so that the stochastic realizations were centered on the deterministic trend:

$$\delta_{t,i} = \delta_t + \varepsilon_{t,i} - \frac{\sigma^2}{2}, \quad \text{where } \varepsilon_{t,i} \sim N(0, 0.15^2)$$

This additional stochastic noise ($\sigma = 0.15$) was intentionally set smaller than the baseline recruitment variability ($\sigma_R = 0.52$) to ensure the underlying decline signal remained statistically detectable above the noise.

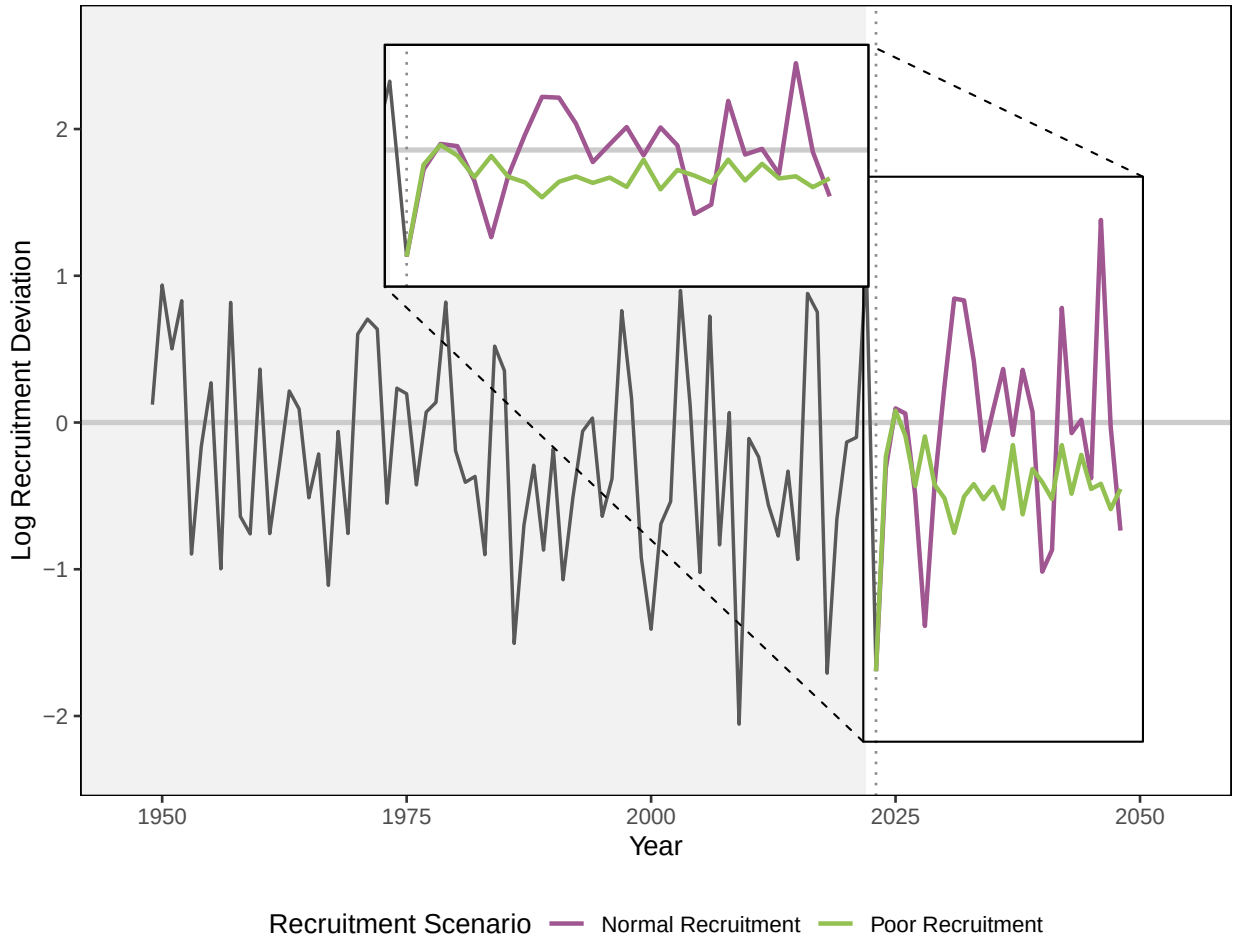

Figure 2. Log recruitment deviations for one iteration over the simulation time period. Recruitment deviations in the historical period (1949-2023, grey shaded area and grey line) were the same for both recruitment conditions, but after 2023 they diverged. The normal (purple line) condition assumed recruitment pattens from the historical period continued into the future. The poor recruitment scenario (green line) assumed there was a 10 year period of declining recruitment, followed by a constant reduced recruitment (compared to the normal).

Initial Fishing Mortality and Selectivity

Initial instantaneous fishing mortality was fixed at 0.012 for the commercial fishery and assumed to start at equilibrium for the non-commercial fishery. Logistic selectivity was modeled for the commercial and non-commercial fisheries and a dome-shaped double

normal selectivity model was used for the research fishing survey (Figure 3). Evidence has shown that the research fishing survey gear tends to select for smaller ‘ōpakapaka and very few larger ‘ōpakapaka, potentially due to the stratified, random design of selecting fishing locations. This “naive” way of selecting fishing location is different from how a commercial fisher would select where to fish because they want to optimize their time and catch larger fish. Additionally, ‘ōpakapaka is a nighttime fishery, but due to constraints, the research fishing survey is only conducted during daylight hours. This could be another reason why the research fishing survey catches fewer large individuals.

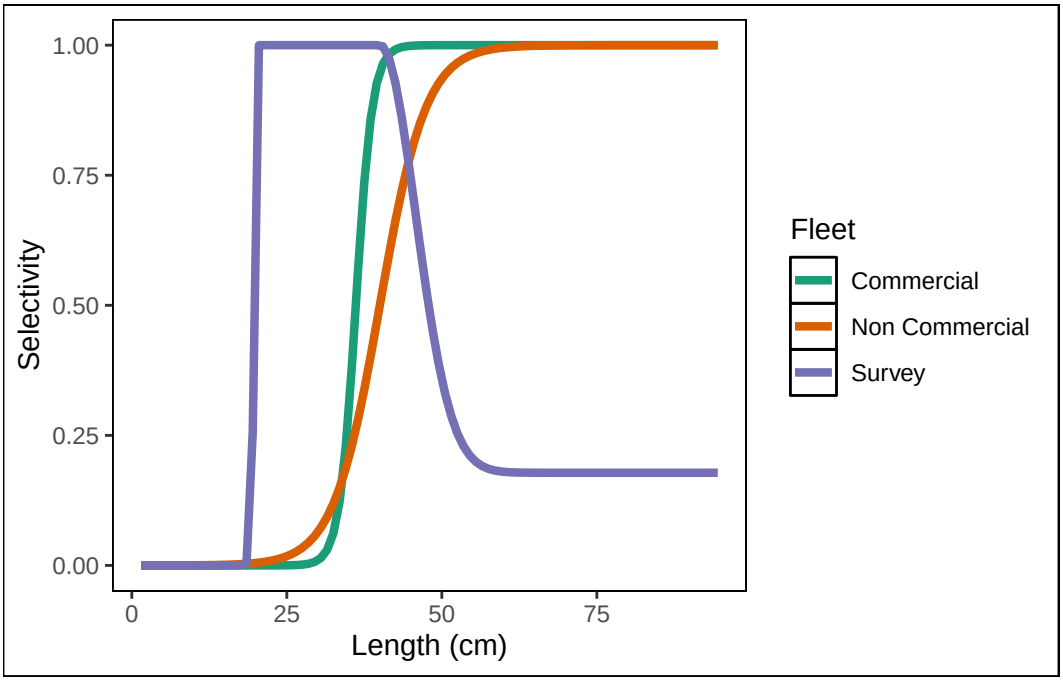

Figure 3. Selectivity functions used for the commercial (green line), non-commercial (orange line), and survey (purple line).

Observation Error Specification

Sampling error (variability in data sampled from the OM) and observation error specified in the EM were the same, ensuring no misspecification of uncertainty. The CV for indices of abundance and effective sample size for length composition remained constant across all years within each scenario (Table 1). The CVs for each effort scenario were determined by fitting a linear regression to actual number of grids sampled and corresponding model-based index of abundance CVs for the seven years of research fishing survey data. Effective sample size was based on the actual number of PSU sampled per year.

Data Sources

All scenarios had some combination of catch, abundance index, and length composition data available for the EM (Figure 4). For all survey scenarios (HSE through XLSE), commercial CPUE and length data were discontinued after 2023, forcing the estimation model to rely entirely on survey-based abundance and length data for the final 25 years. This design allowed us to isolate the effect of survey data quality on assessment performance. In contrast, the NSE scenarios continued using commercial fishery data throughout the entire time series.

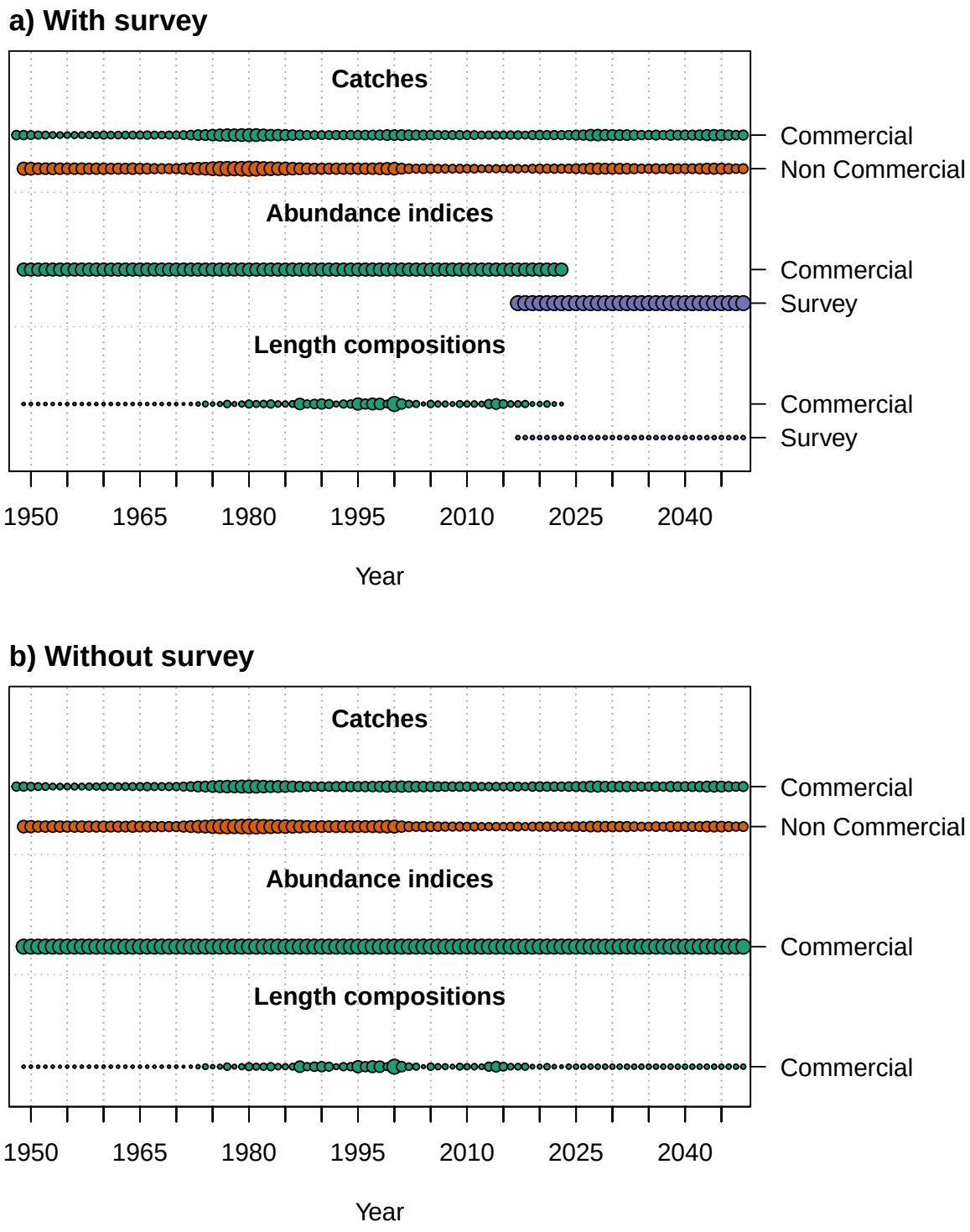

Figure 4. Data generated by the operating model and used by estimation models with (a) and without (b) the survey. Point size indicates relative data amount; colors denote commercial (green), non-commercial (orange), and BFISH survey (purple) data.

Table 1: The observational error used to sample data from the OM for high survey effort (HSE), intermediate survey effort (ISE), low survey effort (LSE), extra low survey effort (XLSE), and no survey effort (NSE) for effort-based scenarios and selectivity-based scenarios. For each survey effort, the number of sampling grids (Grids) that effort would translate to, the resulting index of abundance CV, and effective sample size (effN) for length composition data are shown. All effort-based and selectivity-based scenarios were tested under both normal and poor recruitment conditions.

Scenario	Grids	CV	effN
Effort			
NSE	0	0.20	0
XLSE	257	0.30	15
LSE	407	0.24	30
ISE	557	0.18	45
HSE	632	0.15	60
Selectivity			
LSE-Selectivity	407	0.24	30
ISE-Selectivity	557	0.18	45
ISE-Selectivity-q-prior	557	0.18	45
HSE-Selectivity	632	0.15	60

Scenarios

We evaluated five sampling scenarios to assess how different levels of survey effort affect stock assessment performance under each recruitment condition (Table 1). Survey effort was defined by the number of sampling grids covered, which directly influenced the precision of the resulting abundance index and length composition data. Catch, CPUE, and length composition data were simulated from the OM based on the population dynamics generated by the specific F and recruitment deviation time series (Figure 4).

Survey Effort Scenarios

The scenarios ranged from high survey effort (HSE) with 632 grids to extra low survey effort (XLSE) with only 257 grids. As expected, higher effort translated to more precise data: index CVs ranged from 15% (HSE) to 30% (XLSE), and effective sample sizes for length compositions ranged from 60 (HSE) to 15 (XLSE). The no survey effort scenario (NSE) represented a baseline case where stock assessments would rely solely on fishery-dependent data.

Selectivity Scenarios

In addition to survey effort, we evaluated whether the shape of survey selectivity affects assessment performance. We simulated an alternative gear configuration, producing a logistic selectivity and applied it under poor recruitment conditions at three of the survey effort levels, HSE, ISE, and LSE (Table 1). CV and effective sample sizes for the selectivity scenarios were the same as their counterparts with dome-shaped selectivity (e.g. HSE-selectivity CV = HSE CV) (Table 1). XLSE was not included in the selectivity comparison because this effort level represents a worst case scenario in terms of survey effort and not a likely case.

Catchability Prior Sensitivity Analysis

Preliminary results indicated that logistic selectivity introduces confounding between estimated survey catchability (q) and SSB at intermediate effort. To test whether this identifiability issue could be resolved with modest external information, we re-ran the ISE-selectivity poor recruitment scenario with an informative log-normal prior on $ln(q)$, centered on the OM value with SD = 0.1.

Hyperstability in Fishery Data

For the NSE scenario under poor recruitment conditions, we incorporated hyperstability during the last 25 years for the commercial CPUE data to reflect realistic fishery behavior during population decline (NSE-hyperstable). The CPUE and catch data were modified to not fully reflect the underlying population decline, simulating the tendency of commercial fisheries to maintain catch rates even as fish abundance decreases through improved fishing efficiency, targeting behavior, or fishing in higher-density areas.

Estimation Model

The only structural difference in the EM from the OM was that for the poor recruitment condition, a recruitment regime time block was introduced for the last 15 years. Without the regime, the model was unable to fit the persistent decline in recruitment and the relative errors in outputs were overexaggerated. When fitting the model, all parameters were fixed except for R_0, the regime parameter for the poor recruitment scenarios, catchability for the commercial and survey fleets, and selectivity parameters for the commercial fishery and survey fleet.

Performance Indices

To compare the bias and precision of each sampling strategy, we compared the relative error (RE) between the OM and EM for spawning stock biomass (SSB), fishing mortality (F), age-0 recruitment, and reference points SSB/SSB_{MSST} and F/F_{MSY}. Bias was described by the median relative error (MRE)

$$MRE = median(\frac{EM - OM}{OM})$$

where EM is the estimated value from the EM and OM is the true value from the OM. Precision was described by the variability in relative error across iterations. In particular, we report the bias and precision in the terminal year as this provides information on the long-term impacts of sampling effort on assessment and management abilities. We also evaluated the probability that the terminal year reference points (SSB/SSB_{MSST} and F/F_{MSY}) were 10% greater or smaller than the true reference point values. We believe that managers should be cautious of estimates that fall outside 10% of the true value.

Results

Out of 1,700 EM runs, 99 runs did not converge (maximum gradient was greater than 1e-4). The models with logistic selectivity under poor recruitment conditions had the lowest convergence rates, ranging from 82-85% convergence. Out of the scenarios with dome-shaped selectivity, the NSE scenarios were the only ones that had iterations that did not converge. Overall, model convergence for all sampling scenarios was high.

Effort Scenarios

Under normal recruitment, all effort scenarios exhibited similar bias and precision for terminal-year SSB (Table 2). Relative error remained low, ranging from 2% (SD = 0.154) to 3.6% (SD = 0.136). Notably, the NSE scenario—relying solely on commercial CPUE and length data—performed nearly as well as the highest-effort scenarios. This high performance in the NSE scenario likely stems from the small CV associated with the fishery CPUE index that the survey replaces, and robust effective sample sizes for fishery length data. For scenarios with surveys, precision for SSB over the final 25 years scaled with sampling intensity (Figure 5). For instance, the 95% error interval of SSB for the XLSE scenario was wider (–22% to 38%) than that of the HSE (–12% to 28%), which could have significant influence on reference point estimation.

Under poor recruitment conditions, most sampling scenarios exhibited comparable bias and precision for SSB (Figure 5) and F (Figure 6). However, overall model performance degraded significantly compared to normal recruitment conditions. The NSE-hyperstable scenario was an expected outlier, performing substantially worse than all other configurations with an SSB terminal-year MRE of 38.6% ($SD = 0.294$) (Table 2). For all other scenarios, SSB MRE was more moderate, ranging from 11.9% ($SD = 0.136$) in HSE to 14.4% ($SD = 0.192$) in XLSE.

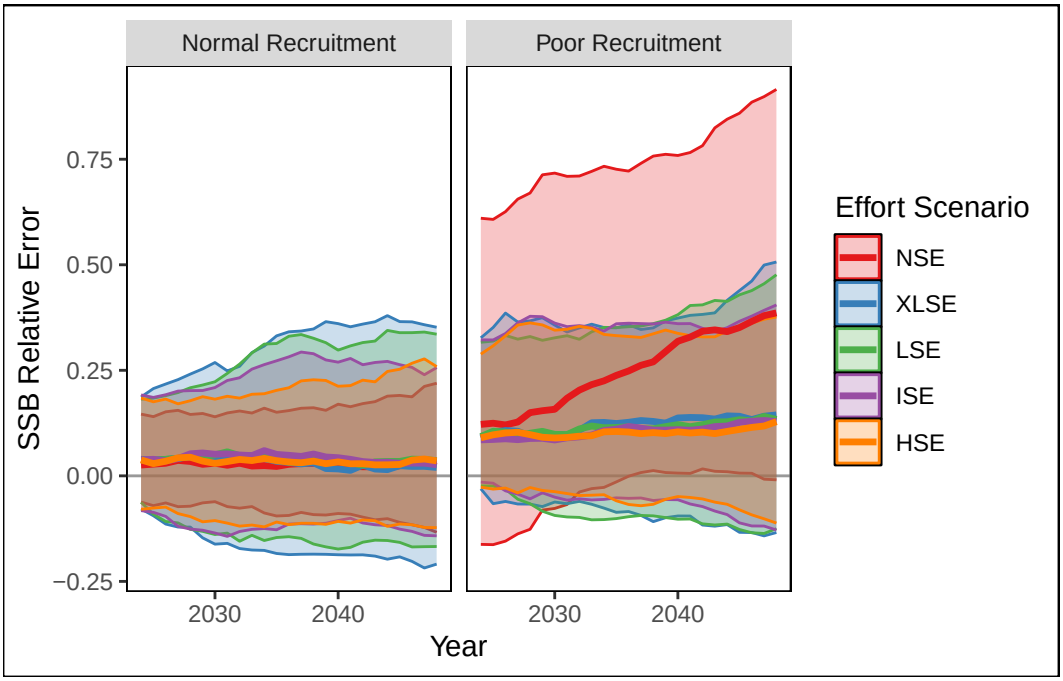

Figure 5. Time series of median (solid line) and 95% quantile (band) relative error of spawing stock biomass for the high (HSE), intermediate (ISE), low (LSE), extra low (XLSE), and no survey effort (NSE) scenarios under both the normal and poor recruitment conditions.

Under normal recruitment, fishing mortality exhibited similar bias and precision across all effort scenarios in the terminal year, though estimates were consistently lower than true values (Table 2). Terminal-year F MRE ranged from –2.4% ($SD = 0.151$) to –3.3% ($SD = 0.103$). Notably, while the XLSE scenario showed a slightly lower bias, it also demonstrated the lowest precision. Conversely, the HSE scenario, despite having slightly higher bias, offered superior precision. The marginal 1% increase in bias in the HSE is a negligible trade-off for the gain in precision and may simply be a simulation artifact. Consistent with SSB patterns, precision for F over the final 25 years declined as sampling effort decreased for scenarios with surveys (Figure 6). The 95% error interval for the XLSE scenario [–23%, 31%] was wider than the more constrained [–18%, 18%] range of the HSE.

Under poor recruitment conditions, estimates of F were less accurate than under normal recruitment (Figure 6). MRE for F ranged from 1.2% ($SD = 0.206$) in NSE-hyperstable to –12.2% ($SD = 0.162$) in the XLSE (Table 2). Interestingly, while the NSE-hyperstable scenario yielded the lowest bias for F over the final decade, it was characterized by much higher variability throughout the projection period ($SD = 0.206$), making the estimates less reliable for consistent management.

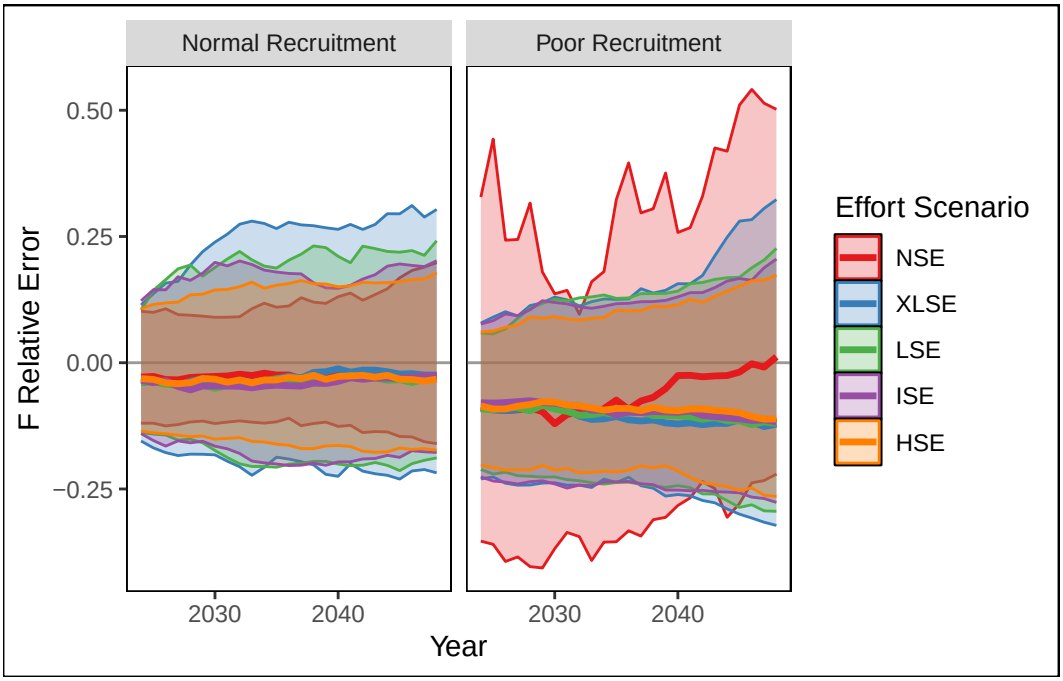

Figure 6. Time series of median (solid line) and 95% interval (band) relative error of fishing mortality for the high (HSE), intermediate (ISE), low (LSE), extra low (XLSE), and no survey effort (NSE) scenarios under both the normal and poor recruitment conditions.

Over the final 25-year period, under normal recruitment conditions, the HSE and ISE scenarios provided the most accurate estimates of true age-0 recruitment, while the XLSE scenario performed the poorest—particularly in the most recent years (Figure 7). Although the XLSE recorded the lowest MRE in the terminal year (Table 2), terminal-year recruitment estimates are inherently unreliable due to limited data observations. A persistent overestimation of age-0 recruitment across all models likely explains the positive bias observed in SSB during the final years of the simulation. Generally, the variability in RE for recruitment was substantially higher than for SSB or F (Table 2), indicating that the estimation model struggles to precisely capture recruitment dynamics regardless of sampling effort.

Under poor recruitment conditions, age-0 recruitment was estimated with similar accuracy in all scenarios except the NSE-hyperstable (Figure 7). Counter-intuitively, terminal-year recruitment estimates were less biased under poor recruitment than under normal recruitment conditions (Table 2). Furthermore, precision was notably higher across all scenarios—including the NSE-hyperstable—throughout the entire projection period (Figure 7).

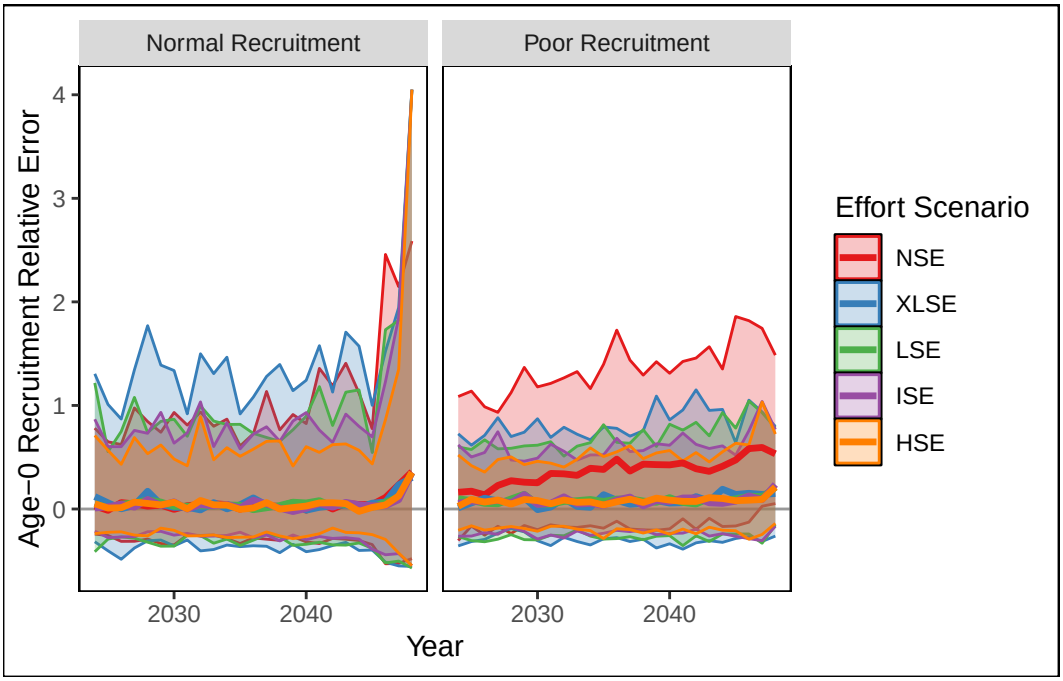

Figure 7. Time series of median (solid line) and 95% interval (band) relative error of age-0 recruitment for the high (HSE), intermediate (ISE), low (LSE), extra low (XLSE), and no survey effort (NSE) scenarios under both the normal and poor recruitment conditions.

Table 2: Median relative error and standard deviation of relative error in the terminal year for spawning biomass, fishing mortality, and recruitment by scenario.

Scenario	Spawning Biomass	Fishing Mortality	Recruitment
Normal Recruitment			
NSE	0.036 (0.100)	-0.031 (0.100)	0.359 (0.931)
XLSE	0.020 (0.154)	-0.024 (0.151)	0.304 (1.400)
LSE	0.036 (0.136)	-0.029 (0.130)	0.351 (1.410)
ISE	0.026 (0.115)	-0.025 (0.110)	0.350 (1.412)
HSE	0.035 (0.109)	-0.033 (0.103)	0.353 (1.418)
Poor Recruitment			
NSE	0.386 (0.294)	0.012 (0.206)	0.533 (0.404)
XLSE	0.144 (0.192)	-0.122 (0.162)	0.150 (0.267)
LSE	0.133 (0.169)	-0.120 (0.139)	0.209 (0.264)
ISE	0.129 (0.146)	-0.117 (0.124)	0.237 (0.254)
HSE	0.128 (0.133)	-0.111 (0.113)	0.212 (0.238)

Under normal recruitment, all models showed similar bias when estimating stock status (SSB/SSB_{MSST} and F/F_{MSY}), but precision degraded noticeably as sampling effort decreased (Figure 8). The NSE scenario had precision levels comparable to the HSE, given the low CV associated with the fishery CPUE index. Median relative error for SSB/SSB_{MSST} ranged from 2.3% to 4% across scenarios (Table 3), with precision (standard deviation) varying from 0.100 (NSE) to 0.153 (XLSE). The 4% precision gap between the XLSE and HSE scenarios represents a meaningful difference that could influence management decisions. Similarly, the MRE for F/F_{MSY} was tightly clustered between 2.8% and 3.1% for all scenarios (Table 3). However, the standard deviation again revealed a 0.04 discrepancy between the HSE and XLSE. This suggests that while all sampling intensities yield similar point estimates for terminal-year F/F_{MSY}, reduced effort compromises precision and increases the risk of significant under- or overestimation.

The HSE scenario demonstrated the strongest performance for estimating terminal-year SSB/SSB_{MSST} and F/F_{MSY} (Figure 8) under poor recruitment conditions. This scenario produced the lowest variability, with MREs of 12.8% for SSB/SSB_{MSST} and –11.5% for F/F_{MSY} (Table 3). Conversely, the NSE scenario performed the poorest for SSB/SSB_{MSST}, with an MRE of 38.9% ($SD = 0.293$). Critically, the true terminal-year stock status was not recovered in the majority of simulation runs for any scenario, as interquartile ranges failed to include zero. This suggests that under poor recruitment, all tested models tend to provide an overly optimistic view of stock status. The only exception was F/F_{MSY} under the NSE-hyperstable scenario, where the MRE was near zero; however, this accuracy comes with a trade-off of extreme uncer-

tainty. The wide range of relative error in the NSE-hyperstable scenario increases the risk of severe overestimation of F/F_{MSY}, potentially leading to unnecessary fishery closures or drastic allocation reductions.

Lastly, the reliability of key reference point estimates remained consistent across all scenarios under normal recruitment conditions (Table 4). The likelihood of incorrectly estimating SSB/SSB_{MSST} (defined as a deviation $> 10\%$) was under 50% for nearly all scenarios, ranging from 51% in the LSE to 30% in the NSE. Similarly, the probability of an incorrect F/F_{MSY} estimate was below 50% for all scenarios, reaching a minimum of 29% in the NSE. These results indicate that under normal recruitment, current sampling efforts generally produce estimates within a 10% margin of the true value the majority of the time. The probability of significant estimation error (deviating $> 10\%$ from the true value) is markedly higher under poor recruitment conditions (Table 4). The likelihood of incorrectly estimating SSB/SSB_{MSST} exceeded 50% for all sampling scenarios, reaching 85% in the NSE. Similarly, the probability of an incorrect F/F_{MSY} estimate was greater than 50% for all scenarios, reaching 67% for the XLSE scenario.

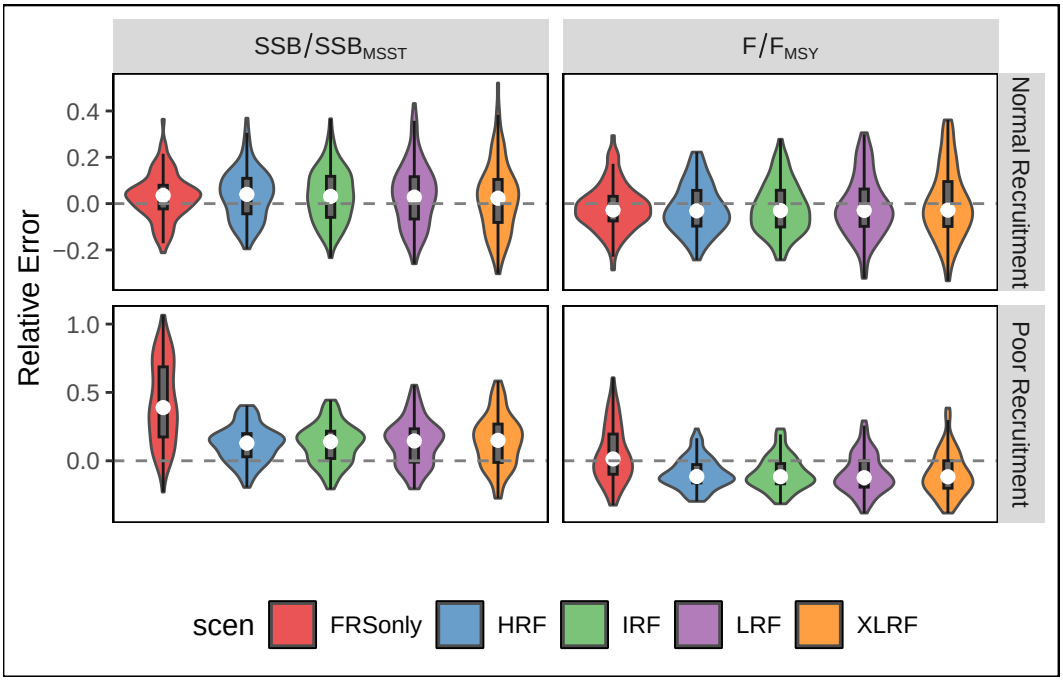

Figure 8. Distribution of relative error for the terminal year stock status (SSB/SSB_{MSST}) and terminal year fishing status (F/F_{MSY}).

Table 3: Median relative error and standard deviation of relative error in the terminal year for SSB/SSB_{MSST} and F/F_{MSY} by scenario.

Scenario	SSB/SSB_{MSST}	F/F_{MSY}
Normal Recruitment		
NSE	0.035 (0.100)	-0.028 (0.101)
XLSE	0.023 (0.153)	-0.028 (0.152)
LSE	0.028 (0.136)	-0.029 (0.132)
ISE	0.031 (0.115)	-0.030 (0.111)
HSE	0.040 (0.109)	-0.031 (0.105)
Poor Recruitment		
NSE	0.389 (0.293)	0.013 (0.205)
XLSE	0.149 (0.191)	-0.117 (0.161)
LSE	0.145 (0.168)	-0.124 (0.140)
ISE	0.140 (0.145)	-0.117 (0.122)
HSE	0.128 (0.132)	-0.115 (0.112)

Table 4: Probability that reference points SSB/SSB_{MSST} and F/F_{MSY} are above or below 10% from the true value for each scenario.

Scenario	SSB/SSB_{MSST}	F/F_{MSY}
Normal Recruitment		
NSE	0.30	0.29
XLSE	0.49	0.49
LSE	0.51	0.44
ISE	0.43	0.44
HSE	0.39	0.37
Poor Recruitment		
NSE	0.85	0.58
XLSE	0.67	0.67
LSE	0.68	0.64
ISE	0.68	0.62
HSE	0.65	0.60

Effect of Survey Selectivity

Independent of survey effort, changing the research survey gear to produce logistic rather than dome-shaped selectivity affected SSB estimation, but the effect was not uniform across effort levels or recruitment conditions (Figure 9). Under normal recruitment conditions, logistic selectivity performed worse than dome-shaped in terms of terminal year SSB MRE and MRE actually slightly increased as effort levels increased (Figure 9, Table 5). At HSE, SSB MRE was 6.2% compared to 5.7% at LSE. As with dome-shaped selectivity, ISE under normal recruitment conditions had the lowest SSB MRE (5.6%) with logistic selectivity. However, under poor recruitment conditions, the patterns were different with logistic selectivity. The highest SSB MRE was LSE, followed closely by ISE (Figure 9) and both were higher than the dome-shaped selectivity scenarios. However, under high survey effort, logistic selectivity performed better than dome-shaped (Figure 9). Interestingly, if an informative prior was applied to catchability under ISE with dome-shaped selectivity, there was noticeable improvement (SSB MRE = 9.2%). Adding an informative prior on catchability when recruitment conditions were poor outperformed models with higher survey effort. This finding can have implications for the trade-offs and statistical properties of the model that are important to consider when making changes to survey design and implementation.

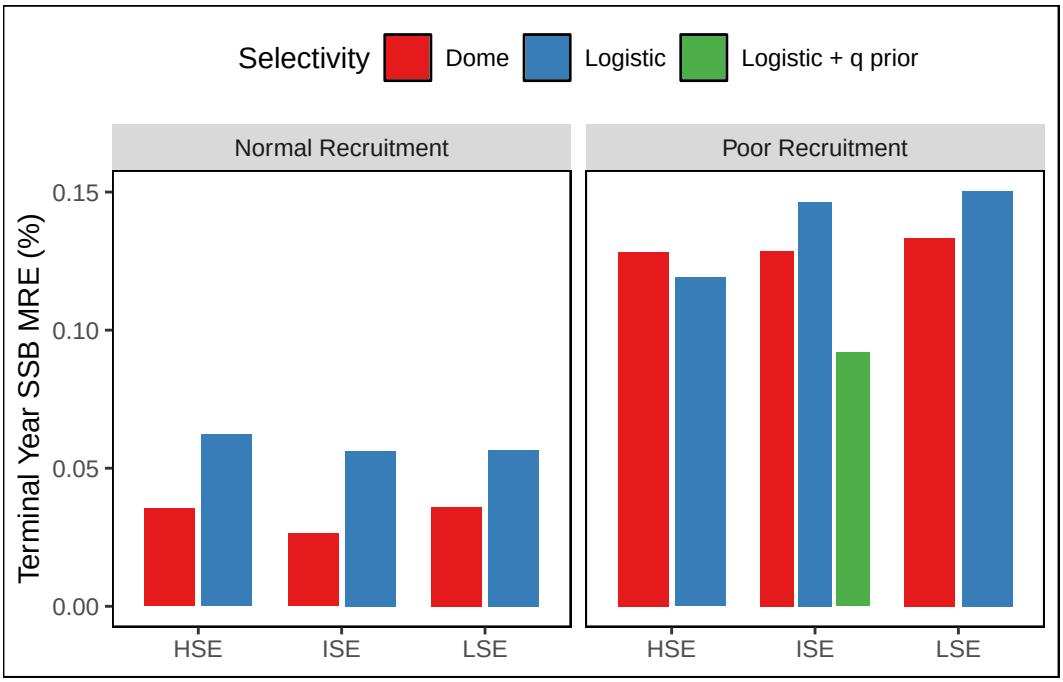

Figure 9. Median relative error of terminal year spawning stock biomass for the high (HSE), intermediate (ISE), and low (LSE) scenarios with dome-shaped (red bars), logistic selectivity (blue bars), and logistic selectivity with an informative prior on q (green bar).

Table 5: Median relative error of terminal year spawning biomass and standard deviation for selectivity scenarios under normal and poor recruitment conditions.

Scenario	Spawning Biomass
Normal Recruitment	
LSE-Selectivity	0.057 (0.144)
ISE-Selectivity	0.056 (0.122)
HSE-Selectivity	0.062 (0.109)
Poor Recruitment	
LSE-Selectivity	0.150 (0.168)
ISE-Selectivity	0.146 (0.148)
ISE-Selectivity-q-prior	0.092 (0.104)
HSE-Selectivity	0.119 (0.136)

This effort-dependent pattern was traced to the confounding of survey catchability and SSB: across all scenarios, terminal-year SSB relative error was strongly correlated with q relative error (Pearson correlation coefficient = 0.71–0.89). This trend is consistent with the known identifiability issue between q and an asymptotic selectivity curve that lacks an interior peak to anchor scale. Applying an informative prior on $\ln(q)$ in the ISE logistic-selectivity scenario reduced SSB MRE from 14.6% to 9.2% and substantially tightened the distribution (SD went from 0.148 to 0.104), supporting catchability identifiability as the mechanism driving the degraded performance under logistic selectivity at intermediate effort.

Discussion

Our results show that the value of a fishery-independent survey is not fixed, it depends on the stability of recruitment, the reliability of the fishery-dependent index, and as our selectivity scenarios demonstrated, on survey design choices such as gear configuration that interact with sampling effort in ways that are not always intuitive. Under normal recruitment, sampling effort primarily dictates the precision rather than the accuracy of biomass and fishing mortality estimates. However, this relationship shifts fundamentally under poor recruitment conditions or regime shifts. In these scenarios, survey effort becomes a determinant of both precision and the ability to accurately characterize stock status. Additionally, a change in gear configuration may not automatically improve the accuracy of estimates, a minimum amount of information is needed for the model to be able to identify and estimate scaling parameters well.

The poor recruitment scenarios revealed a significant optimism bias across all models. When recruitment declined, the interquartile ranges for SSB/SSB_{MSST} and F/F_{MSY} consistently failed to capture the true values, providing an overly favorable view of stock status. This bias was exacerbated by reduced sampling effort. High and intermediate survey effort scenarios (HSE and ISE) demonstrated comparable performance across all metrics, including median relative error and standard deviation of relative error. Lower effort scenarios (LSE and XLSE) maintained similar central tendency measures but exhibited substantially wider confidence intervals, indicating reduced precision in parameter estimates. This pattern illustrates how poor recruitment conditions amplify the negative consequences of reduced sampling effort, creating a compounding effect where assessment reliability deteriorates precisely when accurate population monitoring becomes most critical for management decisions. The performance degradation observed below intermediate effort levels suggests that survey coverage should target a CV between 15-18% for ʻōpakapaka stock management, either through an optimization of the sampling design or maintaining a sufficient number of grids. This is particularly the case given the potential for unexpected recruitment variability in this system.

The NSE scenarios exemplify why it is dangerous to rely solely on fishery-dependent CPUE indices to track population trends. The fishery index provided a complete time series of informative data that allowed the model to accurately estimate population size. However, this was only true under the normal recruitment conditions and once a decline in recruitment was introduced, the model performed far worse than the others in almost every metric. A major assumption of the NSE model is that the fishery data, particularly the CPUE and size data are accurately characterizing the full population. This is likely untrue, as fishers are knowledgeable about where and when to find larger fish and will likely be able to maintain a healthy catch even if the population is declining (i.e. hyper-

stability). Therefore, we should not assume that fishery-dependent data is an accurate, unbiased representation of the true population dynamics.

A key finding of this study is that the effect of gear selectivity on assessment performance was not uniform across sampling effort levels or recruitment conditions. Under normal recruitment conditions, switching from dome-shaped to logistic selectivity actually increased terminal year SSB MRE for all effort scenarios, with the highest effort having the largest MRE. Under poor recruitment conditions, switching selectivity patterns produced small changes in SSB relative error at HSE and LSE, but increased median relative error from 12.9% to 14.6% at ISE. This pattern is consistent with a known identifiability issue between catchability and selectivity in age-structured stock assessment models (Maunder and Piner (2015)). HSE likely provided enough independent information to resolve the confounding despite it, while at LSE the confounding was outweighed by the substantially larger observation error already present in the composition and index data. ISE represents an intermediate condition: sufficient information for the model to converge confidently on a solution, but insufficient to resolve the catchability-selectivity confound, resulting in a consistent, well-defined bias rather than added noise. This was further supported by a targeted sensitivity analysis where an informative prior on catchability reduced median SSB relative error at intermediate effort. Under poor recruitment, the terminal-year SSB median relative error was 9.2%, compared with 14.6% for the equivalent logistic-selectivity scenario without a prior and 12.9% for the dome-shaped-selectivity scenario. Thus, constraining q not only recovered the performance lost under unconstrained logistic selectivity, but produced more accurate terminal-year SSB estimates than the corresponding dome-shaped configuration. This result supports the interpretation that the poorer performance of the unconstrained logistic scenario was driven primarily by confounding between survey catchability and SSB, rather than by logistic selectivity alone. By limiting the ability of q to compensate for changes in abundance, the prior provided an additional source of information that stabilized SSB estimation. However, this benefit depends on the prior being well calibrated: an informative but biased prior could instead transfer bias into estimated SSB.

These results suggest that the consequences of gear-selectivity changes for a fishery-independent survey cannot be evaluated independently of the survey's overall sampling effort, and that intermediate-precision surveys — a common target for cost-constrained monitoring programs — may be particularly susceptible to this form of bias. For BFISH specifically, this implies that any gear modification intended to improve sampling of larger, older ʻōpakapaka should be evaluated jointly with expected survey precision, and that a catchability prior informed by independent data (e.g., a gear calibration or paired-tow study) may be a more practical mitigation.

Our simulation relied on several key assumptions that may not fully capture the complexity of real-world fishery dynamics and data collection challenges. The NSE-hyperstable scenario under poor recruitment assumed complete hyperstability in fishery data, meaning catch rates remained unaffected by population decline throughout the 25-year projection period. While hyperstability is a documented phenomenon in fishery-dependent CPUE indices, sustained recruitment failure would eventually manifest in commercial catch data, suggesting our model may have overestimated the NSE-hyperstable scenario's limitations. Nevertheless, this represents a plausible "worst-case" scenario that highlights the risks of relying solely on fishery-dependent data during periods of stock decline. Additionally, our model simplified future data availability by excluding fishery CPUE and length composition data after 2023, which artificially increased uncertainty even in high survey effort scenarios. In practice, these fishery data streams would continue but would be appropriately weighted within the assessment framework to balance their influence against survey observations. Finally, the poor recruitment scenarios employed reduced variability in recruitment deviations to clearly establish declining trends, whereas natural recruitment variability typically remains high even during periods of decline. This simplification may have amplified the apparent impacts of recruitment failure, as realistic variability could obscure declining trends and complicate early detection of regime shifts.

While consistent long-term monitoring remains ideal, a combination of adaptive sampling strategies and improved data collection techniques could help balance assessment reliability with resource constraints. An adaptive approach could involve reducing survey effort during periods when recruitment appears stable and population indicators show no signs of decline, then increasing sampling intensity when early warning signals suggest recruitment failure or population stress. However, such adaptive strategies must be implemented cautiously, as maintaining data continuity over extended periods provides irreplaceable value for detecting long-term trends and regime shifts. Complementary improvements to data collection could enhance assessment quality without necessarily increasing survey effort, such as incorporating annual age data from the fishery-independent survey to better understand population structure and recruitment dynamics, or refining research fishing methodology in the BFISH survey to reduce coefficient of variation in indices of abundance.

These results highlight several critical considerations for fishery management. The first is that maintaining adequate survey effort is essential for reliable stock assessments, particularly for fishing mortality estimates used in management decisions. The second is that during periods of recruitment failure, enhanced rather than reduced monitoring may be necessary to maintain assessment reliability. We saw a noticeable decrease in our estimation abilities when recruitment was poor and there was a reduced survey effort.

Additionally, scientists and managers should account for increased uncertainty in stock status during periods of both poor recruitment and reduced survey effort (even under normal recruitment conditions). Lastly, changes in gear type may cause additional difficulties in the model if there is not enough information in the data (i.e. effort is not high enough).

Literature Cited

Anderson, Sean C., Cole C. Monnahan, Kelli F. Johnson, Kotaro Ono, and Juan L. Valero. 2014. "Ss3sim: An R Package for Fisheries Stock Assessment Simulation with Stock Synthesis." *PLOS ONE* 9 (4): e92725. https://doi.org/10.1371/journal.pone.0092725.

Andrews, Allen H., Edward E. DeMartini, Jon Brodziak, Ryan S. Nichols, and Robert L. Humphreys. 2012. "A Long-Lived Life History for a Tropical, Deepwater Snapper (Pristipomoides Filamentosus): Bomb Radiocarbon and Lead–Radium Dating as Extensions of Daily Increment Analyses in Otoliths." *Canadian Journal of Fisheries and Aquatic Sciences* 69 (11): 1850–69. https://doi.org/10.1139/f2012-109.

Ducharme-Barth, N. 2023. "Model-Based Relative Abundance Indices for the Main Hawaiian Islands Deep 7 Bottomfish Complex, 2016-2022."

Garner, Steven B., III Patterson William F., Clay E. Porch, and Joseph H. Tarnecki. 2014. "Experimental Assessment of Circle Hook Performance and Selectivity in the Northern Gulf of Mexico Recreational Reef Fish Fishery." *Marine and Coastal Fisheries* 6 (1): 235–46. https://doi.org/10.1080/19425120.2014.952463.

Hommik, Kristiina, Colm J. Fitzgerald, Fiona Kelly, and Samuel Shephard. 2020. "Dome-Shaped Selectivity in LB-SPR: Length-Based Assessment of Data-Limited Inland Fish Stocks Sampled with Gillnets." *Fisheries Research* 229: 105574. https://doi.org/https://doi.org/10.1016/j.fishres.2020.105574.

Hutchings, Jeffrey A. 2009. "Avoidance of Fisheries-Induced Evolution: Management Implications for Catch Selectivity and Limit Reference Points." *Evolutionary Applications* 2 (3): 324–34. https://doi.org/https://doi.org/10.1111/j.1752-4571.2009.00085.x.

Johnson, Kelli F., Sean C. Anderson, Kathryn L. Doering, Cole C. Monnahan, and Christine C. Stawitz. 2024. *Ss3sim: Fisheries Stock Assessment Simulation Testing with Stock Synthesis*. https://github.com/ss3sim/ss3sim.

Luers, Meagan A., Edward E. DeMartini, and Robert L. Humphreys. 2017. "Seasonality, Sex Ratio, Spawning Frequency and Sexual Maturity of the Opakapaka Pristipomoides Filamentosus (Perciformes: Lutjanidae) from the Main Hawaiian Islands: Fundamental Input to Size-at-Retention Regulations." *Marine and Freshwater Research* 69 (2): 325–35. https://doi.org/10.1071/MF17195.

Maunder, Mark N., and Kevin R. Piner. 2015. "Contemporary Fisheries Stock Assessment: Many Issues Still Remain." *ICES Journal of Marine Science* 72 (1): 7–18. https://doi.org/10.1093/icesjms/fsu015.

Methot, Richard D., and Chantell R. Wetzel. 2013. "Stock Synthesis: A Biological and Statistical Framework for Fish Stock Assessment and Fishery Management." *Fisheries Research* 142 (May): 86–99. https://doi.org/10.1016/J.FISHRES.2012.10.012.

OSG. 2006. "OSPool." OSG. https://doi.org/10.21231/906P-4D78.

———. 2015. “Open Science Data Federation.” OSG. https://doi.org/10.21231/0KVZ-VE57.

Pordes, Ruth, Don Petravick, Bill Kramer, Doug Olson, Miron Livny, Alain Roy, Paul Avery, et al. 2007. “The Open Science Grid.” In *J. Phys. Conf. Ser.*, 78:012057. 78th Series. https://doi.org/10.1088/1742-6596/78/1/012057.

R Core Team. 2024. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Richards, Benjamin. 2025. “Annual Report: 2024 Bottomfish Fishery-Independent Survey in Hawai‘i.” *NOAA Technical Memorandum NMFS PIFSC ; 177*. https://doi.org/10.25923/059V-F791.

Sfiligoi, Igor, Daniel C Bradley, Burt Holzman, Parag Mhashilkar, Sanjay Padhi, and Frank Wurthwein. 2009. “The Pilot Way to Grid Resources Using glideinWMS.” In *2009 WRI World Congress on Computer Science and Information Engineering*, 2:428–32. 2nd Series. https://doi.org/10.1109/CSIE.2009.950.

Syslo, John, Megumi Oshima, Hongguang Ma, Nicholas Ducharme-Barth, Marc Nadon, and Felipe Carvalho. 2024. “Benchmark Stock Assessment for the Main Hawaiian Islands Deep 7 Bottomfish Complex, with Projections Through 2029.” https://doi.org/10.25923/5SSG-8D54.

WPRFMC. 2009. “Fishery Ecosystem Plan for the Hawaii Archipelago.” Western Pacific Regional Fishery Management Council. http://www.wpcouncil.org/fishery-plans-policiesreports/hawaii-fishery-ecosystem-plan.