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Data and Management Strategies for Recreational Fisheries with Annual Catch Limits

Committee on Data and Management Strategies for Recreational Fisheries with Annual Catch Limits

Ocean Studies Board

Division on Earth and Life Studies

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The National Academies of
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Preface

The collection of catch data on marine recreational fisheries is difficult, complex, and different from data collection for commercial fisheries. The complexity of recreational fisheries comes from the vast number of species, fishers, entry locations, fishing seasons, and recreational fishers' objectives—from enjoying a day in nature to catching dinner.

As the magnitude and relevance of recreational fisheries increase, so does the demand for better data collection systems. In 2017, the National Marine Fisheries Service of the National Oceanic and Atmospheric Administration (NOAA), also known as NOAA Fisheries, requested that the National Academies of Sciences, Engineering, and Medicine, or "The National Academies," review the Marine Recreational Information Program (MRIP). This national program provides recreational catch data to support the needs of fisheries scientists and managers who are responsible for conducting assessments of fish stocks and establishing fishing regulations to ensure the sustainable management and use of U.S. fisheries resources. The National Academies convened an ad hoc committee that assessed progress in updating marine recreational fisheries data collection through MRIP over the previous decade, and identified potential areas for improvements or modifications to the program that would increase data quality for sustainable fisheries management. That committee released the report *Review of the Marine Recreational Information Program*, which concluded that the difficulties of estimating recreational catches in an accurate, precise, and timely manner with sufficient spatio-temporal resolution to inform in-season monitoring and management against annual catch limits (ACLs) may result in management problems for recreational and mixed-use fisheries. These difficulties may also lead to an erosion of trust in the management system among recreational fisheries stakeholders.

While NOAA Fisheries has made improvements to the MRIP program since 2017, questions remain regarding outstanding challenges limiting the extent to which current survey methods in each region meet the needs of the defined in-season management of recreational fisheries with ACLs. In some cases, adherence to ACLs requires short recreational fishing seasons, which complicates data collection, monitoring, and management. This observation is not new, and warrants the consideration of alternate approaches to optimize MRIP data and complementary data for in-season management. In 2018, the Modernizing Recreational Fisheries Management Act underscored the many differences between commercial and recreational fisheries management, and called for a new National Academies study on how well the MRIP meets the needs of in-season management of fisheries with ACLs as well as how survey methods or management strategies might be modified to better meet those needs. The National Academies convened the Committee on Data and Management Strategies for Recreational Fisheries with Annual Catch Limits in 2020 to conduct this study. This report is a result of that effort.

This report captures the collective wisdom of some of the nation's leading experts in survey sampling and recreational fisheries data and management. I want to express my deep appreciation to every member of the committee for his or her attention, thoughtfulness, and hard work, as well as their wonderful collegiality.

The committee is grateful to NOAA Fisheries for their responsiveness to the many questions and requests for information while developing this report. In particular, we thank the MRIP staff and Gordon Colvin for his guidance throughout the study process. The committee is also grateful to the many individuals who played a role in completing this study. The committee met seven times throughout the course of the study, and would like to extend its thanks to all the individuals from regional councils, NOAA Fisheries, state fisheries agencies, recreational and commercial fisheries organizations, environmental conservation organizations, and others who appeared before the full committee, or provided background information and discussed relevant issues.

Lastly, the committee extends its sincere appreciation to our superb National Academies' staff for their valuable support and many contributions to the project. Study Director Stacee Karras, Assistant Study Director Alexandra Skrivanek, and Senior Program Assistant Trent Cummings were instrumental in keeping the project on course and ensuring the timely completion of the report without compromising quality. Working with this team has been a pleasure and a privilege.

Luiz Barbieri, *Committee Chair*
Committee on Data and Management Strategies for
Recreational Fisheries with Annual Catch Limits

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This report was also greatly enhanced by discussions with participants at the committee's seven meetings conducted as part of this study. The committee would like to especially acknowledge the efforts of those who gave presentations at these meetings: Kelly Denit (the National Marine Fisheries Service of the National Oceanic and Atmospheric Administration [NOAA Fisheries]), Richard Cody (NOAA Fisheries), Russell Dunn (NOAA Fisheries), Tim Sartwell (NOAA Fisheries), Tom Frazer (University of South Florida), Ryan Rindone (Gulf of Mexico Fishery Management Council), Kellie Ralston (American Sportfishing Association [ASA]), Chris Horton (Congressional Sportsmen's Foundation), Michael Drexler (Ocean Conservancy), Sepp Haukebo (Environmental Defense Fund), Gregg Bray (Gulf States Marine Fisheries Commission), Beverly Sauls (Florida Fish and Wildlife Conservation Commission [FWC]), Kevin Anson (Alabama Department of Conservation and Natural Resources), Trevor Moncrief (Mississippi Department of Marine Resources), Harry Blanchet (Louisiana Department of Wildlife and Fisheries), Mark Fisher (Texas Parks and Wildlife Department), John Foster (NOAA Fisheries), John Carmichael (South Atlantic Fishery Management Council), Jessica McCawley (FWC), Genny Nesslage (University of Maryland), Bob Lorenz (private angler), Roy Crabtree (NOAA Fisheries), Andy Strelcheck (NOAA Fisheries), Geoff White (Atlantic Coastal Cooperative Statistics Program [ACCSP]), Amy Dukes (South Carolina Department of Natural Resources), Chris Wilson (North Carolina Department of Environmental Quality [NCDEQ]), Steve Poland (NCDEQ), Carolyn Belcher (Georgia Department of Natural Resources), Ira Laks (Relaks Fishing), Tom Roller (WaterDog Guide Service), Kiley Dancy (Mid-Atlantic Fishery Management Council [MAFMC]), Julia Beaty (MAFMC), Mike Luisi (Maryland Department of Natural Resources), Jeffrey Brust (New Jersey Division of Fish and Wildlife), John Maniscalco (New York Department of Environmental Conservation), Garry Glanden (Delaware Division of Fish and Wildlife), Shanna Madson, (Virginia Marine Resources Commission [VMRC]), Lewis Gillingham (VMRC), Mike Waine (ASA), Charles Witek (private angler), Gordon Colvin (NOAA Fisheries), Rob Andrews (NOAA Fisheries), Chris Kellogg (Northeast Fishery Management Council [NEFMC]), Jamie Cournane (NEFMC), Scott Steinback (NOAA Fisheries), Moira Kelly (NOAA Fisheries), Bob Beal (Atlantic States Marine Fisheries Commission), Geoff White (ACCSP), Jason McNamee (Rhode Island Department of Environmental Management), Samuel Truesdell (Massachusetts Department of Marine Fisheries), Matthew Cieri (Maine Department of Marine Resources), Greg Wojcik (Connecticut Department of Environmental Protection), Kevin Sullivan (New Hampshire Fish and Game Department), Rip Cunningham (private angler), Rick Bellavance (charter boat captain), John Devore (Pacific Fishery Management Council [PFMC]), John Field (NOAA Fisheries), EJ Dick (NOAA Fisheries), Melissa Monk (NOAA Fisheries), Jason Cope (NOAA Fisheries), Jean Opsomer (Westat), Lauren Dolinger Few (NOAA Fisheries), Lynne Mattes (Oregon Department of Fish and Wildlife), Heather Hall (Washington Department of Fish and Wildlife [WDFW]), Dereck Dapp (WDFW), John Budrick (California Department of Fish and Wildlife), Phil Anderson (PFMC), Kurt Iverson (NOAA Fisheries), Jim Hasbrouck (Alaska Department of Fish and Game), Marlowe Sabater (Western Pacific Fishery Management Council [WPFMC]), Kitty Simonds (WPFMC), Hongguang Ma (NOAA Fisheries), and Todd Jones (NOAA Fisheries).

This Consensus Study Report was reviewed as a draft by individuals chosen for their diverse perspectives and technical expertise. The purpose of this independent review is to provide candid and critical comments that will assist the National Academies of Sciences, Engineering, and Medicine in making each published report as sound as possible and to ensure that it meets the institutional standards for quality, objectivity, evidence, and responsiveness to the study charge. The review comments and draft manuscript remain confidential to protect the integrity of the deliberative process.

We thank the following individuals for their review of this report:

MICHAEL ARMSTRONG, Massachusetts Division of Marine Fisheries
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PATRICK SULLIVAN, Cornell University

Although the reviewers listed above provided many constructive comments and suggestions, they were not asked to endorse the conclusions or recommendations of this report nor did they see the final draft before its release. The review of this report was overseen by Andrew Solow, Woods Hole Oceanographic Institution, and Alan Hastings, University of California, Davis. They were responsible for making certain that an independent examination of this report was carried out in accordance with the standards of the National Academies and that all review comments were carefully considered. Responsibility for the final content rests entirely with the authoring committee and the National Academies.

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Summary

INTRODUCTION

The National Marine Fisheries Service (NMFS) of the National Oceanic and Atmospheric Administration (NOAA), also known as NOAA Fisheries, is responsible for the stewardship of the nation's marine resources and the habitats from which they are derived. In support of this mission, NOAA Fisheries collects information on marine recreational angling through the Marine Recreational Information Program (MRIP)—a state–regional–federal partnership and survey program that includes in-person, telephone, mail-in, and other complementary surveys to estimate total recreational catch. MRIP is designed to support the needs of fisheries scientists and managers responsible for conducting assessments of fish stocks and using that information to establish commercial and recreational fishing regulations that optimize the management and sustainable use of fisheries resources.

Marine recreational fishing is conducted across the nation, and is a positive driver of the American marine—or blue—economy. Defined as "fishing for sport or pleasure" in the Magnuson-Stevens Fishery Conservation and Management Act (MSA), it is distinct from commercial or subsistence-oriented fishing in several ways, including the number of participants and diversity of their fishing motivations. With high demand for recreational fishing and pressure of direct harvest on many marine fish stocks, effective marine recreational fisheries management is critical to ensuring the quality and ecological sustainability of this activity. To this effect, the 2007 reauthorization of the MSA mandated that Regional Fishery Management Councils set annual catch limits (ACLs) to prevent overfishing for all managed species in federal waters, as well as accountability measures to prevent ACLs from being exceeded. Councils are responsible for the development of fishery management plans and associated regulations for resources of significance in their respective regions in accordance with a suite of national standards for conservation and management. They are required to account for the total catch from all sources to determine an ACL; therefore, both the determination and implementation of ACLs rely on accurate fisheries data, and directly impacts management of the fishery.

Recreational fisheries catch data tend to be difficult to collect relative to commercial catch data because of the large numbers of participants and access points, and lack of mandatory catch reporting. Survey sampling used to collect recreational catch data covers only a small proportion of anglers and relies on recall as well as direct observation of catches after the actual catch has occurred, which tends to result in catch data that are more uncertain, more sensitive to details of survey design, and less timely relative to the data collected for commercial fisheries.

In 2017, an ad hoc committee of the National Academies of Sciences, Engineering, and Medicine published *Review of the Marine Recreational Information Program,* which assessed progress in updating marine recreational fisheries data collection through MRIP over the previous decade, and identified potential areas for improvements or modifications to the program that would increase data quality for sustainable fisheries management. That report explored the difficulty and complexity of collecting catch data on recreational fisheries, highlighting that in some cases, enforcement of ACLs requires short recreational fishing seasons, which further complicates data collection, monitoring, and management. The 2017 report noted that establishing the MRIP had resulted in significant improvements to recreational catch and effort surveys. However, the demands of in-season management of ACLs often exceeded the temporal and spatial design of the surveys, in some cases, resulting in estimates of harvest with a high degree of imprecision that required the application of accountability measures, such as early season closures and reductions in future recreational ACLs, to offset potential exceedance of the ACL.

The 2017 National Academies study concluded that implementation of ACLs, combined with the enforcement of accountability measures, had created tension, particularly in recreational fisheries, where stakeholders expressed concern over the use of MRIP data to estimate catch limits and determine whether they had been exceeded. The difficulties of estimating recreational catches in an accurate, precise, and timely manner with sufficient spatio-temporal resolution to inform in-season monitoring and management against ACLs could result in not only management problems for recreational and mixed-use fisheries, but also an erosion of trust in the management system among recreational fisheries stakeholders.

Shortly thereafter, the Modernizing Recreational Fisheries Management Act of 2018, or Modern Fish Act (MFA), amended parts of the MSA to reflect the differences between commercial and recreational fisheries management, and required that NOAA take further action to improve federal recreational fisheries management. The MFA also called for a new National Academies study on how well the MRIP meets the needs of in-season management of fisheries with ACLs, and how survey methods or management strategies might be modified to better meet those needs (see Box S.1 for the full statement of task for this study). In 2020, members of the National Academies committee undertaking this study met virtually on seven occasions to gather information. At each meeting, members heard from state and federal employees, as well as regional stakeholders. They also received written input from stakeholders during the information-gathering process necessary to develop this report, and the recommendations and conclusions presented therein.

BOX S.1 Statement of Task

A 2017 report, Review of the Marine Recreational Information Program discusses the difficulty of collecting necessary data on recreational fisheries. In some cases, enforcement of catch limits requires short recreational fishing seasons, further complicating data collection, monitoring, and management. The Modernizing Recreational Fisheries Management Act of 2018 called for a National Academies study on how well the Marine Recreational Information Program meets the needs of in-season management of fisheries with annual catch limits (ACLs). This study will also consider how survey methods or management strategies might be modified to better meet those needs.

This study will evaluate:

A. if and how the design of the Marine Recreational Information Program, for the purposes of stock assessment and the determination of stock management reference points, can be improved to better meet the needs of in-season management of annual catch limits (ACLs);
B. what actions the Secretary, Councils, and States could take to improve the accuracy and timeliness of data collection and analysis to improve or supplement the Marine Recreational Information Program and facilitate in-season management; and
C. alternative management approaches that could be applied to recreational fisheries, consistent with requirements for fisheries with ACLs, for which the Marine Recreational Information Program is not sufficient to meet the needs of in-season management.

This evaluation will include the following:

1. fishery-specific assessment of the in-season management needs of each region;
2. an objective, independent evaluation of how well current survey methods in each region meet the needs of the defined in-season management of recreational fisheries with ACLs;
3. an evaluation of how current ACL in-season management strategies utilize information provided by the current surveys;
4. an assessment of how survey methods and/or management strategies could be modified to better meet the needs for ACL monitoring and accountability measures to ensure that overfishing does not occur; and
5. an assessment of the trade-offs that should be considered when determining appropriate pairing of survey methods with ACL management strategies.

This study concluded that MRIP and the data collections conducted by its federal contractors and regional and state partners were not designed for the purposes of in-season management of recreational fisheries with ACLs. However, this report recognizes the improvements that NOAA Fisheries has made to the MRIP program since 2017 and the unique aspects of recreational fishing that set it apart from commercial or subsistence fishing. It documents the differences among recreational fisheries survey programs, as well as the diversity of in-season, ACL-based management approaches and the management needs of each region. It also presents conclusions regarding outstanding challenges limiting the extent to which current survey methods in each region meet the needs of the defined in-season management of recreational fisheries with ACLs. In response to these challenges, the report presents approaches to optimizing MRIP data and complementary data for in-season management, and provides survey design and methodology options for improving or supplementing the program on a regional or fisheries basis. Further, the report considers the use of alternative management options that have the potential to address management challenges associated with recreational fisheries with ACLs while also serving broader social and economic management objectives.

U.S. FISHERIES MANAGEMENT AND ASSESSMENT

Management of marine recreational fisheries occurs at the intersection of law, policy, and science. It also crosses both federal and state jurisdictions. Regional differences exist regarding the execution, intersection with other management authorities, and practical application of federal requirements in the monitoring and management of marine recreational fisheries.

The Magnuson-Stevens Act and Establishment of ACLs

Marine fisheries in U.S. federal waters are managed under the MSA, which acknowledged the social and economic importance of fishery resources. The MSA established a national program for fisheries conservation and management, including the creation of eight Regional Fishery Management Councils (Councils) composed of representatives of commercial and recreational fishing, NOAA Fisheries, and the marine fisheries agencies of the coastal states.

For all stocks in need of conservation and management, the MSA requires that Councils set ACLs to prevent overfishing and accountability measures to ensure that catches are constrained to ACLs. ACLs are determined on the basis of scientific stock assessments and represent the maximum amount of fish that can be harvested without exceeding the exploitation rate that is estimated to provide the maximum sustainable yield (MSY) from the stock. As required by the MSA, a council cannot exceed the recommended biologically acceptable levels of catch (determined by its Scientific and Statistical Committee) when setting an ACL, and its fishery management plans must include reference points (or reasonable proxies) for all managed species to make determinations of stock status. Reference points, such as MSY, optimum yield, acceptable biological catch and ACLs, serve as thresholds that can be used to evaluate the effectiveness of management measures in preventing overfishing.

The Modernizing Recreational Fisheries Management Act and Recreational Fisheries Management

The 2018 MFA did not alter the MSA's fundamental requirement for ACLs and accountability measures. Instead, it clarified that management approaches for commercial and recreational fisheries should be tailored to the needs of each sector, and highlighted specific approaches that Councils could consider for recreational fisheries management. These include additional methods, such as extraction rates, fishing mortality targets, harvest control rules, and traditional or cultural practices of native communities for managing recreational fisheries. The degree to which Councils employ these methods is determined by the quality and availability of information, and the potential effectiveness of their use is typically evaluated based on the total catch likely to be produced. Ultimately, a variety of approaches are used to monitor stocks and ensure that ACLs are not exceeded. In-season accountability measures compare harvest with the ACL as the fishery is underway, and may trigger a closure or other adjustments (e.g., changes to possession limits or season length), while post-season accountability measures may modify future harvest limits to account for overages.

Stock assessments are central to the fisheries management process and vary greatly in complexity depending on the quality and quantity of available data. While stock assessment models and outputs are similar, each Council region has developed a process for scheduling, conducting, and reviewing assessments that meets regional needs and ensures the quality of science. Implementation of MRIP has greatly improved the recreational catch data used in stock assessments, although challenges remain in obtaining high-quality and timely estimates of recreational fisheries catch.

MRIP and the Management and Monitoring of Recreational Harvest

Recreational monitoring programs often use a combination of mail or internet surveys, telephone interviews, creel surveys, and dockside sampling to estimate the level of catch and other relevant information about the fishery. The accurate and timely estimate of recreational fisheries catch is challenging in the design of monitoring programs and statistical analyses because it occurs over a large number of diffuse access points (boat ramps, marinas, private docks) and is conducted by a large number of participants. These and other characteristics of recreational fisheries make census-based approaches to monitoring and managing catch inherently difficult.

Recreational ACL management therefore tends to rely on a two-step process of (1) instituting size, season and bag limits that are forecast to result in the ACLs being met, and (2) monitoring of catches using a survey-based approach to provide a catch estimate, normally after the recreational season has ended. The setting of size, season, and bag limits to achieve the recreational ACL involves forecasting catches in relation to these limits. Several forecasting approaches may be used to project how a given set of management measures (e.g., size, season, and bag limits) will perform compared with an ACL. Actual performance (i.e., realized vs. projected catch) depends on management uncertainty, which includes both implementation uncertainty (how well management measures met expectations) and uncertainty in estimates of catch. Pursuit of in-season management is focused primarily on reducing management uncertainty to avoid or minimize forgone fishing opportunities.

RECREATIONAL FISHERIES MANAGEMENT SURVEYS

In-season management of recreational fisheries varies by region, and is informed by a combination of MRIP and state-sponsored recreational fishing surveys and data collection programs at the regional and state levels, with the aim of meeting each region's diverse data needs. As a result of technical, logistic and funding constraints, the degree to which data needs are fully met varies among regions and fisheries. While MRIP surveys and catch estimates do not cover all fishable U.S marine waters, the program covers more than 90 percent of all U.S. marine recreational fishing trips and catch in terms of total numbers of recreational fishing trips or total recreational catch. Within their intended scope and design constraints, MRIP data are critically important for fisheries management. Recognizing the limitations, including concerns with precision, most states desire access to raw MRIP data. By utilizing existing infrastructure already developed by regional Fishery Information Networks (FINs), MRIP Regional Implementation Teams provide the framework for integrating regional and state partner input, identifying regional priorities, and ensuring coordination in the development of strategies for addressing stock assessment and management needs for Council-managed recreational fisheries. In many instances, these needs include the development and implementation of specialized recreational surveys (either supplemental or alternative) to address MRIP data limitations.

One of the evolving needs of today's fisheries managers is data on recreational catch that are accurate, precise, and timely and of sufficient resolution to inform in-season monitoring and management against ACLs. Compared with MRIP surveys, supplemental or alternative surveys have achieved a variety of benefits, including greater timeliness of estimates; greater spatial resolution; provision of additional information; and in some cases, possibly, greater precision of estimates. Compared with MRIP surveys—including the Access Point Angler Intercept Survey (APAIS), Fishing Effort Survey (FES), For-Hire Survey (FHS), Northeast Vessel Trip Reporting (VTR) program, Southeast Region Headboat Survey, Southeast Region For-Hire Electronic Reporting (SEFHIER) Program, and Large Pelagic Survey (LPS)—alternative or supplemental surveys have been shown to provide different estimates for recreational catches for the same fishery. Differences among estimates can be moderate, or quite substantial.

Alternative and supplemental surveys have improved timeliness through the use of new technologies (e.g., mobile apps and tablets), as well as reduced lag times in data processing and release. Some alternative surveys, such as Louisiana's LA Creel, Mississippi's Tails n' Scales, Alabama's Snapper Check, and Florida's State Reef Fish Survey, have been certified by NOAA Fisheries, indicating acceptance of their survey designs and estimation methods as scientifically sound and eligible for use in assessment and management. Pacific RecFIN surveys are currently in the process of certification.

While the implementation of MRIP surveys is generally standardized, there is a precedent for adapting coverage to regional characteristics and needs. Given the colder climate of New England, both APAIS and FES are now conducted only during the warmer part of the year in the northeast region. Public perceptions of differences between MRIP and alternative surveys in methodology, final catch estimates, and the precision of the estimates is a source of consternation among anglers, fisheries managers, and other stakeholders, contributing to expressions of concern over the use of data from MRIP to estimate and monitor catch limits. One specific area of concern relates to the need for and challenges of survey inter-calibration[1] (See Chapter 3).

Recommendation: Current efforts by MRIP and its partners in the area of survey inter-calibration should continue and, where significant differences among surveys exist in terms of final estimates or precision, the causes of the differences should be determined and communicated to the public.

OPTIMIZING THE USE OF MRIP AND COMPLEMENTARY DATA FOR IN-SEASON MANAGEMENT

Several attributes of marine recreational fisheries make them difficult to characterize and monitor. While MRIP was developed to address some of these challenges and to generate estimates of recreational fisheries catch and effort that are better-suited for use in stock assessment and management, MRIP surveys were neither intended nor designed to support in-season monitoring of recreational catch. The main products of the MRIP general survey are bi-monthly catch estimates that are informative at the annual scale. While annual estimates of landings and discards are usually adequate for stock assessments of commonly encountered species, annual estimates at the state and regional levels are often considered inadequate for managing recreational fisheries with ACLs, and typically lack adequate precision for species that are rarely intercepted. Modifications to data collection designs and methods, and extensions of current statistical methods may enhance MRIP's contribution to in-season management.

Improving the Precision, Timeliness, and Availability of MRIP Estimates

Mobile apps for smartphones and tablets, for example, offer technologies for improving the efficiency and timeliness of recreational data reporting. With strong support from fishery managers and stakeholders, MRIP and other recreational fisheries data collection programs have greatly improved the development and use of mobile apps and other electronic data collection and reporting platforms. Since 2017, there has been substantial progress on the use of electronic logbooks by the for-hire sector and the ability of interviewers to capture and submit data electronically. In 2021, the Gulf Fisheries Information

[1] The calibration of multiple surveys operating in the same geographic area and covering the same species and fisheries.

Network transitioned all APAIS data collection in the Gulf Region to tablet-based systems and is using automated data transfer is being used to reduce the time needed to deliver the data for MRIP processing. While mobile apps and other technological integrations can improve the efficiency of data collection, however, these technologies alone will not speed up the process if other systemic bottlenecks exist.

Depending on the species and region, final MRIP bi-monthly wave estimates require input from multiple data sources. Relative to the time that a fishing trip actually occurs, each of the contributing data streams can have very different reporting time lags before MRIP can access or utilize the data. While FES, LPS and VTR/SEFHIER data collections are centrally administered by NOAA or its contractors, the rest of the data collected to generate MRIP's bi-monthly estimates is largely decentralized, and led by regional commissions, science centers and state fish and wildlife agencies. MRIP can expect to have all of the needed data within 1 month after the close of each data collection wave, after which an additional 2 weeks of time is needed for MRIP staff to conduct final assessments and review before releasing the official estimates to fishery managers and the public. With additional resources, MRIP might be able to shorten by roughly 2 weeks the time between the end of its current bi-monthly reporting period and the release of preliminary estimates. This would put additional stress on existing MRIP staff and systems, however, and for purposes of in-season management, the benefits of a modest advance in the release of preliminary estimates for bi-monthly waves would be unlikely to justify the costs of accelerating the data processing and estimation phases of each bi-monthly cycle.

It is possible that the raw MRIP data streams could be used to inform more timely catch estimates through such approaches as nowcasting or other in-season projection methods (See Chapter 4).

Recommendation: MRIP should explore the costs and benefits of providing its partner fishery research and management programs in the regions and states with direct access to the continuous streams of raw MRIP data as they are being captured by the MRIP Access Point Angler Intercept Survey (APAIS) and For-Hire Survey (FHS), and the for-hire electronic logbook data programs (Vessel Trip Reporting [VTR], Southeast Regional Headboat Survey [SRHS], Southeast Region For-Hire Electronic Reporting [SEFHIER]). Legitimate and appropriate accessibility to these data should be coordinated through Regional Interstate Fishery Commission programs such as GulfFIN and the Atlantic Coastal Cooperative Program (ACCSP).

Another potential approach to increasing the timeliness of catch estimates is to transition MRIP to monthly rather than bi-monthly waves. Given an approximate doubling of the resources that could be allocated to its survey programs, MRIP could transition to monthly catch estimates that with levels of precision comparable to those of the current estimates for bi-monthly waves. For in-season management applications that rely on tracking MRIP estimates of cumulative catch against ACLs, the greatest advantage of moving to a 1 month cycle would come from monitoring cumulative catch at the end of the odd-numbered months. Other applications of MRIP data, including stock assessment and cross-year management of recreational fisheries, would also benefit from MRIP transition to larger sample sizes required to maintain precision for monthly estimation of catch.

Leveraging Supplemental and Ancillary Data

There are a number of supplementary data sources and analytical approaches likely to improve the precision, timeliness, and adaptability of MRIP data for recreational fisheries subject to ACLs. Supplemental data in the form of state-specific recreational fishery surveys, species-specific surveys (e.g., Red Snapper), location-specific data, fishing tournament data, and voluntarily reported data (e.g., web portal and smartphone-reported data) could be used in combination with MRIP estimates to improve in-season management. Significant challenges would remain, however, concerning the calibration and coordination of supplemental recreational catch and effort data with MRIP estimates. The potential for voluntary reporting to enhance fishery data collection has generated much excitement, but in practice, participation in such programs has invariably been extremely low. Unless these patterns are reversed, reliance on such voluntary data collection systems is unlikely to advance MRIP over the coming years. In addition to MRIP's existing programs to calibrate its data and estimates with those of state surveys, additional statistical methods could be employed to facilitate the integration of data from multiple sources. Similarly, a great variety of ancillary variables in readily accessible electronic format exist that potentially could be combined with MRIP catch estimates to improve the annual and in-season catch forecasts made in support of fishery management (See Chapter 4).

Recommendation: The National Marine Fisheries Service (NMFS) Regional Offices, Science Centers, and state agencies should explore and identify ancillary variables that have high correlations with the Fishing Effort Survey (FES) and Access Point Angler Intercept Survey (APAIS) response propensities, effort, catch per unit effort (CPUE), and catch estimates and supplemental survey estimates for potential use in annual and in-season forecasting models. Ancillary variables available electronically with high frequency (i.e., daily or weekly) would be most useful for in-season management catch forecasts.

Since stock assessments rely on long time series of consistently collected data, and many federally managed stocks straddle state and survey boundaries, inter-calibration of surveys will be essential whenever a single survey is insufficient to support all assessment and management needs. Rigorous survey inter-calibration requires temporal and spatial overlap between surveys (See Chapter 4).

Recommendation: Interstate Fisheries Commissions, States, NOAA Fisheries, and other members of MRIP Regional Implementation Teams should anticipate and take into account the need for inter-calibration and continued survey development when new recreational fisheries surveys and survey methods are considered. These needs should also be clearly communicated to anglers, fishery managers and other stakeholders.

Further development of in-season management approaches utilizing novel statistical methods and additional data sources has the potential to incrementally improve the timeliness and precision of annual catch management. Potential development of modeling and statistical integration methods that draw on MRIP, supplementary, and auxiliary data may improve timely forecasting and tracking of statistics on recreational catch. Combining MRIP survey data with supplemental survey data using multiple-frame methods, for example, may decrease the variance of catch estimates, depending on the relative sample sizes and catch variances of the combined surveys. (See Chapter 4).

Recommendation: The National Marine Fisheries Service (NMFS) Regional Offices and state agencies should explore the possibility of using the following statistical methods, parameters, and approaches as appropriate for the issue at hand:

- **Multiple-frame methods and related methods to combine MRIP data with data from supplemental surveys to reduce the variance (percent standard errors [PSEs]) of catch estimates;**
- **Covariances in catch estimates across MRIP domains, conditional expectations and conditional variances of catch (encompassing identification of the best conditioning variables, including ancillary variables), and the possible use of control variates, to reduce the PSE of catch forecasts;**
- **Bayesian modeling methods that could provide a consistent framework for updating annual and in-season catch forecasts and projections utilizing data streams of different precision and frequency, including MRIP estimates of given precision available by year and by 2-month wave, and estimates from other, supplemental sources that may have different precision and be available with different frequency;**

- **The combination of uninformative priors, an assumption of catch proportional to abundance, and Bayesian updating for forecasting the catch of rare-event species and possibly estimating the population sizes of such species;**
- **Alternative statistical definitions of outlier catch estimates and the adoption of standard definitions to facilitate consistency in management actions;**
- **Change in detection methods in time series data analysis to help answer the question of when an outlier should trigger management change; and**
- **Contemporaneous correlation in the errors across MRIP domains (the Seemingly Unrelated Regression [SUR] method, its extension to situations with heteroskedasticity and autocorrelation, and its implementation within a Bayesian forecasting model, could help reduce the variance and PSEs of catch forecasts).**

ALTERNATIVE STRATEGIES FOR MARINE RECREATIONAL FISHERIES

America's fisheries are among the best-managed in the world, a success attributable in no small part to the MSA. In addition to virtually eliminating overfishing, the law has contributed to the long-term stability of fish stocks, a profitable fishing industry, and a growing blue economy. As noted above, however, the implementation of ACLs combined with the enforcement of accountability measures has created tension in recreational fisheries where the difficulties of estimating recreational catches in an accurate, precise, and timely manner with sufficient resolution to inform in-season monitoring and management against ACLs may result in not only direct management problems but also an erosion of trust in the management system among stakeholders. In response to the recommendations of recreational fisheries organizations and Regional Fishery Management Councils, the MFA specified that NOAA Fisheries and Councils can implement alternative management approaches more suitable to the nature of recreational fishing as long as they still adhere to the conservation principles and requirements established by the MSA. The committee identified several such alternative management approaches with good potential that could be pilot tested. (See Chapter 5).

Recommendation: NOAA Fisheries and MRIP should work in coordination with the Regional Fishery Management Councils, Interstate Fisheries Commissions, and States to, on a region-by-region basis, test the feasibility and potential benefits of alternative management approaches for some recreational fisheries. The committee recommends pilot testing of the following approaches:

- **The use of harvest tags for low-ACL, rare-event species; species of concern; species under Endangered Species Act (ESA) recovery plans; or other species that may not be well suited for sampling by a general recreational fisheries survey like MRIP.**
- **Implementation of a private recreational fisheries license endorsement (or permitting program) focused on identifying the subset of licensed anglers that target Council-managed species (e.g., offshore components of the fisheries). This license registry could then be used to assist in the development of specialized surveys that could improve recreational fisheries data collection for sampling domains that are challenging for MRIP.**

The use of specialized MRIP-supplemental surveys to improve the quality and timeliness of recreational fisheries data for Council-managed species would rely on robust planning and coordination with the MRIP Regional Implementation Team and all of its component partners in the region (interstate fisheries commission, Regional Fishery Management Council, states in the region, and NOAA Fisheries). The implementation of supplemental recreational fisheries surveys solely at the state level and not in close coordination with the full suite of regional partners would likely create difficulties for regional, Council-based assessment and management (See Chapter 5).

Recommendation: Implementation of MRIP-supplemental surveys focused on regional or Council-managed species should be accomplished in close coordination with the Interstate Fisheries Commissions, NOAA Fisheries, and other members of the MRIP regional implementation teams.

The need for timeliness of recreational catch information is driven largely by the fact that ACLs are set and monitored on a strictly annual basis. The relatively short-term consequences of ACL underages or overages result in a high value being placed on meeting the ACL exactly every year. A generalized carry-over provision for recreational ACL underages and overages attributable to implementation error (e.g., closing the season too early) would reduce the need for precise catch management on an annual basis by allowing deviations to be corrected in the following year. Carry-over provisions have been allowed since the 2016 revision of National Standard 1 guidelines, which specify that their use is permitted as long as overfishing is prevented every year. (See Chapter 5).

Recommendation: NOAA Fisheries and the Councils should further evaluate approaches to establishing criteria for the use of carry-over provisions, as well as limits on the amount of unused ACL or acceptable biological catch that could be carried forward. Implementation of such carry-over approaches could allow the recreational sector to achieve a high level of ACL utilization in a way that would be both practical and cost-effective while reducing risks of extreme overages and subsequent payback.

The development and application of accountability measures in recreational fisheries is challenging given the precision and timing of MRIP estimates (See Chapter 5).

Recommendation: NOAA Fisheries should review the National Standard 1 guidelines to ensure that agency guidance with respect to recreational accountability measures aligns with the timeliness and precision of harvest estimates produced by MRIP.

Adoption of mandatory, electronic catch reporting schemes combined with intercept sampling for verification has the potential to bring recreational catch monitoring to a level of precision and timeliness comparable to that achieved in commercial catch monitoring programs. Implementation of such mandatory reporting schemes could be considered for some recreational fisheries where precise monitoring and management are considered crucial. Precise monitoring such as that which could be achieved by using mandatory reporting could also allow, and be further enhanced by, the adoption of rights-based management approaches in recreational fisheries.

Balancing stakeholder needs and the cost of responsiveness to those needs requires consideration of the economic cost and benefits as well as benefits to long-term biological sustainability. The concept of optimum yield (as defined by the MSA) offers opportunities for better informing this discussion (See Chapter 5).

Recommendation: NOAA Fisheries and the Councils should develop a process for engaging recreational fisheries stakeholders in a more in-depth discussion of optimum yield and how it can be used to identify and prioritize management objectives that are better suited to the cultural, economic, and conservation goals of the angling community.

1

Introduction

This chapter sets out the context of the study, the statement of task, and the organization of the report. It provides succinct background information on the nature of recreational fisheries, the federal fishery management framework, and the role of catch data in management. This background provides essential context for the statement of task, for the approach taken in addressing the task, and for the structure of the report.

RECREATIONAL FISHERIES, MANAGEMENT, AND DATA

Marine recreational fishing is a popular activity enjoyed by more than 9 million Americans annually and is a positive driver of the growing American marine—or blue—economy. Recreational fishing is estimated to have had an economic impact of $73 billion, supported 487,000 jobs, and contributed more than $41 billion to the nation's gross domestic product (GDP) in 2017, all increases over the previous year (NOAA, 2020). In 2018, the economic impact of marine tourism and recreation activities, including recreational fishing, grew to $227 billion and contributed $143 billion to the U.S. GDP—more than any other blue economy sector (Nicolls et al., 2020). Marine recreational fishing activities are conducted nationwide.

Defined as "fishing for sport or pleasure" in the Magnuson-Stevens Fishery Conservation and Management Act (MSA),[1] recreational fishing has multiple characteristics that set it apart from commercial or subsistence fishing. Motivations of recreational anglers are diverse. Harvesting of fish is only one of several possible motivations, with others including, for example, spending time in nature, escaping the daily grind, spending time with friends and family, and self-actualization. Some anglers can attain satisfaction without harvesting any fish at all, and certain recreational fisheries are managed primarily for catch-and-release. Recreational fishing is further characterized by large numbers of participants who typically spend only a small fraction of their time fishing and individually harvest only a small number of fish. Commercial fishing, by contrast, tends to involve fewer participants fishing on a full-time or part-time basis and harvesting much larger amounts of fish per individual for the primary purpose of providing seafood for consumption by others and generating income from the sale of product.

Even though individual recreational anglers may harvest very few fish or no fish at all, collectively they exert substantial pressure on many marine fish stocks. This is the result of both direct harvest (which remains an important motivation for many marine anglers) and elevated mortality suffered by fish that have been captured and released alive. For example, it has been estimated that recreational fishing is now the greatest source of removals and fishing mortality in oceanic fish stocks in the Southeastern United States (Shertzer et al., 2019). In some marine fisheries, the demand for recreational fishing is so high that anglers reach the sustainable limits of their harvest a few days after the fishing season begins. It is therefore important for marine recreational fisheries to be managed effectively so as to maintain the quality of the recreational fishing experience and ensure its ecological sustainability for the present and future generations.

The MSA requires fisheries in federal waters to be managed using annual catch limits (ACLs) to ensure their sustainability. ACLs are determined on the basis of scientific stock assessments and represent

[1] Fishery Conservation and Management Act of 1976, Pub. L. No. 94-265 (see https://www.congress.gov/94/statute/STATUTE-90/STATUTE-90-Pg331.pdf).

the maximum amount of fish that can be harvested without exceeding the exploitation rate that is estimated to provide the maximum sustainable yield (MSY) from the stock while accounting for scientific and management uncertainty. The stock assessment methods used to inform ACLs vary in complexity, from assessment models that integrate many different types of data to simple approaches based on landings histories, with the choice of method depending largely on data availability and the importance of the fishery.

Determination and implementation of ACLs is reliant on fisheries catch data. Data on past catches are an important input for the stock assessment models used to determine ACLs. Data on catches in the current year are crucial for implementing the ACLs, i.e., ensuring that catches do not exceed them. Catch data for commercial fisheries are collected through such systems as reporting by seafood dealers, logbooks, and other means that provide a near-complete census of catches in an accurate and timely manner. These systems are enabled by rigorous licensing and reporting requirements for fishers and seafood dealers and by the limited numbers of fishery participants. Since commercial catch data tend to be both accurate and timely, they not only support fisheries stock assessments but also facilitate in-season management in which catches are monitored in near real time, and the fishing season is closed when the ACL is reached.

Catch data for recreational fisheries, on the other hand, are more difficult to collect because of the large numbers of participants and access points and the lack of universal mandatory catch reporting. Recreational fisheries are also challenging because of the great variability across those many anglers in fishing techniques or practices, trip goals or satisfaction drivers, and target species. Although recreational data for the for-hire sector (e.g., charter vessels, headboats) are now increasingly dependent on electronic logbook reporting for a census of permit-holding vessels, catch data for the private recreational sector—which has by far the largest number of participants—are ultimately collected using sample surveys that cover only a small proportion of anglers and rely on angler recall and direct observation of catches. Recreational catch data therefore tend to be more uncertain, more sensitive to details of survey design, and less timely relative to the data collected for commercial fisheries. For example, the Marine Recreational Information Program (MRIP), the most widely used recreational fishing survey in the United States, provides catch estimates with coefficients of variation (CVs) of 20–40 percent (compared with 0–5 percent for commercial catch data). Point estimates changed dramatically, sometimes by factors of 2 or 3, when the design of the survey was modified to improve the representativeness of samples and response rates.[2] The lag between the time at which recreational catches occur and the catches being quantified in MRIP is about 3–4 months on average. These characteristics of recreational catch data have consequences for the assessment and management of recreational and mixed-use (where both commercial and recreational fishing occur together) fisheries.

Assessments of fisheries with large recreational components are more uncertain and may change substantially when survey methods are adjusted. Implementation of ACLs in such fisheries is further challenged by the lack of timeliness in survey data (which typically lag actual catches by weeks or months). Therefore, in-season management of recreational fisheries (and recreational components of mixed-use fisheries) is rare. Instead, recreational fisheries are managed by setting regulations that are projected to restrict recreational catches within the ACL and determining, after the event, whether this has been achieved. If catches turn out to be below the ACL, that underage in catch is normally lost to the anglers, and the associated benefits are forgone. If catches exceed the ACL, accountability measure regulations may require that any overage be repaid in the following season by modifying future harvest limits. The inability to implement the ACL precisely may therefore result in lost fishing opportunities within either the current or the following fishing season, and associated dissatisfaction among anglers. It should be noted that underages can occur for reasons other than the implementation uncertainty of the ACL—for example, inclement weather or regulatory closures unrelated to the stock in question, or unexpected declines in stock abundance—and that such underages can have different management implications. The focus in this report is primarily on underages or overages caused by the implementation uncertainty of the ACL in recreational fisheries.

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[2] This change in survey design, implemented in 2018, was due to the transition from the Marine Recreational Fishery Statistical Survey (MRFSS) to the new and improved MRIP.

The difficulties of estimating recreational catches in a precise and timely manner can cause direct management problems for recreational and mixed-use fisheries. They also contribute to an erosion of trust in the management system among recreational fisheries stakeholders. Other factors affecting trust in and satisfaction with fisheries management include perceptions that the management system offers limited opportunities for engagement by recreational fishing stakeholders and is unresponsive to their inputs (Crandall et al., 2019). Criticism of the federal management of marine recreational fisheries has been brought into the political arena by representatives of the recreational fishing industry. The influential Morris-Deal Report (CSRFM, 2014), developed by a committee convened by Bass Pro Shop founder Johnny Morris and then-president of Maverick Boats Scott Deal, argued that recreational fisheries are inherently different from commercial fisheries, and so need to be managed differently. Partly in response, the National Oceanic and Atmospheric Administration (NOAA) established the National Saltwater Recreational Fisheries Policy (NOAA, 2015). Starting around the same time, NOAA undertook an extensive revision of the MRIP survey methodology; the MRIP survey and its recent improvements have been evaluated in a previous National Academies study (NASEM, 2017). Subsequently, the Modernizing Recreational Fisheries Management Act, or Modern Fish Act (MFA), was signed into law on December 31, 2018. The MFA amended specific portions of the MSA to highlight the differences between management of commercial and recreational fisheries. The MFA requires the federal management agency, NOAA, to implement certain changes, studies, and reviews aimed at reforming the federal management of recreational fisheries. This report addresses one of the requirements of the MFA: to " evaluate…how the design of the Marine Recreational Information Program, for the purposes of stock assessment and the determination of stock management reference points, can be improved to better meet the needs of in-season management of annual catch limits."

The characteristics of recreational fisheries pose unique challenges to management, but they do not obviate the need for these fisheries to be managed effectively, both for their own benefit (maintenance of sustainable fishing quality) and the conservation of national resources and ecosystems. It is therefore crucial to assess how management systems can be reformed in ways that improve management outcomes for recreational and mixed-use fisheries. Management outcomes, in this context, are not limited to regulatory compliance or the ecological sustainability of fisheries, but also encompass economic and social dimensions (Abbott et al., 2018; Asche et al., 2018). That is the fundamental challenge addressed in this report.

STATEMENT OF TASK FOR THIS STUDY

This study follows on the above-referenced National Academies study (NASEM, 2017) focused specifically on the MRIP program and the precision of catch estimates derived therefrom. The current study is concerned specifically with the *use* of MRIP-produced estimates and alternative or supplementary surveys and ancillary information for in-season management of recreational fisheries, and with alternative management measures that may relieve the issues encountered in managing recreational fisheries with ACLs. The statement of task for this study is given in Box 1.1.

REPORT ORGANIZATION

Chapter 2 of this report provides an expanded description of the U.S. fisheries management and assessment framework, including the various components and legal requirements of the federal fishery management system and detailed descriptions of the MSA and MFA. This chapter also contains descriptions of the stock assessment process, determination of reference points, ACLs, and accountability measures, and evaluates fisheries management and stock assessment needs. Chapter 3 details the existing recreational fisheries survey programs and approaches to ACL-based management for the Northeast, Mid-Atlantic, South-Atlantic, Gulf, and Pacific regions. Chapter 4 explores how MRIP-produced catch estimates, supplementary survey data, and ancillary data can be combined and optimized for in-season management. It also provides survey design and methodology options for improving or supplementing the program. Chapter 5 outlines alternative management strategies for recreational fisheries for which MRIP data do not adequately serve the needs of in-season management. It provides suggestions for multiple alternative management options that hold potential to address the ACL management challenges while also serving broader social and economic management objectives.

BOX 1.1 Statement of Task

This study will evaluate:

A. if and how the design of the Marine Recreational Information Program, for the purposes of stock assessment and the determination of stock management reference points, can be improved to better meet the needs of in-season management of annual catch limits (ACLs);
B. what actions the Secretary, Councils, and States could take to improve the accuracy and timeliness of data collection and analysis to improve or supplement the Marine Recreational Information Program and facilitate in-season management; and
C. alternative management approaches that could be applied to recreational fisheries, consistent with requirements for fisheries with ACLs, for which the Marine Recreational Information Program is not sufficient to meet the needs of in-season management

This evaluation will include the following:

1. fishery-specific assessment of the in-season management needs of each region;
2. an objective, independent evaluation of how well current survey methods in each region meet the needs of the defined in-season management of recreational fisheries with ACLs;
3. an evaluation of how current ACL in-season management strategies utilize information provided by the current surveys;
4. an assessment of how survey methods and/or management strategies could be modified to better meet the needs for ACL monitoring and accountability measures to ensure that overfishing does not occur; and
5. an assessment of the trade-offs that should be considered when determining appropriate pairing of survey methods with ACL management strategies.

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2

The U.S. Fisheries Management and Assessment Framework

Management of marine recreational fisheries occurs within a framework of law, policy, and science that crosses both federal and state jurisdictions. The purpose of this chapter is to provide perspective on various components and legal requirements of the federal fishery management system to assist readers who may not be familiar with the U.S. fisheries management process. This includes a review of regional differences in execution, intersection with other management authorities, and practical application of federal requirements in the monitoring and management of marine recreational fisheries. Box 2-1 provides definitions of key terms and abbreviations salient to this review.

MAGNUSON-STEVENS ACT

Marine fisheries in U.S. federal waters (3–200 miles offshore) are managed under the Magnuson-Stevens Fishery Conservation and Management Act (MSA).[1] Originally passed in 1976, the statute recognized the social and economic importance of fishery resources and established a national program for their conservation and management. This included the creation of eight Regional Fishery Management Councils (Councils), which are comprised of representatives of commercial and recreational fishing, as well as the marine fisheries agencies of the coastal states. Each Council is tasked with the development of fishery management plans and associated regulations for resources of significance in its region in accordance with a suite of national standards (see further discussion below) for conservation and management. Broadly, the purpose of the MSA is to prevent overfishing while achieving the optimum yield from each fishery on a continuing basis.

The MSA has been reauthorized and amended twice since its inception. The 1996 reauthorization (the Sustainable Fisheries Act)[2] added several obligations and authorities, including three new national standards. It also mandated that all fishery management plans contain specific information to document catch, such as a standardized method for quantifying bycatch, and an assessment of the amount and mortality of fish caught in recreational catch-and-release programs.

The 2007 reauthorization (the MSA Reauthorization Act)[3] established requirements for Councils to set annual catch limits (ACLs) (annual limits on pounds or numbers of fish that prevent overfishing for all managed species), as well as accountability measures (AMs) (management controls that prevent ACLs from being exceeded or mitigate overages). An important provision was the role of each Council's Scientific and Statistical Committee (SSC) in determining biologically acceptable levels of catch that cannot be exceeded when setting ACLs. Specific to recreational fisheries, the legislation required development of a national angler registry and a comprehensive program to improve the quality and accuracy of recreational catch information collected through the then-existing Marine Recreational Fisheries Statistics Survey (MRFSS).

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[1] Fishery Conservation and Management Act of 1976, Pub. L. No. 94-265 (see https://www.congress.gov/94/statute/STATUTE-90/STATUTE-90-Pg331.pdf).

[2] Sustainable Fisheries Act of 1996, Pub. L. No. 104-297 (see https://www.congress.gov/104/plaws/publ297/PLAW-104publ297.pdf).

[3] Magnuson-Stevens Reauthorization Act of 2006, Pub. L. No. 109-479 (see https://www.congress.gov/109/plaws/publ479/PLAW-109publ479.pdf).

BOX 2.1 Key Terms and Abbreviations

ABC (acceptable biological catch): An annual level of total catch that is based on an ABC control rule and accounts for both scientific uncertainty and the Regional Fishery Management Council's risk policy.

ACL (annual catch limit): An annual level of total catch that cannot exceed the ABC, should account for management uncertainty if an annual catch target (ACT) is not specified, and is the basis for application of accountability measures (AMs).

ACFCMA (Atlantic Coastal Fisheries Cooperative Management Act): Federal law that established the authority of the Atlantic States Marine Fisheries Commission to develop enforceable conservation and management measures for Atlantic coastal fisheries (0–3 miles offshore).

ACT (annual catch target): An annual level of total catch reduced below the ACL and set to account for management uncertainty or to achieve optimum yield.

AMs (accountability measures): Management controls designed to prevent ACLs from being exceeded and to mitigate overages should they occur.

ASMFC (Atlantic States Marine Fisheries Commission): Compact of the Atlantic coastal states formed to promote cooperative management of shared coastal fishery resources.

ASPM (Age-Structured Production Model): Stock assessment model wherein parameters are configured to provide inputs specific to each age class. Required information includes total catch, an index of abundance with a specified selectivity pattern, natural mortality, body weight-at-age, and maturity/fecundity-at-age.

FMP (Fishery Management Plan): Plan that contains specific goals and objectives, fishery description, stock reference points, management measures, and other information for stocks in need of conservation and management.

IA (Integrated Analysis): Stock assessment model that can be age- or length-based and accepts a wide variety of data types with very little preprocessing.

MFMT (maximum fishing mortality threshold): Maximum exploitation rate above which overfishing of a stock occurs.

MRFSS (Marine Recreational Fisheries Statistics Survey): Survey program established by NOAA Fisheries in 1979 to estimate catch and effort for recreational fisheries.

MRIP (Marine Recreational Information Program): Cooperative state–federal–regional program that replaced MRFSS in 2008 and develops, certifies, and implements surveys to measure total recreational fishing catch.

MSA (Magnuson-Stevens Fishery Conservation and Management Act): Federal statute that established a national program of standards and requirements for federally managed fishery resources (3–200 miles offshore).

MSST (minimum stock size threshold): Minimum stock biomass level below which a stock is considered to be overfished.

MSY (maximum sustainable yield): Largest long-term average catch or yield that can be taken on a continuing basis under prevailing ecological, environmental, and fishery conditions.

OFL (Overfishing Limit): Annual level of total catch associated with the maximum fishing mortality threshold (MFMT) and above which overfishing occurs.

OY (Optimum Yield): Amount of fish that will provide the greatest overall benefit to the nation with respect to food production, recreational opportunities, and protection of marine ecosystems. OY is based on MSY as reduced by relevant economic, social, and ecological factors.

SAFE (Stock Assessment and Fishery Evaluation): Reports produced for the North Pacific Fishery Management Council that provide a stock assessment, economic assessment, and ecosystem assessment.

SAW/SARC (Stock Assessment Workshop/Stock Assessment Review Committee): Stock assessment process and peer review managed by the Northeast Region Coordinating Council that serves the New England and Mid-Atlantic Fishery Management Councils and the Atlantic States Marine Fisheries Commission.

SCAA (Statistical Catch-At-Age): Stock assessment model that requires information on total fishery catch, the age of fish captured, and at least one index of abundance.

SDC (status determination criteria): Measurable factors, established on the basis of MSY, used to determine whether a stock is overfished or undergoing overfishing.

SEDAR (SouthEast Data, Assessment, and Review): Stock assessment process developed in the Southeast region that serves the South Atlantic, Gulf of Mexico, and Caribbean Fishery Management Councils; the Highly Migratory Species Division of the National Marine Fisheries Service of the National Oceanic and Atmospheric Administration (NOAA Fisheries); and select species for the Gulf and Atlantic States Marine Fisheries Commissions.

SSC (Scientific and Statistical Committee): Committee of scientific advisors established by each Council to provide ongoing scientific advice for fishery management decisions as required by the MSA.

STAR (STock Assessment and Review): Stock assessment process conducted in the Pacific region serving the Pacific Fishery Management Council.

VPA (Virtual Population Analysis): Stock assessment model that requires annual information on individual age classes (cohorts) of fish, including total catch, weight of fish, and natural mortality.

WPSA/WPSAR (Western Pacific Stock Assessment/Review): Stock assessment and regional peer-review process developed for stocks managed by the Western Pacific Fishery Management Council.

Throughout the 45-year history of the MSA, marine fisheries management has evolved into a multifaceted process with diverse participants: fishers, conservation organizations, trade/industry groups, scientists with expertise in a variety of disciplines (social, economic, biological, statistical), and managers. The involvement of each category of participant is essential for successful management outcomes. The Regional Fishery Management Councils created by the MSA, while a central component of the process, are but one piece (Figure 2.1). In particular, stakeholder participation is necessary for Councils to understand how management approaches under consideration may affect fisher behavior and, ultimately, conservation and use of fishery resources.

Likewise, the information needs of managers to meet legal mandates have evolved with each reauthorization of the MSA. The 2007 requirement for ACLs and AMs imposed new challenges for the use of commercial and recreational catch data, particularly the latter. Prior to this mandate, most marine recreational fisheries were rarely managed in-season. Recreational catch estimates were reviewed annually to evaluate and adjust management measures (e.g., size, season, and bag limits) to constrain harvest to a target.

Although the restructuring of the MRFSS into the Marine Recreational Information Program (MRIP) resulted in significant improvements to recreational catch and effort surveys, the demands of in-season management of ACLs frequently exceed the temporal and spatial design parameters of the surveys (NASEM, 2017). Whereas commercial catch data are collected using census-based techniques (e.g., logbooks, fish dealer trip tickets), often electronically with very short lag times, survey-based recreational catch estimates are produced at 2-month intervals, making it difficult for managers to respond to changes in a fishery as they are happening. This can result in estimates of harvest with a high degree of imprecision requiring the application of AMs (e.g., early season closures or reductions in future recreational ACLs to offset potential exceedance of the ACL). Despite the successes and improvements in U.S. fisheries management under the MSA, many recreational fisheries continue to pose unique challenges for managers. These challenges have led to frustrations among some recreational fishing organizations that perceive the administration of ACLs and application of AMs as more suited to commercial than to recreational fisheries (ASA and TRCP, 2018; CCC, 2016; CSRFM, 2014). Other recreational fishing and independent professional organizations (American Fly Fishing Trade Association [2021], American Fisheries Society [Miller et al., 2018]) have remained supportive of the MSA's provisions for recreational fisheries, viewing them as essential to ensure fisheries sustainability despite implementation challenges.

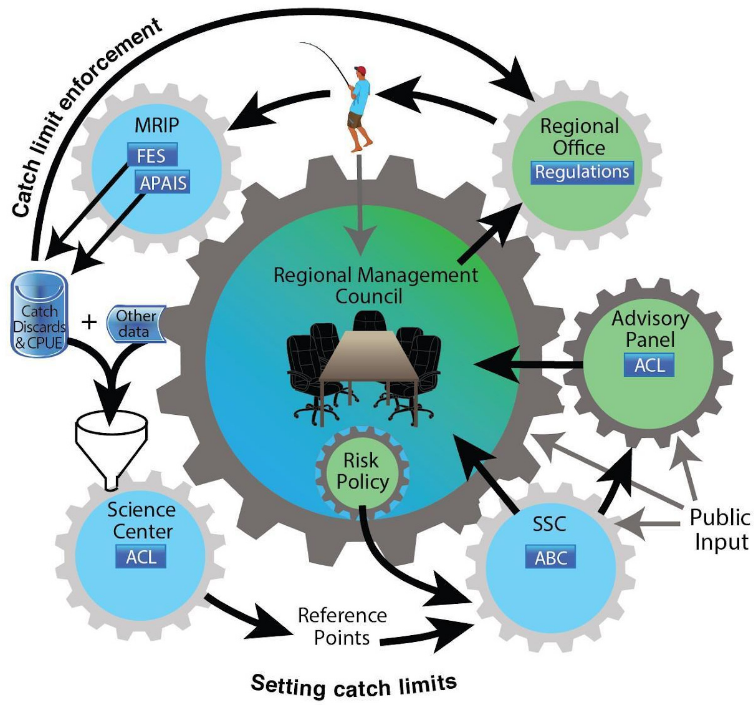

FIGURE 2.1 The fisheries management process for recreational fisheries in federal waters. Different steps in the process are represented by different cogs. Cogs in blue represent primarily scientific processes, while those in green represent societal goals and/or administrative functions. Monitoring of annual catch limits (ACLs) is conducted by the regional Science Centers, primarily using catch data from MRIP. Reference points such as acceptable biological catch (ABC) are set by Council Scientific and Statistical Committees (SSCs) using information provided by the Science Centers, according to each Council's risk policy. Advisory panels provide input on management measures developed by Councils to constrain harvest to the ACL. Management measures approved by the Councils are implemented via regulation by the Regional Offices and communicated to the public through a variety of sources (e.g., Fishery Bulletins, *Federal Register*, Council communications). SOURCE: Adapted from NASEM (2017).

THE NATIONAL STANDARDS

The cornerstone of the U.S. fisheries management process under the MSA is the ten national standards,[4] a set of statutory principles for conservation and management of the nation's fishery resources. All management measures and regulations developed by the Councils must be consistent with these standards, which are summarized as follows:

- *National Standard 1:* Prevent overfishing while achieving optimum yield on a continuing basis.
- *National Standard 2:* Use the best scientific information available in decision-making.
- *National Standard 3:* Manage an individual fish stock as a unit throughout its range where feasible.
- *National Standard 4:* Ensure there is no discrimination among residents of different states and that fishery allocations are fair and equitable.
- *National Standard 5:* Promote efficient use of fishery resources.
- *National Standard 6:* Consider and allow for variations among fisheries and fishery resources.
- *National Standard 7:* Minimize costs and duplication.
- *National Standard 8:* Account for the importance of fishery resources to fishing communities.
- *National Standard 9:* Minimize and avoid bycatch and bycatch mortality.
- *National Standard 10:* Promote the safety of life at sea.

[4] 16 U.S.C. §8151

Each of the national standards is accompanied by a set of guidelines[5] developed by the National Marine Fisheries Service of the National Oceanic and Atmospheric Administration (NOAA Fisheries) on behalf of the secretary of commerce, as required by the MSA. The guidelines are meant to assist the Councils in the development of fishery management plans and implementing regulations by providing the secretary's interpretation of the national standards, against which plans will be reviewed. The guidelines provide detailed instructions for how the Councils may meet these statutory principles and factors they may need to consider in doing so. Together, the national standards and the guidelines create a comprehensive framework for conservation and management of fishery resources. Although the national standards are not listed in order of importance, the precedence of National Standard 1 is clear, as its mandate to prevent overfishing and achieve optimum yield[6] on a continuing basis is at the heart of the MSA.[7] While it intersects with many of the other national standards (e.g., National Standards 2, 3, 6, 8, and 9), consideration of these mandates must not be at the expense of preventing overfishing. It can be challenging for a Council to effectively meet all of the national standards for each management action, as many may be mutually orthogonal depending on the action under development.

National Standards 1 and 2 are most directly related to the committee's statement of task. The National Standard 1 guidelines address a number of items, including the development of ACLs; AMs; and status determination criteria, which are measurable factors used to evaluate whether a stock of fish is overfished or undergoing overfishing. In particular, the establishment of an ACL for a stock is directly dependent on its status determination criteria. The National Standard 2 guidelines describe what counts as scientific information, the criteria for evaluating best scientific information, the validation and verification of scientific methods, and the peer review process. Recreational catch data are but one component of the scientific information used by the Councils and their SSCs to develop ACLs, and are subject to review under National Standard 2.

National Standard 9, which addresses bycatch, is tangentially related to the committee's statement of task. The MSA defines bycatch as "fish which are harvested in a fishery, but which are not sold or kept for personal use, and includes economic discards and regulatory discards."[8] Bycatch contributes to the determination of total catch, where total catch includes all fish retained for any purpose (e.g., sale as food, personal use) plus the mortality of any fish that are discarded.[9] When establishing ACLs, Councils are required to account for the total catch from all sources. Accurate quantification of bycatch and bycatch mortality can be challenging, however, particularly for recreational fisheries. Individual angler skills can impact the survivability of discarded fish, and current recreational surveys collect only information on the total number of discards for a species (i.e., no length or weight data are obtained). Both factors can contribute to scientific uncertainty, which directly impacts the determination of an ACL and may indirectly impact the management of a fishery.

Fishery Management Plans (FMPs)

FMPs are the vehicles by which Councils meet the MSA mandate to conserve and manage the nation's fishery resources in a manner that provides optimum yield on a continuing basis. The MSA requires the Councils to develop FMPs for all fisheries that are determined to be in need of conservation and management.[10] The national standards provide the foundation upon which all FMPs are built and against which they are evaluated. Each FMP describes a set of comprehensive management objectives for the fishery and any problems those objectives are meant to address. This includes balancing diverse social and

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[5] 50 CFR §600(d)
[6] 16 U.S.C. §1802(33)
[7] 16 U.S.C. §1801(b)(4)
[8] 16 U.S.C. §1802(2). This does not include species managed under a recreational catch-and-release only program, in which possession is prohibited.
[9] 50 CFR §600.305(f)(1)(i)
[10] 16 U.S.C. §1852(h)(1)

economic interests with the biological needs of the stock or stocks under management. Ideally, FMP objectives are reviewed periodically as conditions in the fishery change.

In addition to management objectives, FMPs have a number of statutorily required elements.[11] These include a description of the fishery (e.g., affected species; gear types; number of vessels; harvest; revenues; commercial, recreational, and for-hire participation; social and economic information); identification of essential fish habitats; development of a standardized method for reporting and assessing bycatch; specification of management reference points for the stock(s) of interest (e.g., maximum sustainable yield, optimum yield, ACLs); development of AMs to prevent ACLs from being exceeded; and rebuilding plans for stocks that are overfished. FMPs must also contain a fishery impact statement that analyzes the biological, social, and economic impacts of conservation and management.

Additionally, the MSA provides for discretionary provisions[12] that Councils may include in their FMPs to achieve management goals, such as the use of fishing permits; closed seasons or areas; restrictions on catch composition (e.g., minimum size, possession limits); conditions or limits on the use and types of fishing gear; limits on participation and access; incentives to reduce and avoid bycatch; and requirements regarding the submission and collection of data. Collectively, these provisions represent the management measures that Councils typically use (either singly or in combination) to meet the objectives of an FMP. Councils may amend FMPs at any time to adjust their required or discretionary provisions to ensure that management goals and statutory obligations are addressed.

The development of an FMP or amendment is an open, public process. It begins with the identification of an issue (or set of related issues) by a Council and/or stakeholders. Once the issue has been characterized, the Council solicits general public input through a process called “scoping,” which provides an opportunity for the public to express concerns about the issue or issues, suggest approaches or solutions, and identify impacts that may occur. The information thus gathered is used to inform the Council’s development of management alternatives for addressing the issue. Once these alternatives have been analyzed, a second round of stakeholder feedback is obtained through public hearings to gather input on the alternatives. After review of public comments, the Council selects preferred alternatives and submits the FMP or amendment to the secretary of commerce for review. The secretary may approve, partially approve, or disapprove the FMP or amendment based on whether it meets the national standards and additional MSA requirements, as well as other applicable laws. Further opportunity for public input is provided during secretarial review of the amendment, as well as during the rulemaking process to implement proposed management measures.

Management Reference Points

One of the statutorily required components of FMPs is the specification of reference points for a stock or stocks of fish. Reference points include stock status determination criteria, as well as maximum sustainable yield (MSY), optimum yield (OY), acceptable biological catch (ABC), and ACLs for all species or stocks within an FMP.[13] Reference points serve as thresholds or limits, and are a means of evaluating the effectiveness of management measures in preventing overfishing.

One of the most important reference points is MSY, which is defined as the largest long-term average catch or yield that can be taken from a stock or stock complex under prevailing ecological, environmental, and fishery conditions.[14] Estimates of MSY are most often derived from quantitative stock assessment models and should incorporate biological, ecological, and environmental factors as well as catch information. Because MSY for a stock is influenced by interactions with other stocks and the surrounding ecosystem, it should be reestimated as conditions change. Status determination criteria (SDC), the measurable factors used to determine whether a stock is overfished or undergoing overfishing, are

[11] 16 U.S.C. §1853(a)
[12] 16 U.S.C. §1853(b)
[13] 50 CFR §600.310(b)(2)(iv)
[14] 50 CFR §600.310(e)(1)(i)(A)

established on the basis of MSY. These criteria include the minimum stock size threshold (MSST), which is a minimum level of biomass below which the stock is considered overfished (i.e., no longer able to produce MSY); the maximum fishing mortality threshold (MFMT), which is an annual rate of maximum exploitation above which the stock is undergoing overfishing (i.e., jeopardizing its ability to produce MSY); and the overfishing limit (OFL), which is the annual level of total catch in numbers or pounds of fish associated with the MFMT. Any catch above the OFL will result in overfishing.[15]

ABC and ACL reference points are derived directly from the OFL. To determine an ABC, each Council must first establish a risk policy that ensures a 50 percent or less likelihood of exceeding the OFL for each species under management.[16] A Council's SSC is responsible for incorporating the Council's risk policy with the scientific uncertainty in the estimate of OFL to produce a recommended ABC, such that ABC ≤OFL. This management procedure, i.e., accounting for both risk and scientific uncertainty in the determination of an ABC, is known as an ABC control rule and must be included in Council FMPs.[17] A Council then uses the ABC as the basis for setting an ACL that accounts for management uncertainty (e.g., ability to accurately monitor and/or control harvest), such that ACL ≤ABC for each managed stock. Councils are not allowed to exceed the ABC recommendations of their SSCs when setting an ACL.[18]

The MSA defines OY as the amount of fish that will provide the "greatest overall benefit to the nation" with respect to food production, recreational opportunities, and the protection of marine ecosystems.[19] It is also established on the basis of MSY, but is reduced from MSY according to relevant social, economic, and ecological factors. Similar to MSY, it is a long-term average yield, although it represents the desired rather than the maximum yield from a stock and therefore cannot be greater than MSY. Defining OY for a stock can be challenging for Councils given the range of factors to be considered, available information, and differing stakeholder priorities and needs. It may be expressed quantitatively (as numbers or pounds of fish) or qualitatively, but it must be defined using the best scientific information available and supported by the management measures and reference points within an FMP. The National Standard guidelines describe OY as a "decisional mechanism" for resolving the conservation and management objectives of the MSA and balancing multiple interests in determining the greatest overall benefit to the nation.[20] Above all else, OY must prevent overfishing. While OY (a long-term yield) is not directly linked to ACLs (annual yields), the ACL framework supports achievement of OY by preventing overfishing. For further discussion of OY with respect to management of recreational fisheries, see Chapter 5.

INTERSECTION OF STATE AND INTERSTATE FISHERIES MANAGEMENT WITH THE MSA

The provisions of the MSA apply only to species under federal management and only in waters from 3 to 200 miles offshore; the states retain management authority for all marine species within 3 miles of shore ("state waters") or the outer limit of their jurisdictions.[21] For those fish and fisheries subject to the MSA, all catch, regardless of whether it occurs in state or federal waters, is applied to the federal ACL.

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[15] A description of these various elements related to ACL monitoring and a visual representation of the difference among OFL, ABC, ACL, and annual catch target (ACT) can be found at https://www.fisheries.noaa.gov/southeast/sustainable-fisheries/frequent-questions-annual-catch-limit-monitoring.

[16] The requirement that ABC have a 50 percent or less likelihood of exceeding the OFL is included in the National Standard 1 guidelines at 50 CFR §600.310(f)(2). The legal precedent for this is *Natural Resources Defense Council v. Daley*, 209 F.3d 747 (D.C. Cir. 2000), in which the court held that harvest levels approved by the National Marine Fisheries Service (NMFS) must have at least a 50 percent likelihood of achieving the target fishing mortality rate.

[17] 50 CFR §600.310(f)(2)

[18] 16 U.S.C. §1852(h)(6)

[19] 16 U.S.C. §1802(33)

[20] 50 CFR §600.310(b)(2)(ii)

[21] The state waters boundaries of Texas, Puerto Rico, and the Gulf coast of Florida extend to 9 nautical miles offshore. See https://www.gc.noaa.gov/gcil_maritime.html#3m.

States are encouraged to implement compatible regulations for federally managed species within state waters to aid in conservation and management, enforcement, and public understanding of regulations.[22] Several states (e.g., South Carolina and Georgia) have statutes or regulations that automatically complement federal rules in state waters for species subject to the MSA, while others (e.g., North Carolina and Florida) have a flexible administrative process that allows for timely adoption of regulations in state waters to complement any federal rule changes. The MSA does provide for the secretary of commerce to intervene should a state's actions (or inaction) threaten the effectiveness of a federal fishery management plan.[23] However, this provision has rarely been applied.

The MSA also allows for Councils to delegate management authority for a species to the states. For example, the North Pacific Fishery Management Council's Salmon FMP has delegated all authority to the State of Alaska to manage both commercial and recreational Salmon fisheries in federal waters open to those activities.[24] Likewise, the Gulf of Mexico Fishery Management Council recently delegated authority for management of specific components of the recreational Red Snapper fishery in federal waters to the states, after several years of inconsistent state and federal regulations that led to shortened recreational seasons in federal waters.[25] The Pacific Fishery Management Council employs a slightly different approach for all of its FMPs, whereby the Council develops commercial management measures, while the states of California, Oregon, and Washington develop preferred recreational management measures that are adopted by the Council during the specifications process.[26]

Interstate Fisheries Commissions

Prior to the adoption of the MSA in 1976, three interstate fisheries commissions were formed by compacts of the coastal states: the Atlantic States Marine Fisheries Commission (ASMFC) (1942), the Pacific States Marine Fisheries Commission (1947), and the Gulf States Marine Fisheries Commission (1949). Each of the interstate compacts was ratified by Congress, and established to promote a coordinated approach to research, conservation, and management of shared fishery resources among the states within their jurisdictional waters. All of the interstate commissions provide data warehousing and management of fisheries information networks, as well as coordination of various programs of interest to member states (e.g., habitat, fishery-independent surveys, aquaculture, social/economic data, stock assessments). Additionally, the ASMFC and the Gulf States Marine Fisheries Commission have developed interstate FMPs for species of interest. However, the ASMFC is unique among the three commissions in that any Atlantic coast state included in an interstate FMP must implement the measures required for conservation and management of a species or risk the secretary of commerce's imposing a noncompliance moratorium in that state's waters.[27] This authority was not conferred until passage of the Atlantic Striped Bass Conservation Act (1985) and the Atlantic Coastal Cooperative Fisheries Management Act (ACFCMA; 1993).[28] Under the ACFCMA, the ASMFC is responsible for determining whether a state is in compliance with the required management measures and for forwarding any determination of noncompliance to the secretary of commerce for consideration and possible action. No similar federal oversight applies to the programs and activities of the other interstate commissions.

While the ACFCMA is less prescriptive than the MSA, it does mandate development of a set of standards and procedures for preparation and implementation of interstate FMPs, which is detailed in the

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[22] 50 CFR §600.310(f)(4)(iii).

[23] 16 U.S.C. §1856(b)

[24] See https://www.npfmc.org/wp-content/PDFdocuments/fmp/Salmon/SalmonFMP.pdf

[25] See https://gulfCouncil.org/fishery-management/implemented-plans/reef-fish

[26] As an example, see documentation of the groundfish FMP specifications process: https://www.pCouncil.org/documents/2019/10/fs12-Groundfish.pdf.

[27] In the case of Atlantic striped bass, the secretary of the interior is responsible for determining whether a moratorium is required.

[28] Atlantic Striped Bass Act of 1985, 16 U.S.C. §§5151–5158; Atlantic Coastal Fisheries Cooperative Management Act of 1993, 16 U.S.C. §§5101–5108.

ASMFC's Interstate Fishery Management Program Charter.[29] The statute specifically states that interstate FMPs should promote conservation and be based on the best scientific information available.[30] However, the ACFCMA does not require the use of ACLs or AMs as does the MSA. Furthermore, interstate FMPs are not subject to such federal laws as the National Environmental Policy Act or Administrative Procedures Act, as each state's legislative and/or administrative procedures are used to implement required management measures.[31]

The ACFCMA also provides for support from the secretaries of commerce and the interior in the development of interstate management programs, and requires coordination and collaboration with the East Coast Councils for fisheries that occur in state and federal waters. Currently, the ASMFC has joint management authority with the Councils for four species, and complementary management for four species and one species complex (coastal sharks). For species under joint management, both the ASMFC and the respective Council must agree upon management measures for implementation to occur, and they usually meet together to facilitate this collaboration. For species under complementary management, the ASMFC can implement measures in state waters that allow for more flexible utilization of the resource by the states, but with the intent of providing comprehensive management across state and federal jurisdictions.

Regardless of whether a joint or complementary management approach is used, the ASMFC is subject to the requirements of the MSA in a de facto manner for species cooperatively managed with the Councils, in particular the requirements for ACLs and AMs.[32] This has created some challenges in managing fisheries with a significant recreational component, given the administrative requirements of the MSA; the National Standard 1 guidelines; and the timeliness, accuracy, and availability of recreational catch information through MRIP. Currently, the ASMFC and the Mid-Atlantic Fishery Management Council are engaged in a cooperative "Recreational Reform Initiative" for the four species under joint management (Summer Flounder, scup, black sea bass, and bluefish). This effort is focused on addressing stability in recreational management measures, flexibility in the management process, and alignment of recreational access with fish availability and stock status. Issues under consideration include approaches for better incorporating MRIP uncertainty into management (e.g., methods for smoothing outlier catch estimates, use of an "envelope of uncertainty"), protocols for use of multiyear management measures, and possible approaches to improving recreational catch accounting, among others (see Chapter 5 for a detailed description of these issues).

THE MODERNIZING RECREATIONAL FISHERIES MANAGEMENT ACT

The Modernizing Recreational Fisheries Management Act of 2018, also known as the Modern Fish Act (MFA), was signed into law on December 31, 2018, and amended specific portions of the MSA to highlight the differences between management of commercial and recreational fisheries. In addition to the current study, it commissioned reports regarding allocations in mixed-use fisheries and use of limited access privilege programs. It also required development of guidance and best practices for state recreational licensing programs, and a cooperative effort to incorporate additional sources of data (particularly with regard to recreational fisheries) from state agencies and nongovernmental entities into management and scientific processes. Finally, it identified the use of specific management approaches for recreational fisheries.

It is important to note that the MFA did not change the fundamental requirements of the MSA for ACLs and AMs for all managed species. It amended the findings of the MSA to include a policy statement acknowledging the benefits of both commercial and recreational fishing activities, but declares that "science-based conservation and management approaches should be adapted to the characteristics of each

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[29] See http://www.asmfc.org/files/pub/ISFMPCharter_Aug2019.pdf

[30] 16 U.S.C. §5104(a)(2)(A)

[31] 16 U.S.C. §5104(b)(1); Interstate Fisheries Management Program Charter, Section 7, available at http://www.asmfc.org/files/pub/ISFMPCharter_Aug2019.pdf.

[32] 16 U.S.C. §5103(b)(1)(B)

sector" because of their differences.[33] The MFA also added a paragraph to the MSA that, as part of their required functions, Councils have the authority to use "extraction rates, fishing mortality targets, harvest control rules, or traditional or cultural practices of native communities" in managing recreational fisheries.[34] However, the legislation specifically states that this is in addition to complying with the requirements to establish ACLs and AMs, rebuild overfished fisheries, prevent overfishing, and comply with the National Standards.

Extraction rates, fishing mortality targets, and harvest control rules are among the methods currently used by the Councils in managing fisheries, but the degree to which they are employed is determined by the quality and availability of information. Regardless of the method used to set a management target, any of these approaches can be translated into an amount of fish in pounds or numbers associated with that target. Even for management frameworks that do not require the use of ACLs (see Chapter 5), the potential effectiveness of recreational management measures (e.g., season, size and possession limits) is generally evaluated based on the total catch likely to be produced.

ROLES OF STOCK ASSESSMENT IN FISHERIES MANAGEMENT

Stock assessments are the backbone of sustainable fisheries management and provide critical scientific information necessary for the conservation and management of fish stocks. Stock assessments are designed to answer such management questions as the following: What is the current status of a fish stock relative to established targets (e.g., Is the stock experiencing overfishing? Is the stock overfished?)? How much can fishermen catch while maintaining a healthy and sustainable fish stock? If a stock is overfished and/or subject to overfishing, what management action is needed? The answers to these questions are required by the MSA, which calls for the use of the best available scientific information to advise U.S. commercial and recreational fisheries management so as to ensure a healthy balance among sustainable fish stocks, ecosystem health, and productive coastal communities. In the United States, NOAA Fisheries conducts annual stock assessments to monitor the condition of approximately 200 federally managed fish stocks and stock complexes (defined as fish groups of similar stocks managed) per year under relevant FMPs produced by the eight Councils.

A typical stock assessment usually involves defining stock structure, collecting and processing fisheries-dependent and fisheries-independent data, performing mathematical and statistical modeling of the data to estimate the dynamics of fish stock status and size, evaluating the impacts of fishing on the stock, and projecting harvest levels following harvest control rules predefined in FMPs to achieve the management target (e.g., maximum sustainable long-term yield). Stock assessments also estimate reference points (see the previous section on management reference points), which are often used in harvest control rules to quantify management goals for target fishing mortality and fish stock biomass and to define management limits for fishing mortality and stock biomass levels to avoid. Comparing estimated fishing mortality and fish stock biomass against fishing mortality and stock biomass reference limits, respectively, makes it possible to determine whether overfishing occurs (i.e., rate of removal is too high) and whether a fish stock is overfished (i.e., stock biomass is too low). Based on the harvest control rules defined in the relevant FMPs, the stock assessment results are used to develop ABCs that can be then used to set ACLs. High-quality stock assessments, often depending on the quality and quantity of input data used in assessment modeling, provide scientific information with which to ensure continuity and consistency in developing fisheries management actions.

DATA AND MODELS USED IN STOCK ASSESSMENTS

Stock assessments usually require three primary categories of data: catch, stock abundance measures, and biological data. These data are usually obtained from fisheries-dependent and fisheries-

[33] Pub. L. No. 115-405 §2
[34] Pub. L. No. 115-405 §102(a)

independent monitoring programs. Fisheries-dependent programs target commercial and recreational fisheries to collect such key fisheries statistics as catches, discards, and biological data. Fisheries-independent programs collect data reflecting spatio-temporal changes in fish stock size and relevant biological data, such as size composition and key life history information, and are based on statistically rigorous field surveys. The quality and quantity of these data determine the quality of stock assessment results, which in turn influences the effectiveness of fisheries management in achieving defined goals. To ensure the highest-quality stock assessments, these data must be accurate and sufficient for describing the dynamics of fish stocks and must be made available for stock assessments in a timely fashion. The quantity and quality of the data available for a stock assessment play a critical role in the choice of stock assessment models, as well as in determination of whether an assessment is feasible. For some stocks, the available data preclude the use of model-based approaches, and alternative methods (e.g., average catch or third-highest catch over some time period) must be used to generate catch advice.

Stock assessment models usually consist of three different types of submodels: population dynamics models that describe fish life history and stock dynamics, observational models that link predictions of population dynamics models with observed values for key fisheries statistics, and statistical models that quantify observational and/or process errors for use in formulating statistical likelihoods in modeling for estimation of fish population dynamics. Stock assessment models vary greatly in their formulations and complexity, depending on the data quality and quantity and the biological and statistical assumptions made in assessment modeling (see Table 2.1).

For a fishery with only catch data available, the stock assessment models used often require no assumptions about fish population dynamics The input data include catch and some expert opinions on either natural mortality and stock depletion or sustainability of the recent catch. The output includes advice on whether the recent average catch is sustainable. The assessments estimate no biological reference points. An example of such a model is the Depletion Corrected Average Catch (DCAC; MacCall, 2009). This type of model usually provides only a placeholder until direct information on stock status and/or trends becomes available.

Time series models used in stock assessments also have minimal or no assumptions on fish population dynamics. The minimum data requirement is catch or an abundance index time series (e.g., An Index Method [AIM]; NOAA Fisheries Toolbox). The output does not include biological reference points and is restricted to qualitative advice about whether the stock is trending up or down or is stable and whether it is approaching a possible trigger for management action. The models cannot provide advice on the absolute level of a fish stock or the direct effect of fishing on the stock.

Biomass dynamics and production models consider only aggregate biomass and require a time series of catch and relative abundance index (e.g., Dynamic Schaefer or Pella-Tomlinson model; Prager 1994). The models can provide estimates of such biological reference points as MSY, B_{MSY} (the total stock biomass at MSY), and F_{MSY} (the fishing mortality rate that produces MSY). They can also yield current biomass relative to B_{MSY} and current F relative to F_{MSY}. These models require good contrast in the time series of catch and abundance index data and cannot incorporate any individual life history information.

Delay-difference models have assumptions about population dynamics similar to biomass dynamics models but include at least two life stages, one typically for fish before recruitment, and some somatic growth relationship and natural mortality. Minimum data requirements include catch, an abundance index, and inputs for body growth function and natural mortality (e.g., Catch-Survey Analysis; Collie and Sissenwine, 1983). Their outputs and limitations are similar to those of biomass dynamics models, although these models have more flexibility and more biological realism.

Age-structured production models incorporate the full age structure of a stock and consider a spawner-recruitment relationship, natural mortality, body weight-at-age, maturity-at-age, fishery selection-at-age, and multiple fishing fleets. Minimum data requirements include catch, abundance index with specified selection pattern at age, natural mortality, body weight-at-age and maturity/fecundity-at-age (e.g., Age-Structured Production Model [ASPM]; Depletion-Based Stock Reduction Analysis) (Dick and MacCall, 2011). The outputs and limitations of these models are generally similar to those of biomass dynamics models, but more closely match the actual age-selection characteristics of fisheries and abundance indices.

Virtual Population Analysis (VPA)–based models calculate population abundance-at-age directly from catch-at-age data and natural mortality, with age-specific abundance indices being used for tuning. Minimum data requirements include complete and high-quality catch-at-age and weight-at-age data for every time step, as well as one abundance index for calibration (e.g., XSA, ADAPT, VPA2BOX). The models can provide such key information as estimates of stock size and fishing mortality. Estimation of uncertainty in these models can be challenging, and the models work best when fishing mortality rates exceed natural mortality rates.

Statistical catch-at-age (SCAA) models assume age-structured population dynamics, with the minimum data requirements being catch, a statistical sample of catch age composition, and an abundance index (e.g., ASAP, AMAK, SAM, many custom ADMB coded applications). Some missing catch-at-age data are allowed (in contrast to VPA). The models can estimate stock size, fishing mortality, and biological reference points to provide complete advice on status determinations and forecasts of which limit and target catch levels are attainable.

Integrated Analysis (IA) models are highly general with regard to the types of data that can be included. They analyze data with as little preprocessing as possible, such as by using length composition data in the age-length key directly rather than inputting the derived age composition data into the model. IA models have two subcategories: length-based and age-based. For the length-based IA models, population dynamics are length-structured, with a growth transition matrix to update length composition between consecutive time steps. The models can incorporate natural mortality, growth, and size composition data, allowing for the estimation of (possibly time-varying) selection patterns for fishery and abundance indices. The minimum data requirements include catch, an abundance index, and length composition data (missing data allowed). Some examples of the length-based IA models include CASAL, CASA (Sullivan et al., 1990), and the American lobster stock assessment model (Chen et al., 2005). The models can generally provide complete advice on status determinations and forecasts of limit and target catch levels. The structure of the age-based IA models is similar to that of the age-structured models discussed above, which includes modeling of recruitment as deviations, allowance for multiple areas and multiple growth patterns, use of time-varying dynamic and observational processes with possible environmental covariates, and internal estimation of growth using age-at-length data. Typical input data include catch, multiple abundance indices, age and/or length composition data, age-at-length data, tagging, natural mortality, and movement (e.g., Stock Synthesis version v.3.30.15; Methot et al., 2020).

STOCK ASSESSMENT PROCESS

NOAA Fisheries works with its partners in each management region to conduct stock assessments. Fisheries scientists from a variety of backgrounds and institutions often participate in these assessments. The public and the industry have increasingly been involved in stock assessment and regional review processes and are able to involve themselves in discussions and ask questions during assessment and review. This participation helps the public better understand assessment results and provides scientists valuable information about the fishery under review. The complete stock assessments are peer-reviewed by an independent panel of experts. Although the general process, inputs, and outputs are similar, under the auspices of NOAA Fisheries, each management region has developed stock assessment and review processes that suit its particular needs. Each region can determine the frequency of scheduling, reviewing, and using stock assessment results in management based on the quality and quantity of available fisheries, abundance, and biological data; the structure and diversity of local fisheries; available technical and financial resources, and the defined regional stock assessment and management processes.

TABLE 2.1 Stock Assessment Models

Stock Assessment Model	Population Dynamics Assumption	Minimum Data	Typical Input Data	Management Advice	Comments
Catch-only model (e.g., Depletion Corrected Average Catch [MacCall, 2009])	Often not assumed	Catch	Catch and expert opinion on natural mortality, stock depletion, or suitability of the recent catch	Advice on the sustainability of recent average catch	Often used as a placeholder until other models become available
Time series model (e.g., An Index Method [AIM], NOAA Fisheries Toolbox)	Often not assumed	Catch or abundance index time series	Catch and abundance index time series	Advice on stock trends	No advice on the absolute level of fish stock or the fishing mortality
Biomass dynamics or production model (e.g., A Stock Production Model Incorporating Covariates [ASPIC] [Prager, 1994])	Aggregate biomass dynamics controlled by a low number of parameters	Catch and one relative abundance index	Minimum data and additional relative abundance indices	Maximum sustainable yield (MSY), B_{msy}, F_{msy}, and current and historical B and F	Good contrast in the time series and no consideration of life history and size/age compositions
Delay-difference model (Catch-Survey Analysis [Collie and Sissenwine, 1983])	Similar to biomass dynamics but with at least two life stages, one typically for fish before recruitment; often include some somatic growth relationship and natural mortality	Catch, abundance index, inputs for body growth function and natural mortality	Minimum data, with the abundance index consisting of a recruitment index and a recruited (adult) index	MSY, B_{msy}, F_{msy}, and current and historical B and F	Good contrast in the time series
Age-structured production model (e.g., Age-Structured Production Model [ASPM] [Dick and MacCall, 2011])	Consider full age structure, a spawner-recruitment relationship, natural mortality, body weight-at-age, maturity-at-age , fishery selection-at-age, and multiple fishing fleets	Catch, abundance index with specified selection pattern at age, natural mortality, body weight-at-age and maturity/ fecundity-at-age	Minimum data plus additional abundance indices	MSY, B_{msy}, F_{msy}, and current and historical B and F	When using a deterministic stock-recruitment relationship (as in "standard" ASPM), biases will arise if fluctuations in recruitment are a prominent feature of the stock's dynamics
Virtual Population Analysis (VPA)–based models (e.g., XSA, ADAPT)	Population abundance-at-age directly calculated from catch-at-age and natural mortality; often use age-specific abundance indices for tuning; minimal assumptions concerning selection-at-age patterns	High-quality catch-at-age and weight-at-age for every time step and one abundance index for calibration	Minimum data and several age-specific abundance indices	Historical and current B and F, and biological reference points if stock-recruitment relationship can be defined	Needs complete, high-precision catch-at-age data; best when fishing mortality rates exceed natural mortality rates

continued

TABLE 2.1 Continued

Stock Assessment Model	Population Dynamics Assumption	Minimum Data	Typical Input Data	Management Advice	Comments
Statistical catch-at-age models (e.g., ASAP, SAM)	Age-structured, incorporating natural mortality, recruitment deviations, and selectivity	Catch, statistical sample of catch-age composition, abundance index; some missing catch-at-age data are allowed	Catch, abundance index, statistical sample of age composition of catch and abundance index	Generally, complete advice on stock status determinations and forecasts of limit and target catch levels are attainable	If the spawner recruitment dynamics are not embedded in the model, a separate analysis is usually needed to derive MSY-based quantities
Integrated models with length-structured population dynamics (e.g., CASA [Sullivan et al., 1990; Chen et al., 2005])	Length-structured life history and fishery processes, with growth transition matrix to update length composition between consecutive time steps	Catch, abundance index, length composition data (missing data allowed)	Catch, abundance index, length composition data	Generally, complete advice on status determinations and forecasts of limit and target catch levels	Mainly for species difficult to age
Integrated models with age-structured population dynamics (e.g., Stock Syntheses [Methot, 2020])	Age-structured life history and fishery processes	Catch and an abundance index	Catch, multiple abundance indices, age and/or length composition data; age-at-length data; tag-recapture data, natural mortality and movement, and stock structure (including genetics) data	Generally, complete advice on status determinations and forecasts of limit and target catch levels	High model complexity, potential overparameterizing and overfitting

SOURCE: Generated by the committee.

New England and Mid-Atlantic Management Regions

The NOAA Fisheries Northeast Fisheries Science Center conducts stock assessments to support the New England and Mid-Atlantic Fishery Management Councils and the Atlantic States Marine Fisheries Commission. The Northeast Region Coordinating Council directs the stock assessment process, which includes two assessment tracks: management and research. Management track assessments, designed to be simple, efficient, and flexible, provide routine updated advice to directly inform management action. This allows the inclusion of data that have recently been collected, revised, or corrected, ensuring that the estimates of stock biomass and other stock parameters used for quota setting are updated on a regular basis. The management track assessment process includes the collection and compilation of all relevant data and input information and development of primary and back-up assessment plans, which are then reviewed by the Assessment Oversight Panel and the Northeast Region Coordinating Council; conduct of the assessment; and scientific peer review. The management track assessment yields catch estimates from all commercial and recreational sources, including landings and discards; abundance index estimates; annual fishing mortality, recruitment, and stock biomass estimates over time; biological reference points; and stock status determination.

Research track assessments are much more complex, focusing on research topics or individual stocks. Such an assessment evaluates an issue (e.g., retrospective problem), new dataset (e.g., new survey, revised recreational data), or new model applicable to many stocks and considers extensive changes in data, models, or stock structures. The results can provide the basis for future management assessments. The research track assessment process usually includes selecting a research topic, creating a working group to develop research goals and objectives through a research plan and terms of reference, conducting research, presenting research results to a peer review panel, and advising management and future management track assessment.

For both management and research track assessments, the Stock Assessment Workshop (SAW) and Working Groups (WGs) prepare stock assessments, which are peer-reviewed by the Stock Assessment Review Committee (SARC) and the Council's Scientific and Statistical Committee (SSC), composed of leading scientists in fisheries stock assessment, economics, and social science. The reviewed stock assessment reports are then published. These published peer-reviewed reports form the scientific basis for managing fish and invertebrate marine resources in the Northeast and Mid-Atlantic regions of the United States.

South Atlantic, Gulf of Mexico and Caribbean Management Regions

NOAA's Southeast Fisheries Science Center and Southeast Regional Office use the SEDAR (SouthEast Data, Assessment and Review) process for stock assessments to develop best available scientific information for advising fisheries management in the South Atlantic, Gulf of Mexico, and Caribbean Fishery Management Councils; the Atlantic States and Gulf States Marine Fisheries Commissions; and NOAA's Highly Migratory Species (HMS) Division. The SEDAR program guidance is provided through a steering committee, composed of representatives from the three Councils, two Commissions, and three NOAA Fisheries Offices.

SEDAR is operated as a Council process and originally included three approaches with varying levels of complexity: the SEDAR benchmark, standard, and update assessments. In 2014, the Southeast Fisheries Science Center and other regional partners proposed a number of changes designed to increase both assessment throughput and thoroughness. One of these changes was a shift to a cycle of research track and operational assessments similar to what is done in some other regions. The research assessment track is designed to produce a peer-reviewed stock assessment model that is updated in subsequent operational assessments to generate management advice. This cycle should increase quality because research track assessments are not rushed to completion under the pressure of needing to provide management advice (as often happened with benchmark assessments in the previous SEDAR process). It also should increase throughput because data providers can plan ahead. Additionally, data providers will not have to recalculate data inputs multiple times as they did for the original benchmark process since no management advice is produced during a research track assessment. Final updated inputs are not required until the operational assessment is conducted.

An operational assessment may be an update of the previous assessment or may allow for slight modifications. The Southeast Fisheries Science Center will decide what is necessary and can be accommodated in the overall schedule. The first SEDAR research track assessment began in 2019, and the first operational assessments were conducted in 2020.

All SEDAR workshops and webinars are open to the public, and all information related to those assessments is available online. Public comment, in person or in writing, is accepted throughout the process, as well as during subsequent review and action by the cooperating agencies.

Pacific Management Region

The Pacific Fishery Management Council (PFMC) also uses benchmark and update assessment approaches to develop stock assessments for advising fisheries management on the U.S. West Coast. A benchmark/full assessment usually includes developing and compiling input data from commercial and recreational fisheries and scientific surveys; modeling stock dynamics (often using Stock Synthesis); conducting rebuilding analysis (for fish stocks subject to rebuilding plans) and additional analyses requested by the PFMC; estimating key fisheries parameters (e.g., selectivity, natural mortality, productivity, recruitment, stock size, and fishing mortality); considering uncertainty and model sensitivity; and estimating overfishing limit (OFL) using MSY proxy and stock status (percentage of virgin biomass). The STock Assessment Review (STAR) process is used for an independent and interactive 4- to 5-day peer review with a final SSC review. The goal of an update assessment is to update prior benchmark assessments with new or revised data in previously used series. No new series are allowed, and model structure remains the same for the update assessments, which are reviewed by the full SSC following initial review by the SSC Groundfish or Coastal Pelagic Species Subcommittee.

North Pacific Management Region

The Stock Assessment and Fishery Evaluation (SAFE), providing information concerning the past, present, and possible future condition of the stocks, marine ecosystems, and fisheries in the Bering Sea and Aleutian Islands (BSAI) Area and Gulf of Alaska (GOA) Area, is used by the North Pacific Fishery Management Council (NPFMC) to determine annual harvest levels for each managed stock in the North Pacific. The SAFE usually includes three separate reports: stock assessment report, economic status report, and ecosystem status report. SAFE reports, devoting one chapter to each stock or stock complex, are produced each year in time for the December meeting of the NPFMC. A SAFE with new or revised stock assessment models is usually previewed at the September Plan Team meeting and considered again by the team at its November meeting for recommending final specifications for the following two fishing years. The Plan Team review is based on presentations by Alaska Department of Fish and Game and NOAA Fisheries Alaska Fisheries Science Center scientists, with opportunity for public comment and input.

The SAFE stock assessment report also includes a recommendation for the OFL and ABC for each stock and stock complex managed under the FMP for the next two fishing years, in addition to the information on the dynamics of fish stock. The OFL and ABC recommendations of the Plan Team are reviewed by the SSC, which may confirm the team’s recommendations or develop its own. The team and SSC recommendations, together with social and economic factors, are considered by the Council in determining total allowable catches (TACs) and other measures used to manage the fisheries. Neither the author(s), team, nor SSC typically recommends TACs.

Western Pacific Management Region

The Western Pacific Stock Assessment (WPSA) is a cooperative effort of the Western Pacific Regional Fishery Management Council (WPFMC), NOAA Fisheries Pacific Islands Fisheries Science Center, and Pacific Islands Regional Office designed to provide the best available scientific information for advising the Pacific Islands region fishery management.

The WPSA includes two types of stock assessment: benchmark and update stock assessments. A benchmark stock assessment provides the first assessment of a specific stock or includes large changes in modeling and/or input data to previous assessments. An update assessment is conducted to rerun a previously reviewed model with additional years of data only.

Both benchmark and update stock assessments are reviewed in the WPSA Review (WPSAR) process. The WPSAR defines roles and responsibilities, summarizes the review scope and terms of references, and describes the review schedule in coordination with the larger WPFMC process. The reviewed stock assessments are then sent to the WPFMC SSC, which reviews them and provides catch advice based on the harvest control rules defined in the relevant FMP.

The stock assessment process in each management region has evolved over time. In general, data quality and quantity have been greatly improved for many stock assessments. The complexity of benchmark assessments has increased with more sophisticated and flexible modeling frameworks that can incorporate multiple sources of data, better quantify the dynamics of fish stocks and fishing fleets, and improve understanding of uncertainty. The assessment category or approach is usually determined based on uncertainty in data and model outputs. The complexity of some assessments is reduced with the use of data-moderate assessment methods and the simplification of appropriate benchmark assessments. Assessment contributions from state agencies have declined over time.

APPLICATION OF ABCS, ACLS, AND AMS IN THE MANAGEMENT PROCESS

According to National Standard 1 Guidelines, for all stocks and stock complexes that are "in the fishery," the Councils must evaluate and describe the following items in their FMPs and amend the FMPs, if necessary, to align their management objectives so as to end or prevent overfishing: (1) MSY and SDCs; (2) OY; (3) ABC control rule; and (4) mechanisms for specifying ACLs and AMs.

Although varying among the regions, ABC should be based, when possible, on the probability of overfishing when the ABC is in place, denoted P*. Because catch estimates are uncertain, an estimated catch equal to the ABC may result in a larger actual catch, and this larger actual catch may result in overfishing. An estimated catch equal to the stock's ABC results in overfishing with probability P*. P* cannot by law exceed 50%.Choosing a lower level for ABC reduces P* and reduces the risk of overfishing. A control rule is often used to help characterize the risk of overfishing while optimizing yield for alternative proposed management measures under different levels of scientific uncertainty.

Each Council must develop ABC control rules in coordination with its SSC. The SSC must recommend the ABC to the Council. An SSC may not always follow the ABC control rules in recommending an ABC, but must justify such a recommendation. Actual ABC control rules vary by Council. Some Councils have adopted a single framework for all FMPs, while others have different frameworks for each FMP. Most Councils attempt to various degrees to set ABCs below the OFL in a way that reflects and captures scientific uncertainty.

As discussed previously, the MSA requires ACLs and AMs in federal fisheries to end and prevent overfishing. For a fishery, an ACL is typically developed from and may have a value lower than the ABC to account for management uncertainty (e.g., uncertainty in the ability of management measures to constrain catch). Alternatively, Councils may set an annual catch target (ACT) that is lower than the ACL to account for management uncertainty, but they are not required to do so. If the total catch of a stock is approaching or exceeds its ACL, fishery managers use AMs to ensure that the limit is not exceeded or to correct for any overage. AMs can be some combinations of size limits, trip limits, gear restrictions, and even seasonal closures. All federal fisheries currently operate under ACLs, with the exception of internationally managed fisheries and stocks with a short life span (<1 year) that are exempt from ACL requirements unless subject to overfishing.[35] An ACL may be exceeded for many reasons: the population size of the stock is actually smaller than estimated in the stock assessment, catch rates or effort is higher than expected, and bycatch and/or catch in state waters may be higher than anticipated. Thus, data need to be collected throughout the fishing season to evaluate the amount of fish caught and determine whether the catch falls below or above the ACL. If a fishery meets or is approaching an ACL, managers may implement an in-season closure. If a fishery exceeds the catch limit, managers may consider whether to reduce the following season to make up for overages, and whether to set measures more conservatively the next fishing season. Such AMs, whether in-season or postseason, are required under the MSA as a key tool to prevent overfishing.

Many, particularly commercial, fisheries have in-season management mechanisms for which the amount and type of catch and bycatch in the fisheries are monitored in real time during the season according to the ACL and allocations by gear, sector, and seasonal apportionments that are prescribed in regulation and defined in the harvest specifications. The fisheries will be closed or remain open based on the catch estimated according to in-season monitoring in comparison with the ACL. In-season monitoring programs typically rely on both observer data and landings information to generate estimates of total catch, including at-sea discards. In commercial fisheries, observer information, dealer landing reports, and at-sea production reports are combined to provide an integrated source for fisheries monitoring and in-season decision making (Cahalan et al., 2010; 2014).

CHALLENGES POSED BY RECREATIONAL FISHERIES DATA FOR STOCK ASSESSMENTS

The most important piece of information for all the stock assessment models is the amount of fish removed from a stock by commercial and recreational fishing activities. A national network of various fishery-dependent monitoring programs was developed to collect catch data for stock assessments. Port monitoring programs, often conducted in partnership with state agencies and fisheries commissions, record commercial catch receipts to provide an estimate of commercial landings and associated biological samples of the length, sex, and age of fish. Logbook programs recorded by commercial fishermen track fishing location, gear, and catch. On-board observer programs have biologists observe fishing operations on a certain proportion of fishing vessels and collect data on the amount of catch and discards, which has greatly improved the quality of commercial fisheries data.

Recreational monitoring programs often use telephone interviews, mail surveys, creel surveys, and dockside sampling to estimate the level of catch and other relevant information (e.g., effort) by the recreational fishery. However, accurate and timely estimates of recreational fisheries catch, particularly discards, are especially challenging in monitoring program designs and statistical analysis because of wide-ranging coastlines and the large number of participants in recreational fisheries. Good spatio-temporal sampling coverage is often difficult, as is controlling the various factors that may influence the quality of the data collected in recreational sampling programs. Methods used in commercial fisheries, such as on-board observer programs, can be impractical to implement for the private component of recreational fisheries. To improve the quality of recreational data, NOAA Fisheries has worked with its partners to develop MRIP to collect information on the number of recreational fishing trips and the number of fish caught using in-person, telephone, and mail fishing surveys. A certification program has been developed to ensure that a specialized or supplemental recreational fisheries monitoring program is scientifically sound and yields high-quality recreational fisheries catch data.

[35] See Pub. L. No. 109-479 §104(b), MSA §303 note (a)(15), which added the requirement for ACLs and AMs, "shall not apply to a fishery for species that have a life cycle of approximately 1 year unless the Secretary has determined the fishery is subject to overfishing of that species." However, the requirement for status determination criteria, MSY, OY, and ABC still apply. One example of a species not subject to these requirements is the penaeid shrimp fishery off the Southeast.

In 2018, a series of changes was made to MRIP to provide more accurate estimates of fishing effort; these changes included transitioning from the Coastal Households Telephone Survey (CHTS) to the mail-based Fishing Effort Survey (FES) and incorporating private boat anglers in Hawaii and the Atlantic and Gulf Coasts. These improvements resulted in increased catch estimates for the entire MRIP time series that also induced changes in the scale of assessment models, often altering managers' previous understanding of stock status and dynamics. Overall, MRIP has greatly improved the quality and quantity of recreational fisheries statistics (NASEM, 2017), which, in combination with a commercial fisheries monitoring program, greatly improves the estimates of total removals for many fisheries. However, challenges remain in obtaining high-quality and timely estimates of recreational fisheries catch for stock assessments and management (e.g., average weights of discards). The advances and difficulties highlighted here are pertinent to the committee's statement of task to evaluate how the design of MRIP might be improved or supplemented to meet both science and management needs.

MANAGEMENT AND MONITORING OF RECREATIONAL HARVEST

In-season management of commercial fisheries in the United States is possible because catches are obtained by a limited number of licensed commercial fishermen, landed in a limited number of ports, and sold through licensed seafood dealers. Reporting is obligatory for many commercial fishermen and seafood dealers. These features have evolved naturally and are reinforced by licensing requirements that restrict entry into the seafood sector.

As discussed previously, recreational fisheries are characterized by high numbers of participants, who on average spend only a small part of their time fishing; a large number of diffuse access points (boat ramps, marinas, private docks); and absence of a marketing system and associated data collection. Moreover, the number of participants in recreational fishing is essentially uncontrolled since licenses often are not limited, and indeed, fisheries agencies typically strive to increase rather than limit license sales because unlicensed recreational anglers add to the uncertainty of catch estimates. For all these reasons, it is difficult to obtain recreational catch estimates using census-based approaches or even surveys with a high level of coverage (recreational surveys typically cover at most a few percent of recreational fishing trips). As a consequence, recreational ACL management is hindered by catch sampling programs that lack both the precision and the timeliness needed to implement in-season management, and by a lack of direct control over recreational effort and catch.

Recreational ACL management therefore generally relies on a two-step process of (1) instituting size, season, and bag limits that are estimated to result in the ACL being met; and (2) monitoring catches using a survey-based approach to provide a catch estimate, normally after the recreational season has ended. If the catch estimate is at or below the ACL, no further action is taken, and any unused ACL is forgone. If the catch estimate is above the ACL, AMs may be in place that require overages to be paid back in the next fishing season. In any case, overages or underages will be accounted for in subsequent stock assessments, but such feedbacks are neither direct nor immediate.

The setting of size, bag, and season limits to achieve the recreational ACL involves forecasting catches in relation to these limits. A variety of forecasting approaches can be used for this purpose. For example, forecasts may be based on a deliberative committee process with ad hoc use of such considerations as changes in stock abundance or assumptions about angler responses to regulations (e.g., the PFMC Groundfish Management Team approach). Advanced statistical forecasting methods are widely used in other fisheries, and have proven to provide reliable forecasts, particularly in fisheries where consistent interannual and seasonal trends in catch rates are observed (Farmer and Froeschke, 2015; Farmer et al., 2020). Statistical forecasting methods use statistical models to forecast future catch without having to explicitly capture underlying mechanisms, such as by modeling angler behaviors. More recently, mechanistic (process-based) approaches that explicitly model angler behaviors and other factors have become available (Lee et al., 2017). The three approaches (committee-based ad hoc, statistical forecasting, and mechanistic models) have different advantages and disadvantages in terms of forecasting accuracy, process understanding, transparency, and opportunities for stakeholder participation. At present, different approaches are used in different fisheries, and therefore, a direct intercomparison has not been possible.

Recreational overages or underages may be the result of either implementation uncertainty (which occurs when the predetermined size, bag, and season limits fail to result in the projected catch) or uncertainty in the survey estimate of catch (e.g., it is possible that catches were actually within the ACL, but the survey returned a higher catch estimate). Both are components of management uncertainty. Substantial underages or overages may be more commonly associated with implementation uncertainty than with uncertainty in survey estimates, though this has not been formally evaluated. For example, the Mid-Atlantic Fishery Management Council has noted that even when recreational management measures have remained consistent across years, resulting estimates of harvest have varied significantly.[36] Since overages can have severe short- and long-term consequences (AMs, reduced future catches, stock status changes to overfished/overfishing), Councils may enact safety buffers in recreational fisheries where overages occur frequently. For example, the Gulf of Mexico Fishery Management Council implemented a 20 percent buffer (20 percent reduction of ACT below ACL) for Red Snapper for several years to reduce the risk of overages resulting from implementation error.

The quest to implement in-season management for recreational fisheries stems from a provision in National Standard 1 that calls for FMPs to include in-season management and monitoring whenever possible, and from a desire to reduce management uncertainty in recreational fisheries, thereby avoiding underages and overages and the associated loss of fishing opportunities. As described above, there are substantial structural challenges associated with the implementation of in-season management in recreational fisheries that are not easily overcome with changes in survey design alone. Moreover, it should be noted that current methods of ACL management perform reasonably well in many recreational fisheries where underages or overages of more than a few percent are uncommon. The following chapters review recreational fisheries with ACLs in all regions to identify fisheries in which frequent underages or overages call for management improvements that could be achieved with in-season management approaches, and the specific challenges associated with implementation of such approaches in these fisheries. Also considered are alternative approaches to improving management outcomes that may be more feasible than in-season management in some cases.

We close by noting that, while effective in-season management of fisheries managed under open access maintains fisheries catches within ACLs and therefore avoids overfishing, it often leads to economically and socially suboptimal outcomes. This is well-documented for commercial fisheries, and similar arguments can be made for recreational fisheries (Sutinen and Johnston, 2003; Abbott et al., 2018). By contrast, rights-based approaches, such as catch shares for charter operators or harvest tags for private recreational anglers, may improve ACL compliance while simultaneously generating other economic and social benefits. Again, such approaches are discussed in subsequent chapters.

CONCLUSIONS

Conclusion: For all stocks in need of conservation and management, the MSA requires that Councils set ACLs to prevent overfishing and AMs to ensure that catches are constrained to ACLs. As required by the MSA, a Council cannot exceed the recommended ABC from its SSC when setting an ACL, and its FMPs must include reference points (MSY, OY, and SDCs) (or reasonable proxies) for all managed species with which to make determinations of stock status (i.e., overfished and overfishing).

Conclusion: The MFA did not alter the MSA's fundamental requirement for ACLs and AMs. Rather, it clarified that management approaches for commercial and recreational fisheries should be tailored to the

[36] See the January 2021 staff memo on the joint Atlantic States Marine Fisheries Commission/Mid-Atlantic Fishery Management Council Recreational Reform Initiative regarding potential challenges associated with development of a harvest control rule (pp. 10–11): https://www.mafmc.org/s/Tab01_Rec_reform_memo_Feb2021_v2.pdf.

needs of each sector, and highlighted specific approaches that Councils could consider for recreational fisheries.

Conclusion: Stock assessments are the scientific backbone of the fisheries management process and vary greatly in complexity depending on the quality and quantity of available data. While stock assessment models and outputs are similar, each NOAA Fisheries–Council region has developed a process for scheduling, conducting, and reviewing assessments that meets regional needs and ensures the quality of scientific information. Implementation of MRIP has greatly improved the recreational catch data used in stock assessments, although challenges remain in obtaining high quality and timely estimates of recreational fisheries catch.

Conclusion: A variety of approaches are used to monitor stocks and ensure that ACLs are not exceeded. In-season AMs compare harvest with the ACL as the fishery is underway and may trigger a closure or other adjustments (e.g., changes to possession limits or season length), while postseason AMs may modify future harvest limits to account for overages.

Conclusion: The characteristics of recreational fisheries make census-based approaches to monitoring and managing catch inherently challenging. Several forecasting approaches may be used to project how a given set of management measures (e.g., size, season, and bag limits) will perform in comparison with an ACL. Actual performance (i.e., realized vs. projected catch) depends on management uncertainty, which includes both implementation uncertainty (how well management measures met expectations) and uncertainty in estimates of catch. Pursuit of in-season management is focused primarily on reducing management uncertainty to avoid or minimize forgone fishing opportunities.

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3

Existing Recreational Fisheries Surveys and ACL-BASED Fisheries Management

The aim of this chapter is to provide background on the network of the Marine Recreational Information Program (MRIP) and state-sponsored recreational fishing surveys and data collection programs, and how the combination of these data-gathering efforts is currently used at the regional and state levels to support in-season management. Chapter 4 explores potential improvements to the data collection designs and methods and extensions to current statistical methods that could enhance MRIP's contribution to in-season management.

CRITERIA FOR RECREATIONAL FISHING SAMPLE SURVEYS OR CENSUSES

Four key criteria are highly relevant when considering the use of MRIP and other recreational fishing sample surveys or censuses for in-season management of fisheries with annual catch limits (ACLs): (1) the total error of the estimates; (2) timeliness, or the time lapse between the actual fishing activity and availability of estimates; (3) the flexibility of design, methods, and processes to adapt a survey's or census's data for uses outside of its initial intent; and (4) the direct and indirect costs of expanding or changing the data collection program.

Total Error of Estimate

The total error of an estimate is defined as the difference between the value of the estimate and the "true" population value of the statistic (e.g., total catch for a particular MRIP domain). Total error of an MRIP catch estimate or other survey estimate is a function of the variance (precision) and bias of the estimate, which are inherent in the sampling design, the sampling frame, the data collection method, the data processing method, and the estimation procedure (Biemer, 2010; Groves et al., 2009). In theory, the total error of an estimate is quantified as the mean squared error: $MSE(\hat{\theta}) = Var(\hat{\theta}) + Bias^2(\hat{\theta})$. In practice, the "measurable" probability sample survey designs employed in the MRIP and other, MRIP-certified programs enable estimation of the variance component of the MSE directly from the sample data. However, except in extremely rare cases where true population values are known or can be derived from external sources, the bias component of total error for a survey cannot be measured directly. Furthermore, although statistics computed from a complete census of the target population (i.e., mandatory logbook program) should in theory be free of sampling errors, they are still subject to nonsampling errors (i.e., response variance, coverage bias, nonresponse bias, and reported errors).

For MRIP, the variability of an estimate is indicated by Percent Standard Error (PSE):

$$PSE(\hat{\theta}) = \frac{\sqrt{var(\widehat{\theta})}}{\hat{\theta}} = \frac{se(\hat{\theta})}{\hat{\theta}} \cdot 100$$

where:
θ= the true value of a population statistic
$\hat{\theta}$= an estimate of θobtained from a single sample of data
$var(\hat{\theta})$= the variance of $(\hat{\theta})$
$se(\hat{\theta})$= the standard error of $(\hat{\theta})$

Throughout this chapter and the balance of this report, the term "precision" is also used to describe the variability of the sample estimates. PSE and precision are inversely related: an estimate with large variability has a large PSE but low precision. The precision of MRIP estimates is a function of a number of "controllable" features of the sample design and sample selection: the survey sample size; the complexity of the sample design (i.e., multiple-stage, clustering of observations); and the efficiency of the sample stratification. The choice of the estimator for a population statistic such as total recreational catch of a species (see below) also determines the precision of estimates. In addition to sample design features and estimator choice, the precision of sample estimates is influenced by variability in the weighting factors used in estimation to compensate for potential bias due to sample noncoverage, nonresponse, or reporting errors (see below).

MRIP sample design and variance estimation methodology are described in detail by Papacostas and Foster (2018). A review of that document, as well as the National Academies report on the MRIP program and methods (NASEM, 2017) confirms that MRIP is using robust, scientifically correct methods to estimate the precision of estimates generated from data collected in its multiple survey and logbook inputs. The National Academies (2017) report does include the recommendation that MRIP explore the use of replicated variance estimators that better capture the impacts of nonresponse weighting and poststratification/calibration on the precision of estimates. That remains a valid but not essential recommendation for the program.

The general term "accuracy" refers to the degree to which bias is absent from a statistical estimate (i.e., low bias indicates high accuracy). The bias of a survey estimate or census value is the difference between the expected value of the survey estimate and the true value of the statistic in the target population.

$$Bias(\hat{\theta}) = E(\hat{\theta}) - \theta$$

where:
θ= the true value of a population statistic
$\hat{\theta}$= an estimate of θobtained from a single sample of data
$E(\hat{\theta})$= the statistical expectation (mean value) of the estimate over the sampling design, i.e., the long term average of the estimate of θ when the sampling process is repeated a large number of times based on the sampling design.

Throughout this chapter and the balance of the report, this definition of bias is used in discussing accuracy, keeping in mind that low bias indicates high accuracy. Under MRIP's design-based approach to estimation, the statistical expectation or expected value of an estimate, $E(\hat{\theta})$, is the mean value that would be obtained if the exact same sample design, data collection, data processing, and estimation procedures were independently replicated an infinite number of times. $E(\hat{\theta})$ would be the average of the individual estimates, $\widehat{\theta s}$, from each sample in that infinite series. Given that the true population value to be estimated, θ, is not known, and few if any surveys (including MRIP) have the luxury of employing large numbers of simultaneous independent replications even to estimate $E(\hat{\theta})$, the true bias of estimates can rarely be exactly quantified. Instead, MRIP, MRIP-certified survey programs, and scientifically sound survey programs in general strive to employ statistical methods and procedures that are designed to minimize or eliminate bias in estimates. At the sample design stage, MRIP employs probability sampling to eliminate bias in sample selection and model-based calibration along with other weighting adjustments to minimize estimation bias due to frame undercoverage and survey nonresponse.

Under the total survey error model (Groves, 1989), potential sources of bias in MRIP estimates may arise from three major sources: sample frame coverage bias, nonresponse or noncooperation bias, and measurement error. Most sources of potential bias in the MRIP data that are recognized by the MRIP program (Papacostas and Foster, 2018) and the 2017 National Academies peer review of the MRIP program (NASEM, 2017) are listed in Table 3.1 along with a brief description of any current methods used by MRIP to attenuate or eliminate the potential bias.

TABLE 3.1 Potential Sources of Bias in MRIP's Data and MRIP Methods for Attenuating or Eliminating Major Biases in MRIP Estimates of Catch Per Unit Effort (CPUE), Effort, and Total Catch

Type of Bias	Source	MRIP Components Impacted	MRIP Compensation Strategy
Sample Frame Coverage	Noncovered public access and shore fishing sites	APAIS	MRIP works with its regional and state partners to continuously update the sample frame of public access points.
	Noncovered private marinas, launches, and fishing sites.	APAIS	MRIP assumes that catch per unit effort (CPUE) for fishing trips from private-access sites is equal to that for covered public-access sites on the sample frame.
	Noncovered for-hire vessels	FHS (in combination with logbook programs VTR, SEFHIER, and Southeast Region Headboat Survey)	APAIS intercept sampling provides data to adjust estimates for trips by for-hire vessels not covered by FHS, SEFHIER, or VTR.
	Noncovered trips by out-of-state anglers (noncoastal states)	FES	APAIS intercept sampling provides data with which to adjust FES survey estimates for trips by residents of noncoastal states.
Nonresponse, noncooperation	Dockside intercept nonobservation due to refusal,[1] high traffic volume, or staff scheduling issues	APAIS	APAIS survey staff record the number of nonsampled trips in the count of total trips at a survey site. Adjustment is made using weights based on inverse of local completion rates at the PSU and sample trip levels.
	Mail survey nonresponse	FES	MRIP uses Dillman Tailored Design Method mail survey nonresponse follow-up (Dillman et al., 2014). Model-based nonresponse weighting adjustment is used to adjust for final nonresponse. The National Academies report (NASEM, 2017) proposes special annual nonresponse follow-up studies focused on selective nonresponse due to angler avidity and other characteristics.[2]

continued

[1] In APAIS, “". . . unsampled fishing trips occur . . . when anglers refuse to be interviewed" (Papacostas and Foster 2021, p. 9). Non-random refusal (e.g., response propensity correlated with CPUE) is a possible source of nonresponse bias in APAIS estimates of CPUE (Bethlehem, 2011, pp. 43-45).

[2] For example, nonresponse bias in FES estimates of total trips could occur due to correlation between an angler's response propensity and the angler's number of fishing trips (Bethlehem 2011, pp. 43-45).

TABLE 3.1 Continued

Type of Bias	Source	MRIP Components Impacted	MRIP Compensation Strategy
	Telephone survey nonresponse	FHS	MRIP uses nonresponse follow-up of initial nonrespondents, model-based nonresponse weighting adjustment for final nonresponse, and dockside validation samples.
	Logbook noncooperation, delayed reporting	VTR, SEFHIER, Southeast Region Headboat Survey	MRIP uses follow-up of noncompliant vessel operators and permit holders, and adjustment to estimation weights to account for residual nonresponse.
	Structural missing data on fishing location for reported trips	FES	Data from the APAIS intercept survey are used to allocate FES trips to three categories of fishing location.
Measurement Error	Misclassification of species, fishing location	APAIS	MRIP uses training and certification of MRIP intercept survey field staff.
	Underreporting of released/discarded fish	APAIS	MRIP uses on-board observation for a special APAIS sample of for-hire vessels. There currently are no current validation data for private boat and shore anglers.
	Recall bias—incorrect recall of numbers, dates, locations, and modes of angler trips by household members	FES	Research is conducted on the effect of the length of the recall period. Measurement issues are recognized in design of survey materials and question items.
	Recall bias, incorrect reporting	FHS	MRIP uses an FHS dockside validation survey for a subsample of each week's sample of for-hire vessels. VTR or SEFHIER logbook reports are used for FHS vessels covered under one of these logbook programs.

From reviewing the entries in Table 3.1, it is clear that, like all major statistical programs, MRIP faces many challenges in its efforts to eliminate or attenuate potential biases in its data that could result in bias for final estimates. While MRIP employs many best practices in its attempts to compensate for coverage, nonresponse, and measurement error, the potential for some bias remains. The most important of these concerns are identified in the National Academies report (NASEM 2017). The January 2021 advent of the mandatory Southeast Region For-Hire Electronic Reporting (SEFHIER) program in the South Atlantic and Gulf Regions and the almost complete transition to electronic reporting for all major for-hire logbook programs (Vessel Trip Reporting [VTR], South Carolina logbook program, Southeast Region Headboat Survey, SEFHIER—see below) has certainly improved the sample coverage of the for-hire sector and reduced reporting delays and increased reporting accuracy for this MRIP "fishing mode" domain. Likewise, introduction of electronic recording in the MRIP Access Point Angler Intercept Survey (APAIS) intercept surveys should reduce the potential for biases that can enter the data capture and data processing phases of the survey process. From the many entries listed in Table 3.1, there are two areas of bias reduction that warrant continuing high priority in MRIP methodological research:

- validation of measurement strategy to better quantify the rate of discarded fish by all angling modes; and
- continued research on the potential for nonignorable nonresponse bias in the FES, both that which can be corrected through the use of auxiliary variables (i.e., MAR - missing at random) and that which cannot be corrected (i.e., MNAR, or missing not at random) through weighting and calibration using fully measured covariates, an example being nonrepsonse bias, in which anglers with a greater number of trips report at a higher rate relative to occasional or infrequent anglers.

Timeliness

Timeliness refers to the length of time between an event of interest (in the present context, actual fishing activity) and the availability of survey estimates related to the event (e.g., estimates of total catch). The shorter the length of time between the event and the estimate, the better is the timeliness. Timeliness is governed by the primary aims of the survey program, the complexity of the survey design, and the procedures and time required for data cleaning, data processing, estimation, and quality assurance/quality control functions that must occur after the survey data are collected.

Timeliness is of key importance if recreational fishing survey estimates are to be used effectively for in-season management. MRIP currently targets the release of preliminary estimates 45 days after the close of each 2-month data collection wave (e.g., estimates are released on September 15 for the June–July data collection wave).

Although none of the current survey or mandatory logbook programs that contribute to the bimonthly MRIP estimates can deliver the required data inputs in real time, it may be possible to reduce the time lapse between actual fishing activity and access to data needed for estimation to less than a month, maybe less than 2–3 weeks, through the use of weekly sampling/reporting and electronic data capture and transfer. Presently, a primary factor limiting significant improvement in the timeliness of release of MRIP estimates is the bimonthly Fishing Effort Survey (FES; see below) which is the source of MRIP fishing effort (E) data for private boat and shoreline anglers.

In a 2011 report (Salz et al., 2011), the MRIP team addressed the issue of more timely release of MRIP recreational fishery data. The findings of that report and any new developments that might lead to more timely release of MRIP estimates and data for purposes of in-season management are covered in more detail in Chapter 4 of this report.

Flexibility

The flexibility of a survey design denotes its ability to be adapted for uses outside of its initial intent. Given the charge to the committee, a key question is whether the current MRIP design and procedures are flexible enough to support, directly or indirectly, existing needs for in-season management of recreational fisheries. Chapter 4 examines how MRIP in combination with external data sources and new statistical methodology can better adapt to the specialized needs of fisheries scientists and managers charged with the responsibility for in-season management under ACLs.

Cost

The committee’s charge does not explicitly include assessment of the costs of the current MRIP program or how financial support for the program might be allocated to improve MRIP’s contribution to meeting the data challenges of in-season management. Nevertheless, it is not possible to evaluate new procedures or alternative statistical methods without some consideration of the financial cost involved. For example, one clear solution for achieving greater substate spatial resolution for bimonthly survey estimates would be to substantially increase the size of the weekly APAIS intercept samples. In fact, states can use state funds to increase the basic APAIS sample size to improve the precision of catch per unit effort (CPUE) estimates for locations and time periods of high fishing intensity or special management interest.

MRIP OVERVIEW

As described below, the data collection, statistical aggregation, and reporting of marine recreational survey data and estimates of total catch vary across regions and even by state within a region. MRIP is the direct source of the National Oceanic and Atmospheric Administration (NOAA) National Fisheries Management Service's (NOAA Fisheries') recreational marine fishery catch estimates for federally managed species in four of the seven regions established under the Magnuson-Stevens Fishery Conservation and Management Act (MSA): North Atlantic (Maine, New Hampshire, Massachusetts, Rhode Island, Connecticut); Mid-Atlantic (New York, New Jersey, Delaware, Maryland, Virginia); South Atlantic (North Carolina, South Carolina, Georgia, East Florida), and Gulf of Mexico (West Florida, Alabama, Mississippi) (Papacostas and Foster, 2018). In the Gulf region, the Louisiana state-managed, MRIP-certified LA Creel survey program receives MRIP support but has delegated direct responsibility for collecting the necessary catch and effort data and producing bimonthly and annual estimates of total catch. Texas runs its own program of recreational marine fisheries data collection and estimation that is independent of MRIP (NOAA Fisheries, 2014; Papacostas and Foster, 2018).

If measured by miles of coastline for U.S. states and territories, the fraction of fishable marine water that is covered by the MRIP surveys and catch estimates is far from complete. However, in terms of total numbers of recreational fishing trips or total recreational catch, the MRIP surveys and the data they generate cover more than 95 percent of all U.S. marine recreational fishing trips and catch (Figure 3.1). Of the estimated 194,000,000 angler trips in 2018, the Atlantic Coast and Gulf Coast accounted for an estimated 96 percent (97 percent of catch in number of fish landed) (NMFS, 2020).

Recreational catch data and estimates for the Pacific (California, Oregon, Washington) are the responsibility of the states and the RecFIN program of the Pacific States Marine Fisheries Commission (PFMC). These surveys are included in this study because they receive annual funding from MRIP, and the data are used for PFMC management. The Alaska Department of Fish and Game manages its own survey data collection programs and disseminates estimates through the Alaska Fisheries Information Network. The data collection and estimation methodologies employed by these four mainland Pacific states are in various stages of MRIP certification and consequently are eligible for MRIP financial and technical support. MRIP regional partners in Hawaii are in the process of transitioning to a revised survey design, and MRIP certification is part of the plan for the new survey program that will cover the recreational fishery in Hawaiian waters. In the Western Pacific, regional partners in the U.S. territories (American Samoa, Guam, and the Commonwealth of the Northern Mariana Islands) are working with MRIP consultants to review their current recreational fishery survey designs.

MRIP is a state–regional–federal partnership that develops, improves, and coordinates a network of regional recreational fishing data programs (NASEM, 2017). MRIP is a NOAA program that is charged with producing the recreational harvest data mandated by the MSA (discussed further in Chapter 2). The program supports science-based decision making in fisheries management that is part of the larger, general call of the Information Quality Act[3] to maximize the quality, objectivity, utility, and integrity of information (including statistical information) disseminated by federal agencies. As required under the MFA, the MRIP program also funds research projects designed to evaluate new technologies and methods (e.g., electronic reporting methods) and supports the evolving data needs of fisheries managers.

[3] Pub. L. No. 106-554 §515(a)

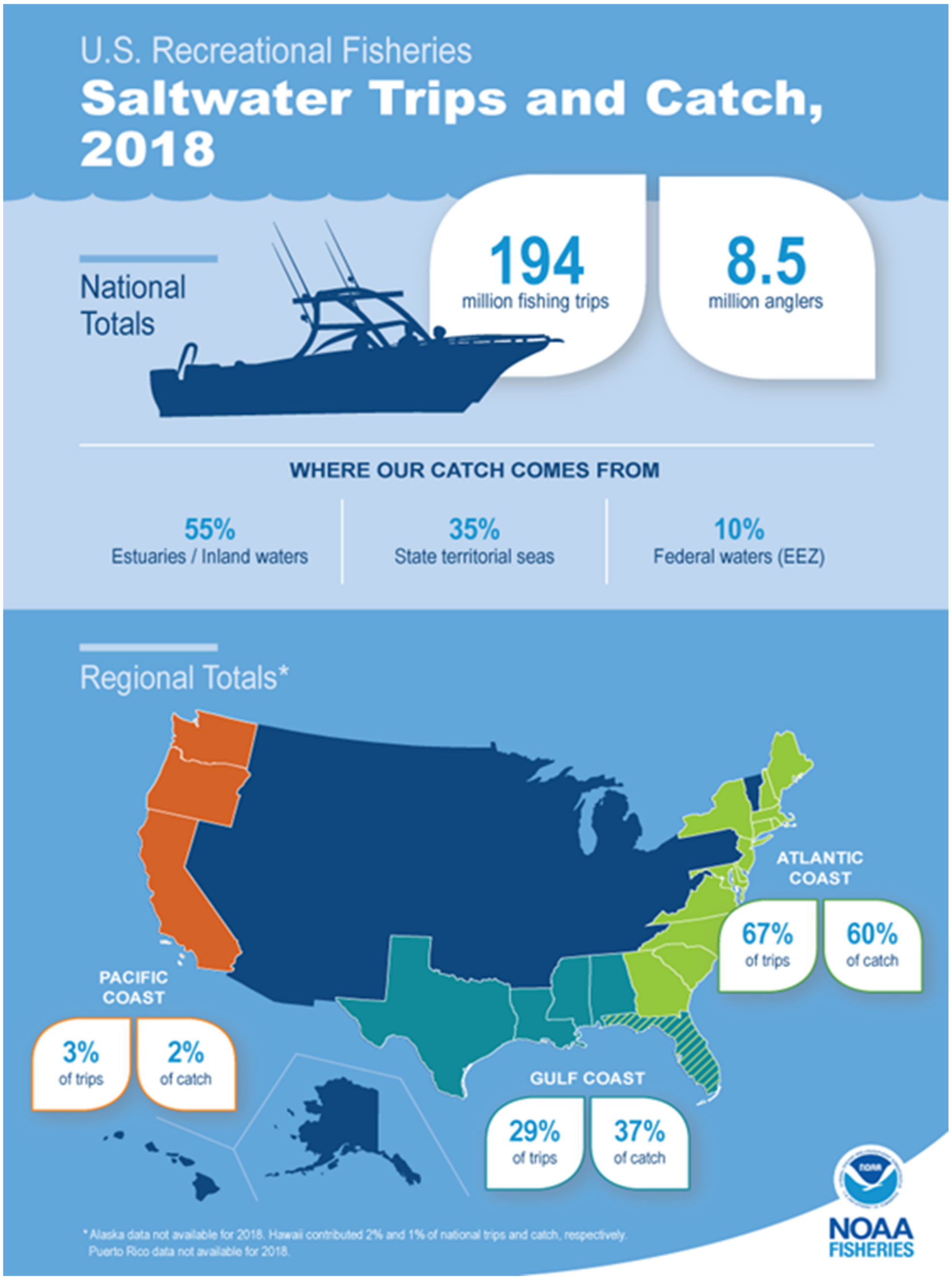

FIGURE 3.1 2018 Recreational Saltwater Trips and Catch. Hawaii contributed 2 percent and 1 percent of national trips and catch, respectively. Data for other Pacific islands, the Alaska region and the Puerto Rico region were not available for 2018. SOURCE: NOAA Fisheries (2020).

MRIP is a network or collection of surveys including the APAIS and the FES. The precision of MRIP surveys is indicated by PSE, discussed earlier, and is generally influenced by such factors as sample size, temporal/spatial scale, and rare-event vs. common species. For instance, in a presentation to this committee, MRIP staff showed estimates of catch and associated PSEs at different temporal and spatial scales to make the point that annual estimates produced by MRIP are typically better than those derived from single waves, and regional estimates are better than state estimates.

MRIP Organization and Regional Partnerships

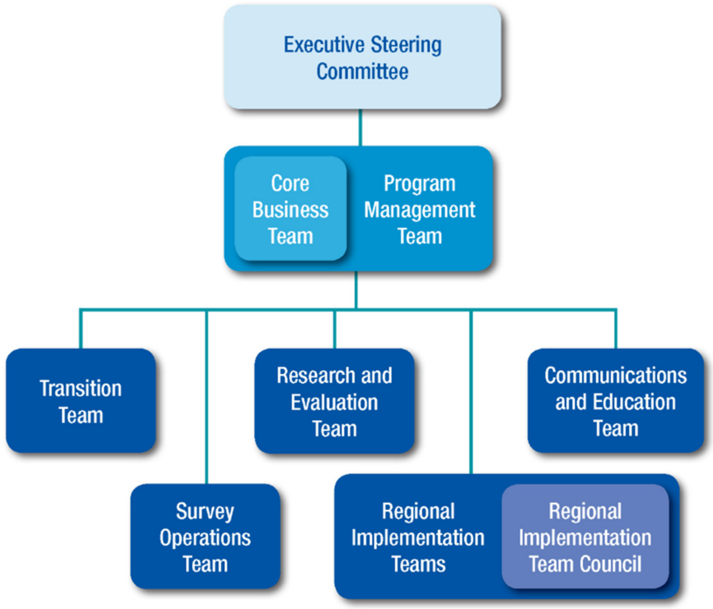

FIGURE 3.2 MRIP organizational chart (effective November 2018). SOURCE: NOAA Fisheries (2021).

Figure 3.2 illustrates the organizational structure of MRIP, including its Executive Steering Committee; senior leadership (Program and Business Management); and technical/operational teams that support federal-level survey operations, research and evaluation, and education/communications. Key features of the third tier in this organizational chart are the MRIP Regional Implementation Teams and the Regional Implementation Team Council (NOAA Fisheries, 2021). MRIP established the Regional Implementation Teams to develop MRIP Regional Implementation Plans that identify regional needs for catch and effort data, and to identify, prioritize, and provide cost estimates for desired additions and improvements to regional data collection programs. The established regional Fishery Information Networks (FINs) host the MRIP Regional Implementation Teams for the Atlantic, Pacific, and Gulf of Mexico regions via the Atlantic Coastal Cooperative Statistics Program (ACCSP), the Gulf Fisheries Information Network (GulfFIN), and the Pacific Recreational Fisheries Information Network (RecFIN), respectively. Ad hoc Regional Implementation Teams have been established to develop MRIP Regional Implementation Plans for the Caribbean, the Pacific Islands, and Alaska and for Atlantic highly migratory species. In all cases, the teams are set up to include representatives from, at a minimum: the NOAA Fisheries Office of Science and Technology; the applicable NOAA Fisheries Regional Office and Fisheries Science Center; and the applicable Interstate Marine Fisheries Commission and members or, in the absence of an Interstate Commission, representatives of state and territorial governments; the applicable Regional Fishery Management Council (Council). To support the Regional Implementation Teams and to facilitate their communications with the MRIP Executive Steering Committee and Program Management Team, a MRIP Regional Implementation Council is established, composed of representatives of each Regional Implementation Team, usually the FIN Program Manager or the chair of the Ad Hoc Team.

From an operational, survey implementation perspective, these regionally oriented teams reflect the fact that primary responsibility for many (but not all) MRIP-sponsored data collection activities has been transitioned to its regional partners. These regional partners can in turn assign actual data collections (often APAIS) to state agencies. MRIP has also established a certification process in which individual states, such as Louisiana (LA Creel), receive MRIP funds to support a state-run recreational fishing survey that conforms to MRIP-approved methodological standards but also permits the state to adapt the data collections to unique aspects of the relevant recreational fishery within that state.

MRIP's collection, processing, and statistical integration of recreational fishery catch and effort data require coordinated contributions from its NOAA Fisheries professional staff, its federal contractors, and its regional and state partners (NASEM, 2017). To understand how this MRIP network of data producers and integrators can contribute to the aims of in-season management of recreational fisheries one can turn to a description of features of the individual survey programs—the management, scope, sample design, and precision of estimates, and the timeliness of access to the raw data and statistical estimates based on that data.

MRIP Recreational Fishing Survey Coverage

Figure 3.3 illustrates the geographic coverage of the various MRIP and partner survey programs. The survey programs that are managed directly by MRIP through its contractors or NOAA Regional Science Centers include the FES, the For-Hire Survey (FHS), the Northeast Vessel Trip Reporting (VTR) program, the Southeast Region Headboat Survey, the Southeast Region For-Hire Electronic Reporting (SEFHIER) program, and the Large Pelagic Survey (LPS). MRIP survey operations staff also maintain the sample frame and sample selection for the APAIS program; however, for most of the Atlantic Coast and Gulf regions, the APAIS data collection is performed by state agency personnel, and the initial data processing is coordinated by Regional Fishery Commission information networks. In the Gulf region, LA Creel is an MRIP-certified state-run survey that substitutes for FES and APAIS data collection for Louisiana recreational fisheries.

Three Gulf states—Mississippi (Tails n' Scales), Alabama (Snapper Check), and Florida (State Reef Fish Survey)—conduct specialized recreational surveys designed to improve estimation of catch of Red Snapper and other marine reef species. The Texas Parks and Wildlife Department conducts its own recreational Angler Survey, which is not part of MRIP. Puerto Rico recreational marine fisheries are covered by the FES and APAIS programs, but data collection has been suspended since hurricane Maria, which occurred in September 2017.

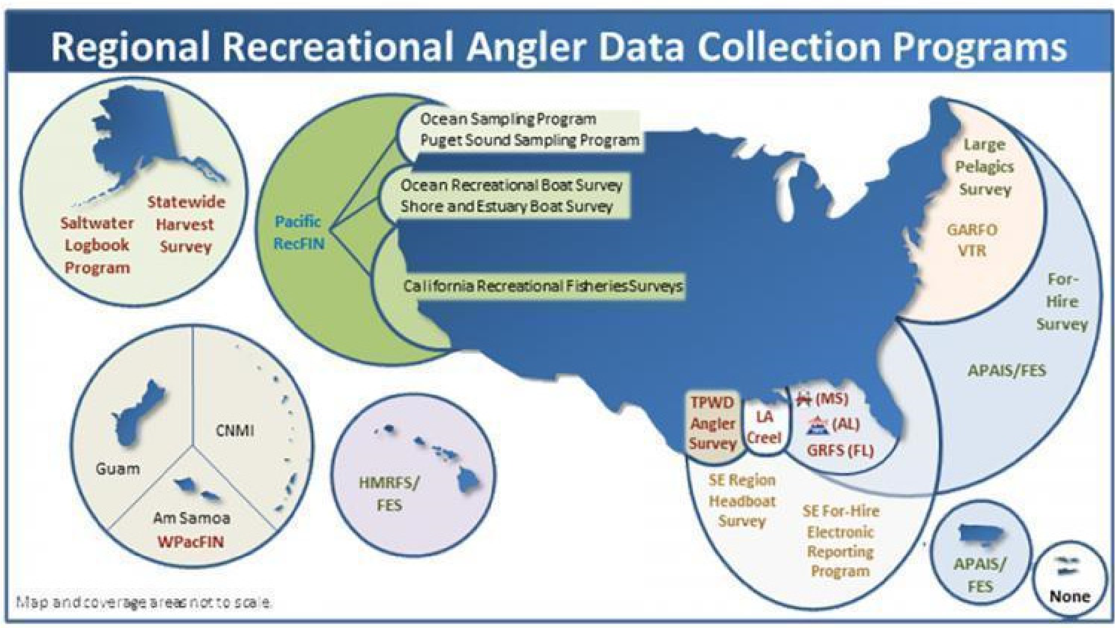

FIGURE 3.3 Recreational fisheries survey coverage within the United States. The majority of these surveys are at least in part supported by MRIP. The Texas Parks and Wildlife Department survey and the surveys conducted in Alaska are not supported by MRIP. SOURCE: NOAA Fisheries (2014).

On the continental Pacific coast, the MRIP-affiliated RecFIN program coordinates final processing and dissemination of catch estimates for California, Oregon, and Washington. With partial MRIP support, each of these states fields its own recreational fishing survey programs: California Recreational Fisheries Surveys, Oregon Ocean Recreational Boat and Shore/Estuary Boat Surveys, and Washington Ocean and Puget Sound Sampling Programs. The State of Alaska manages its own Saltwater Logbook program, an annual Statewide Harvest Survey, and special Southeast Alaska dockside intercept surveys each August and September to support its data needs for fishery stock assessment and limited in-season management (Chinook Salmon in Southeast Alaska). Though the State of Alaska currently receives no MRIP funding for its surveys, associated data are used for NPFMC management.

In Hawaii, recreational catch and effort data are collected through the Hawaii Marine Recreational Fishing Survey angler intercepts and the MRIP FES programs. The Western Pacific Fisheries Information Network (WPacFIN) assembles and distributes data for the U.S. Territories of American Samoa, Guam, and the Commonwealth of the Northern Mariana Islands.

The following subsections describe key features of each of the survey programs managed by MRIP and MRIP partners, including the major state supplemental programs. The descriptions of each of these programs focuses on features that bear most directly on the utility of the data for in-season management and monitoring of recreational catch: timeliness of access to the data, accuracy (coverage biases, reporting bias corrections), precision of estimates (if sample-based), and spatial/other resolution of fishing effort and catch.

MRIP: Access Point Angler Intercept Survey (APAIS)

A detailed description of the APAIS survey program and its components is found in Papacostas and Foster (2018). APAIS involves intercept interviews at public-access fishing sites and is designed to estimate catch rates and trip characteristics. APAIS uses a stratified, clustered multistage design. The APAIS primary sampling unit (PSU) is a site cluster-day-time interval. PSU sampling probability is based on fishing intensity, with high-traffic fishing sites having a higher probability of selection. The sample frame for APAIS is centrally administered by the MRIP Survey Operations Team and includes publicly accessible locations (i.e., shore-based sites, piers, marinas, boat launches) that are established sites where recreational fishing occurs or to which recreational fishing boats will return after a trip. Individual states may supplement the basic regional MRIP samples to increase the precision of estimates of catch for selected species or substate geographic domains. As of March 2021, all APAIS intercept data on recreational catch for the Atlantic Coastal and Gulf Coast regions were captured electronically, making raw data potentially available within a short period of time after the actual intercept sampling has taken place. Note that the APAIS intercept interviews also provide information on nonresident angler trips that are not covered by the FES sample frame or charter/guided trips not covered by the permit frame for the FHS. These data are used in turn to develop weighting adjustments that are applied to estimation of total fishing effort (trips) from the FES mail and FHS telephone surveys (Papacostas and Foster, 2018).

MRIP: Fishing Effort Survey (FES)

The FES is a self-administered, address-based mail survey used to estimate private boat and shore mode fishing effort (trip) estimates for in-state resident anglers. The FES is conducted annually in six 2-month waves. The survey is focused on coastal states and stratified by coastal vs. noncoastal county and whether or not fishing licenses are matched with addresses. From January through December (Waves 1–6), the FES is administered in North Carolina, Florida, Alabama, Mississippi, and Hawaii. All other states—with the exception of Maine—are sampled from March through December (Waves 2–6); Maine is sampled from May through October (Waves 3–5). The FES has been administered in Puerto Rico, but MRIP data collection efforts have been suspended in this region as the territory rebuilds following Hurricane Maria in 2017.

Sample selection is a simple random sampling of households in each stratum (Papacostas and Foster, 2018). The survey approach involves three mailings (Dillman et al., 2014): an initial mailing of all survey materials, a reminder postcard 1 week later, and a follow-up survey 3 weeks later.

MRIP Headboat and For-Hire Surveys

MRIP estimates of recreational marine fisheries catch and effort include domain-specific estimates defined by year, wave, region, state, fishing mode (for-hire, private vessel, shoreline), area fished (in-shore, state ocean waters, or federal ocean waters), species, and catch type (harvested, released). Estimation of recreational catch by the for-hire mode is supported by special surveys and data collections that either are distinct from or supplement data collected with the standard probability sample methodologies used in the MRIP APAIS (catch) and FES (effort) surveys. The for-hire sector includes both recreational charter fishing and headboat excursions—the latter often defined as larger party boat or charter operations that routinely take more than six paid customers per outing.

The fraction of total annual recreational catch that can be attributed to the for-hire domain is highly variable across many of the other MRIP temporal, geographic, and species-specific reporting domains. Table 3.2, originally published in a 2016 ACCSP report, highlights the variability in the 2014 for-hire proportion of total recreational catch for selected species in the Mid-Atlantic region. Anglers on headboats and charter boats accounted for an estimated 54 percent of the 2014 black sea bass landings in that region. That same year, the for-hire domain accounted for a much smaller 17.7 percent of black sea bass landings in the North Atlantic region. The for-hire proportion of 2014 landings for bluefish was similar across the two regions: Mid-Atlantic (15 percent) and North-Atlantic (22.7 percent).

TABLE 3.2 Mid-Atlantic Region: Percent of 2014 Landings (listed as the percentage of fish harvested) by Charter and Guide Boat Landings, and Inventory and Comparison of For-Hire Data collections of the Number of Fish Harvested, by Species, in the Atlantic and Gulf of Mexico

Species	For-Hire Harvest	Private Harvest	% Landed For Hire
Black Sea Bass	542,039	456,482	54%
Atlantic Croaker	472,854	4,745,202	9%
Bluefish	467,661	2,748,567	15%
Summer Flounder	415,713	1,580,775	21%
Striped Bass	384,348	904,071	30%

SOURCE: ACCSP (2016) Recreational Fisheries Program, Arlington, VA.

As Illustrated in Figure 3.3 above, MRIP catch and effort data for the for-hire domain are currently obtained from multiple data collection programs, including (clockwise from the Northeast to Alaska), the VTR, the FHS, the Southeast Headboat Survey, the California Recreational Fisheries Survey, the Oregon Recreational Boat Survey (ORBS), the Washington Ocean Sampling Program and Alaska Saltwater Logbook Program and Statewide Harvest Survey, and the Hawaii Marine Recreational Fishery Survey and data collections of WPacFIN. In addition, MRIP supports the Large Pelagics Survey (LPS) to collect catch and effort data for the highly specialized recreational fisheries for Tuna, sharks, billfishes, swordfish, and other offshore species. Since January 2021, the SEFHIER program also has been providing catch and effort data for the for-hire domain of the South Atlantic and Gulf region recreational fisheries.

MRIP data collection and catch estimation for the for-hire domains have a comparative advantage over reporting for the private vessel and shoreline domains in the form of many federal and state registration and licensing programs for headboats, charter operators, and fishing guides, as well as the special permitting and registration requirements for vessels targeting highly migratory and other federally managed species. With limited exceptions, MRIP and its partners obtain effort data directly from mandatory logbook programs or high-intensity sample surveys and interviews with for-hire headboats, charter boats, and guide operators. Some but not all programs also perform on-site validation surveys to establish the accuracy of logbook self-reports or reports from telephone surveys. On the Atlantic Coast, region-level CPUE data for the for-hire domains are obtained through the MRIP APAIS dockside intercept sampling for charter boats and special headboat "at-sea" observations. Various Atlantic Coast states (Massachusetts, Rhode Island, Delaware, Virginia, and North Carolina) supplement the MRIP APAIS sampling with additional sampling to achieve greater precision for catch estimates. In the Pacific Region and Alaska, mandatory logbooks, at-sea observations, and dockside sampling generally combine the collection of effort and catch data. Possibly the most developed of the joint effort/catch data collections may be the Alaska Saltwater Sportfishing Logbook (see below).[4]

MRIP reports catch estimates by state, fishing mode, and species for bimonthly waves. Typically, MRIP estimates for the for-hire and other domains are published 45 days after the close of a wave (e.g., August 15 for the May–June 2-month wave). However, most MRIP and state programs that collect data on the for-hire domain are organized around weekly samples or weekly/daily logbook reporting. Individual state partners to the MRIP program often have access to their for-hire effort as well as effort and catch data within a week after trips occurred, and estimates can be available to state and regional managers with as brief as a 1- to 2-week lag. The committee heard from several state managers responsible for specific Pacific region fish stocks that they reviewed incoming catch and effort data on a daily basis or after a weekend of high fishing effort.

MRIP bimonthly estimates and annual estimates of recreational catch are based on inputs from multiple population frames and multiple data collection or logbook reporting programs. There is consistent support from individual experts (Donaldson et al., 2013) and cooperative programs, such as the ACCSP (2017), for a comprehensive approach to for-hire data collection. These same publications also call for improvements in the data collected on selective or required discards/returns by for-hire fishermen, as well as methodology to validate the accuracy of other self-reported data obtained through logbooks or other mandatory reporting systems. Efforts are underway to develop comprehensive reporting across the for-hire marine recreational fishery based on more standardized logbook/e-logbook reporting (ACCSP, 2017; Brick, 2018; NOAA Fisheries, 2019a, 2019b; NASEM, 2020).

As noted above, data inputs to MRIP bimonthly and annual reporting of recreational catch by the for-hire modes are derived from a patchwork of sources, which in turn must be carefully integrated using established, predominantly design-based statistical estimation methods (Papacostas and Foster, 2018). The following subsections provide summary descriptions of each of the MRIP and MRIP partner programs that contributes data to MRIP reporting of total catch from headboat and charter boat modes. In addition to these MRIP or MRIP-supported/certified partner programs, individual states support independent data collection programs for registered for-hire vessels.

GARFO Vessel Trip Reporting (VTR) Program

From Maine to North Carolina, the NOAA Fisheries Greater Atlantic Regional Fisheries Office (GARFO) operates the VTR. The VTR program covers approximately 900 headboat and charter fishing vessels that hold federal permits. Under the VTR, all permitted vessel operators must complete daily trip reports and angler effort. The VTR reports are filed weekly, and by November 2021 all VTR reporting was expected to be electronic. Jointly, the VTR and FHS (see below) provide partially overlapping dual-frame coverage of headboats and charter vessels that operate from Maine to North Carolina. Since 2017, MRIP bimonthly and annual catch estimates have used VTR effort reports for vessels also sampled in the FHS telephone survey; the VTR can provide coverage of fishing trips by for-hire vessels that are not covered in the FHS telephone survey frame. The VTR does not provide coverage of charter and guide boat operations that fish exclusively in state waters and do not hold a permit to fish in federally managed waters. Effort data for these state-only for-hire operations are surveyed in the FHS or covered by state-managed logbook

[4] See https://www.adfg.alaska.gov/index.cfm?adfg=SFGuidesLicense.Logbook.

programs, such as the Maryland Charter Fisheries Logbook program or South Carolina Department of Natural Resources Charter Logbook initiative.

The MRIP For-Hire Survey

Along the Atlantic Coast and the Gulf Coast of Florida, Alabama, and Mississippi, MRIP and its state partners operate the FHS. The universe for the FHS includes all for-hire charter vessels and private guides regardless of whether they fish in federal or state waters (or both). The sample frame for the FHS is developed and maintained for MRIP by state partners. It is compiled by integrating federal and state permit and licensing databases covering charter boats and guide boat operators, and verifying that the permitted vessel is active (i.e., actively offering for-hire trips) before they are included in the frame. New vessels are also added to the frame when they are discovered during dockside intercepts or through local and web-based advertising. Stratified samples are selected weekly from the sample frame, and the designated vessel representative is contacted by telephone by a state representative. Each telephone interview collects effort data on trips (number of anglers, hours spent fishing, and species targeted) taken during a 1-week reporting period. MRIP summarizes the data from the FHS weekly samples and rolls the weekly data into the standard bimonthly and annual reports. As noted above, for the Mid-Atlantic and New England regions, if a sample FHS vessel is also a mandated VTR reporter, the VTR effort data are used in lieu of the FHS report for that vessel. In the South Atlantic and Gulf regions, sample frames for the FHS and the Southeast Region Headboat Survey (SRHS; see below) are separate and do not overlap; thus the two surveys are independent.

The Southeast Region Headboat Survey

The SRHS is a long-standing program of the NOAA Southeast Fisheries Science Center. The survey has operated along the southeast U.S. Atlantic since 1972 and in the Gulf of Mexico since 1986. The geographic coverage of the SRHS spans the South Atlantic and Gulf Coast from North Carolina to Texas. The universe for the SRHS includes approximately N = 1650 headboats that are federally licensed to target offshore reef fish. Since 2013, all headboats in this region holding these federal permits have been required to file weekly e-logbook reports that include daily summaries of number of anglers, catch by species, and other data elements. To adjust for underreporting of trips in the e-logbook filings, port agents also record data on trips taken by headboats included in the SRHS population. The catch and effort data collected through the SRHS program are integrated with the FHS effort data and the APAIS intercept and at-sea sampling programs to produce MRIP bimonthly and annual estimates of catch.

Southeast Atlantic For-Hire Electronic Reporting (SEFHIER) Program ("Sea Fire")

NOAA Fisheries launched the SEFHIER program in early January 2021. The purpose of this expanded electronic reporting program is to provide more accurate and reliable fisheries information about for-hire catch, effort, and discards. Under SEFHIER, all federal Gulf reef fish and/or coastal migratory pelagic charter and headboat permit holders and all federal South Atlantic Snapper–Grouper, Atlantic coast migratory pelagics, and Atlantic Dolphin Wahoo charter/headboat permit holders are required to report fishing effort and landings electronically. Permit holders file electronic reports for each permitted vessel using one of two approved applications: eTrips/mobile2 or VESL.

Permit holders in the South Atlantic region are required to file trip-level reports once each week. Reports from South Atlantic region permit holders are due each Tuesday following the Monday–Sunday fishing week covered by the report. Reporting for Gulf region permit holders is virtually in real time. Each trip must be declared electronically before leaving the dock or launch, and the final report of catch and effort must be filed before any retained fish are offloaded upon return from a trip.

Currently, the SEFHIER program allows headboats that are included in the SRHS to continue to use their VESL reporting application to file trip reports. Likewise, for-hire vessels with a South Carolina charter fishing vessel license can meet SEFHIER requirements by continuing to report weekly to the South Carolina for-hire logbook program. In both cases, a duplicate SEFHIER report is not required.

MRIP Large Pelagics Survey (LPS) and NOAA Highly Migratory Species (HMS) Reporting Programs

Originating in 1992, from Maine to Virginia, MRIP also conducts the LPS—a specialized program designed to support the information needs of stock assessment and fishery management for pelagic fishes including Tuna; billfish; swordfish; sharks; and other pelagic species that are under federal management, such as Wahoo, Dolphin, and Amberjack. The universe of fishing activity covered by the LPS includes vessels that fish for these pelagic species and hold a NOAA Fisheries HMS permit.[5] This includes both permitted private boat fishing activity and permits issued to charter and headboat operators. The LPS programs includes three components: the Large Pelagics Intercept Survey (LPIS), the Large Pelagics Telephone Survey (LPTS), and the Large Pelagics Biological Survey (LPBS). The LPIS and LPTS contribute to the estimation of total catch for large pelagic species, while the LPBS contributes biological data needed by NOAA scientists for assessing age and growth rates and related information on population health.

The LPIS is an intercept survey, conducted dockside. Captains of returning private and for-hire vessels provide data for a 1-week reference period on catch and effort, including number of anglers and time spent fishing. The LPIS on-site direct observations also provide data on catch and effort by vessels that are not covered by the sample frame of permit holders. Approximately 3–5 percent of LPS fishing vessels are sampled each week for the LPIS. The LPTS is a weekly telephone survey of designated representatives for permitted vessels, sampling and interviewing approximately 10 percent of vessel operators on the permit frame during each week of the fishing season. In the LPTS survey, vessel representatives report the number of LPS trips taken during the previous 1-week period. Design-based, ratio-type (CPUE x E) estimates of total catch and the raw data are produced monthly with a 1-month lag and shared with U.S. and international fishery management partners.

Highly Migratory Species Permit Reporting and Catch Card Report Programs

From Maine to the Gulf of Mexico, headboat and charter boat operators who hold a NOAA HMS permit may also be required to file a report of Billfish, Swordfish, and Bluefin Tuna landings and releases within 24 hours of a successful trip. Reports may be filed at a permit office, by a catch reporting app, or using a toll free number. Permit holders are also required to participate if contacted for the MRIP surveys (FHS, LPTS, LPIS). In addition, the HMS reporting program selects a sample of permit holders to complete a Pelagic Fisheries Vessel Logbook covering catch of all federally managed species. Under the program, LPS vessels may also be sampled, to include an on-board observer on fishing trips.

Maryland has extended the HMS reporting methodology and requires all charter boat and headboat operators to use a catch card or harvest tagging to record and report catch of Bluefin Tuna, Marlin, Swordfish, Sailfish, and federally managed shark species. In North Carolina, both a catch card and tag are required before an HMS catch can be removed from the vessel.

HMS catch data generated under these NOAA and state-managed programs are available within 1–2 weeks of report filings but are not currently used in producing MRIP bimonthly or annual catch estimates.

MRIP Certification Process for Specialized and Alternative Surveys

Several states have designed and initiated recreational fishing surveys as alternatives or supplements to MRIP. Four of these surveys—Louisiana's LA Creel, Mississippi's Tails n' Scales,

[5] See https://www.fisheries.noaa.gov/recreational-fishing-data/types-recreational-fishing-surveys#large-pelagics-survey; https://www.fisheries.noaa.gov/atlantic-highly-migratory-species/atlantic-highly-migratory-species-reporting.

Alabama's Snapper Check, and Florida's State Reef Fish Survey—have been certified by NOAA Fisheries, indicating acceptance of their survey designs and estimation methods as scientifically sound and capable of providing the best scientific information available. Additionally, the Pacific RecFIN-administered state surveys are currently in the certification process. The two overarching principles of the certification process are meeting a shared set of standards and undergoing an independent peer review (Box 3.1).

BOX. 3.1 MRIP Standards and Independent Review Criteria for Specialized and Alternative Surveys

Certified survey designs and estimation methods must meet applicable survey and data standards and undergo peer review against the following criteria:

- Sample survey designs follow formal probability sampling protocols, with known inclusion probabilities at all sampling stages.
- Estimation methods appropriately weight sample data to account for the sampling design. Both point and variance estimates are produced.
- Methods are in place to measure and/or correct for potential biases due to under-coverage, non-response, and/or response errors.
- The sensitivity of the accuracy of the survey to potential sampling and non-sampling errors is understood, and measures to evaluate, reduce and/or limit that sensitivity are described.
- The sensitivity of the survey design to potential implementation errors is documented, and measures to evaluate, reduce, and/or limit that sensitivity are described.
- New survey design and/or estimation methods are compared to the design and/or methods they will replace, as well as any other certified survey components currently used to estimate the same population parameters. The relative statistical validity and efficiency of each are described.
- The survey design and/or estimation methods are collecting data and/or producing information that meet science and management needs.

SOURCE: Excerpted from NOAA Fisheries (https://www.fisheries.noaa.gov/recreational-fishing-data/recreational-fishing-survey-design-certification).

Beyond certification, NOAA Fisheries has additional requirements and processes in place for transitioning from MRIP to other surveys, as well as maintaining accountability after transitions. The transition process is overseen by the MRIP Transition Team, which is composed of NOAA and state fisheries agencies, and the process is particularly important for understanding differences between estimates for use in management processes. In some scenarios, the transition process may require benchmarking or calibration. Benchmarking involves conducting side-by-side comparisons of MRIP and another survey to assess the consistency of resulting estimates. Calibration involves converting the historical estimates of MRIP to align with the currency of the new estimates.

Coordination of Specialized and Alternative Surveys

With the increase in specialized and alternative surveys, there is often a need to coordinate surveys or integrate data from multiple surveys for use in stock assessment and management. For instance, estimating the total catch or effort for a region can require integrating the data from multiple surveys with differing methodologies, which can pose a number of challenges. Through the process established by the MRIP Regional Implementation Teams, regional FIN networks, including federal and state partners, have been actively working on identifying and addressing issues involved in survey integration and calibration. However, these topics remain highly salient, as survey integration or calibration is complex and may at times lead to outcomes that are unintuitive to stakeholders.

REGION-BY-REGION SUMMARY OF MANAGEMENT AND SURVEYS

New England

The major recreational fisheries managed by the New England Fishery Management Council (NEFMC) include Atlantic Cod, Haddock, Pollock, Winter Flounder, and Atlantic Wolffish. State-managed fisheries include Scup, Black Sea Bass, Tautog, and Weakfish.

Because of the colder climate of New England, MRIP surveys are conducted for only part of the year. APAIS surveys are conducted for Waves 2–6, with the exception of Maine, where only Waves 3–6 are implemented. Massachusetts has funded supplemental MRIP surveys since 2013 that include 400 additional surveys in Waves 3–5. These additional surveys are aimed at improving precision for estimates of Black Sea Bass, Striped Bass, Bluefish, and Summer Flounder.

In-season management is generally not used in New England. Fisheries management agencies from both Rhode Island and Massachusetts expressed reluctance to consider in-season management and identified a variety of common concerns, including data availability, uncertainty, and outreach to anglers as major challenges.

Atlantic

The Atlantic States Marine Fisheries Commission (ASMFC) is responsible for managing 27 species or groups. Several species are managed jointly with regional Councils. In general, ASMFC does not favor in-season adjustments to ACLs and instead promotes stability and multiyear regulations. ASMFC also embraces alternative management strategies, with striped bass fisheries being managed with a target fishing rate instead of absolute removals.

Mid-Atlantic

The major recreational fisheries managed by the Mid-Atlantic Fishery Management Council (MAFMC) currently include Summer Flounder, Bluefish, Scup, Black Sea Bass, Atlantic and Chub Mackerel, and Golden and Blueline Tilefish. The first four are managed jointly with the ASMFC, with joint approval of ACLs and most management strategies. Through this management arrangement, bag limits, size limits, and seasons often vary between federal and state waters.

The process for setting ACLs in the Mid-Atlantic region begins in August of the preceding year. Current-year MRIP data through Wave 4 are used to project the full year's recreational harvest, and projections are then compared with the following year's harvest limit. Decisions to increase or decrease the overall federal and state harvest limits are made from mid-December at MAFMC and ASMFC meetings through April, when any changes for the following season are implemented. A major challenge for this process is species for which Wave 5 data are particularly important for reducing uncertainty in projections, and there is rarely time to incorporate these data before the December MAFMC and ASMFC meetings.

In-season management is not currently used in federal waters. In fact, the MAFMC's 2013 Omnibus Recreational Accountability Amendment[6] actually removed the ability of the NOAA Fisheries regional administrator to close the recreational fishery in season if recreational harvest was projected to exceed the ACL. An argument in support of this restriction was that in-season closures had a disproportionate negative impact on states with fishing seasons later in the year.

In-season management in state waters is also rare in the Mid-Atlantic region. In-season management has frequently been suggested by recreational fishing stakeholders, particularly for black sea bass and Summer Flounder. However, managers have expressed concerns related to the timing and uncertainty of estimates, as well as the significant investments in staff time required.

[6] MAFMC Omnibus Recreational Accountability Amendment: https://www.mafmc.org/actions/omnibus-recreational.

South Atlantic

Similar to the Gulf of Mexico, the South Atlantic supports many species in recreational demand. These include multiple species of Snappers and Groupers, as well as Dolphin (Mahi), Wahoo, and king and Spanish Mackerel (which are managed jointly with the Gulf of Mexico). ACLs are set or adjusted in response to a stock assessment rather than through an annual specifications process. Management measures (e.g., size, season, and bag limits) may also be modified at that time to constrain harvest to the ACL or meet management objectives. It should be noted that of the 35 stocks or stock complexes managed under ACLs, half are unassessed; their ACLs are set using approaches based entirely on catch data.

In-season management of ACLs occurs for all but seven stocks in the form of recreational fishery closures if an ACL is approaching its limit or has been met. Between 2017 and 2019, in-season closures were applied eight times across five stocks. However, because of the timing and availability of MRIP data, most closures occurred well after an ACL had been exceeded. All monitored stocks have postseason accountability measures (AMs) that may include adjustments to season length or bag limits the following year and payback of overages if the total combined ACL (recreational and commercial) is exceeded. The South Atlantic Council is considering modifications to recreational AMs to allow more flexibility in management and better align AMs with the precision and timeliness of MRIP data (see Chapter 5 for more detailed information).

States along the South Atlantic have also developed supplemental surveys, but the majority of these efforts are not designed to collect quantitative catch and effort data. Florida, where the Florida Reef Fish Survey is conducted, is one exception. The South Atlantic Council has also considered options for private recreational permitting and reporting that might improve existing catch and effort data produced by MRIP (see Chapter 5 for more detailed information on these efforts). The Council recently convened a working group that includes both state agency and MRIP representatives specifically to explore approaches to recreational reporting in the region.

The South Carolina Department of Natural Resources (DNR) conducts the South Carolina DNR Charter Logbook program, in which all licensed headboat and charter fishing operations are required to complete daily logbooks covering catch and effort. Licensed operators are required to file their logbook by the 10th of each month, covering all trips taken since the last filing period. Currently, the South Carolina DNR Charter Logbook data are not incorporated into the MRIP bimonthly or annual estimates of catch.

Gulf of Mexico

All five states in the Gulf of Mexico have developed alternative or supplemental surveys to MRIP for estimating recreational fishing effort and catch (Table 3.3).

Alabama's Snapper Check requires that private-vessel anglers report Red Snapper catches and encourages Greater Amberjack and Triggerfish reporting before fish are landed in that state. In 2018, Alabama's Snapper Check was certified by MRIP. Snapper Check consists of two complementary components: an electronic reporting system and a dockside access point intercept survey. The information electronically reported by anglers is validated and corrected using information observed through the dockside intercept survey.

In Louisiana, LA Creel has been conducted in place of the MRIP general survey since 2014. LA Creel couples an on-site intercept survey with a telephone survey to estimate total landings of recreational fisheries species. LA Creel's telephone survey is designed to estimate total effort in number of trips, whereas the access point survey estimates harvest rate. Timeliness is a major strength of LA Creel, with estimates produced as frequently as weekly when needed. These estimates are also adaptable and can be produced for various time periods, geographic regions, and fishing modes.

In Texas, the Parks and Wildlife Department has conducted the Texas Parks and Wildlife Creel Survey (TPWCS) in place of MRIP since 1974. The TPWCS involves on-site intercept interviews at boat access sites throughout the state. Its primary focus is on private-boat fishing in state waters, but offshore and for-hire fishing are also included. The TPWCS collects data on harvest but not on discarded fish.

TPWCS data collection occurs year-round, but estimates are produced only twice yearly, after the high season (May 15–November 20) and low season (November 21–May 14).

TABLE 3.3 Gulf of Mexico Supplemental Surveys for Recreational Catch

	Alabama	Florida	Louisiana	Mississippi	Texas
Program	Snapper Check	Florida State Reef Fish Survey	LA Creel	Tails-n-Scales	Texas Parks and Wildlife Creel survey
Metrics	Catch, Effort	Catch, Effort	Catch, Effort	Catch, Effort (Near Census)	Harvest Estimates Only
Mode(s)	Website, Mobile App, Dockside Paper Forms, Phone Call-in (ended in 2017)	Mail, Intercept	Intercept, Telephone	Trip Registration, Intercept	Intercept
Species / Taxa	Red Snapper (mandatory), Amberjack (optional), Triggerfish (optional)	Reef fish	Multiple state & federal species	Red Snapper	Multiple state & federal species
Years	2014–present (MRIP-certified in 2018)	2015–present in Gulf; 2020–present in Atlantic	2014–present	2015–present	1974–present
Seasonality	Fishing seasons of the species covered	Year-round	Year-round	Private recreational Red Snapper season	Year-round
Timeliness (Estimate Frequency)		Monthly	Weekly	Real-time	Twice annually
Cost	$75,000	$3.0M	$1.9M	$60,000	

SOURCE: Generated by the committee.

Pacific

The Pacific Council has fishery management plans (FMPs) for Salmon, Groundfish, coastal pelagic species (CPS), highly migratory species (HMS), and ecosystem-based management. Among the species included in the FMPs, only Salmon, Pacific Halibut, and Groundfish are actively managed in season. The Council uses catch estimates provided by each state for in-season management and stock assessments. The state programs that generate these estimates include the Washington Ocean Sampling Program (OSP), Washington Puget Sound Sampling Program (PSSP), Oregon Ocean Recreational Boat Survey (ORBS), and California Recreational Fisheries Survey (CRFS). These state sampling programs, administered by RecFIN and partially funded by MRIP, replaced the NOAA Fisheries MRFSS on the Pacific Coast in 2003–2004. The main reason for this change was to support Salmon and Pacific Halibut in-season management, in which estimates are needed on a weekly basis.

Another main difference between these state surveys and the MRIP surveys, besides the short data turnaround, is in how effort surveys are conducted. The on-site effort surveys conducted by the three states are considered a census on each sampling day. The daily census is then expanded by the ratio of total days to total sampled days within strata. Daily observed catch is expanded to stratum level based on the same approach. The on-site effort survey works well in the Pacific Northwest, especially in Washington State, because of the rugged coastline, surf conditions, the lack of infrastructure, and therefore limited access to coastal ports or beaches. Table 3.4 summarizes the recreational surveys in the Pacific region. Details of associated sampling designs, protocols, and estimation procedures can be obtained from RecFIN.

TABLE 3.4 Summary of state recreational surveys: Washington Ocean Sampling Program (WA_OSP), Washington Puget Sound Sampling Program (WA_PSSP), Oregon Ocean Recreational Boat Survey (OR_ORBS), and California Recreational Fisheries Survey (CA_CRFS).

	WA_OSP	**WA_PSSP**	**OR_ORBS**	**CA_CRFS**
Metrics	Catch (Retained, Discarded), Effort	Catch (Retained, Discarded), Effort	Catch (Retained, Discarded), Effort	Catch (Retained, Discarded), Effort
Mode(s)	On-site effort count (census); dockside interview for catch, boat-based	Effort: phone survey for non-salmon species; on-water boat survey or aerial survey for salmon Catch or catch per unit effort (CPUE): dockside interview, boat-based	On-site effort count (census); dockside interview for catch, boat-based	Pacific region (PR): on-site effort count; dockside interview for catch, boat-based Pacific coast: capture/recapture (commercial passenger fishing vessel [CPFV] log and on/off-site trip validation) for effort; dockside and on-board interview, boat-based Man-made: On-site effort count, on-site interview, shore-based Beaches and Banks: effort phone survey; onsite interview, shore-based ○ PR—private access and nighttime effort: off-site phone survey; proxy interviews from PR, boat based
Species / Taxa	Salmon, Halibut, and other selected finfish	All finfish species, except forage fish	All finfish species, plus Dungeness crab	All species in Pacific Fishery Management Council (PFMC) fishery management plans (FMPs): coastal pelagic and coastal migratory species, highly migratory species, Groundfish, Salmon, and in-shore species and other anadromous species.
Years	1990–present	2003–present	1979–present	2004–present with various breaks in lower-priority modes
Seasonality	March–October	Year-round	Year-round with caveats	Year-round
Timeliness (Estimate Frequency)	Weekly for Salmon and Halibut; monthly for Groundfish and Tuna	Groundfish: 2-month wave with roughly a 2-month lag Salmon: daily to biweekly, depending on needs Halibut: weekly	Weekly for Salmon and Halibut; monthly for Groundfish and Tuna	Monthly estimates with approximately 45-day delay; anticipated catch values (ACVs) using model-based approach, semimonthly and replaced with California Recreational Fisheries Survey (CRFS) estimates when available

continued

TABLE 3.4 Continued

	WA_OSP	WA_PSSP	OR_ORBS	CA_CRFS
Estimation approach	Observed catch expanded by on-site effort count (census)	**Groundfish**: CPUE total effort estimate **Salmon**: observed catch expanded by on-site effort count **Halibut**: combination of Ocean Sampling Program and Salmon approaches	Observed catch expanded by on-site effort count (census)	**CRFS modes**: CPUE total effort estimate **ACV**: observed catch expanded by on-site effort count (census)
Program annual cost (recent year average)	**Total: $1.2M** MRIP: $361K State: $160K Other federal fund: $690K	**Total: $3.5M** MRIP: $25K State: $900K Other federal fund: $2,575K	**Total: $1.5M** MRIP: $348K State: $242K Other federal fund: $910K	**Total: $5.1M** MRIP: $1.5M State: $3.6M Other federal: Not available

SOURCE: Generated by the committee.

Pacific Salmon In-season Management

The United States and Canada signed the Pacific Salmon Treaty in 1985 to manage Pacific Salmon. The Pacific Salmon Commission (PSC) is a decision-making body for cooperative management of Pacific Salmon. A comprehensive new agreement was established in 1999, and the treaty was reaffirmed in 2019. The PSC establishes overall reduction and exploitation objectives for Salmon stocks from Alaska to the Oregon–California border at its annual meetings. Preseason fisheries guidelines for many Alaskan and Canadian fisheries are set by the PSC, while preseason guidelines for many of the southern U.S. (Washington, Oregon, and California) fisheries are set in the Pacific Fishery Management Council (PFMC) process. The PFMC process ensures that stock returns meet the guidelines set by the PSC and by NOAA when a stock is listed under the Endangered Species Act (ESA). In the postseason evaluation, when much of the season-setting process occurs during the PFMC process for southern U.S. fisheries, those fisheries must meet both PSC and federal ESA guidelines. The PFMC specifies ACLs only for California Sacramento River fall Chinook, California Klamath River fall Chinook, and Washington Willapa Bay Coho stocks. Weekly catch estimates for all Salmon stocks are produced by state agencies for purposes of managing the fishery relative to available allocation. State fishery managers track catch closely throughout the season and coordinate with NOAA Fisheries and other state managers to close the fisheries when catch is projected to reach the subarea allocation.

Pacific Halibut In-season Management

Management of Pacific Halibut is accomplished through the International Pacific Halibut Commission (IPHC), an international organization established by a convention between Canada and the United States in 1923. The IPHC conducts stock assessments and sets coastwide total allowable catch, area apportionment, and other fishery regulations. The PFMC process establishes catch allocation and sharing plans among the three states based on the apportionment set by the IPHC for the PFMC region. State sampling programs (Table 3.4) collect data for estimating recreational catch and effort. Weekly estimates are produced by state agencies for purposes of managing the fishery relative to available allocation. State fishery managers track catch closely throughout the season and coordinate with the IPHC, NOAA Fisheries, and other state managers to close the fisheries when catch is projected to reach the subarea allocation.

Groundfish In-season Management

The PFMC manages more than 100 Groundfish species listed in its FMP. Analysts at the NMFS Northwest and Southwest Fisheries Science Centers and state agencies conduct Groundfish stock assessments to support PFMC management. The Council adopts overfishing limits (OFLs) and sigma (scientific uncertainty) recommended by its Scientific and Statistical Committee (SSC), determines P* (risk tolerance), and adopts acceptable biological catch (ABC)/ACL and catch allocations after considering recommendations from its advisory bodies, primarily its Groundfish Management Team and the Groundfish Advisory Subpanel. The state agencies adopt conforming rules and monitor catches. Groundfish in-season management is implemented by NOAA Fisheries and state agencies. Before the fishing season, the Groundfish Management Team uses projection models, reviewed by the SSC, to evaluate and set state rules for the forthcoming fishing season. State sampling programs, summarized in Table 3.4, monitor fishing activities and provide monthly catch estimates. If needed, these estimates can be made available weekly during Salmon and Halibut seasons. Raw sampling data are available to managers at the end of each sampling day.

North Pacific (Alaska)

The North Pacific Fishery Management Council does not manage fisheries in season. As in the PFMC region, management of the Salmon and Halibut fisheries is coordinated with the PSC and IPHC, respectively. The Alaska Department of Fish and Game (ADF&G) participates in in-season management only for Chinook (King) Salmon in Southeast Alaska. In contrast with the PFMC region, Halibut is not managed in season in the Alaska region. The majority of Alaska marine recreational fishing occurs in state waters, with the exception of Halibut. Statewide, ADF&G requires all charter businesses and guides to maintain detailed daily logs for each angler trip. The Alaska Saltwater Logbook data form collects information on the date of each trip, individual angler name and license number, primary fishing location (Salmon and bottom fish), and numbers of fish by species—kept and released. Charter operators and guides must file the completed paper logbook forms or submit electronic forms within 1 week of a completed trip. Annually, ADF&G also conducts a mail survey of licensed angler households. In 2020, the Alaska Sportfishing Survey was sent to approximately 47,000 randomly selected Alaska resident and nonresident households with a licensed angler. The survey asks anglers to use retrospective recall to report the number of days fished (guided and not guided) by members of their household and to report the number of fish caught and harvested by location. Data gathered through the annual ADF&G Saltwater Logbook program, Sport Fishing Survey, and special dockside creel surveys are combined to produce annual estimates of harvest and released catch by species and location. These estimates are publicly disseminated during the following year through the Alaska Fisheries Information Network.

Western Pacific

Hawaii Marine Recreational Fishing Survey

The Hawaii Marine Recreational Fishing Survey is conducted by the Hawaii Division of Aquatic Resources (DAR) and MRIP (Ma and Ogawa, 2016; Ma et al., 2018). Since 2003, this program has yielded annual recreational catch estimates by combining phone interviews conducted by the Coastal Household Telephone Survey (CHTS) for estimating total fishing effort with an access point intercept survey (i.e., on-site fisher interviews), which together can be used to estimate CPUE for boat-based and shore-based activities. The fishing effort survey was switched from a phone to a mail survey in 2018. Prior to the switch, both phone and mail surveys were conducted in 2017, and effort estimates derived from mail surveys were found to be higher than the estimates from phone surveys for both shore- and boat-based recreational fishing activities. The differences may result from a reduction in the number of households with landline phones over time; however, no correction factors are available for 2003 to 2016. The pre-2003 recreational catch estimates are not available. In a recent Uku (Gray Snapper; *Aprion virescens*) stock assessment, the pre-2003 catch was estimated based on the assumption that recreational catch would be proportional to the Hawaii population size, and the recreational fishery participation would increase with overall population in Hawaii. High uncertainty tends to be associated with the Hawaii Marine Recreational Fishing Survey's recreational catch estimates.

U.S. Territories of American Samoa, Guam, and the Commonwealth of the Northern Mariana Islands

The Western Pacific Fisheries Information Network coordinates recreational fishing creel surveys in these U.S. territories. Currently, there is no active in-season management of recreational fisheries in this western Pacific region, although Network representatives indicated it is very much part of their planning process and are seeking needed assistance from MRIP. The existing surveys in the territories are currently not officially part of MRIP, but U.S. Fish and Wildlife Service grant funding has been available to support MRIP consultation on survey design improvements.

MRIP ESTIMATION OF RECREATIONAL CATCH FOR FISHERIES MANAGEMENT

MRIP Data Aggregation, Cleaning, Weighting, and Estimation

MRIP produces wave (bimonthly) estimates of total catch of each species for multiple domains of the marine recreational fishery in the Atlantic and Gulf regions. Geographically, estimates for each applicable species are produced by region and state within a region. Separate state-level estimates for each relevant species are produced for the location of catch, defined as in-shore, near-shore (<3 mi or <10 mi depending on state declaration), and offshore (in the federal exclusive economic zone [EEZ]). For each state, total catch for each species is estimated for three fishing modes: shore angler, private boat, or charter/for-hire.

MRIP statistical methodology for producing these domain-specific estimates of recreational fisheries catch and effort is summarized in a detailed NOAA Fisheries report published in 2018 (Papacostas and Foster, 2018). The MRIP methodology for estimating total catch for each domain centers on separate estimation of two components: total effort (E), measured in numbers of angler trips, and mean "catch rate" (C/E), and measured in numbers of fish caught per angler trip (see below; Figure 3.4).

For all three fishing modes (shore, private boat, for-hire vessel), the MRIP estimation of the C/E component is based on probability samples and the angler intercept data collected in the MRIP APAIS program either dockside or on board as part of the special APAIS sampling for licensed headboats that hold permits to fish federal waters. Following each 2-month APAIS wave, MRIP computes weighted estimates of mean C/E by species for each subregion, state, substate region (county), mode (shore, private boat, for-hire), and location (inland, nearshore, offshore) (see Papacostas and Foster, 2018). MRIP estimates of the catch rate are computed for each domain (D) using a design-based weighted estimator of mean catch per angler trip (Papacostas and Foster, 2018):

$$C/E = \bar{y}_{D,k} = \frac{\sum_{h=1}^{H} \sum_{i=1}^{n_h} \sum_{j=1}^{m_{hi}} I_{D,hij} \cdot w_{hij} \cdot y_{hij,k}}{\sum_{h=1}^{H} \sum_{i=1}^{n_h} \sum_{j=1}^{m_{hi}} I_{D,hij} \cdot w_{hij}}$$

where:
D indicates the domain for the estimate (region, state, fishing mode, fishing location)
$h=1,\ldots,H$ represents the APAIS primary stratum (pseudo-stratum)
$i=1,\ldots,n_h$ represents the sample PSU within stratum h
$j=1,\ldots,m_{hi}$ represents the jth angler's trip observed within stratum h and PSU i
$I_{D,hij}$ is an indicator (0,1) equal to 1 if observation (h,i,j) belongs to domain D (0 otherwise)

w_{hij} is the APAIS weight for angler trip observation (h,i,j)
$y_{hij,k}$ is the species K catch (number, pounds) for angler trip observation (h,i,j)

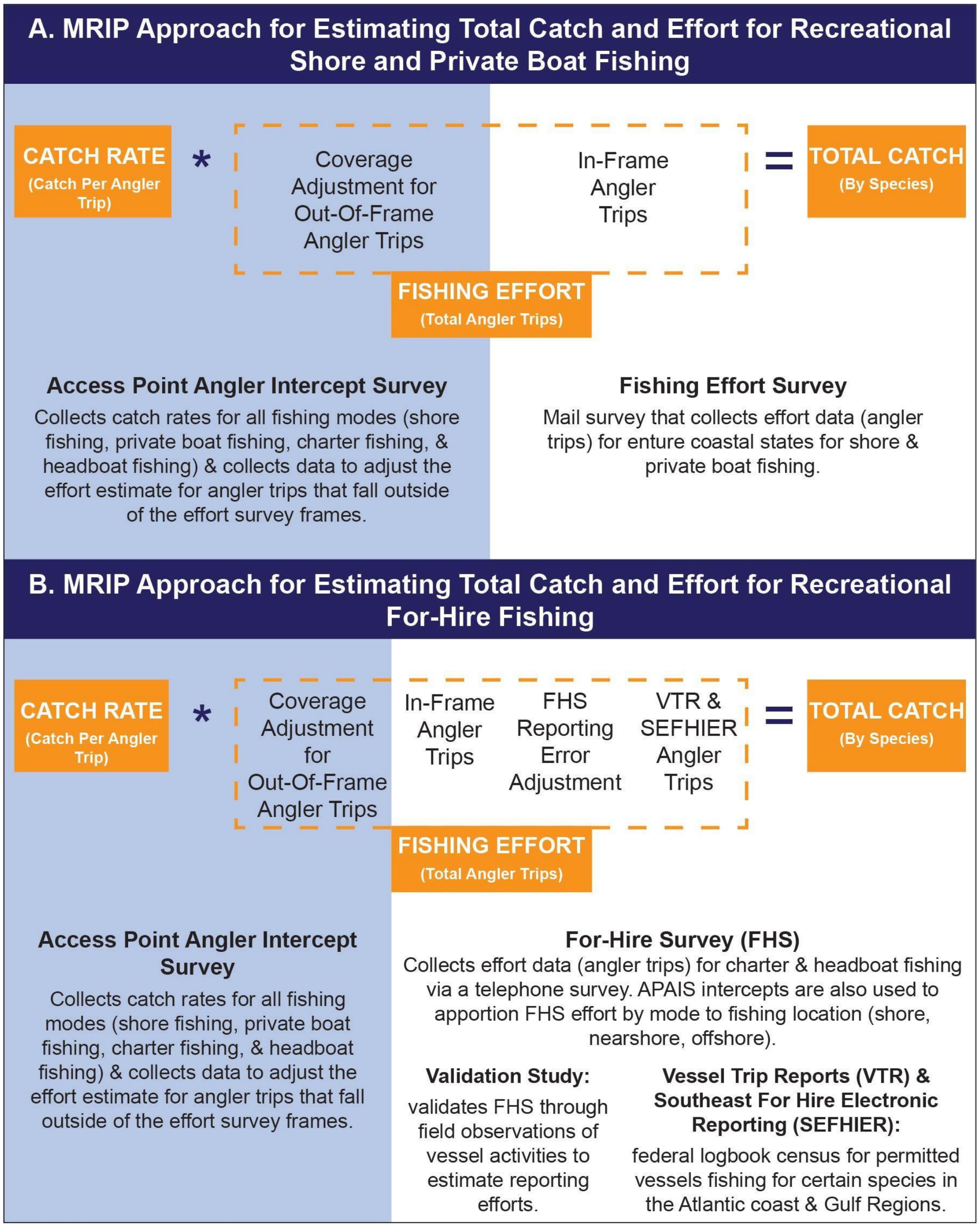

FIGURE 3.4 How data inputs from the MRIP Access Point Angler Intercept Survey (APAIS), Fishing Effort Survey (FES), and For-Hire Survey (FHS) and the Vessel Trip Reporting (VTR) and Southeast Region For-Hire Electronic Reporting (SEFHIER) programs contribute to estimation of the total effort (E) and mean catch rate (C/E) components of the total catch estimator. Panel A describes estimation for the shore and private boat domains. Panel B describes the different data inputs and weighting used to estimate E and C/E for the recreational for-hire domain. SOURCE: Adapted from a similar figure presented in the 2018 NOAA Fisheries methodology report (Papacostas and Foster, 2018).

Standard errors of the estimates of catch rates are estimated using robust Taylor Series Linearization methods that account for the influence of the sample design stratification, clustering, and weighting on the variance of the estimates.

Given these estimates of catch per unit effort (C/E) for each species (k) and domain (D), MRIP separately estimates the total effort, E (expressed in angler trips), for each domain, D, from the FES. The bimonthly estimation of total catch, Yk,D, for each species and domain is then computed as the product of the C/E and the E estimates for each domain.

Estimates of total angler trips (E) for the shore and private boat fishing modes are based on retrospective trip reporting by anglers responding to the FES mail survey. Following each 2-month wave of data collection, the FES data gathered in that wave are used to estimate total angler effort, E, for each coastal state and fishing mode (shore, private boat). The FES mail survey captures information on each angler trip for the reporting period, including the state in which the trip occurred and the fishing mode (shore or private boat). Prior to estimation, each FES respondent household is assigned an analysis weight that includes factors for the base sample inclusion probability, an adjustment for survey nonresponse, calibration to census populations for the sample strata, and an APAIS-based coverage adjustment for nonresident anglers who would not be eligible for the FES stratified sample of coastal state households and fishing license holders. Using a form of the Horvitz Thompson estimator for a population total, the FES analysis weights are then applied to the survey reports of trips to derive estimates of total angler trips for state x shore/private boat domains. The FES does not collect information on the fishing location (inland, near-shore, offshore) for individual trips. Instead, total angler trips for state x mode domains are apportioned to three fishing locations based on estimated proportions of trips observed in the APAIS intercepts.

Estimation of for-hire angler effort (E) is based on data collected in the FHS telephone survey. In specific strata of for-hire vessels, census data from special logbook or legacy survey programs are used in lieu of the FHS telephone interview data—VTR logbook data in the Northeast and Mid-Atlantic and SRHS data for headboats with permits to fish in the South Atlantic and Gulf. Since January 2021, SEFHIER data has also been used in lieu of FHS data for some strata of the for-hire recreational fishery. FHS telephone survey reports and the VTR/SRHS/SEFHIER logbooks provide detailed information for each trip that occurred within the assigned reporting period, including the location fished. The FHS also includes a validation component in which dockside checks are used to verify the accuracy of trip reports and develop weighting adjustment to correct for potential underreporting in the weekly telephone survey.

Bimonthly weighted estimates of total recreational angler catch, $\hat{Y}_{k,D}\hat{Y}_{k,D}$ for each reporting domain (D) are computed as the product of the FES/FHS-based estimates of effort and the APAIS-based estimates of the CPUE, C/E:

$$\hat{Y}_{D,k} = (C/E) \cdot E = \bar{y}_{D,k} \cdot \hat{T}_D$$

where:
$\bar{y}_{D,k}$ indicates the mean catch of species k per angler trip in MRIP reporting domain D
$\hat{T}_D$ is the FES/VTR/FHS-based estimate of total recreational angler trips in MRIP reporting domain D

For the private recreational domain, APAIS-based estimates of C/E are based on data collected at public-access sites, while the FES-based estimates of effort include anglers using both public-access and private-access sites. Hence, an assumption in the MRIP catch estimates is that in a given domain, C/E for anglers using private-access sites is the same as C/E for anglers using public-access sites. There is some evidence, however, that C/E is lower for fishers using private-access sites than for those using public-access sites (Ashford et al., 2010, 2011, 2013). Previous National Academies studies that reviewed both MRFSS (NRC, 2006) and MRIP (NASEM, 2017) indicated that this issue has important implications for the estimation of total catch (potential bias),[7] especially in situations where the proportion of private sites is

[7] "Estimates of CPUE may be biased if anglers accessing the water from private access points or from little known

appreciable. A study completed by MRIP in 2016 (the FES Follow-Up Study) used data collected via follow-up mail and online survey to look at differences in C/E between public- and private-access sites.[8] However, the MRIP Research and Evaluation Team found that response rates were low, and sample sizes were too small for properly evaluating noncoverage error in APAIS.[9] A subsequent and ongoing MRIP study (the FES Boat Survey), expected to be completed in 2021, utilizes the FES sampling design to estimate the distribution of boat trips by access type, fishing area, and boat type.

In general, estimates for larger domains are computed as the sum of estimates for the smaller domains. For example, a bimonthly estimate of the total recreational catch of Bluefish for New York is derived by summing over the domain-level Bluefish catch estimates for the combinations of fishing location and fishing mode.

MRIP releases its preliminary estimates of total catch by recreational fishery domain approximately 45 days after the close of each bimonthly wave (e.g., August 15 for the May–June wave). As noted above, the catch rate (C/E) data from the APAIS dockside and on-board observations are recorded electronically, and although they must then be subjected to MRIP standard quality control processes, statistical access to the raw data is not the time-limiting factor in the production and release of MRIP catch estimates. Focusing on the effort (E) data, most data collection for the FHS and the VTR and SEFHIER logbook programs occurs within 1–2 weeks of the date on which the fishing trip occurred. The FES mail survey methodology requires a slightly longer period for all returns from the final 2-week sample period to be received. Consequently, it is approximately 2 weeks after the end date of the bimonthly wave before the majority of the raw data can be assembled and undergo the required data management, quality control, and scientific review steps that must be completed before final estimates are compiled and published.

MRIP releases its bimonthly and annual catch estimates by species and recreational fishery domain through the NOAA Fisheries website.[10] Fisheries managers and the public can access the individual-level catch data from the APAIS intercept program website.[11] Annual species-specific catch estimates (commercial and recreational) for all regions and states are also posted on the NOAA Fisheries site.[12] The annual estimates of recreational catch posted at this site include not only the MRIP estimates for the Atlantic region, the Gulf, and Hawaii, but also estimates for Texas; RecFIN estimates for California, Oregon, and Washington; and Alaska Fisheries Information Network estimates for Alaska.

SUMMARY OF SURVEY PRECISION AND TIMELINESS OF MRIP AND OTHER SURVEYS

The desire to improve the timeliness or precision of recreational catch and harvest estimates has been expressed by several previous reports or working groups, including in a 2011 workshop hosted by NOAA Fisheries (Salz et al., 2011), the 2017 National Academies report on MRIP (NASEM, 2017), and the earlier National Academies study of the predecessor MRFSS program (NRC, 2006), and multiple MRIP regional implementation plans.

While the following chapter explores potential pathways to improving the timeliness of MRIP data in more detail, it is worth noting here that the 2011 workshop yielded six recommendations to this end: (1) moving toward 1-month waves; (2) reducing lag times (from data collection to data provision); (3) developing forecast models from early survey returns; (4) encouraging the development of other forecasting models for estimating catch and effort; (5) continuing to explore electronic reporting technologies; and (6)

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public access points differ in their fishing (e.g., fishing modes, areas and species targeted, effort and success rate) from those accessing the water from well-documented public access points" (NRC, 2006, p. 64). "The lack of intercept information from most private access means that the use of CPUE requires the strong assumption that catch and effort are equal between anglers using public and private access" (NASEM, 2017, p. 34).

[8] See https://www.st.nmfs.noaa.gov/Assets/New-MRIP/FINAL_2016-17_IP_Update-11.21.16.pdf.

[9] Personal communication. Rob Andrews, John Foster, NOAA Fisheries MRIP Research and Evaluation Team, November 2020.

[10] See https://www.fisheries.noaa.gov/topic/recreational-fishing-data.

[11] See https://www.fisheries.noaa.gov/recreational-fishing-data/recreational-fishing-data-downloads.

[12] See http://fisheries.noaa.gov/foss.

further developing innovative methods for addressing data timeliness and management needs for specific fisheries contexts, including small catch limits or short seasons. This historical context is important for evaluating the relative strengths of other state and regional surveys described in this chapter and summarized here. For instance, while MRIP has not transitioned from 2-month waves to shorter intervals, multiple state and regional surveys have done so. In the Gulf of Mexico region, for example, both Florida and Louisiana's state survey programs are MRIP-certified and designed to produce either monthly or weekly estimates for at least some species.

The specific question of the timeliness of the release of catch estimates has also been a long-standing concern of MRIP and was studied in depth in the 2011 workshop (Figure 3.5; Salz et al., 2011). At that time, the conclusion of the MRIP report (Salz et al., 2011) was that with modest additional resources, the time period for release of preliminary catch estimates could be shortened to 30 days after the end of each wave (e.g., August 1 for the May–June wave estimates).

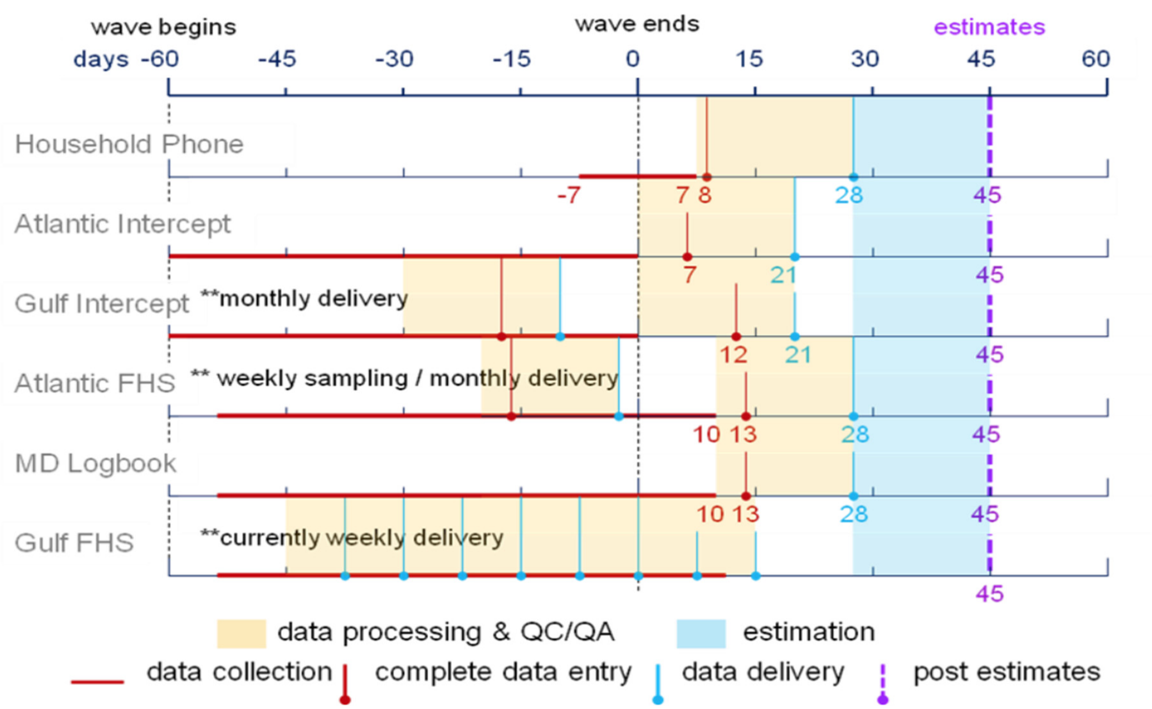

FIGURE 3.5 The timeliness of data collection and processing for component surveys of Atlantic and Gulf of Mexico recreational catch estimates. SOURCE: Salz et al., 2011.

When considering the precision of MRIP or other surveys, it is important to take into account the purpose for which the resulting data will be used. For instance, MRIP is designed as a general survey, and its precision is greatest for annual estimates at larger geographic scales; the precision of MRIP estimates is much lower for shorter periods of time and smaller geographic areas. The precision of MRIP estimates also varies by species depending on such fishery characteristics as limited distribution and low catch rates. In contrast, state and specialized surveys can offer improved precision for certain taxa or contexts (e.g., reef fish fisheries in the Gulf of Mexico, Salmon fisheries in the Pacific Northwest). However, the narrower focus (taxa, geography, and season) and various methodologies involved in these surveys can pose challenges for fisheries managed across multiple states or regions, as more cohesive, region-wide estimates of recreational catch are needed for Council-managed fisheries.

Improvements in the timeliness and precision of catch and effort estimates for recreational fisheries have been described as high priorities in several recent regional MRIP implementation plans. In GulfFIN's 2016–2018 implementation plan, for example, improving timeliness and precision was listed as important for improving the management of fisheries with ACLs, as well as reducing buffers between ACLs and annual catch targets (ACTs). In the South Atlantic, the ACCSP MRIP Implementation Plan[13] specifically addresses the potential value of transitioning to 1-month waves for better managing species in northern areas where fishing may be concentrated within a single month, such as when certain fish species are migrating through. In addition to describing region-specific challenges or research needs, the regional MRIP implementation plans also highlight the current context for and importance of better coordinating catch and effort surveys among states, regions, and MRIP.

The following section summarizes the context and issues related to the timeliness, precision, and adaptability of surveys described in this chapter. Chapter 4 goes a step further to describe how these surveys could be improved for current management and in response to desires for in-season management. Chapter 5 describes the more detailed approaches and pathways for alternative management strategies that would leverage and build on these surveys.

CONCLUSIONS AND RECOMMENDATION

Conclusion: Within their intended scope and design constraints, MRIP data are critically important for fisheries management. Recognizing the limitations of these data, including concerns about precision, most states desire access to raw MRIP data.

Conclusion: By utilizing existing infrastructure developed by regional Fishery Information Networks (FINs), MRIP Regional Implementation Teams provide the framework for integrating regional and state partner input, identifying regional priorities, and ensuring coordination in the development of strategies for addressing stock assessment and management needs for Council-managed recreational fisheries. In many instances, these needs include the development and implementation of specialized recreational surveys (either supplemental or alternative) to address limitations of a general survey such as MRIP.

Conclusion: Compared with MRIP surveys, alternative or supplemental (state) surveys have achieved a variety of benefits, including greater timeliness of estimates; greater spatial resolution; provision of additional information; and possibly in some cases, greater precision of estimates.

Conclusion: Alternative and supplemental surveys have improved timeliness through the use of new technologies (e.g., mobile apps and tablets), as well as reduced lag times in data processing and release.

Conclusion: Compared with MRIP surveys, alternative or supplemental surveys have been shown to provide different estimates for recreational catches for the same fishery (stock and area). Differences between estimates can be moderate, or quite substantial.

Conclusion: Public perceptions of differences between MRIP and alternative surveys in methodology, final catch estimates, and the precision of the estimates are a source of consternation among anglers, fisheries managers, and other stakeholders.

> **Recommendation: Current efforts by MRIP and its partners in the area of survey inter-calibration should continue and, where significant differences between surveys exist in terms of final estimates or precision, the causes of the differences should be determined and communicated to the public.**

Conclusion: While the implementation of MRIP surveys is generally standardized, there is precedent for adapting coverage to regional characteristics and needs. For instance, both APAIS and FES are conducted during only the warmer part of the year in the northeast region.

[13] See http://www.asmfc.org/files/Meetings/2017SummerMeeting/ACCSPCoordinatingCouncilSupplemental.pdf.

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4

Optimizing Use of MRIP Data and Complementary Data for In-Season Management

Previous chapters of this report have described the process of setting annual catch limits (ACLs) for federally managed species and the current procedures being used by regions and states for in-season and general management of recreational fisheries. Several attributes of marine recreational fisheries make them difficult to characterize and monitor. Recreational fisheries are diverse and dispersed, and obtaining timely and reliable catch and effort data can be challenging (NRC, 2006; NASEM, 2017a). Although MRIP was developed to address some of these challenges (NRC, 2006) and generate estimates of recreational fisheries catch and effort that are better suited for use in assessment and management, as indicated in Chapter 3, MRIP surveys were not intended or designed to support in-season quota monitoring. The main products of the MRIP general survey are bimonthly catch estimates that are relatively precise at the annual and regional (i.e., multistate) scale (ACCSP, 2017; GulfFIN, 2016; NASEM, 2017a). Annual estimates of landings and discards are usually adequate for stock assessments of commonly encountered species. However, annual estimates at the state and regional levels are often considered inadequate for managing recreational fisheries with ACLs (GulfFIN, 2016) and may lack adequate precision for species that are rarely intercepted (ACCSP, 2017; NASEM, 2017a).

Chapter 3 provides a broad overview of the current recreational fisheries surveys (both MRIP and state surveys) and describes the challenges associated with meeting the diverse data needs for in-season management in each region. This chapter expands on that discussion, introduces potential improvements to the sampling design and data collection methods, and explores extensions to current statistical methods to address the question of whether and how MRIP can be improved or supplemented to better meet the needs of in-season management. Specifically, this chapter addresses the following components of the Committee's statement of task (Chapter 1, Box 1.1): "actions the Secretary, Councils, and States could take to improve the accuracy and timeliness of data collection and analysis to improve or supplement the MRIP and facilitate in-season management," and "an assessment of how survey methods and/or management strategies could be modified to better meet the needs for ACL monitoring and AMs [accountability measures] to ensure that overfishing does not occur."

IMPROVING THE PRECISION, TIMELINESS, AND AVAILABILITY OF MRIP ESTIMATES

As described in Chapter 3, MRIP is a multipurpose survey program designed to support the needs of fisheries biologists and managers charged with conducting assessments of fish stocks and on that basis establishing commercial and recreational fishing regulations that provide optimal use of the resource over time. To that end, in the Atlantic and Gulf regions, MRIP produces bimonthly and annual estimates of recreational catch by species, state, fishing mode, and fishing location. At its current funding level, sample sizes, and timetable for release of estimates of total catch, MRIP and its multiple contributing sources of survey and logbook data are not designed to be the primary source of the timely and precise information needed to support responsive in-season decision making by regional and state fishery managers. This is not a new conclusion.

The report of a previous National Academies committee (NASEM, 2017a) charged with reviewing the revised MRIP program makes the following statement concerning the bimonthly Fishing Effort Survey (FES), which is MRIP's source of data on recreational fishing effort for shore-based and private boat anglers: "The FES is designed to produce cross-sectional (i.e., yearly) fishing effort estimates by state.…Requiring the FES to produce precise estimates for in-season estimation is not feasible given time and funding constraints. Doing so would require specialized surveys for this purpose" (NASEM, 2017a, p. 55). Although MRIP cannot be viewed as the primary source of catch and effort data necessary to meet the timeliness and precision requirements of in-season management, its structured data collections, data streams, and estimates can certainly contribute to in-season management when statistically integrated with supplemental data collections and auxiliary data sources (as discussed later in this chapter).

The statistical information requirements for effective in-season management are demanding. Data and estimates must be specific to species and fishery domains (location, mode), accurate (free from sampling and nonsampling biases), precise (have low uncertainty due to sampling variance), timely (as close to real time as possible), and affordable (constrained by budget limitations). This section addresses the interrelated requirements of precision, timeliness, and affordability, examining steps that MRIP might take to enhance timeliness and the associated impact on the precision of estimates and cost (Groves, 1989).

Improving Precision in High-Importance Domains by Reallocating Sampling Effort

Through its standard data collection programs (the Access Point Angler Intercept Survey [APAIS] in particular), MRIP might enhance its existing sampling design and sample allocation in ways that would support the specialized needs of the individual regions and states. For example, MRIP could use a weighted allocation for the APAIS intercept sample to improve monitoring of catch during high-intensity fishing periods, similar to what is done in support of improved sampling during Florida's Red Snapper recreational fishing season.

Increasing the Speed of Existing MRIP Data Collection, Processing and Release

A focus on the timeliness with which fishery managers can access and use MRIP data is by no means new. A detailed report issued in 2011 by the National Oceanic and Atmospheric Administration's (NOAA's) National Marine Fisheries Service (NOAA Fisheries) (Salz et al., 2011) presents an in-depth discussion of the issues involved in various approaches to improving the timeliness of the estimates produced by the Marine Recreational Fisheries Statistics Survey (MRFSS)/MRIP. That report's coverage of the alternatives for improving timeliness and the feedback from stakeholders who participated in a project workshop remains highly relevant to the charge of this Committee. At the risk of some oversimplification, the potentially complementary approaches to improving the timeliness of MRIP estimates or the more "timely use" of MRIP data streams in in-season management can be grouped as follows.

Electronic Reporting

Mobile apps for smartphones and tablets offer technologies for improving the efficiency and timeliness of recreational data reporting. Several state and regional surveys already use app-based electronic reporting.

The 2017 National Academies report on MRIP (NASEM, 2017a) identifies four ways in which electronic data collection could be integrated with MRIP: (1) using electronic logbooks by the for-hire sector, (2) enabling interviewers to capture and submit data electronically, (3) allowing anglers to self-report data electronically, and (4) using electronic monitoring to validate self-reported data.

Since 2017, there has been substantial progress on options (1) and (2). In the for-hire domain, electronic data capture and submission of recreational catch and effort data is now standard practice in the Vessel Trip Reporting (VTR), Southeast Region Headboat Survey (SRHS), the South Carolina Logbook program, and the newly launched Southeast Region For-Hire Electronic Reporting (SEFHIER) program. The Atlantic Coastal Cooperative Statistics Program (ACCSP) has been active in developing electronic reporting applications. In the MRIP APAIS program, the transition from paper forms to electronic data capture and reporting is virtually complete. The ACCSP coordinates the MRIP APAIS data collections for the Atlantic Coast regions and in 2019 converted all data collection and transfer for that intercept survey from paper to electronic modes. On March 1, 2021, the Gulf Fisheries Information Network (GulfFIN), with support from the ACCSP, transitioned all APAIS data collection in the Gulf region states to tablet-based systems, and automated data transfer is being used to reduce the time needed to deliver the data for MRIP processing and quality assurance/quality control (QA/QC) processing. In addition, some real-time QA/QC functions can now be incorporated directly into the actual table-based data collection applications. One advantage of electronic data capture is that it is relatively easy to make small changes or addition to the data collection instruments.

As the transition to electronic reporting and data capture moves forward, it will be important to maintain standardization over time in the recording instruments to the extent possible. Frequent changes to the content and format of the survey instruments and reporting forms will require corresponding updates to subsequent data cleaning and data processing systems. This in turn will impact the timeliness with which final estimates can be produced, thereby potentially offsetting some of the time savings realized with electronic data capture.

Shorter time period between MRIP data collection and release of primary estimates

MRIP could retain the current bimonthly wave and annual reporting timing but through staffing increases or process changes, might shorten the elapsed time between the end of each wave and the release of preliminary estimates. The life cycle for MRIP's bimonthly wave estimates of catch for each species by recreational fishery domains includes five basic phases: sample design and preproduction, active data collection, data transfer, data processing and QA/QC, estimation and reporting. As described in Chapter 3, depending on the species and region, final MRIP wave estimates require input from multiple data sources: the APAIS, the FES, the For-Hire Survey (FHS), VTR, SEFHIER, the SRHS, the South Carolina Logbook program, LA Creel, and the Texas Parks and Wildlife surveys. Relative to the time a fishing trip actually occurs, each of the contributing data streams can have very different reporting time lags before MRIP can access or utilize the data. SEFHIER electronic reports for the Gulf region must be filed daily. APAIS intercept sample data that contribute to catch rate estimation, estimation of adjustments for FES for FHS noncoverage, and validation of FHS telephone survey reports are collected daily. Northeast VTR and South Atlantic SEFHIER catch and effort reports are filed roughly within 1 week of the covered fishing trips. Sample-based FHS telephone reports of effort for chartered or for-hire trips retrospectively cover 1-week reference periods, but completion of the telephone interviews for each weekly sample may extend several weeks after the last day of the reporting period. Currently, the rate-limiting component in the life cycle of MRIP estimates is the FES. Presently and for the foreseeable future, the FES is essential for generating state-level estimates of the total number of trips by private boat and shore anglers. The FES mail survey design utilizes weekly stratified, probability samples of licensed angler and general household addresses that are rolled out over the 2-month wave of data collection. However, since FES effort estimates are based on the complete sample for fixed 2-month periods, MRIP must allow additional time to perform nonresponse follow-ups on the initial mailings, as well as several weeks after the end of each wave for respondents' survey forms to be returned.

The collection of data required to generate MRIP's bimonthly estimates is to a large extent decentralized. Regional Interstate Commissions, NOAA Fisheries' Regional Science Centers, and state fish and wildlife agencies are all directly engaged in the actual data collection for the APAIS intercept samples; the SRHS; and in the case of Louisiana, the MRIP-certified LA Creel survey. In 2020, the FHS also shifted from contractor-led to state-led data collections. The FES, the Large Pelagics Survey (LPS), and VTR/SEFHIER remain the three MRIP data collections that are centrally administered by NOAA or its contractors. Although data cleaning and processing can also be decentralized, and the assimilation of all the data from the various data collection agents is greatly facilitated by established systems and procedures, MRIP cannot produce its final estimates of recreational catch until all the data have been delivered. Generally, MRIP can expect to have all the needed data within 1 month after the close of each data collection wave. Upon receipt of the many data inputs, final QA/QC on the compiled data, generation of estimates and standard errors, and a final review by the MRIP team must be performed before the official estimates can be released to fishery managers and the public. The MRIP team needs approximately two additional weeks to complete these final steps. The result is that MRIP aims to release its preliminary estimates of recreational catch 45 days after the final day of each bimonthly reporting wave.

The committee did not directly investigate with the MRIP team the costs and benefits of shortening the length of time between the end of a wave and the date on which preliminary estimates could be released. However, the authors of the 2011 NOAA report (Salz et al., 2011) on the timeliness of data on marine recreational fisheries did undertake a study of this question. The conclusion at that time was as follows: "The analysis indicated that modest reductions in lag time (about 7 days maximum) could be achieved for both the data delivery and estimation phases if additional resources (i.e., cost) were available. The combined effort could result in preliminary wave estimates being released about 31 days after the end of a wave instead of the current 45 days. Reducing lag beyond this point would put considerable strain on the process and could start to negatively affect the accuracy (sic) of estimates."

Another point in this discussion of shortening the period of time before MRIP data can be used to inform in-season management relates to the release of raw data before MRIP estimates have been produced. In presentations to the Committee, a number of fishery scientists and managers at the region and state levels expressed strong interest in having timely access to data that would enable them to monitor recreational fishing effort and catch rates more continuously. This is especially true for managed species with short fishing seasons or intense periods of recreational fishing activity. MRIP-certified supplemental surveys, such as LA Creel and the Pacific Coast RecFIN surveys, as well as other supplemental surveys, such as Snapper Check and Tails n' Scales, have been implemented to provide such recreational catch data very soon after the fishing activity has occurred. Some state agencies also supplement the basic MRIP APAIS sample to increase the precision of estimates for specific species and periods of fishing activity. Increasingly, Regional Interstate Commissions and state agencies are playing a direct role in the electronic data collections for APAIS and the FHS telephone survey. Electronic reports from the VTR program, the SRHS, the South Carolina Logbook program, and SEFHIER should be available within 1–2 weeks of the actual fishing activity covered by the report. The FES samples require a time lag to allow for return of the mail survey questionnaire, and in raw form, these data may not play as strong a role in continuous monitoring relative to the APAIS intercept data, FHS data, and for-hire logbook reports. However, since each 2-month wave of the FES employs weekly probability sample releases, the weekly samples could be available within 3–4 weeks after each weekly sample has been released.

Rigorous MRIP processes for producing the bimonthly estimates of catch for state domains will certainly require time after the end date of each wave to integrate all of the needed data, perform basic data management/cleaning, compute estimates, and perform QA/QC on the official estimates. However, with appropriate caveats on its sample properties and statistical uses, it may be possible for MRIP to make the raw data streams from APAIS, the weekly FHS samples, and the for-hire logbook programs more accessible to state and regional managers in near real time. Preliminary weights could also be assigned to the sample-based APAIS and FHS observations.

Increased MRIP Sampling (Wave) Frequency

Another strategy for improving the timeliness of MRIP data estimates for use in in-season management would be to transition from bimonthly to monthly waves for data collection and reporting of catch estimates. This strategy would have clear advantages for in-season management of species populations for which fishing intensity is not highly variable over time or species access is not limited by such natural factors as migratory patterns or seasonal barriers (e.g., weather). This strategy would be less advantageous for in-season management of species for which fishing seasons are short (e.g., Gulf Red Snapper) or species for which the annual recreational catch is highly concentrated in 1 or 2 months (e.g., North Carolina Wahoo). MRIP conducted a cost/benefit study of moving from its current bimonthly reporting schedule to more timely monthly reporting waves (Salz et al., 2011). The costs and benefits of a transition to monthly reporting are heavily dependent on what is assumed about the desired level of precision for the new monthly estimates. The general conclusion of MRIP's investigation was that to maintain an equivalent level of precision for monthly catch estimates, a roughly two-fold increase in the APAIS, FES, and FHS sample sizes would be needed—each monthly sample size would need to be equal to those currently fielded for each 2-month wave. The required doubling of these sample sizes, combined with the added fixed costs for the additional staff and systems enhancements needed to move to 1-month reporting waves, would require roughly a doubling of the MRIP budget for data collection and estimation activities.

Following sampling theory for simple random samples, the alternative of simply allocating half of the existing sample sizes to each month of the existing 2-month wave would result in an approximately 40 percent increase in the standard errors of the 1-month estimates of catch relative to the precision for the current bimonthly estimates. (Precision for estimates that pool data for 2 months should remain relatively unchanged.) Since coefficients of variation (expressed as percent standard errors) of the bimonthly catch estimates for the MRIP domains are already a concern, the alternative of moving to a monthly reporting cycle without investing additional resources in expanding the monthly samples would not provide sufficient precision of monthly estimates for most in-season management purposes.

The extent to which the transition to monthly waves would shorten the time required for the data processing, estimation, and QA/QC phases of each reporting period is uncertain. As noted, staffing at the state, regional, and federal levels would need to be expanded, and systems would need to be enhanced to accommodate the monthly waves. Most of the current activities required to produce catch estimates—data collection, data processing, data transfer and assimilation, estimation, and final QA/QC—would not change under the monthly reporting alternative. Assuming the current time lag of 45 days, preliminary catch estimates reflecting fishing effort in May would be released July 15, while estimates reflecting June fishing activity would be available in mid-August (the same date that estimates incorporating June data are available under the current bimonthly reporting cycle). Therefore, for purposes of monitoring cumulative catch against ACL targets, monthly reporting would offer a true timing advantage for the first month of each current bimonthly wave (i.e., January, March, May, July, September, and November).

Forecasting Between Waves Using VTR, SEFHIER, and Early APAIS/FES Returns

MRIP and its regional and state partners could further develop simple statistical methods for forecasting total catch and effort using existing MRIP data streams (e.g., VTR, SEFHIER, APAIS daily intercepts sampling, early FES/FHS returns) captured with a shorter time lapse (daily, weekly, biweekly) between the actual fishing trip and the data capture.

Through MRIP and related fisheries programs, NOAA Fisheries has made a number of major advances in the population coverage, statistical efficiency, and timeliness of its monitoring of recreational marine fisheries. The electronic reporting requirements of the VTR and SEFHIER programs for federally licensed headboats, charter vessels, and guide boats imply that comprehensive raw data on fishing activity (both catch and effort) in the for-hire domain may be available as soon as 1 week after a fishing trip has occurred. Regional and state partners now assist MRIP in electronic or telephone data collection for the APAIS and FHS. Allowing a reasonable amount of time for survey follow-ups, data cleaning, and processing, usable data at the state level might be available within a month of when a fishing trip occurred. Similar to what was discussed above regarding the release of MRIP raw data, in coordination with MRIP and Regional Interstate Commission programs, such as GulfFIN and ACCSP, regions and states could begin to utilize these data long before they had been centrally compiled to generate the official MRIP estimates. For species and domains for which there is a correlation between for-hire catch rates and effort and private vessel/shore-based catch or APAIS-sampled trips and FES reports of effort, these early-access sources of data might be used to develop usable forecasts of total catch long before all the standard data inputs to MRIP estimates had been compiled (Farmer and Froeschke, 2015).

SOURCES OF SUPPLEMENTAL AND ANCILLARY DATA

Regional federal and state fishery managers, working together with the NOAA MRIP team, could take steps to maximize the joint use of MRIP estimates, supplemental survey data, and ancillary data (covariates) to improve annual and in-season catch forecasts. This section looks at methods for integrating supplemental and ancillary data with MRIP catch estimates to improve catch forecasts.

For example, Gillig and colleagues (2000) investigated the effects of the following ancillary variables on fishing effort (trips) per angler, targeting Red Snapper in the Gulf of Mexico in the early 1990s:

- cost of the trip to the angler,
- angler's household income,
- Red Snapper catch per unit effort (CPUE),
- CPUE squared (to detect a possible nonlinear effect of CPUE),
- angler's fishing experience in years,
- year of fishing experience squared (to detect a possible nonlinear effect of fishing experience), and
- dummy variable indicating whether the angler owned a boat.

The authors found that trip cost, household income, Red Snapper CPUE, fishing experience, and boat ownership all had statistically significant effects on angler fishing effort for Red Snapper.

- In a study focused on developing recreational catch forecasting models for several fish species in the South Atlantic and Gulf regions, Farmer and Froeschke (2015) found that "future forecasting modeling could explore the use of management regulation [e.g., bag limits, size limits] time series as covariates, and also evaluate the utility of economic predictors of recreational fishing effort such as per-capita U.S. Gross Domestic Product or mean fuel prices.…When a stock assessment is available…exploitable abundance may be a useful predictive covariate for landings forecasting models."

In a recent application of forecasting models to Gulf of Mexico Red Snapper, Farmer and colleagues (2020) considered the following ancillary variables for the purpose of forecasting catch rates and average fish weights in federal waters:

- year,
- year of stock rebuilding plan,
- season length,
- weekend days,
- fishable days (based on weather),
- previous year's average weight or catch rate,
- Red Snapper quota,
- spawning stock biomass (from stock assessment),
- fuel prices,
- per capita GDP, and
- Google Trends searches for Red Snapper.

Of these, the investigators found that year, year of rebuilding plan, spawning stock biomass, and the previous year's catch were consistently useful predictors, with the previous year's catch being the most commonly selected predictor across alternative forecasting models.

This section describes sources of potential supplemental and ancillary data that could be integrated with MRIP estimates to improve the accuracy, precision, or timeliness of in-season catch forecasts. The sources are categorized according to whether they would provide (1) supplemental data on recreational effort and catch; or (2) supplemental data on some other, ancillary, variable that could be useful for improving forecasts of recreational effort and catch. Chapter 5 also considers supplemental surveys in the context of alternative management strategies.

Supplemental Data on Recreational Fisheries Effort and Catch

State-Specific Supplemental Survey Data

As reviewed in Chapter 3, data from state-specific recreational fishery survey programs may be used to supplement data collected by MRIP. States may choose to supplement the basic APAIS sample allocation at particular locations or times of the year or in the case of Louisiana, to include APAIS-like sampling of its MRIP-certified LA Creel program. MRIP assists in these cases by selecting the supplemental samples for the states from the sample frame it maintains.

Particularly demanding in-season management challenges (e.g., Gulf Red Snapper, Pacific Salmon) have forced the regions and states to develop supplemental survey data collections designed specifically to meet the management needs for individual species or species groups. Examples include Florida's State Reef Fish Survey, Alabama's Snapper Check, and Mississippi Tails n' Scales and iSnapper (see Chapter 3). When supplemental surveys are needed to meet in-season management challenges, MRIP should continue its efforts to support such regional and state efforts to ensure that these special, highly focused data collections can be integrated to the fullest extent possible with the ongoing MRIP data collections or integrated statistically using methods covered later in this chapter (Citro, 2014; Lohr and Raghunathan, 2017; Rao, 2021). The proliferation of uncalibrated and uncoordinated supplemental survey programs could reduce the consistency and comparability of catch estimates across regions, states, and fishing modes. State-sponsored supplemental surveys could suffer from discontinuity over time due to fluctuations in state funding levels. Proliferation of uncalibrated and uncoordinated supplemental surveys could also lead to increased conflicts among states or fisheries sectors (recreational vs. commercial) over the "correct" catch estimates to be used for fishery quota allocation or ACL monitoring.

Species-Specific Supplemental Data

Data from supplemental, species-specific studies or surveys, where and when available, could be used to supplement the standard MRIP catch estimates to improve projection/forecast models used for annual and in-season management. Examples of such surveys include Alabama's Snapper Check;[1] Florida's State Reef Fish Survey;[2] and a potential, supplemental, "deepwater" survey being considered by MRIP (Foster and Voorhees, 2015). Fishery managers might be able to improve the precision (decrease percentage standard errors [PSEs]) of catch forecasts by combining the data from such species-specific surveys with the traditional MRIP-produced effort and catch estimates using multiple-frame survey methods (described below), for example.

Location-Specific Supplemental Data

In some locations, supplemental data on effort, such as vessel traffic, may be available. For example, in some areas, such as Texas and the Northeast, where vessels typically depart from specific ports, counts of vessel departures may be available in addition to more general angler survey data. Similarly, in some areas, such as the Pacific Coast harbors (ODFW, 2021) and selected Florida East Coast inlets (Red Snapper Survey; Sauls et al., 2017; Sauls and Lazarre, 2019), vessel traffic may be restricted to "bottleneck" river outlets or sandbar crossings where vessel count data are collected. In these cases, data may be collected

[1] See https://research.dcnr.alabama.gov/Snapper.
[2] See https://myfwc.com/fishing/saltwater/recreational/state-reef-fish-survey.

using various methods, including field observer hand tallies (Sauls et al., 2017), video recordings with later human vessel identification and counting (Pacific Coast; Mid-Atlantic Fishery Management Council [MAFMC] Ocean City, Maryland, pilot project[3]), and video with artificial intelligence/machine learning automated vessel identification and counting (ODFW, 2021). As with species-specific supplemental data, fishery managers might be able to improve the precision (decrease PSEs) of catch forecasts by combining location-specific supplemental data with traditional MRIP-produced effort and catch estimates using multiple-frame survey methods (described below), for example.

Fishing Tournament Supplemental Data

Saltwater fishing tournaments may provide another source of information on recreational fishing effort or catch. For instance, many fishing tournaments provide long-standing records of participation rates and catches. These data sources have been used to reconstruct historical patterns of catches, size or abundance (Powers et al., 2013; Rehage et al., 2019), but they may also be useful as leading indicators of declining catch rates or other shifts within the fisheries.

Voluntary Supplemental Data

Mobile reporting apps are now being widely used by headboat and charter operators that are required to file catch and effort reports in mandatory reporting programs such as SEFHIER. App-based reporting provides another potential pathway to more efficient effort and catch reporting for private boat and shore-based fishing activity. As recommended in the above-referenced 2006 National Academies report (NRC, 2006), electronic data collection, including smartphone apps, electronic diaries, and web portals that anglers could use to enter data, should be evaluated further as an option for the FES. Since 2017, there has been substantial progress on the use of electronic logbooks by the for-hire sector and on permitting interviewers to capture and submit data electronically. Programs that leverage electronic reporting capabilities include iAngler (2018), iSnapper (2018), Snapper Check (2018), and Tails n' Scales (2018). Snapper Check and Tails n' Scales include both electronic reporting and validation via dockside sampling. These programs are discussed in greater detail in Chapters 3 and 5.

Additionally, in 2019, NOAA Fisheries completed an assessment of the status and potential of electronic reporting options for private anglers in the form of three MRIP-supported studies designed to guide future efforts on electronic data reporting (e.g., Brick, 2018)[4] and an MRIP Research and Evaluation Team review of the iAngler and iSnapper Reporting Programs (NOAA Fisheries, 2019). MRIP also completed a test of a web-push design for the FES in 2020,[5] which resulted in response rates that were 7–11 percentage points lower than FES response rates and results that were less timely and cost-effective relative to the FES design at the time. Furthermore, several studies have shown that, while anglers are generally supportive of such approaches, sustaining participation is a major challenge. One recent study of Louisiana anglers found that while 84 percent used mobile phone apps and 80 percent were willing to report their catches, only 1 percent actually followed through with reporting (Midway et al., 2020). The representativeness of anglers who report data voluntarily, such as through apps, is also unclear. Coverage bias and nonresponse bias, in particular, are important concerns with voluntary report data that need further investigation.

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[3] The MAFMC began a pilot project in 2020 to explore use of video technology to record vessels entering/exiting the Ocean City, Maryland, inlet as an alternative method for estimating effort. Project delays have occurred as a result of the COVID-19 pandemic. See project description at https://www.mafmc.org/s/2_Project-Plan-Video.pdf.

[4] See https://www.fisheries.noaa.gov/feature-story/noaa-fisheries-explores-electronic-reporting-supplemental-source-recreational-fishing.

[5] See https://www.st.nmfs.noaa.gov/pims/main/public?method=DOWNLOAD_FR_DATA&record_id=1856.

Supplemental Data on Ancillary Variables

Ancillary variables, such as commercial fishery catch and effort, weather (air temperature and precipitation), water depth, ocean conditions (e.g., seawater temperature, currents), fuel prices, unemployment rate, fishing access infrastructure, boat ownership, social media search terms, and electronic device use and location, could be combined with MRIP recreational catch estimates in projection models to improve both annual and in-season catch forecasts. For example, Rao and Molina (2015) stress that "the success of any [small-area] model-based [estimation] method depends on the availability of good auxiliary data. More attention should therefore be given to the compilation of auxiliary variables that are good predictors of the study variables." Cruze (2015) presents a model for integrating survey data and ancillary information for purposes of estimating crop yields.

This section identifies several categories of potential ancillary variables; data sources for the variables; and selected examples of applications to recreational fishery management, where available.

Commercial Fishery Landings and Effort

State fisheries agencies collect commercial fisheries data through "trip ticket" programs. To the extent that recreational fishing effort and catch are correlated with commercial fishing effort and catch, it may be possible to use commercial fishery data to improve annual and in-season recreational catch and effort forecasts made with recreational fishery projection models. In addition to the degree of correlation between commercial fishery and recreational fishery data, the usefulness of commercial fishery data would depend on the accuracy and precision of the commercial data, the frequency with which the data are collected, and the timeliness with which they are made available. For example, since 1994 North Carolina has mandated trip-level reporting of commercial fisheries landings through the North Carolina Division of Marine Fisheries (NCDMF) Trip Ticket Program (NCDMF, 2021).

Many other states have modeled their trip ticket programs on the North Carolina program. For each trip, trip tickets collect data on the fisherman, the dealer purchasing the product at dockside, the transaction date, the number of crew, the area fished, the gear used, and the quantity of each species landed. Seafood dealers are required to complete a trip ticket for each transaction at the time and place of landing (one trip ticket per trip). A separate trip ticket is required for each fishing trip; hence, trip tickets can be used to estimate effort (fishing trips). Dealers submit trip ticket forms monthly to the NCDMF. Trip tickets for any given month must be received by the NCDMF on or before the 10th of the following month. For example, tickets recorded from January 1 to January 31 are due to the NCDMF by February 10. Trip tickets may be submitted electronically. The data are uploaded to the ACCSP on a quarterly basis.[6] Data on commercial effort and landings are also published annually in the NCDMF's Annual License and Statistics Report. Historical data on pounds and value landed can be accessed through the NCDMF Commercial Fisheries Landings Statistics Selection Tool.[7] New electronic trip reporting programs, such as ACCSP's SAFIS/eTrips program,[8] allow commercial fishermen to record required catch and effort data while still at sea and to submit the data directly and electronically to ACCSP upon reaching shore. Such programs have the potential to increase the timeliness of the availability of commercial fisheries data. SAFIS/eTrips is currently used by the New Hampshire Fish and Game Department, Rhode Island Division of Fish and Wildlife, Massachusetts Division of Marine Fisheries, Connecticut Department of Energy and Environmental Protection, New York State Department of Environmental Conservation, New Jersey Division of Fish and Wildlife, Delaware Division of Fish and Wildlife, Maryland Department of Natural Resources, and NOAA-Greater Atlantic Regional Fisheries Office (GARFO).

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[6] See https://www.accsp.org.
[7] See http://portal.ncdenr.org/web/mf/statistics/comstat.
[8] See https://www.accsp.org/what-we-do/safis.

Water Depth

Recreational fishing catch and CPUE typically vary by water depth. MRIP currently tracks fishing effort, catch, and CPUE by three general fishing locations (inland, nearshore, and offshore) that correspond roughly to water depth, but in the future, higher resolution or more precise fishing location data may be available (collected, e.g., via depth finders, GPS devices, smartphone apps) though either voluntary or mandatory programs that would facilitate correlation of fishing location that would facilitate correlation of fishing location with water depth. For example, a mobile app designed for documenting marine mammal sightings passively records the GPS locations of users every 30 seconds to provide high resolution data on effort and sightings (Hann et al., 2018). There is a growing body of research on these technologies, including their accuracy, feasibility, and use by stakeholders (Specht et al. 2019; Baker et al. 2016; Jiorle et al. 2016; Papenfuss et al. 2015; Hinz et al. 2013; Gallaway et al. 2003). NOAA provides free electronic navigation chart (ENC) information that includes water depth in electronic, geographic information systems (GIS)–compatible format.[9] The ENC data are updated weekly. The NOAA ENC Direct to GIS service supports extracting ENC data into GIS-supported formats.[10] Similarly, the U.S. Army Corps of Engineers provides depth data for inland U.S. navigable waters, including river systems that may host saltwater species during portions of their life cycle.[11]

Weather and Oceanographic Conditions

Recreational fishing effort may be affected by weather and ocean conditions. To the extent that these weather and ocean condition variables are correlated (either positively or negatively) with recreational fishing effort or catch, it may be possible to use weather data to improve annual and in-season recreational fishery catch and effort forecasts made with recreational fishery projection models. In addition to the degree of correlation between the weather data and the recreational fishery data, the usefulness of weather data would depend on the accuracy and precision of the data, the frequency with which the data are collected, and the timeliness with which they are made available. Auffhammer and colleagues (2013) provide an extremely useful introduction to the use of weather and climate data in forecasting models, including common pitfalls, issues of correlation between weather variables, correlation over time, spatial heterogeneity and spatial correlation, and aggregation bias. Blanc and Schlenker (2017) provide a useful discussion of the issues that arise when aggregating weather data over time, including a comparison of alternative methods that can be used to aggregate weather data.

It is well known that air temperature and precipitation affect recreational fishing effort (Fraidenburg and Bargmann, 1982). For example, Powers and Anson (2016) found that weather was a significant predictor of fishing effort in the Gulf of Mexico Red Snapper fishery and that weather "likely imposes a greater influence during shorter seasons given the limited days available to fishermen." Anglers may find unusually high or low temperatures unpleasant, which may decrease fishing effort, while unusually mild temperatures (for the season) may increase fishing effort (Dundas and von Haefen, 2020). Recent evidence suggests that outdoor recreationists find daily average temperatures around 82 °F to be optimal (Obradovich and Fowler, 2017). While overcast skies and light drizzle (<¼ inch of precipitation per day) may have a slight positive effect on fishing effort (due to anecdotal evidence among anglers that overcast days tend to increase fishing success), heavier rainfall reduces fishing effort (Dundas and von Haefen, 2020). Powers and Anson (2016) also found that precipitation was negatively correlated with fishing effort.

NOAA's Physical Sciences Laboratory (NOAA-PSL[12]) provides daily precipitation data for a spatial grid of 0.25 degrees longitude by 0.25 degrees latitude.[13] This corresponds to a grid of spatial

[9] See https://www.nauticalcharts.noaa.gov/charts/noaa-enc.html.
[10] See https://www.nauticalcharts.noaa.gov/data/gis-data-and-services.html#enc-direct-to-gis.
[11] See https://navigation.usace.army.mil/Survey/InlandCharts.
[12] See https://psl.noaa.gov.
[13] See https://psl.noaa.gov/data/gridded/data.unified.daily.conus.rt.html.

locations approximately 17 miles apart in the north–south direction and approximately 15 miles apart in the east–west direction at the latitude of Wilmington, North Carolina (34.2 °N, 77.9 °W). Historical data are available for 1948 to the present. Daily maximum and minimum air temperature data are available for a spatial grid of 0.5 degrees longitude by 0.5 degrees latitude.[14] This corresponds to a grid of spatial locations approximately 34 miles apart in the north–south direction and approximately 29 miles apart in the east–west direction at the latitude of Wilmington, North Carolina (34.2 °N, 77.9 °W). Historical data are available for 1979 to the present. NOAA-PSL also provides an online tool for extracting monthly or seasonal time series of precipitation and temperature variables.[15]

The National Centers for Environmental Prediction's (NCEP's) North American Regional Reanalysis (NARR) provides eight times daily data on temperature, winds, and precipitation for 1979 to the present for a spatial grid of 0.3 degrees longitude by 0.3 degrees latitude.[16] NOAA's National Centers for Environmental Information Climate Data Online Data Tools provide daily and sometimes hourly weather data by weather station.[17]

Oceanographic variables, such as winds at sea, wave height, seawater temperature, tide, and current direction and strength may affect fishing effort or catch (Powers and Anson, 2016, 2019). If winds at sea are strong and waves are high, fishermen may make fewer fishing trips for safety reasons, and any trips taken may result in smaller catches because of the increased difficulty of operating gear in rough conditions. Seawater temperatures, tides, and currents may affect the spatial distribution and abundance of fish, which in turn may affect recreational fishing effort and catch.

The U.S. National Data Buoy Center (NDBC) provides oceanographic data collected by a network of ocean buoys worldwide[18] (Figure 4.1). The "active stations file" provides an online list of all 1,432 active stations (buoys, oil rigs, fixed stations, etc.).[19] This file provides metadata on station ID, latitude, longitude, station name, station owner, program to which the station belongs, and type of data reported for all active stations on the NDBC website.

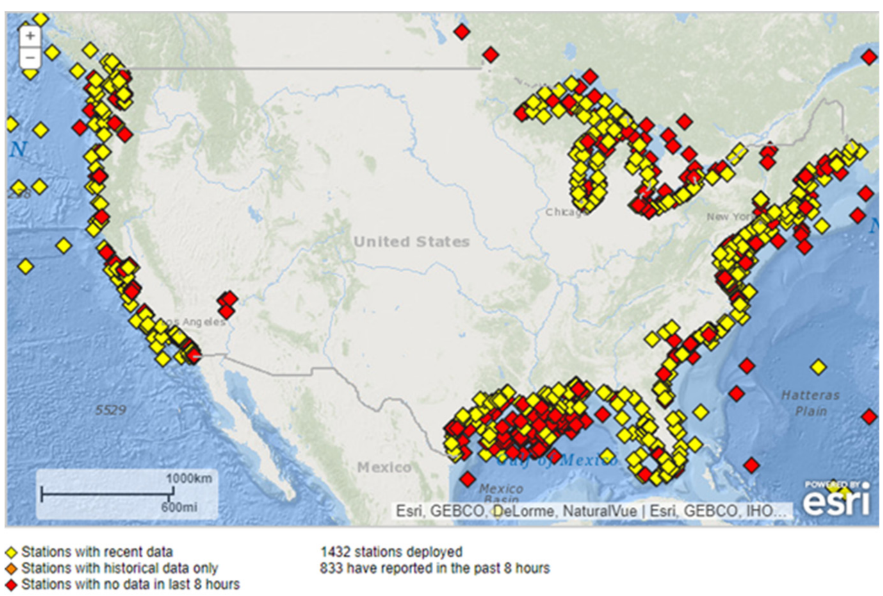

FIGURE 4.1 Ocean Buoy Network, U.S. National Data Buoy Center (NDBC). SOURCE: https://www.ndbc.noaa.gov/.

[14] See https://psl.noaa.gov/data/gridded/data.cpc.globaltemp.html.
[15] See https://psl.noaa.gov/data/timeseries.
[16] See https://psl.noaa.gov/data/gridded/data.narr.html#detail.
[17] See https://www.ncdc.noaa.gov/cdo-web/datatools.
[18] See https://www.ndbc.noaa.gov.
[19] See http://www.ndbc.noaa.gov/activestations.xml.

The data elements available for download by station from the NDBC include (NDBC, 2015)

- air temperature,
- conductivity,
- currents,
- salinity,
- sea level pressure,
- water level,
- water temperature,
- waves, and
- winds.

Not all stations collect data on all data elements. Data posted to the NDBC web server are stored in ASCII files that can be downloaded via HTTP. The "Realtime Directory"[20] contains the current (last 45 days) data by station. The "Latest Observation File"[21] contains essentially the same data elements; however, instead of having the observations from a single station, the file has the most recent observation (provided that the observation is less than 2 hours old) from all stations hosted on the NDBC website. Since this file has multiple stations, it also contains the position information (latitude and longitude) for each station. The file is relatively small, less than 100 KB, and is updated approximately every 5 minutes. Historical data files are available by station.[22] Some stations are equipped with "BuoyCAM" cameras that provide periodic online photos during daylight hours.[23]

The National Hurricane Center's "Blue Water Mariners" program provides a new, experimental, online graphical ocean conditions forecast for mariners that travel the open ocean.[24] The graphic provides information on current wind and wave heights and 12-hour forecast predictions out to 5 days for preset domains over the tropical North Atlantic, Caribbean, Gulf of Mexico, and tropical eastern North Pacific[25]. The National Hurricane Center also provides online access to daily sea surface temperature (SST) maps[26] based on data from the National Climatic Data Center (NCDC). These maps are based on ship and buoy SST data supplemented with satellite SST retrievals. In addition, the NOAA Climate Prediction Center constructed a monthly 1-degree global SST climatology using these analyses.

Medium-Term Climate Trends and Fluctuations

Medium-term trends in climate due to the early effects of gradual climate change and medium-term climate fluctuations due to El Niño and La Niña events may affect the magnitude, seasonal distribution, and geographic distribution of coastal recreational fishing effort and catch. Medium- and longer-term fisheries policy and management may need to consider ancillary variables related to climate change, El Niño, and La Niña.

Medium-term trends in climate due to the gradual effects of climate change on temperature and precipitation may affect recreational fishing effort and catch. Through simulation modeling, Dundas and von Haefen (2020) investigated the implications of several Intergovernmental Panel on Climate Change (IPCC) climate change scenarios (representative concentration pathways [RCPs]) for recreational fishing using daily temperature and precipitation projections for 2020–2099 (USBR, 2013) for more than 750 locations in the Atlantic and Gulf Coast regions. They found as follows:

[20] See http://www.ndbc.noaa.gov/data/realtime2.
[21] See http://www.ndbc.noaa.gov/data/latest_obs/latest_obs.txt.
[22] See http://www.ndbc.noaa.gov/station_history.php?station=XXXXX, where XXXXX is station number.
[23] See https://www.ndbc.noaa.gov/buoycams.shtml.
[24] See https://www.nhc.noaa.gov/news/Whats_New_Marine_Composite_Page.pdf.
[25] See https://www.nhc.noaa.gov/marine/forecast/enhanced_atlcfull.php.
[26] See https://www.nhc.noaa.gov/sst.

> …climate change forecasts overwhelmingly suggest that the realized temperature [probability] distribution in any given future time period is likely to shift to the right (i.e., hotter than usual)....predicted trips decline on average about 2.7% across RCP scenarios in the short term (2020–49) and up to 7.6% in the long run (2080–99)….regional estimates under RCP 8.5 (business as usual) suggest that the demand [i.e., fishing effort] response to rising temperatures is likely negative in the Gulf (–26%) and Southeast (–15%), regions that are relatively hotter in the baseline, and positive in the cooler region of New England (17.3%)….[the simulations also indicate] substantial declines in predicted trips in warmer months (May through October; waves 3–5) and trip increases in cooler months (November through April; waves 1, 2, and 6)….These results are also consistent with previous findings suggesting that warm weather recreation may shift northward and to cooler seasons in the future (Massetti and Mendelsohn, 2018) and that the economic impacts of climate are region-specific (Hsiang et al., 2017, p. 224)

These researchers also note that intraday substitution of fishing activity (i.e., shifting coastal fishing from day to night to avoid extreme daytime heat) is likely to increase as the climate warms.

The U.S. Bureau of Reclamation provides online access to downscaled climate projections for the contiguous United States by location.[27] These data are intended "to provide access to climate and hydrologic projections at spatial and temporal scales relevant to some of the watershed and basin-scale decisions facing water and natural resource managers and planners dealing with climate change."

Medium-term fluctuations in climate due to El Niño and La Niña events may also affect recreational fishing effort and catch. El Niño and La Niña are the opposite phases of ENSO, or the El Niño-Southern Oscillation.[28] Originating in the tropical Pacific Ocean, ENSO is Earth's single most influential natural climate pattern. El Niño and La Niña alternately warm and cool large areas of the tropical Pacific—the world's largest ocean—which significantly influences atmospheric circulation patterns that connect the tropics with the middle latitudes, which in turn modifies the midlatitude jet streams. By modifying the jet streams, ENSO can affect temperature and precipitation across the United States and other parts of the world. El Niño produces cooler and wetter weather over the U.S. South Atlantic and Gulf regions in the winter, but has little effect on summer weather. In contrast, La Niña produces warmer and dryer weather over the U.S. South Atlantic and Gulf regions in the winter, but like El Niño, has little effect on summer weather. The pattern can shift back and forth irregularly every 2–7 years (i.e., "medium-term" climate fluctuations), and each phase triggers predictable disruptions of temperature, precipitation, and winds.

To the extent that the El Niño and La Niña cycle is correlated with recreational fishing effort or catch, it may be possible to use ENSO data to improve annual and in-season recreational fishery catch and effort forecasts made with recreational fishery projection models. ENSO data may be correlated with recreational fishing catch and effort for two, interrelated reasons: first, ENSO effects on temperature, precipitation, and runoff in coastal nursery areas may affect the spatial distribution, migration, and/or abundance of target species (Morley et al., 2018; Pinsky et al., 2013), affecting catch rates; second, ENSO effects on precipitation and wind (and catch rates) may affect the recreational fishing effort of anglers (Dundas and von Haefen, 2020). As with other data types discussed above, the usefulness of ENSO data would depend on the accuracy and precision of the data, the frequency with which the data are collected, and the timeliness with which they are made available.

The NOAA National Weather Service Climate Prediction Center's North American Multi-Model Ensemble (NMME) climate model (Kirtman et al., 2014) is being used to make ENSO predictions[29] and probability forecasts for precipitation, temperature, and sea surface temperature for North America.[30]

It can be shown that ENSO has a relationship to the relative frequency of seasonal climate *extremes* in the United States. The frequencies of these extremes vary by region and by season. The NOAA-PSL has

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[27] See https://gdo-dcp.ucllnl.org/downscaled_cmip_projections.
[28] See https://www.climate.gov/enso.
[29] See https://www.cpc.ncep.noaa.gov/products/NMME/current/plume.html.
[30] See https://www.cpc.ncep.noaa.gov/products/NMME/probindex.shtml.

produced an online tool[31] that plots the increased or decreased risk of extreme warm/cold (or dry/wet) seasons during an ENSO event. These forecasts, predictions, and risk estimates could be used to drive ENSO variables included in recreational fishing projection/forecasting models.

Economic Conditions

Economic variables, such as fuel prices, per capita GDP, and unemployment, may affect recreational fishing effort. Higher fuel prices increase the cost of recreational fishing trips and may decrease fishing effort. Higher per capita GDP increases household wealth, which may increase fishing trips. Higher unemployment may reduce household income, which may reduce effort for higher-priced modes of recreational fishing, such as charter fishing. On the other hand, higher unemployment and lower household income may increase effort for lower-priced recreational fishing modes, such as shore-based fishing. To the extent that these economic variables are correlated (either positively or negatively) with recreational fishing effort or catch, it may be possible to use such economic data to improve annual and in-season recreational fishery catch and effort forecasts made with recreational fishery projection models. For example, Farmer and colleagues (2020, p. 14) found that "per capita GDP was a useful predictor for private catch rates, possibly indicating more anglers on the water during years with favorable economic conditions. Fuel price was also a useful predictor…."

As with other variables discussed above, in addition to the degree of correlation between economic data and recreational fishery data, the usefulness of economic data would depend on the accuracy and precision of the data, the frequency with which the data are collected, and the timeliness with which they are made available.

The U.S. Bureau of Economic Analysis (USBEA) provides information on per capita GDP on annual, seasonal, quarterly, and inflation-adjusted ("real") bases.[32] This information is available online in several formats from the FRED economic data portal of the Federal Reserve Bank of St. Louis.[33] Annual and quarterly per capita GDP data are also available by state[34] and by county.[35]

The U.S. Energy Information Agency (USEIA)[36] provides information on gasoline and diesel fuel prices per gallon on a weekly basis by region of the country.[37] The data are available for download in spreadsheet format.

The Current Employment Statistics (CES) program of the U.S. Department of Labor, Bureau of Labor Statistics[38] produces detailed industry estimates of employment, hours, and earnings of workers on payrolls. Each month, CES surveys approximately 144,000 businesses and government agencies, representing approximately 697,000 individual worksites. CES National Estimates produces data for the nation, and CES State and Metro Area produces estimates for all 50 states, the District of Columbia, Puerto Rico, the Virgin Islands, and about 450 metropolitan areas and divisions. Data on current employment, unemployment, and the unemployment rate are available online.[39]

Fishing Access Infrastructure

Fishing access infrastructure consists of fixed assets that facilitate angler access to recreational fishing opportunities. Fishing access infrastructure may increase recreational fishing effort and catch by

[31] See https://psl.noaa.gov/enso/climaterisks.
[32] See https://www.bea.gov/data/gdp/gross-domestic-product.
[33] See https://fred.stlouisfed.org/series/A939RC0A052NBEA.
[34] See https://www.bea.gov/data/gdp/gdp-state.
[35] See https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas.
[36] See https://www.eia.gov/petroleum/gasdiesel.
[37] See http://www.eia.gov/oil_gas/petroleum/data_publications/wrgp/mogas_history.html.
[38] See https://www.bls.gov/ces.
[39] See https://www.bls.gov/bls/newsrels.htm#OEUS.

lowering the cost to anglers of accessing fishing locations along the coast and in the open ocean. To the extent that recreational fishing effort and catch are correlated with fishing access infrastructure, it may be possible to use infrastructure data to improve *annual* recreational catch and effort forecasts made with recreational fishery projection models. Infrastructure data may be less useful for improving *in-season* forecasts, as the quantity and quality of infrastructure rarely change within a season because construction time is usually longer than a fishing season. An exception would be the sudden loss of infrastructure due to a disaster (e.g., hurricane strike) or regulatory change (e.g., closing a boat ramp or bridge for repair, closing a beach because of water quality problems). For example, reductions in beach width have been found to reduce shore fishing effort, although some of that “lost” effort is displaced, for example, to nearby pier or jetty infrastructure (Whitehead et al., 2009). Again, in addition to the degree of correlation between infrastructure and recreational fishery data, the usefulness of infrastructure data would depend on the accuracy and precision of the infrastructure data, the frequency with which the data are collected, and the timeliness with which they are made available.

Fishing access infrastructure may be open to use by the public, such as in the case of boat ramps, fishing piers, bridges, jetties, and beaches, or it may be privately owned, such as in the case of private marinas and boat slips and docks attached to private residences.

The MRIP APAIS program uses data on public infrastructure in developing fishing pressure weights to improve APAIS estimates. MRIP maintains an online database of saltwater fishing access sites that serves as the sample frame for the APAIS survey of recreational anglers. This Public Fishing Access Site Register[40] contains information on more than 3,800 marinas, boat ramps, beaches, and other public fishing access sites along the Atlantic and Gulf Coasts from Maine to Louisiana, including information on infrastructure at each location, such as the number of boat ramps, number of parking spaces, lighting at night, tackle shops, fuel docks, cleaning stations, and nearby restaurants and hotels. For Texas, which is outside of MRIP, an interactive map[41] of coastal public boating access locations and amenities is maintained by the Texas General Land Office.[42]

In addition to the data on public fishing access infrastructure, data on private infrastructure might also be used to improve recreational effort and catch estimates. Data on private infrastructure are not currently collected by MRIP, but such data could be gleaned from other sources. For example, licenses or permits may be required to construct private docks or boat slips in some areas, and it may be possible to obtain lists of these locations from local permitting agencies. Google Earth could be used to search for private marinas and boat slips, perhaps with the aid of machine learning algorithms to identify relevant infrastructure features. The Google Earth search engine can search for linear features perpendicular to a shoreline (Gorelick et al., 2017), which could help in identifying private docks and piers. Real estate databases, such as the Multiple Listing Service[43] of the National Association of Realtors,[44] typically include information on the waterfront status of property parcels and whether single-family residence parcels have a boat slip. For duplex, multiplex, condominium, and single-family parcels in a homeowners association (HOA), such databases often indicate whether each parcel has an assigned boatslip in a communal dock/marina, access to unassigned boatslip(s) in a communal dock/marina, or no boatslip access.

These data on public and private infrastructure could be used to help explain differences across regions and across years in MRIP output effort and catch results. This might improve estimates of the initial (season-start) conditions for in-season projection models or within-season projections in cases in which new infrastructure is projected to become available within the season (e.g., a new boat ramp will open, repairs will be completed on a fishing pier).

[40] See https://www.fisheries.noaa.gov/recreational-fishing-data/public-fishing-access-site-register.
[41] See https://cgis.glo.texas.gov/txcoasts.
[42] See https://www.glo.texas.gov.
[43] See http://www.mls.com.
[44] See https://www.nar.realtor.

Boat Ownership

Boat ownership may increase recreational saltwater fishing effort by increasing the accessibility of deeper-water fishing areas to anglers. Boat ownership may also increase effort by reducing the cost of a fishing trip by decreasing reliance on more expensive charter boat and headboat fishing modes. Access to alternative deeper-water fishing areas may also increase CPUE in some cases, and increases in CPUE may further increase effort. For example, Gillig and colleagues (2000) investigated boat ownership as an ancillary variable to explain the number of fishing trips per angler targeting Red Snapper in the Gulf of Mexico in the early 1990s. The researchers found that anglers who own boats take more Red Snapper trips relative to anglers who do not own boats. Therefore, the proportion of anglers that own boats may be a useful ancillary variable for the purpose of forecasting recreational saltwater fishing effort and catch. State recreational fishing vessel ownership registries could be combined with saltwater fishing license registries to determine the proportion of saltwater anglers that own boats, as well as how this proportion varies over time and by geographic region.

Social, Cultural, and Demographic Factors

Fishing effort is influenced by a wide variety of social and cultural factors, some of which may be useful as ancillary variables in effort forecasting models. For example, it is well known that fishing effort varies by the day of the week (weekdays vs. weekends) and is affected by holidays (Powers and Anson, 2016). The dates of fishing tournaments and seafood festivals may also affect effort, and the dates of such events are usually available from state resource management agencies. Demographic factors, such as age and ethnicity, may affect fishing effort as well. For example, communities with larger vs. smaller proportions of older anglers may have different preferences regarding fishing modes, target species, and trip frequency. As another example, communities with different ethnic backgrounds may celebrate different holidays, with different implications for fishing effort. Demographic data are available at the county level from the U.S. Census Bureau's Quick Facts data tool.[45]

Substitute Recreational Activities

The availability of substitute outdoor recreational activities, such as deer hunting and duck hunting (Gentner and Sutton, 2008; Oh et al., 2013; Sutton and Oh, 2015), may also affect recreational fishing effort. The seasonal dates of such activities are available from state resource management agencies. As overlapping management seasons can force choices among substitutable activities, understanding the management of competing activities could potentially improve predictions of fishing effort. However, it is widely known that recreational fishers are heterogeneous in their characteristics and preferences (e.g., avidity, specialization), and this context would influence substitution choices (Oh et al., 2013).

Disaster Events

Disasters such as hurricanes and oil spills can have large, if transitory, effects on recreational fishing effort and catch. Hurricanes can affect recreational fishing effort before, during, and after making landfall. Before landfall, anglers must spend time preparing their boats to weather the storm. During landfall, a period that can last from a few hours to a few days, severe wind and waves reduce fishing effort to zero. Following landfall, anglers must often deal with loss of electrical power, roads blocked by fallen trees, children at home because of school closings, loss of infrastructure, or even damage to boats and homes. To the extent that these hurricane strikes are correlated (either positively or negatively) with recreational fishing effort or catch, it may be possible to use data on hurricane strikes to improve annual and in-season recreational fishery catch and effort forecasts made with recreational fishery projection

[45] See https://www.census.gov/programs-surveys/sis/resources/data-tools/quickfacts.html.

models. Again, in addition to the degree of correlation between hurricane strikes and recreational fishery data, the usefulness of hurricane strike data would depend on the accuracy and precision of the data, the frequency with which the data are collected, and the timeliness with which they are made available.

Even relatively "weak" storms can have significant impacts on fishing effort. A recent example from commercial fishing in North Carolina makes the point. Dumas (2021) surveyed the full population of North Carolina commercial fishermen (N = 2,496, response rate 22.7 percent [n = 566]) in early 2020 regarding fishing activity during 2019. Hurricane Dorian, a Category 1 hurricane, struck North Carolina on September 5–6, 2019 (USNWS, 2019). On average statewide, in addition to missing 2 days of fishing during the actual hurricane strike, survey respondents reported missing five fishing trips before the hurricane strike and an additional nine fishing trips after the hurricane strike because of actions necessary to prepare for and recover from the hurricane.

The U.S. National Hurricane Center produces 5-day and 2-day tropical weather outlooks[46] that could be used to inform recreational fisheries projection models. Hurricane forecast error methodology and verification procedures[47] are also available. For pre–fishing season forecasts, historical hurricane data are available with which to develop seasonal probability distributions for hurricane strikes for particular locations. The Atlantic HURDAT2 dataset is available online in a comma-delimited, text format with 6-hourly information on the location, maximum winds, central pressure, and (beginning in 2004) size of all known tropical and subtropical cyclones.[48]

Oil spills may also have significant impacts on recreational fisheries. For example, Tourangeau and colleagues (2017) and English and colleagues (2018) report on the effects of the *Deepwater Horizon* oil spill that occurred on April 20, 2010, 50 miles off the coast of Louisiana on recreational shore-mode fishing in the Gulf of Mexico. During the first 8 months following the spill, there was a 45.5 percent reduction in beach-based recreational fishing trips in the North Gulf region (i.e., Louisiana to Apalachicola, Florida) and a 22.9 percent reduction in such trips along the west coast of Florida. There was also a 32.8 percent reduction in trips to non–beach shore locations (i.e., fishing from piers, bridges, jetties, etc.) in the North Gulf region. In the period from 9 to 18 months following the spill, the number of beach-based recreational fishing trips remained 10.1 percent below the baseline level. Of the trips that did not occur in the North Gulf or west Florida study regions, approximately 39 percent still occurred but were relocated to the coastal areas of Texas and the east coasts of Florida and Georgia. Results from such studies give some indication of the duration and magnitude of the impacts of disasters on recreational fishing effort, including spatial relocation of fishing effort outside the region of immediate impact.

Internet, Cell Phone, and Social Media Activity

Internet, cell phone, and social media activity patterns could provide another source of continuous data on fishing effort in season. For example, in a case study in Scotland, Mancini and colleagues (2018) investigated the use of photos uploaded to Flickr as an indicator of nature-based recreation on a national scale and at several regional spatial and temporal resolutions. The researchers found that spatial and temporal patterns in photographs of wildlife uploaded on Flickr[49] are reliably described by known survey measures of visitation and that this relationship is reliable down to a 10 km scale resolution.

[46] See https://www.nhc.noaa.gov/gtwo.php?basin=atlc&fdays=5.

[47] See https://www.nhc.noaa.gov/verification.

[48] See https://www.nhc.noaa.gov/data/#hurdat.

[49] Mancini and colleagues (2018) describe how they accessed and used the Flickr data: "Data from Flickr were collected through the Flickr API (Flickr Services, 2021) and R software], using the packages RCurl version 1.95.4.7, XML version 3.98.1.3 and httr version 1.1.0 to communicate with the API, request and download the data. Dates and geographic coordinates associated with the photographs were used to select only those taken in the [national park] between 2009 and 2014. A bounding box was used to query the Flickr API and then a polygon shapefile of the [national park] was used to select only the photographs taken inside the boundaries of the park. We downloaded the following metadata associated with the photographs: photograph and user ID, the date when the photograph was taken and the geographic coordinates of where it was taken. To avoid bias coming from having a small number of very active users,

Merrill and colleagues (2020) estimated daily visitation to water recreation areas in New England using commercially available cell phone location data[50] and ancillary variables. By combining these data with on-the-ground observations of visitation, the authors fit a model for estimating daily visitation for 4 months to more than 500 sites. However, spotty cellphone connectivity in remote areas is one limitation of this method, and spatial autocorrelation and the statistical assumptions made by the providers of cell phone data are issues for further investigation.

A study by social scientists at NOAA's Southeast Fisheries Science Center explored the potential use of regression-based models of Google Trends to estimate in-season harvest rates in the context of changing fishery conditions (Carter et al., 2015). For instance, internet search volume for the term "Red Snapper season" was found to be highly correlated with Red Snapper harvest levels. The study also demonstrated that a "nowcasting" model enhanced with Google Trends data was 29 percent more accurate than predictions based on the previous fishing season. The authors argue that such approaches could improve management responsiveness in fisheries, particularly those in which conditions often change.

Remote Sensing

Remote-sensing and satellite technologies have fundamentally changed the way data are collected and used to forecast the weather, study the climate, manage land resources, and monitor many other natural resources. Early connection of satellite remote-sensing data to fishery was made in the 1970s when it was found that lights from fishing boats can be detected with low-light imaging data collected at night by sensors flown on satellites. Nevertheless, remote sensing was not established as a reliable tool for surveying fishing activities until more recently, when advances in satellite technology and data science techniques finally made this possible. The launch of Google Earth Engine[51] (Gorelick et al., 2017), a cloud computing platform for processing and analyzing global satellite and other geospatial and observation data, had greatly reduced barriers to the use of remote-sensing data. This technology has great potential to provide low-cost auxiliary data that could be used to infer fishing effort and help improve in-season management.

Recent literature has established that three types of remote-sensing data can be used effectively to survey fishing activities. One is Automatic Identification System (AIS) data, the position signal broadcast by ships and picked up by satellite-based receivers. The second is the low-light imaging data collected by

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we used the combination of user ID and date to delete multiple photographs from the same user on the same day, thus retaining only the first photograph taken every day by each user. By counting the number of photographs retained in each month we then obtained the monthly number of Flickr visitor days in the [national park] (a person taking at least one photograph a day in the [national park]). To quantify changes in the popularity of Flickr over the years, we used the number of active users (i.e. users posting content on Flickr)."

[50] Merrill and colleagues (2020) describe how they accessed and used cell phone data: "We purchased data products processed by a third-party provider, Airsage, Inc. This provider creates population-level estimates of human mobility derived from a panel of over 120 million devices using location information from smartphone applications (see S1 File). The data provider processes this device-specific locational information. Before we receive it, the data is anonymized and aggregated to contain no personally identifiable information. We do not obtain any device-level information, nor raw device GPS locations, but instead, we obtain aggregated summaries of visitation by recreation site and estimates of the visitors' origin census block-group geographies. The data provider translates their sample to population-level estimates using weights based on the share of the population their sample represents by census-tract geographies. The cellular device sample we purchased data from includes about 30% of the U.S. population but varies by tract and month. To obtain the cell data for the sample geographies of interest, we spatially buffered (added area) around the water-access sites which were designated as line or point features in the original spatial databases. In consultation with the data provider and after attempting a range of spatial buffers, a 100-meter buffer was chosen to balance specificity in capturing water recreation visits (i.e., not capturing ancillary points of interest in geographies, like restaurants or stores, for example) with the accuracy of the locational information. We sent the defined water recreation areas to the data provider as a set of geographic extents, or polygons, and they returned the aggregated and anonymized processed data in tabular form. We . . . include the entirety of this dataset available with the code package associated with this work at https://github.com/USEPA/Recreation_Benefits.git."

[51] See https://earthengine.google.com.

the National Aeronautics and Space Administration (NASA)/NOAA Visible Infrared Imaging Radiometer Suite (VIIRS). Both of these datasets are publicly available and can be downloaded and analyzed for free through the Google Earth Engine. The third type of remote-sensing data, currently under development, is remote sensing of outdoor parking lot utilization (such as parking lots at public-access boating locations).

In a study published in the journal *Science* (Kroodsma et al., 2018), the authors organized an interdisciplinary team of data scientists, software engineers, ecologists, and economists to design artificial intelligence algorithms that processed 22 billion AIS position signals and turned them into the time and place of fishing activities. The result was a global dynamic footprint of industrial fishing effort with unprecedented spatial and temporal resolution. This methodology is used by the Global Fishing Watch (GFW) to produce a Daily Fishing Hours dataset, which provides estimates of fishing effort measured in hours of inferred fishing activity. These data are available on the Google Earth Engine and can provide valuable information for local fishery management.

Although AIS data have been shown to be very effective at mapping industrial fishing efforts, the data do have two limitations. One is that AIS typically covers only the larger boats used in industrial fishing, and most of the boats used in recreational fishing will not be detected. Another is that the ship operator can disable or tamper with the AIS to evade detection. VIIRS data can serve as a complementary data source to overcome the limitations of AIS data. Currently VIIRS is on board two satellites, the Suomi NPP, launched in 2011, and the NOAA-20, launched in 2017. NOAA's Earth Observation Group produces a nightly global mapping of VIIRS boat detections, which is publicly available online.[52] The VIIRS Day/Night Band (DNB) data are available through Google earth engine. Several recent publications have established that a combination of AIS and VIIRS data can be used effectively to survey certain fishing activity (see, for example, Chen et al., 2019; Geronimo et al., 2018; and Ruiz et al., 2020).

As satellite, artificial intelligence, and machine learning technologies improve, progress is being made in counting filled and unfilled parking spaces in parking lots for the purposes of forecasting general parking demand and improving the efficiency of consumer parking activity in urban areas and transportation in general (Cisek and Lin, 2017; Glaab, 2017; Lambrides et al., 2018; Zambanini et al., 2020). However, such technology could also be used to detect the parking lot utilization percentage at coastal public-access boating locations via satellite remote sensing for use as an ancillary variable that could be useful for forecasting fishing effort on a timelier basis. The percentage of filled parking spaces at public boat ramps is likely correlated with daily fishing effort and in the near future could be assessed daily (electronically, remotely, and automatically), and the data used to help forecast fishing effort on a daily basis. Glaab (2017) notes: "The developed process for parking area detection is robust and achieved a detection accuracy above 95 percent with respect to parking area capacity in fully-exposed image areas. However, the process is not able to sense parking areas that are hidden by objects like roofs or trees."

METHODS FOR INTEGRATING MRIP, SUPPLEMENTAL AND AUXILIARY DATA

MRIP can continue its efforts to identify innovative approaches to data collection and data sharing that will support improvements in in-season management. Included in these innovation efforts is continued work on modeling and statistical integration methods (Allen, 2017; Zhang and Chambers, 2019) that draw on MRIP data streams, supplementary data, and auxiliary data to improve timely forecasting and tracking of both point-in-time and cumulative statistics on recreational catch. This section presents several lines of potential development related to catch forecast modeling using MRIP data and other available data sources.

Small Area Estimation Methods

Small-area estimation (Rao and Molina, 2015) considers the problem of producing reliable estimates of parameters of interest and the associated measures of uncertainty for subpopulations (areas or domains) of a finite population for which samples of inadequate size or no samples are available. An

[52] See https://www.ngdc.noaa.gov/eog/viirs/download_boat.html.

example would be attempting to produce reliable estimates of fish catch for MRIP domains with small sample sizes. Areas (domains) are considered "small" if the sample size for the area is not large enough to yield direct estimates of the variables of interest (means, totals, ratios, etc.) with adequate precision (i.e., sufficiently low PSE).

Direct Estimation Methods

The traditional, "direct" methods for producing estimates for a small area are those based solely on the sample data collected within the small area and perhaps auxiliary data describing the same small area. Direct estimates (Cochran, 1977) are generally "design-based" in the sense that they make use of "survey weights," and the associated inferences (e.g., standard errors, confidence intervals) are based on the probability distribution induced by the sample design, with the population values held fixed. Although direct methods typically produce unbiased estimates, it is often not possible to achieve a sufficiently large overall sample size to achieve acceptable precision (PSE) for small-area domains of interest. For example, to produce reliable estimates for small areas the size of school districts, a sample of at least one in six households would be required nationwide (Rao and Molina, 2015).

The problem of low precision in small-area domains that is typical for direct estimation methods may be ameliorated somewhat by applying "compromise sample allocation" (Rao and Molina, 2015, Section 2.7). Compromise sample allocation is achieved by "oversampling" small areas, that is, shifting some of the sample effort from "nonsmall" areas to "small" areas. This can sometimes substantially increase the precision of the estimates for small areas at the cost of a slight decrease in precision for aggregate estimates over the total population. In an example involving the Canadian Labour Force Survey, Singh and colleagues (1994) found that compromise sample allocation could reduce the coefficient of variation (CV) of the direct estimate of the number of unemployed persons from 17 percent to 9.4 percent for small areas while increasing the CV of the aggregate estimate at the province level from 2.8 percent to only 3.4 percent and the CV of the aggregate estimate at the national level from 1.36 percent to only 1.51 percent.

Indirect Estimation Methods

In cases in which sample size and compromise sample allocation are not sufficient to produce reliable estimates for small areas, "indirect" estimation methods can be used. This approach moves away from design-based/direct estimates to indirect, model-dependent estimates. Other terms for indirect estimation include "nontraditional," "small-area," "model-based," "model-dependent," and "synthetic" methods. Increasing the precision (reducing the mean square error) of the estimates for small areas beyond what is achievable with direct estimators is the main reason for using indirect estimators. For example, Young (2019) and Cruze and colleagues (2019) provide an overview of many model-based techniques currently used by the U.S. Department of Agriculture's National Agricultural Statistics Service (USDA NASS) (e.g., Cruze and Benecha, 2017). Wang and colleagues (2012), Nandram and colleagues (2014), and Cruze (2016) developed model-based approaches for combining multiple sources of survey data with other sources of information, with the aim of improving the NASS crop forecasting process (NASEM, 2017b). The forecasts precede the publication of end-of-season state estimates, similar to the situation in which in-season forecasts of fish catch are needed for in-season management before the end-of-season final catch estimates are available.

The indirect, model-dependent approach employs a statistical model for a small area that links variables of interest and auxiliary data and/or "borrows strength" from other small areas or other time periods. Regression models, mixed-effect models, and spatial-temporal models are typically used to bring information from auxiliary data and data in related areas (domains) to the estimation process. The availability of good auxiliary data and determination of suitable linking models are crucial to the development of indirect estimates. See, for example, Cruze (2015) and Erciulescu et al. (2019), which present models for integrating survey data with auxiliary sources of information to estimate crop yields, and Wang et al. (2018), which uses regression and spatial models to estimate proportions in small areas in the National Resource Inventory survey.

The issues of aggregation over domains and benchmarking are important for indirect estimators (Erciulescu et al., 2018). Aggregation refers to the problem of ensuring that estimates produced at different domain levels (e.g., county, state, and region) are consistent. Benchmarking refers to the problem of ensuring that area-wide estimates are consistent with external, overall estimates (e.g., Bell et al., 2013; Erciulescu et al., 2019; Nandram et al., 2019; Pfeffermann and Barnard, 1991). Solutions to these problems can depend on the type of estimate desired—a numerator, a denominator, and/or their ratio (e.g., fish catch, fishing effort, and catch per effort). Simultaneously estimating a *set* of desired statistics (e.g., a numerator, a denominator, and their ratio) is a difficult problem because the final triplet estimates need to satisfy identity constraints (ratio of numerator to denominator) as well as benchmarking constraints at multiple aggregation levels. Erciulescu and colleagues (2018) explore different methods of constructing model-based estimates for two totals and their ratio at lower-level domains that aggregate to fixed values at upper-level, aggregate domains.

Indirect estimators can be classified by the source of data from which they "borrow strength:" A "domain indirect" estimator makes use of y-values from another domain but not from another time period. A "time indirect" estimator uses y-values from another time period for the domain of interest but not from another domain. A "domain and time indirect" estimator uses y-values from both another domain and another time period.

Indirect estimators can be further categorized as "synthetic," "composite," or "James-Stein" (or shrinkage) (Rao and Molina, 2015, Sections 3.2–3.4).

Synthetic Estimators

"Synthetic" estimators combine a direct estimator that is reliable for the total, aggregate area, with the assumption that the small areas have the same characteristics as the large area, to derive better estimates for the small areas. The Horvitz-Thompson direct estimator is typically used for the large area. Synthetic estimators typically use auxiliary information at the area level or at the individual sample unit level (e.g., Cruze, 2015). (For cases in which the only available auxiliary information is the population area sizes, the broad area ratio estimator can be used.) An example of a synthetic estimator is a regression that estimates the relationship between the variable of interest and auxiliary variables for the non–small areas in a region, which is then used to produce estimates of the variable of interest for small areas in the region. Hansen and colleagues (1953, pp. 483–486) described the first application of a synthetic regression estimator in the context of a radio listening survey.

Although synthetic estimators may reduce the variance (PSE) of estimates for small areas, they typically produce biased estimates. If the assumption that small areas have the same characteristics as the large area is not fulfilled, for example—if selection effects cause systematic differences in the target variable between a small domain and the population—then synthetic estimators can be heavily biased. Furthermore, for some synthetic estimators, the estimates for small areas do not add up to the direct large-area estimate. In such cases, adjustment is needed to ensure the coherence of estimates at different levels of aggregation.

Composite Estimators

"Composite" estimators are the weighted average of a direct estimator and a synthetic estimator, sometimes with a different weight for each domain. This estimator is more useful when there is substantial variation in sample sizes across domains. The weight(s) are typically optimized to minimize the mean square error (MSE) of the composite estimator; however, it is often the case that even sizable deviations from the optimal weight do not produce a significant increase in the MSE of the composite estimator. Composite estimators represent an attempt to achieve a balance between the low-precision problem of direct estimators and the bias problem of synthetic estimators. The larger the sample size in the small-area domains, the more weight should be placed on the direct estimator.

Sample-size-dependent (SSD) estimators are composite estimators with simple weights that depend only on the domain counts or the domain totals of an auxiliary variable. General SSD estimators provide consistency when aggregated over different characteristics because the same weight is used for all of them. UnforTunately, general SSD estimators for subdomains do not add up to a direct estimator at a large-area level; however, a simple ratio adjustment can correct this problem. As an example, Statistics Canada now uses the Fuller-Rao method (Fuller and Rao, 2001) for its official labor force statistics production. Bonnery and colleagues (2013) found that the Fuller-Rao method outperformed the direct estimation method when applied to U.S. Current Population Survey data on U.S. unemployment rates. Opsomer and colleagues (2003) provide another example of a regression composite estimator applied to watershed erosion.

James-Stein Estimators

In general, many statistical methods attempt to produce unbiased estimates with the lowest possible variance. For example, in the traditional linear regression statistical model with independent and identically distributed normal errors, the least-squares estimator or the maximum likelihood estimator can be used to produce unbiased estimates with minimum possible variance. “Stein rules” (Stein, 1955; Judge et al., 1985, Chapter 3; Judge and Bock, 1983) are statistical methods that attempt to produce estimates with even lower variance, but at the cost of allowing a bit of bias in the estimates. Given the typically large variance in forecasts of fish catch, fishery managers may be willing to accept a little bias in the catch estimates if the variance (PSE) can be reduced substantially. For example, a fishery manager might be willing to accept 5 percent bias in the catch estimate if the PSE can be reduced from 70 percent to 30 percent.

James and Stein (1961) developed an estimator that, under squared error loss, has lower expected loss for all possible values of the unknown parameters relative to the least-squares estimator. This means that the unbiased least-squares estimator has higher MSE compared with the biased James-Stein estimator. “James-Stein estimators” are a special case of a composite estimator in which the weights are the same for all small-group domains. This ensures good precision for the group of small areas but not necessarily for individual small areas that have unusually large or small deviations from the mean. However, the estimate of the weight is very reliable because it comes from pooling over small areas. Large gains in precision can be achieved over traditional design-based estimates without assuming a model for the individual small-area parameter weights.

Other estimators similar to, or derived from, the James-Stein estimator have been developed for various applications (Efron and Morris, 1975), including incorporation into Bayesian model frameworks (Efron and Morris, 1973). James-Stein rules used in conjunction with inequality restrictions on the parameters, so-called “positive Stein rules” can achieve MSE even lower than that of the James-Stein rule (Judge and Bock, 1978). Stein rules in general are simply a type of pretest estimator that is used to optimally combine unrestricted and restricted least-squares estimators. (In fact, if some parameter restrictions [equality or inequality restrictions] are known to be true, then the restricted least-squares estimator can produce unbiased estimates with MSE lower than that of simple least squares [Judge, 1985, Chapter 3]).

For example, the “Fay-Herriot” method (Fay and Herriot, 1979) is a popular implementation of the James-Stein rule concept. The Fay-Herriot method has been applied to estimate per capita income and poverty in small towns (NRC, 2000) and agricultural crop yield and acreage (Cruze et al., 2019), as well as to calibrate Coastal Household Telephone Survey (CHTS) and FES survey data in MRIP (Papacostas and Foster, 2018, pp. 62–66).

Although James-Stein rules may produce good estimates on average across all observations in the dataset, they may not do so for particular data points, such as outliers. To limit the maximum bias possible for the estimate of any particular data point, Fay and Herriot (1979) use an inequality-restricted form of the James-Stein rule. The inequality restrictions limit the maximum bias while still achieving much of the reduction in MSE. It is important to note that Fay and Herriot (1979) present several other versions of James-Stein rule estimators that are appropriate for various circumstances, including estimators incorporating ancillary variables, and estimators can be integrated with a Bayesian modeling framework. If fishery managers are willing to accept some amount of bias in catch forecasts, then it may be possible to develop custom, "Stein rule"–like estimators to reduce the variance (PSEs) of catch forecasts and lower the forecasts' overall MSE.

Small Area Models

Small-area models are small-area estimation methods that account for differences in variation among areas (domains) beyond those explained by auxiliary variables included in the model. Unlike the global (averaged over small areas) measures of precision produced by synthetic estimators, area-specific measures of precision (PSEs) can be associated with each small-area estimate.

The essence of all small-area methods is the use of auxiliary data available at the small-area level, such as administrative data or data from the last census. These data are used to construct predictor variables for use in a statistical model that can be used to predict the estimate of interest for all small areas. The effectiveness of small-area estimation depends initially on the availability of good predictor variables. One key distinction in small-area models is between situations in which the auxiliary data are available for the individual units in the population and those in which they are available only at the aggregate level for each small area. In the former case, the data can be used in unit-level models, whereas in the latter they can be used only in area-level models. Aggregate-level (or area-level) models are the models that relate small-area direct estimators to area-specific auxiliary variables. Such models are necessary if unit- (or element-) level data are not available. Unit-level models are the models that relate the unit values of a study variable to unit-specific auxiliary variables.

Area-Level Models

Area-level models rely on area-specific auxiliary data and typically assume that the sampling variance in each domain is known and that the model in each domain is the same as the population-level model. The Fay-Herriot (1979) model is an example of an area-level model. Extensions of the Fay-Herriot model address multiple response variables, correlation in sampling errors across areas, and spatial effects. Rao and Yu (1992, 1994) present a Fay-Herriot model based on time-series cross-section data. Nandram and colleagues (2019) present a Fay-Herriot model in a Bayesian framework. The panel that authored a recent National Academies report (NASEM, 2017b) on improving small-area estimates for agricultural variables found that USDA-NASS was pursuing area-level models (Cruze et al., 2016; Erciulescu et al., 2019). In the report, the panel suggests starting with area-level models. It is straightforward to add covariates to such models. The covariates may be added via a simple linear model or via a more flexible form, such as those used in the machine learning literature; it would be best to begin with simple, interpretable models. The panel suggests that NASS begin by exploring county-level models using the area-level spatial Fay-Herriot model to describe survey measurements. Each alternative data source could be given its own data model, linked to the larger model in a hierarchical Bayes framework.

Unit-Level Models

Unit-level models rely on unit-specific auxiliary data. A critical assumption for unit-level models is that the sample values within an area obey the assumed population model; that is, sample selection bias is absent.

Bayesian Approaches

There are also now a number of Bayesian approaches, including empirical Bayes (EB) and hierarchical Bayes (HB), which can be used to estimate small-area models and the variability of small-area estimates (e.g., Nandram et al., 2014; Wang et al., 2012; Cruze, 2016). According to the above-referenced National Academies report (NASEM, 2017b) on improving small-area estimates for agricultural variables:

The panel believes that the Bayesian approach holds great promise as recent developments have allowed combining design-based estimates with space–time smoothing models. For example, Mercer and colleagues (2015) effectively use a spatial Fay-Herriot (1979) model in the context of modeling childhood mortality based on complex survey data. The basic idea is to assume a hierarchical model in which the first stage is taken as the asymptotic distribution of the direct (design-based) estimator.

Software Implementation

Molina and Marhuenda (2015) produced the R software package "sae" for conducting small-area estimation.[53] Small-area estimation procedures are also available in SAS (Mukhopadhyay and McDowell, 2011).

Capture-Recapture Methods

Liu and colleagues (2017) present the "capture-recapture" methodology (King and McCrea, 2019) for combining MRIP data with angler smartphone data (in this case, captured by the Texas iSnapper program) to estimate total catch. The investigators developed several statistical estimation models in which "all the proposed estimators allow measurement error in the self-reports and do not make any assumptions about their representativeness." The capture-recapture estimators are compared with one that "makes use only of catch observed in the validation sample but not self-reports of catch" (i.e., MRIP estimates). The authors discuss the assumptions, strengths, and weaknesses of the capture-recapture method, report on simulations conducted to assess the relative strength of the estimators, present the results of an example in which they attempted to estimate the total catch of Red Snapper in 2015 in Texas by recreational anglers in private boats using data from the iSnapper program, and provide recommendations regarding which estimator might be preferred depending on conditions in the fishery. Stokes and colleagues (2021) discuss three types of nonsampling error (undercoverage, matching error, and lack of independence between APAIS intercept and smartphone reporting rate) that can occur when MRIP data and self-reported data from smartphone apps are used to estimate catch using capture-recapture methods. The researchers estimate the bias in catch estimates from each source of nonsampling error in an application to recreational fisheries in the Gulf of Mexico in 2017.

Multiple-Frame Methods

Multiple-frame survey methods may be of interest when considering the potential use of additional, special-purpose surveys to supplement MRIP in order to reduce the variance and PSEs of catch estimates used for in-season management. The use of multiple-frame methods has been discussed and recommended in previous MRIP reviews (NRC, 2006, pp. 9, 63, 64, 67, 81-82, 113-114; NASEM, 2017, p. 149). In a multiple-frame survey, probability samples are drawn independently from multiple sample frames; usually, the samples are drawn using separate surveys, and the data from the separate surveys are then combined and analyzed together. For example, one survey might be MRIP, and another survey might be Florida's State Reef Fish Survey (SRFS). Sample frames may overlap; for example, the MRIP and SRFS sample frames overlap for the domain of Florida reef fish anglers. The union of the sample frames is assumed to cover the finite (angler) population of interest. When a multiple-frame survey uses just two sample frames, it is called a dual-frame survey. FES is a dual-frame survey, using both a list frame of licensed anglers and a secondary list frame based on the U.S. Postal Service address-based frame of households (NASEM, 2017, p. 124). APAIS and FES also have different sampling frames: APAIS is based on a spatial-temporal frame,

[53] See http://cran.r-project.org/web/packages/sae/sae.pdf.

and FES is based on an address (list) frame. MRIP combines information from the two frames to produce total catch estimates.

Hartley (1962) found that a dual-frame survey can cost far less than a single-frame survey that achieves the same precision. Of more interest in the case of combining MRIP with supplemental surveys, Hartley also found that a dual-frame survey can reduce the variance of estimates of population totals (such as total fish catch) compared with a single-frame survey of the same cost. Others[54] have since extended the Hartley methodology. Hartley applications concentrate on a situation in which one frame completely covers the population of interest but is expensive to sample, while the other frame is cheap to sample but covers the population incompletely. The MRIP survey is generally assumed to cover completely the population of licensed recreational saltwater anglers, while other, special-purpose surveys do not cover the population completely but may give more detailed information on a particular domain, such as Florida reef fish anglers, within the overall population of anglers.

Multiple-frame surveys are becoming more common as surveyors attempt to increase the precision of survey estimates at the least cost, especially for subdomains of the population (Lohr and Rao, 2006). For example Madans and colleagues (2001) discuss multiple-frame surveys in the context of supplementing information from the U.S. National Health Interview Survey (NHIS). Supplemental surveys may be conducted at the state level and then combined with information from the NHIS for improved estimation at the state level. Andrews and colleagues (2010, 2013) conducted pilot studies applying multiframe methods to fisheries surveys in North Carolina, but did not address the particular issue of variance reduction for the purpose of in-season management.

The example presented in Appendix A, on multiple-frame methods, illustrates how Hartley's basic dual-frame estimator could be applied to the case of combining existing MRIP survey estimates with a supplemental survey for the purpose of reducing the variance of a catch forecast. Several new methods developed in the recent literature have an advantage over traditional methods. Skinner and Rao (1996) and Lohr and Rao (2006) developed a pseudo-maximum likelihood estimator (PMLE) that can be used to combine complex survey data from two or more sampling frames with high efficiency. One common issue in combining survey data from multiple frames is that the response variables from different surveys are often not identical. Measurement error modeling is a useful approach to integrate such survey data (Park et al., 2017). Another promising new approach for combining data from multiple independent surveys is model-assisted imputation, in which a working model is built at the unit level to generate estimates of variables of interest in survey A using auxiliary variables in survey B (Kim and Rao, 2012). A projection estimator can be constructed by applying the survey weights in survey B to the synthetic value, which is asymptotically unbiased under certain general conditions. Combining multiple frame surveys is not a trivial task. The effectiveness of this approach depends on the coverage and sample size of the supplemental surveys, the correlation of variables in different surveys, and the magnitude of the measurement error. One also need to consider the cost of building models to connect multiple surveys in addition to the cost of supplemental surveys when planning for a multiple-frame approach.

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[54] Hartley (1974) and Fuller and Burmeister (1972) found that multiframe estimators minimize the variance among the class of linear unbiased estimators of a population total, such as the total catch of a population of anglers. Cochran (1964) compared the variance of multiple-frame estimators with that of screening estimators having the same total sampling cost. Rao (2003) examined the uses of multiple-frame surveys for small-area estimation, where a sample from an area frame may be supplemented by less-expensive samples from list frames. Bankier (1986) and Kalton and Anderson (1986) developed single-frame estimators in which observations are weighted according to their inclusion probabilities for the two frames. Skinner (1991) proposed raking ratio estimators for the situation in which simple random samples are taken from each frame, and Skinner and Rao (1996) derived a pseudo-maximum likelihood estimator (PMLE) for the response variable for dual-frame surveys using complex designs. Lohr and Rao (2000) compared the asymptotic efficiencies of dual-frame estimators and found that the PMLE combined high efficiency with applicability to complex surveys. Lohr and Rao (2006) extended the PMLE of Skinner and Rao to the case of more than two sample frames and conducted a simulation study to explore the finite-sample properties of alternative estimators for simulated two-frame and three-frame designs; they found that "the PMLE is a good choice for a wide variety of conditions."

Statistical Data Integration for In-Season Management: Integrating Data from Multiple Sources

Collecting probability-based sample survey data such as MRIP and supplemental fishery survey data is expensive, and survey-based estimates alone are unlikely to meet all the data needs of in-season management under current budgetary constraints. Statistical data integration is an active research area that provides tools for combining MRIP and supplemental fishery survey data with nonprobability survey data for valid statistical inference. The challenge is to overcome the small sample size in survey data sources and the selection bias and undercoverage in big data sources to produce estimates that are asymptotically unbiased with high precision. Lohr and Raghunathan (2017) performed an early review and identified some limitations of the existing methods at that time. Kim and colleagues (2018) developed a hierarchical multilevel model for integrating survey data, administrative records, and remote-sensing data to improve subarea estimates of planted acreages for different crops. Chen and colleagues (2020) developed a general framework for constructing doubly robust estimates based on nonprobability sample data and auxiliary data from a probability survey sample. Kim and Tam (2020) developed a two-step regression-based data integration method for the Australian Agricultural Census that can handle the measurement errors in both probability samples and big data sources. Rao (2020) gives an up-to-date overview in this area and provides more detailed discussion of the application to small-area estimation. These recently developed methodologies can be applicable to integrating recreational fishery data for in-season management.

Model-Based Projections/Forecasting/Nowcasting Approaches

Statistical models for forecasting, or projecting, fish catch with a timely frequency are critical for fisheries management (Farmer and Froeschke, 2015; Makridakis et al., 2008; Stergiou and Christou, 1996), especially under an ACL (Farmer et al., 2020; Lee et al, 2017). Catch per time period must be forecast before the season begins so that total, cumulative catch can be forecast and the appropriate season length to meet the ACL determined. In cases in which it is desirable to hold season length constant, catch forecasts are still necessary to determine what changes in other management tools, such as bag or size limits, may be necessary to meet the ACL under a fixed season length. Forecasts are also necessary for applying in-season or postseason AMs, including predicting closure dates. Forecasts are useful as well for establishing a "status quo" catch and estimating the catch under alternative management scenarios when comparing the potential biological and socioeconomic impacts of alternative management actions.

This section briefly reviews existing forecasting methods that have been applied to catch forecasting in fisheries management and describes some potential new methods. The discussion focuses on methods that could be used to improve the accuracy and precision of catch forecasts based on MRIP catch estimate data, perhaps integrated with additional data from supplemental surveys and ancillary variables. The methods assume that the MRIP catch estimates will be produced using the existing MRIP methodology, or perhaps with modifications to the methodology that would support more frequent MRIP catch estimates (e.g., perhaps monthly or weekly rather than the current bi-monthly estimates). However, modifications to the existing MRIP methodology would likely require technological innovations or additional funding (i.e., increased sampling). When combined with supplemental or ancillary data, some of the methods described in this section may also be useful for increasing the timeliness and frequency of in-season catch forecasts using the current MRIP methodology.

As an example of an existing forecasting model, Lee et al. (2017) developed a bioeconomic model for forecasting recreational catch of cod and haddock in the Northeast Region that integrates a model of angler demand for recreational fishing trips with an age-structured stock dynamics model. The model has been in use since 2012. The model combines past MRIP estimates, stock assessment results, and a model of angler trip behavior to project catch, discards and the effects of recreational removals on the fish stock. The model can make forecasts by month and can project out 3-4 years. The model relies heavily on in-season MRIP data, but the high PSEs (low precision) of MRIP estimates limit their usefulness; furthermore, as waves progress within a season, the PSEs increase. The model is especially useful for forecasting the impacts of alternative management policies (e.g., size limits and possession limits) and fishery parameters (e.g., discard mortality rates and fish length distributions) on recreational catch and discards. Although there are several directions for potential model improvement (e.g., allowing anglers to reallocate/shift trips across waves, incorporating information on weather and general economic conditions, considering contemporaneous correlation, etc.), this model is a good example of how a forecasting model using MRIP data can contribute to fishery management under ACLs.

Leveraging Covariances and Conditionals Across Domains

MRIP provides estimates of fish catch and its variance by *domain*, where a domain is defined as a particular combination of fish species, 2-month wave time period, geographic state or substate location, fishing area (inshore, state ocean waters, or federal ocean waters), and fishing mode (private boat, shore-based, charter, or headboat). Typically, information from only one domain is used by fishery managers to forecast catch for that domain. This approach neglects information in patterns that may exist in the data *across domains* that might be useful for increasing the precision (decreasing the PSEs) of catch and effort *forecasts*, such as those made for the purpose of in-season management by fishery managers using the MRIP output estimates.

When fish catch in one domain moves together with fish catch in another domain, the *covariance* between the two fish catches is positive. When the catches move in opposite directions, the covariance between the two catches is negative. The focus here is not on covariances due to sampling errors in the MRIP survey sampling methodology, but on covariances that reflect the true, underlying relationships among the variables (catches) being estimated by MRIP. In other words, assuming that MRIP perfectly measures catch and that each MRIP estimate is statistically independent (as intended) of every other MRIP estimate, some catches would covary because they were being driven by the same underlying variables.[55]

For example, one might expect that the covariance between the catch of two species in a particular location that prefer the same water temperatures would be positive because when the water is warm, both species would be more abundant in that location and catches of both would be higher, whereas when temperatures are low, both species would be less abundant and catches of both would be lower.[56] Inversely, one might expect that the covariance between the catch of two species that prefer different water temperatures would be negative.

As another example, the catches of predator and prey species might have a negative covariance (high predator concentrations result in low prey concentrations, and low predator concentrations result in high prey concentrations). Or, if increases in the Dolphin population led to increased Dolphin catches in both the charter boat and private boat fisheries, and decreases in the Dolphin population led to decreased catches in both fisheries, then the covariance in Dolphin catch between the two fisheries would be positive. As yet another example, if the Dolphin population increased off the coasts of both North Carolina and South Carolina, one might expect the Dolphin catch in both states to increase, and one would expect the covariance to be positive between the North Carolina Dolphin and South Carolina Dolphin catches.

The covariance in catch across MRIP domains is likely not zero for many domain combinations. The reason behind this observation is that MRIP produces a catch estimate for each domain by multiplying

[55] In a simple linear regression forecasting model context, suppose one regresses the time series of Spanish mackerel catch on the time series of king mackerel catch. Suppose (as intended) that MRIP produces a time series of statistically independent estimates of the catch of each species at each point in time. Then, while the (autocorrelation-adjusted) errors in the regression model would be independently (and for the sake of discussion identically) distributed, the estimated *regression coefficient* would likely be positive, because the catches of Spanish and king mackerel tend to move up and down together. The discussion here is concerned with the *regression coefficient* as an indicator of correlation, and hence covariance, between the catches rather than with the MRIP sampling program that produced the catch estimates.

[56] As another example of potential correlation in catches across species, Lee et al. (2017) note: "If cod and haddock are co-located in the ocean, then the number of cod caught on a trip is likely to be positively correlated with the number of haddock caught on that trip."

an estimate of fishing effort (i.e., fishing trips) for the domain by an estimate of the catch per unit effort (i.e., catch per fishing trip), or CPUE, for the domain. The estimates are weighted such that the effort estimate is statistically independent of the CPUE estimate *within a domain*. However, the effort in one domain may be correlated with the effort in another domain, not because of any problems with the MRIP sampling or estimation methodology but simply because the true efforts are actually moving in the same direction.

For example, if anglers increased trips to two fishing areas over time, then the effort in both areas would increase together—the efforts in the two areas would be correlated over time and not independent. MRIP would produce statistically independent estimates of each effort data point, but the actual effort variables themselves would not be independent, either because there was a true causal relationship between the variables or because there was a third "driver" variable influencing both effort variables. Similarly, CPUE in one domain may not be independent of CPUE in another. For example, suppose that warm seawater temperatures increased the local abundance of two different fish species in a given area, then the CPUE for both species (both domains) would increase together—the CPUEs would be correlated across species and not independent.

Finally, effort is likely not independent of CPUE across locations or time periods. For example, Gillig and colleagues (2000) investigated the effect of Red Snapper CPUE (from the Marine Recreational Fishing Statistics Survey [MRFSS]) on fishing effort (trips per angler) targeting Red Snapper for reef fish anglers in the Gulf of Mexico in 1991. The researchers conducted a cross-section study and found that CPUE was correlated with fishing effort. This implies that the covariance between fishing effort and CPUE across locations is not zero. Similarly, the covariance between fishing effort and CPUE across time periods is likely not zero. Fish length and the length distributions of fish catch may also be correlated by fishing location, time period or fishing mode; for example, Lee et al. (2017) note: "If fish aggregate by size then the lengths of fish caught on a trip are likely to be positively correlated. …Human behavior, such as angler skill or targeting, could also produce positive or negative correlations between [catch] numbers and length within and across species."

Appendix B, on Leveraging Covariances and Conditionals, provides examples of some methods that use covariances between domains and the concepts of conditional expectations and conditional variances to improve catch forecasts made by fishery managers. The first section of Appendix B describes how the covariance in catches across domains depends on the covariance of effort (trips) and the covariance of CPUE across domains. The second section describes how conditional expectations and conditional variances might be used to decrease the variance (PSE) of catch forecasts made by fishery managers. The third section describes how covariances, conditional expectations, and catch information across domains and such auxiliary variables as wind speed, water temperature, or fuel prices could be used to improve catch forecasts and reduce their variance. The fourth section points out the important role of covariances when fishery managers choose to aggregate or disaggregate MRIP catch estimates across domains after receiving the catch estimates from MRIP, with a subsequent note on why covariances among catches in a multispecies fishery constrained by a binding ACL will likely be negative. The final section of Appendix B describes how covariances could be used together with the methodology of control variates to reduce the variance of catch forecasts.

Despite the possibility of improving catch forecasts through the use of auxiliary variables and forecasting models, these methods may not lead to significant forecast improvements in some situations. For example, the Oregon Department of Fish and Wildlife (ODFW, 2012) found that Yelloweye Rockfish, a rare species with highly variable catch that often reaches its ACL before the catch limits of other non-overfished Groundfish species: " . . . do not appear to be strongly related to economic indicators (e.g., gas prices, stock market, unemployment), weather (e.g., wind, waves, or ocean condition (wind and waves interaction together), or strength of other fisheries (e.g., Tuna, Halibut, and Salmon harvests) (Figures 6-3). Weak relationships between the mentioned indicators and Yelloweye impacts would lead to poor goodness of fit with multivariate analysis (e.g., regression), and would lead to wide prediction intervals with little value for management purposes. Until more accurate predictions of Yelloweye Rockfish impacts can be made, inseason management of Groundfish fisheries will have to remain reactionary." Thus, the applicability of these methods will likely need to be evaluated on a fishery-by-fishery basis, or perhaps for categories of fisheries that share similar characteristics.

Spatial-Temporal Models

Spatial-temporal statistical projection/forecasting models attempt to explain the values of one or more dependent variables (such as catch of one or more fish species) based on past values of the dependent variables, and perhaps based on the current and past values of other, independent ancillary variables (such as estimates of stock abundance, season, weather, fuel prices, or the catch of other species) (Hanson et al., 2006). In doing so, spatial-temporal models make use of covariance relationships and conditional relationships among variables, as discussed in the previous section; in this sense, spatial-temporal models can be considered extensions of the concepts discussed in the previous section.

MRIP provides estimates of catch and the variance (PSE) of catch by species. In addition, for each species, MRIP provides these estimates by geographic location, fishing mode, fishing area, and time period. Spatial models attempt to explain the differences in MRIP catch estimates across geographic locations (that is, across "space"), fishing modes, or fishing areas; temporal models attempt to explain the differences in MRIP catch estimates across time periods (that is, across time). Spatial-temporal models attempt to explain differences in MRIP catch estimates across both space and time.

From the perspective of constructing projection/forecasting models of fish catch, fishery managers are very forTunate to have the MRIP estimates of fish catch and the variance of fish catch by species and for different geographic locations and time periods. The MRIP estimates provide a wealth of information that can be used, likely in combination with data on supplementary and ancillary variables, to construct projection/forecasting models of annual catch and catch by 2-month wave. Farmer and Froeschke (2015) found that "federal projection assumptions have been refined over time to better account for changes in average weights and daily catch rates. These refinements have led to increasingly more accurate predictions" (NMFS-SERO 2013, 2014, 2015, 2016).

Better forecasting models can lead to more opportunities for anglers. For example, because of the accuracy of the federal for-hire forecasts for Red Snapper in the Gulf, the Gulf Council recently reset the component ACT buffer for the federal for-hire component of the Red Snapper fishery from 20 percent to 9 percent below the federal for-hire component ACL, allowing a greater harvest while meeting the ACL (GMFMC, 2019). Where data are sufficient, it may be possible to develop models that produce catch estimates for more frequent time periods, such as by month or week. Good (accurate and precise) projection/forecast models that produce timely and high-frequency forecasts are needed for in-season management.

Cross-Section (Spatial) Models and Spatial Heteroskedasticity

Cross-section models are spatial regression models that attempt to explain the variation in catch of a given species across different geographic locations, in a given fishery (fishing mode), for a given time period. Each observation in the model is fish catch at a different location, where all the catches occur during the same time period. Supplementary and ancillary variables can be used as explanatory variables in an attempt to determine the factors that cause the catch of a given species in a given fishery to differ across locations at a given time. These models make use of MRIP estimates of mean catch and the variance in catch at different locations for a given species in a given fishery at a given time period. The MRIP estimates of the means and variances of catch for a particular species in a particular time period usually differ by location. These models typically exhibit "spatial heteroskedasticity"—the variance in catch differs across geographic locations at a given point in time (Judge et al., 1985, Chapter 11). In cross-section models that account for heteroskedasticity, the variance of catch is allowed to vary across locations, but the variance in one location is independent of the variance in another (in contrast to the spatial autocorrelation and "seemingly unrelated regression" SUR models discussed below, in which the variances are not independent across locations).

If catch projection/forecasting models do not account for heteroskedasticity, then although estimates of the forecast model parameters will be unbiased, estimates of the variance (and thus standard errors) of the parameters will be biased, and the direction of bias will be uncertain. Furthermore, the estimate of the variance (PSE) of the catch forecast itself will be biased and the direction of bias uncertain.

Time Series (Temporal) Models and Temporal Heteroskedasticity

Time series models are temporal regression models that attempt to explain the variation in catch of a given species across multiple time periods, in a given fishery (fishing mode), at a given geographic location. Each observation in the model is fish catch at a different time period, where all the catches occur at the same location. These models make use of MRIP estimates of mean catch and the variance in catch across different time periods for a given species in a given fishery at a given geographic location. The MRIP estimates of the means and variances of catch differ across the different time periods. Supplementary and ancillary variables are used as explanatory variables in an attempt to determine the factors that cause the catch of a given species in a given fishery to differ across time periods at a given location. These models typically exhibit "temporal heteroskedasticity"—the MRIP estimates of the variance in catch differ across time periods (Judge et al., 1985, Chapter 11). In time-series models with heteroskedasticity, the variance of catch is allowed to vary across time periods, but the variance in one time period is independent of the variance in another (in contrast to the temporal autocorrelation models discussed below, in which the variances across time periods are not independent).

Again, if catch projection/forecasting models do not account for heteroskedasticity, then although estimates of the forecast model parameters will be unbiased, estimates of the variance (and thus standard errors) of the parameters will be biased, and the direction of bias will be uncertain. Furthermore, the estimate of the variance (PSE) of the catch forecast itself will be biased and the direction of bias uncertain.

Temporal Autocorrelation Models

Temporal autocorrelation models (Judge et al., 1985, Chapters 7–10), also called "autoregressive" or "moving average" models, are time-series models in which the dependent variable in the current time period in a particular location (say, the catch of a particular fish species in the current time period in a particular location) may be affected by past values of the dependent variable in that location (past catches of the species in the location). In this situation, the effects of an unexpected "shock to the system" in one time period may linger for subsequent time periods, affecting catch in subsequent time periods. For example, the effects of unexpectedly good recruitment in one year might be observed in several subsequent years. Similarly, the negative effects of an unexpected hurricane strike on effort and catch might linger for several 2-month wave time periods. Temporal autocorrelation models estimate the magnitude of such lingering effects and estimate how long the effects might persist.

If autocorrelation is present between MRIP estimates of catch (across either years or waves), then although the estimates of forecast model parameters will be unbiased, estimates of the variance (and thus standard errors) of the model parameters will be biased, typically downward, which means that fishery managers are more likely to conclude that a variable in the model has a statistically significant effect on catch when in fact it does not. Furthermore, if autocorrelation is present, the variance (PSE) of a catch forecast made using the model will typically be biased downward. If the variance is biased downward, then the PSE of the catch forecast is underestimated.

MRIP catch estimates are derived from APAIS estimates of catch per trip and FES estimates of trips. Autocorrelation across time in APAIS estimates of catch per trip for a particular species could be caused by variable recruitment, for example, which leads to a recruitment "pulse" flowing through the fish population over succeeding years. (Negative autocorrelation could also occur within a season, as high catch per trip early in the season could reduce the target population, leading to low catch per trip later in the season.) Autocorrelation could also occur across time for FES trip estimates. For example, if trips depend, in part, on the level of unemployment or fuel prices (or on catch per trip, and catch per trip is autocorrelated across years because of recruitment pulses), and the level of unemployment or fuel prices are themselves autocorrelated (which they often are), then the autocorrelation in unemployment, fuel prices, etc. will induce autocorrelation in trips. Autocorrelation in either trips or catch per trip will likely induce autocorrelation in catch.

A time series model of catch will almost certainly include the values of catch from previous time periods ("lagged" values of catch) as explanatory variables. That is, the model will include lagged values of the dependent variable among the explanatory variables. Such models are called "autoregressive" or AR models (Judge et al., 1985, Chapters 7 and 8). For such models, the covariances between catches from different time periods are nonzero and are important (yet another reason why covariances are important). Durbin's h test (Durbin, 1970), among others, can be used to test for autocorrelation in a model with lagged values of the dependent variable.

In addition, the current value of catch may be affected not only by random effects (random errors) in the current time period but also by the lingering effects of random errors from previous time periods. Time series models that capture the lingering effects of random errors are called "moving average" or MA models (Judge et al., 1985, Chapters 7 and 8).

Time series models of fish catch would likely include both autoregressive and moving average effects; such models are called ARMA models (Ives et al., 2010). ARMA models are often "nonstationary"; that is, the variance in catch may explode over time (especially if the fish stock is rebuilding), or the covariance pattern between catches from different time periods may change over time. If the catch data are nonstationary, they may need to be "differenced" to achieve stationarity before further analysis. ARMA models using differenced data that render the data stationary are said to be "integrated," and so such models are termed ARIMA models (Box and Jenkins, 1976; Judge et al., 1985, Chapters 7 and 8).

Furthermore, looking at MRIP catch estimates over time will almost certainly reveal seasonal patterns, which implies autocorrelation between seasons as well as across years. In the case of seasonal patterns, differencing the data by season or by month may also be required to achieve stationarity (Box et al., 2013). ARIMA models that include differencing by season are known as "seasonal ARIMA" or SARIMA models (Judge et al., 1985, Chapters 7 and 8).

Farmer and Froeschke (2015) compared generalized linear models (GLMs), generalized additive models (GAMs), and seasonal autoregressive integrated moving average (SARIMA) models in terms of fit, accuracy, and ability to forecast landings of four representative fish stocks that support recreational fisheries in the southeastern United States. These investigators found that "the GAMs provided the best fit to the observed data; however, the modeling approaches of the SARIMA model and GLM provided the best forecasts for most scenarios. The SARIMA model and GLM also provided the best predictions of the seasonal trend in landings, a desirable feature for in-season quota monitoring." Although, "no single model is likely to perform best for all stocks of interest," the researchers found that

> SARIMA models performed well across a range of time series and would serve as an appropriate starting point for forecasting landings….The SARIMA models can accommodate but do not require additional covariates for either model building or forecast, a distinct advantage over the GLM and GAM….The SARIMA model mean forecasts were generally unbiased in fits to observed data although confidence limits were consistently greater than those produced from GLMs or GAMs….Although GAM's flexibility consistently provided the best fits to the input data, the SARIMA model most often provided the best fit to the final year in the time series, the most reliable forecast, and the best track to the in-season cumulative landings curve….The SARIMA model was more sensitive and the GLM was less sensitive to recent trends, providing useful "bookends" for forecasts.

Not surprisingly, the researchers found that "the time span of input data affected forecast accuracy from all model types considered." One drawback of SARIMA models is that they "can sometimes generate negative catch forecasts," in which case the SARIMA models "are likely overfitting a recent trend [in catch]…." Simulation studies were conducted to compare several different methods of addressing this drawback, and the conclusions were that replacing the negative catch values with the catch values from the most recent year of fishing "improved forecast accuracy over replacement with zero values in most cases….In summary, post hoc replacement of negative SARIMA model values with landings from the most recent year of fishing is recommended."

Farmer and colleagues (2020) present a case study of using SARIMA methods to forecast Gulf Red Snapper catch in federal waters under an ACL. The purpose of the study was to use SARIMA methods to better estimate catches so that season lengths could be set to maximize fishing opportunities while maintaining catch below the ACL. Specifically, the objectives of the study were to "utilize historic information on state-specific catch rates for both the private angling and federal for-hire components along with covariates that impact recreational catch rates to predict catch rates for 2013–2017. Predicted federal catch rates for 2017 were used to predict the federal Red Snapper season length….for the recreational private and federal for-hire components, while accounting for predicted catches during proposed state seasons." The investigators identified "the best-fitting model with meaningful covariates for each state and component combination, evaluated the retrospective performance of the forecasting method, and applied our forecasts to predict the 2017 federal season." Importantly, MRIP estimates of mean catch and the variance of catch were used to identify the best model and to make catch forecasts using the model.[57] This provides a workable example of how MRIP estimates can be incorporated into a catch forecasting model. The investigators note that "improvements upon this approach may explicitly incorporate the behavioral response of anglers into landings forecasts" (Lee et al., 2017).

Another characteristic of catch data over time is that the effect of an ancillary variable on catch, say, the effect of a "temperature shock" (where temperature is an ancillary variable in the model) on an inshore fish stock, may linger over time. Time series models that include lingering effects of ancillary variables are called "distributed lag models" (Judge et al., 1985, Chapters 9 and 10). In distributed lag models, a system of weights on the ancillary variables rather than differencing may be preferred for analyzing seasonal data (Pesando, 1972). In addition to the Farmer and Froeschke (2015) models, an example of a relatively simple, yet general, time series model that incorporates both autoregressive effects (the effects of past catch on current catch) and distributed lag effects (the effects of both current and past values of ancillary variables on current catch) is that of Hendry and Richard (1983); this model includes quite a few other, common time series models as special cases.

Spatial Autocorrelation Models

Spatial autocorrelation models are cross-section models that allow the error in one location to "ripple out" and affect the error in other locations. The purpose of this is to allow the effects of an unexpected "shock to the system" to spread across locations. For example, the effects of unexpected rain might decrease catch in the rainy location but increase catch in nearby sunny "substitute" locations. Spatial autocorrelation models estimate the magnitude of the ripple effect and estimate how far it actually reaches. UnforTunately, spatial autocorrelation models typically require distance data on a relatively fine scale, calculated from GPS coordinates or using a GIS database together with georeferenced locations, and such data are not currently available for saltwater angler fishing locations. As a result, the present study will instead address the issue of spatial correlation by considering contemporaneous correlation of catch between larger geographic regions (e.g., states) or fishing areas (e.g., inshore, nearshore, offshore) within a Seemingly Unrelated Regression framework (see discussion below). In the future, alternative data

[57] Specifically, "Parametric bootstrapping techniques were used to directly incorporate variance estimates from the surveys into the projection framework for all projections. The selected linear model function for each state and mode was iteratively fit to 1000 bootstrapped samples of input data for that state and mode based on the mean and variance for those observations. Bootstrapping treated annual catch and weight data as truncated normal distributions with a minimum of zero and a mean and standard deviation from each sampling data source. Regression outputs included the mean and standard error for predicted mean weights and catch rates by state and mode" (Farmer et al., 2020).

collection methods, such as smartphone apps, may permit the collection of the fine-scale data necessary for spatial autocorrelation models.

Time Series–Cross-Section Models

Time series–cross-section models (Judge et al., 1985, Chapter 13) combine data on multiple locations and multiple time periods. The dependent variable (e.g., catch of a particular species) depends on the location, the time period, and any other ancillary variables included in the model (e.g., fishing mode, weather, fuel prices). These models may include heteroskedasticity, autocorrelation, or spatial correlation. Engle (1982) presents the classic autoregressive conditional heteroscedasticity (ARCH) model in which both heteroskedasticity and autocorrelation (but not spatial autocorrelation) are allowed; that is, the variance in catch is different for each location, and the variance in catch at a particular location is allowed to vary over time depending on past values of catch at the location. Blanc and Schlenker (2017) provide a discussion of panel data models, a type of time series–cross-section model that can be developed when data are available on the *same* cross-sectional units at each point in time, as opposed to a *sample* of (possibly different) cross-sectional units at each point in time. The collection of panel data on recreational anglers has been discussed in previous MRIP reviews (NRC, 2006, p. 82) “to gather angler trend data and to improve the efficiency of data collection.”

Contemporaneous Correlation Across Domains (SUR Models)

Typically, information on only one fish species is used to forecast catch for that species. This approach neglects information in patterns that may appear in the data *across species* (or across other MRIP domains, such as fishing modes) that might be useful for increasing the efficiency (decreasing the PSEs) of catch and effort forecasts necessary for in-season management.

In particular, patterns might exist in the errors of the estimates across domains, such as across fish species or fishing modes. For example, suppose an unforeseen weather event (e.g., a hurricane) that is not in the catch forecast models for two species of fish affects the catch of both species, causing an unexpected decrease in catch for both species. The forecast model for each species would overestimate the catch of its respective species in the year that the hurricane occurred. Both models would forecast catch above the actual catch for the hurricane year; there is a pattern—the forecast catch is above the actual catch for both models at the same time. Both models erred in the same way, at the same time: both had an error in the same direction at the same time; that is, the errors in both moved together, and those errors are said to be *contemporaneously correlated*.

The SUR method (Zellner, 1962) may in some cases provide a way to improve the efficiency (decrease the PSEs) of catch forecasts made by fishery managers using MRIP output estimates of mean catch, variance (PSE) of catch, and covariance of catches across domains. The purpose of SUR estimation is to make use of contemporaneous correlation in the errors across models (across domains) to improve the efficiency (decrease the PSEs) of forecasts produced by each model (for each domain). The method is called “seemingly unrelated regression” because in some versions of these models, the model equations have no variables in common; the models are related only by their contemporaneously correlated error terms. There appears to be no connection between the models because they have no variables in common, yet they are related through their contemporaneously correlated error terms.

Appendix C, on contemporaneous correlation SUR models, presents the classic SUR model and several extensions. SUR methods are likely to be most useful in situations in which the contemporaneous correlations in errors across equations (across domains) are large. If the SUR method is extended further to allow the errors in one time period in one domain to depend on the errors in all other domains in previous time periods, the vector autoregressive (VAR) model results.

Bayesian Models

Bayesian modeling methods (Doll and Jacquemin, 2018; Punt and Hilborn, 1997; Staton and Catalano, 2019) could be used with MRIP data and/or complementary data (e.g., from state data collection programs) to update catch estimates for the purpose of in-season management of recreational fisheries with ACLs. For example, a Bayesian model that uses MRIP mean catch and PSE estimates to parameterize prior probability distributions and then uses MRIP mean catch and PSE estimates by wave to update priors could provide a method for optimally updating catch estimates and forecasts, setting season lengths, and determining dates of season closures.

From the perspective of the single-species in-season recreational fishery manager, the biological state of the fishery is summarized by the ACL (from a fishery modeler's perspective, the ACL is the key biological state variable that is fixed within a fishing season but may vary from season to season). The ACL summarizes the best available science regarding the biology of the fishery and the quantity (numbers or pounds) of fish that may be harvested within a season while maintaining the biological integrity of the stock and avoiding such legal thresholds as overfished and overfishing conditions. A second, important state variable that is typically fixed within a fishing season but may vary from season to season is the set of fishery regulations (other than season length) in place at the beginning of the season. For example, traditional fishery regulations that are typically held fixed within a season include size limits, bag limits, trip limits, gear restrictions, etc. Other, "alternative" fishery regulations that may be implemented in the future (but that would likely be held fixed within a season) include harvest tags, recreational registration/stamps, depth/distance-based management, harvest rate/recruitment-based management, a "reef fish" (multispecies aggregate) season, and barotrauma reduction device requirements, among others (GAFGI, 2017; Haddad, 2017). Alternative fishery regulations are discussed in greater depth elsewhere in this report, but for the purposes of the present discussion, the set of all traditional and any alternative fishery regulations in place at the beginning of the fishing season is assumed to remain fixed for the season (but may vary from season to season), and this set of regulations describes the "regulatory state" of the fishery for the season.

Given the initial state of the fishery's biology for the season, as embodied in the ACL, and given the state of fishery regulations in place for the season, the present discussion focuses on the management problems of (1) setting the fishing season length, and (2) determining whether and when to close the fishing season to achieve a desired level of risk, as measured by the probability of exceeding the ACL. This focus appears appropriate given the Committee's statement of task (Box 1.1 in Chapter 1) and recent research indicating the importance and value of fishing season length and predictability to recreational anglers (e.g., Young et al., 2019). The apparent importance to anglers of longer and more predictable fishing seasons implies a management need to maximize the length and predictability of fishing seasons while meeting biological and regulatory constraints. This management task is made more difficult by the many uncertainties inherent in fishery management: uncertainty in the level of angler effort/trips; CPUE uncertainty; weather uncertainty; economic uncertainty (e.g., fuel costs, unemployment rate); and biological uncertainties within the season, including target species location and density, which can be affected by such variables as prey and predator distributions and ocean conditions (e.g., temperatures, currents).

Although many uncertainties exist for in-season fishery management under ACLs, uncertainty can often be reduced over time through learning, leading to better management outcomes. The traditional approach to modeling learning in a management context is to introduce a statistical probability distribution, known as a "Bayesian prior," that characterizes the manager's beliefs about the possible values of uncertain model components (LaRiviere et al., 2018). Uncertainty can be reduced over time as managers receive new data (e.g., from MRIP or supplementary state programs), and these data are used to update managers' beliefs about uncertain model components and improve management decisions through a statistical process known as "Bayesian updating." This Bayesian approach (DeGroot, 1970, 1980; Hey, 1985) is adopted and applied here for optimizing the use of MRIP data (and potentially other data, such as those from state programs) for in-season fishery management under ACLs.

The Bayesian approach has several advantages, including the ability to make use of either MRIP data alone, supplementary (e.g., state survey) data alone, or a combination of the two. Further, the approach can be used to measure the incremental management value of adding supplemental data to MRIP data, or vice versa. The Bayesian approach can be used to measure the value of additional information, such as the value of collecting MRIP data more frequently, or the value of adding other, ancillary data, such as weather, economic, or remote-sensing data, to existing data streams (e.g., Lazar et al., 2008; Staton and Catalano, 2019; Wieand, 2008). In addition, the approach can be used to measure the value of disaggregating or segmenting management areas into smaller, more targeted management zones. For data-poor species, the approach can be used to measure the value of implementing new data collection programs. Because of space limitations, not all of these potential applications can be examined in detail here. A few of the most relevant applications are covered, and suggestions regarding how the methodology can be extended to other applications are included in the associated Appendix D, on Bayesian methods.

Within a Bayesian modeling framework, incorporating new data into the decision-making process—either new data that become available over time or new data from other data sources—is known as "learning." Several types of management learning can be distinguished (LaRiviere et al., 2018). In "non-adaptive management" (NAM) learning, the state of the system (fishery) at the beginning of the management horizon (fishing season) is assessed at the beginning of the season, the state is assumed to remain constant over the management horizon (season), and management decisions are made in advance for the period of the management horizon. For example, NAM would be using the best scientific information available at the beginning of the fishing season (MRIP data, state program data, or whatever) to set the fishing season length and a season closure rule for determining when to end the fishing season. Under NAM, the fishing season length and season closure rule would not be changed within the season as new data (from MRIP waves, state programs, or elsewhere) became available.

In contrast to NAM, under "passive adaptive management" (PAM), managers update their beliefs about the state of the system as new data arrive. For example, under PAM, as new data arrive from MRIP waves, the fishing season length and/or season closure rule is readjusted to best meet management objectives. PAM describes the current state of management for most recreational marine fisheries in the United States. The analysis below presents suggestions for improving PAM and describes a framework for evaluating whether various proposed policy modifications might contribute to its improvement.

Although not pursued in detail here because of space limitations, a third type of management learning, "active adaptive management" (AAM), is possible when additional management actions that provide additional data can be taken within the management horizon. These additional management actions typically have a cost, so the question becomes whether the additional information from the additional actions are worth the cost. For example, fishery managers currently using MRIP data to manage a fishery using PAM within a fishing season may ponder whether the additional data from an additional, optional/supplementary data collection action, such as a "snap" boat ramp survey or a snap poll of a random sample of anglers by phone or smartphone app, is worth the cost (in terms of staff time to quickly organize, implement, and evaluate the data from the supplementary snapshot). Under AAM, the manager can choose to deviate from the planned PAM policy path. Doing so may be optimal if the expected gains from making better future decisions based on the additional data from the "snap" program outweigh the costs of the program. A Bayesian framework can be used to analyze AAM-type decisions. AAM does not always lead to better management outcomes relative to PAM (Hauser and Possingham, 2008; Springborn and Sanchirico, 2013).[58] The benefits of using PAM or AAM relative to NAM have been found to depend on

[58] In many cases, the net improvements in management outcomes from AAM relative to PAM have been found to be modest. Using simulation approaches, Bond and Loomis (2009), Rout and colleagues (2009), Springborn and Sanchirico (2013), and Fackler (2014) all found that the expected management gains from AAM relative to PAM are relatively small, in the range of 0.1–3.0 percent. The likely reason is that in these models, AAM policies often lead not to fundamentally different information but to faster acquisition, which generates a modest net payoff. However, in situations in which initial information is poor and downside risks are high, the information from AAM was found to function as a form of insurance—exploration under AAM uncovered potential errors and protected against large

the level of uncertainty in the system; the higher the level of uncertainty, the greater are the benefits for PAM or AAM relative to NAM (Hauser and Possingham, 2008; Rout et al., 2009; Springborn and Sanchirico, 2013; Tol, 2014).

Clark and Kirkwood (1986) applied Bayesian learning models to the problem of determining optimal annual harvest quotas for commercial fisheries with uncertain stock abundance caused by natural fluctuations. The Clark and Kirkwood model assumes that the stock size is uncertain when the annual quota must be decided because of uncertainty in recruitment. The model uses Bayesian learning to determine the stream of annual harvests across years that maximize the present value of the fishery. Clark and Kirkwood (1986) also provide a method for calculating the maximum expected benefit that could result from additional information (in their example, stock surveys), namely the increase in expected return resulting from ideally perfect surveys. Conrad and Clark (1987) and Clark (1990) developed a Bayesian learning model for determining the optimal allocation of fishing effort across multiple fishing locations within a fishing season. However, these authors did not consider the problem of in-season management to meet an ACL, where new information arrives within the season.

An example of a Bayesian model that could be used by managers to set season lengths and decide on season closure dates under an ACL is presented in Appendix D. The example developed in the appendix is a modified version of the Clark (1990) model. The example focuses on the management of a single-species fishery located in a particular geographic region, but the approach could be extended to multiple-species and/or multiple-region fisheries. It is important to note that computer code exists in R to implement such a Bayesian model. Training in how to implement the Bayesian R code was presented at the American Fisheries Society conference as an educational/training workshop (Staton and Hershey, 2020).

Machine Learning Approaches

The use of emerging science and technology, such as artificial intelligence or machine learning techniques, has the potential to further transform recreational fisheries data collection designs, methods, and analysis to better meet the needs of in-season management. This topic is explored in greater detail in Chapter 5.

Decomposing the Effect if Changes in Stock Abundance and CPUE Among Anglers Who Enter, Exit or Remain in the Fishery

A change in stock abundance due to such factors as management actions or exogenous environmental changes will likely affect CPUE. In turn, a change in CPUE will likely affect fishing effort and catch. When stock abundance increases, fishery managers may want to know how related increases in fishing effort and catch are partitioned between existing anglers and "new" anglers who are drawn into the fishery by the increase in CPUE. Similarly, when stock abundance decreases, fishery managers may want to know how related decreases in fishing effort and catch are partitioned between anglers who remain in the fishery and anglers who drop out of the fishery altogether.

In a cross-section study, Gillig and colleagues (2000) investigated the effect of Red Snapper CPUE (from MRFSS) on fishing effort (trips per angler) targeting Red Snapper in the Gulf of Mexico in 1991. CPUE varied across fishing locations. The authors show how to decompose the conditional mean of fishing effort (conditional on the values of ancillary variables) into two categories: effort from those anglers who had and had not previously been fishing for Red Snapper. This decomposition is useful for determining how an increase in fishing effort reflects increased fishing opportunities for existing anglers vs. increased opportunities for "new" anglers attracted to the fishery. For their dataset, the authors found that a 10 percent increase in catch rate (CPUE) resulted in a 14.6 percent increase in recreational Red Snapper trips, which was decomposed into a 12.3 percent increase in trips by anglers new to the fishery and a 2.3 percent increase

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negative impacts (Springborn, 2014).

in trips by anglers who had previously been part of the fishery. This method could be used in a similar manner to analyze the effects of a decrease in stock abundance and CPUE on fishing effort.

Rare-Event Species

Alternatives to the Normal Distribution

The MRIP program provides estimates of the mean and variance of catch by domain, such as by species. These estimates of mean and variance are often used by federal, regional, and state fishery managers to parameterize a probability distribution of catch for the purpose of making catch forecasts or projections within a season or for the next season, and for the purpose of determining the probability that catch might exceed some specified management threshold, such as an ACL.

Two of the most commonly used probability distributions for these purposes are the normal distribution and the Poisson distribution. The normal distribution is typically the default distribution and is appropriate for commonly caught species that have relatively large sample sizes in MRIP data, while the Poisson distribution can be more appropriate for modeling so-called "rare-event" species that have small sample sizes in MRIP data. For the purpose of calculating the probability that the catch of a rare-event species will exceed a given ACL for that species, which is better, normal or Poisson? Appendix E provides an example of the type of analysis that can be used to identify the appropriate catch probability distribution for the purpose of catch forecasting in the case of a rare-event species.

Although the example presented in Appendix E focuses on the choice between the normal and Poisson distributions for the purposes of modeling the probability that the catch of a rare-event species will exceed a given ACL for that species, similar methods could be used to decide whether other, alternative distributions for count data, such as the negative binomial, truncated Poisson, Truncated negative binomial, zero-inflated Poisson, or zero-inflated negative binomial, might provide even better approximations with less error compared with the normal and Poisson distributions.[59] The negative binomial distribution is similar to the Poisson distribution, but the variance is allowed to differ from the mean. For example, Gillig and colleagues (2000) compared the Poisson distribution with two versions of the negative binomial distribution for modeling recreational fishing effort targeting Red Snapper in the Gulf of Mexico in the early 1990s. For their dataset, these authors found that the negative binomial performed better than the Poisson for predicting fishing trips per angler. The zero-inflated Poisson and zero-inflated negative binomial distributions may provide better approximations with less error when there are many "zeros" (zero catch) in the data, compared with the number of zeros that would be expected when using a Poisson or negative binomial distribution.

Inverse Sampling

Haldane (1945) (see also Cochran, 1977, Section 4.5) developed the "inverse sampling" method to estimate the proportion of individuals with a rare characteristic in a population. In a fisheries context, so-called rare-event species could be considered members of a population with a rare characteristic. Using standard methods, it is difficult to determine the sample size that would be sufficient to estimate the proportion of rare individuals in the population while achieving a desired PSE for the estimate; this difficulty arises when the proportion of rare individuals in the population is less than 10 percent, which is typically the case for many rare-event species. In such situations, the sample size required to achieve a required PSE can vary greatly for small differences in the proportion of rare-event species in the population. So, one faces the irony of needing to know the true proportion to obtain an estimate of that same proportion with a specified PSE. The Haldane (1945) method is to prespecify a particular number of rare-event species to be caught, and then proceed to catch fish (both rare and common species together) until the prespecified

[59] See, for example, Hellerstein and Mendelsohn (1993), Ozuna and Gomez (1994, 1995), Haab and McConnell (1996), Englin and Shonkwiler (1995), and Long (1997).

number of rare fish is caught. Intuitively, the smaller the proportion of rare fish in the overall fish population, the longer it will take to catch the prespecified number of rare fish. Cochran (1977) shows that an advantage of the Haldane (1945) method is that it allows one to control the PSE of the estimate without prior knowledge of the proportion of rare-event species in the population. Appendix F presents the Handane method with applications to the management of rare fish species.

Uninformative Priors, Catch Proportional to Abundance, and Bayes' Rule

Under the assumption that the catch of various fish species is in proportion to their prevalence in the overall fish population, so-called "uninformative prior" probability distributions in combination with Bayes' rule may offer a method of modeling rare-event fish species. For example, suppose that in a particular time period and geographic area, fishermen catch r fish of a particular rare species and c fish of other species (including both common species and other rare species). Suppose that this is all the information fishery managers have about the particular rare species in that geographic area; that is, fishery managers are starting from almost nothing.

Suppose next, as is likely to be the case, that the proportion P of the particular rare fish species in the general fish population at the location is unknown. A common definition of an unknown proportion is that the proportion is equally likely to be any value between 0 and 1; this excludes 0 and 1, because it is known that some rare fish exist because r of them were caught, but that not all the fish are rare because c fish of other species were also caught. The assumption that any proportion is equally likely is an example of an uninformative prior probability distribution.

Given only one time period of catch information (r and c), what is the probability distribution of the proportion P of the particular species of rare fish in the general fish population in the location of interest? Furthermore, what is the expected (mean) catch of the particular species of rare fish and the variance of the catch of this rare species? If a fishery-independent estimate is available for the total fish population (including all species, both rare and common, together) caught by the fishery at the location, what is the expected total population (and variance) of the particular rare species at the location? Appendix G presents a method based on uninformative prior probability distributions, catch proportion to abundance, and Bayes' rule that can be used to answer these questions to facilitate management of rare species when almost no information is available.

Outliers: Defining and Identifying

Traditional Methods

MRIP provides estimates of recreational fish catch and variance of catch by 2-month wave and by year. Fishing regulations are typically based on recent MRIP catch estimates or means/projections/forecasts derived from MRIP catch estimates. The influence of so-called "outlier" MRIP estimates (estimates that are unusually large or small relative to other MRIP estimates from other time periods or locations) on mean catch or catch forecasts is an important in-season fishery management issue. The questions of how to define an outlier, how to decide whether an outlier of a given magnitude is a change point and should trigger a change in management policy, and how to update management policy given a triggering outlier, are important for fishery managers. For example, recent research on forecasting recreational catch in the South Atlantic and Gulf regions (Farmer and Froeschke, 2015) found that "future forecasting modeling should attempt to incorporate uncertainty in wave-specific recreational landings estimates to avoid model overweighting of outliers that may be an artifact of survey design." A necessary step toward addressing this issue is to determine how to define and identify outliers. This section describes some of the traditional concepts and methods used to define and identify outliers in the context of a catch forecasting model.

An outlier is an observation that is abnormally far from other observations in a random sample of a population (Hawkins, 1980). One traditional rule of thumb used to define an outlier is any observation that lies outside 1.5 times the interquartile range (IQR), below the first quantile (Q1), or above the third quantile (Q3). In the context of direct MRIP estimates, Q1, Q2, and IQR can be determined by design-based variance estimators and normal approximation, which is related to sample size. However, if each catch estimate is considered individually and the sample size within the domain is not large, a particular estimate can exhibit large deviations from the typical values by chance as a result of sampling error alone. The threshold for declaring an estimate an outlier can be substantially higher when the sample size is small.

Another traditional method used to identify outliers relies on the statistical concepts of "leverage" and "discrepancy." As an example, consider a very simple forecasting model that is based on a dataset consisting of MRIP catch estimates (X) and matched with other MRIP catch estimates (Y) that occur "t" time periods later. A data point in the dataset is an MRIP catch estimate X and a matching MRIP catch estimate Y that occurs t time periods later. Based on the "current" MRIP catch estimate X, the purpose of the forecasting model is to predict the MRIP catch estimate Y that occurs t time periods later. In this context, an outlier data point is one with a high leverage, a high discrepancy, or both.

The *leverage* of a data point measures how far its value of X is from the average value of all the X's in the dataset. Although high leverage alone does not affect the parameter estimates of the model, high leverage does decrease the standard errors of the parameter estimates, which can make it appear as if a predictor variable (X) has a statistically significant effect on the forecast of Y when in fact it does not. The leverage of a particular data point is measured by the hat value, h (statistical software can calculate a hat value for each data point). The values of h ranges between 1/n and 1, where n is the sample size, and the average value of h in a dataset is k/n, where k is the number of parameters in the forecasting model. A rule of thumb is that data points with h values greater than $2 \cdot (k/n)$ are typically considered outliers.

The *discrepancy* of a data point measures how far its Y value is from the value of Y that would be predicted for that data point using the forecasting model. If there is a large difference (discrepancy) between the value of Y predicted by the model and the actual value of Y in the dataset, the data point has a large discrepancy. In contrast with leverage, a data point with a large discrepancy may affect the parameter estimates of the model; data points with high discrepancy also increase the standard errors of the parameter estimates, which can make it appear as if a predictor variable X does not have a statistically significant effect on the forecast of Y when in fact it does. The discrepancy of a particular data point can be measured by the studentized residual (statistical software can calculate the studentized residual for each data point). A rule of thumb is that data points with studentized residuals greater than 2 are typically considered outliers.

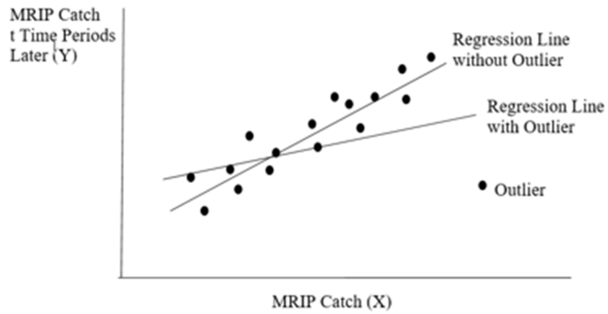
The above "rules of thumb" can be used to classify potential outliers into four categories. The four categories are illustrated in Figure 4.2 in the context of the simple, example, linear catch forecasting model described above.

A plot of the leverage of each data point against the studentized residual of each data point can be used to assess potential outliers visually. Any data point that is in the upper-right quadrant of the graph (any data point with leverage $h > 2 \cdot (k/n)$ and studentized residual >2) has both a high leverage and a high studentized residual, and therefore could be considered an outlier. Such data points have the largest potential effects on the forecasting model—they can affect the parameter estimates (e.g., both the intercept and the slope in the graphs in Figure 4.2), as well as the standard errors and statistical significance of the parameter estimates.

Other, more advanced, methods of outlier detection include: "Cook's D" value and "DFITS" values, that combine the leverage and discrepancy information in more sophisticated ways, Chauvenet's criterion, Grubb's test for outliers, Dixon's Q test, Peirce's criterion, Tukey's fences, Mahalanobis distance, and the ASTM (American Society for Testing and Materials) E178 Standard Practice for Dealing with Outlying Observations. Sources that discuss issues related to identifying outliers in weighted survey responses, such as those produced by MRIP, include: Hulliger (1995), Li and Valliant (2015) and section 5.2 of Heeringa et al. (2017).[60]

[60] R software to implement some of the methods discussed by Li and Valliant can be found here: https://cran.r-project.org/web/packages/svydiags/index.html.

Outlier with large leverage and large discrepancy

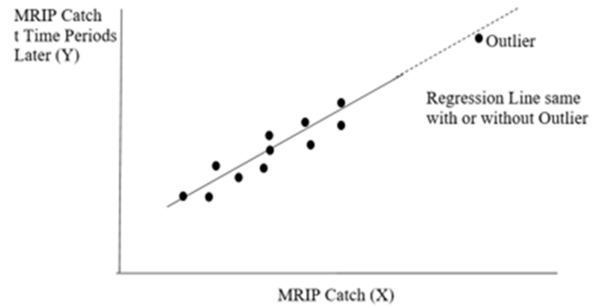


The outlier affects the parameter estimates of the model (in the example graph above, both the intercept parameter and the slope parameter are affected).

Because large leverage and large discrepancy have opposite effects of the standard errors of the parameters, it is unclear in this case how the outlier will affect the statistical significance of the parameters.

A data point that has both a large leverage and a large discrepancy is said to have a large "influence" on the forecasting model.

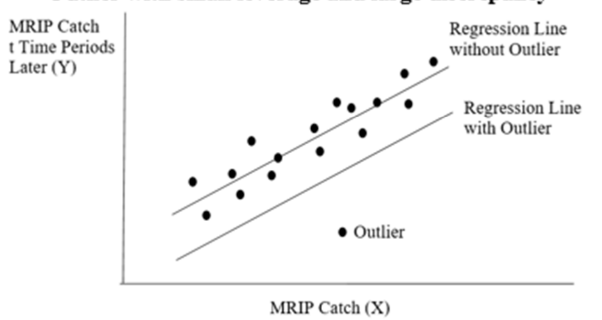
Outlier with large leverage and small discrepancy



The outlier does not affect the parameter estimates of the model (in the graph above, neither the intercept parameter nor the slope parameter is affected).

An outlier with large leverage decreases the standard errors of the parameter estimates. This can make it appear as if X has a statistically significant effect on Y when in fact it does not.

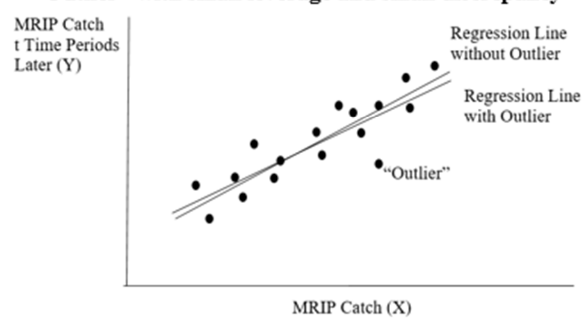
Outlier with small leverage and large discrepancy



The outlier affects the parameter estimates of the model (in the example graph above, the outlier affects the intercept parameter but not the slope parameter).

An outlier with large discrepancy increases the standard errors of the parameter estimates. This can make it appear as if X does not have a statistically significant effect on Y when in fact it does.

"Outlier" with small leverage and small discrepancy



The outlier will have little effect on the parameter estimates of the model (in the example graph above, neither the intercept nor the slope is significantly affected by the outlier, so there is not much change in the regression line).

Because both leverage and discrepancy are small, the outlier should not have much of an effect on the standard errors of the parameter estimates.

This case describes a data point that *appears* to be an outlier when viewed on a graph, but in fact its X and Y values are not unusual enough to significantly distort the parameter estimates or the standard errors of the parameter estimates.

FIGURE 4.2 Outlier classification based on leverage and discrepancy. SOURCE: Generated by the committee.

Outliers may be of particular concern in design-based sampling programs, such as FES, that use Horvitz-Thompson variance estimates (Hulliger 1995). In the presence of outliers, Horvitz-Thompson estimators remain unbiased, but the variance is increased. Sample observations of large magnitude with small inclusion probabilities have a particularly large influence on the Horvitz-Thompson estimator.
If an outlier is detected, there are four basic remedies:

- Leave the outlier in the dataset, but use a data transformation (such as logging X, Y, or both) to reduce the undesirable effects of the outlier.
- Leave the outlier in the dataset, but add a dummy variable to the dataset, where the dummy variable has the value 1 for the data observation with the outlier data point, and the value 0 otherwise. The purpose of the dummy variable is to represent the effects of variables outside the model that are affecting the outlier data point (i.e., causing it to be an outlier) but are not affecting the other data points.
- Replace the outlier in the dataset with the "nearest," "non-suspect" data point (also known as "Winsorising").
- Drop the outlier from the dataset ("trimming").
- Leave the outlier in the dataset, but switch to a "robust estimation" modeling technique. Several approaches to robust estimation have been proposed, including R-estimators, L-estimators and M-estimators. M-estimators now appear to be preferred due to their generality and efficiency (Hulliger 1995, Huber and Ronchetti, 2009).

If an outlier were to occur, fishery managers would first check to ensure that the outlier was not due to an error in the data or in data processing.[61] If the outlier was not due to an error, managers would need to decide whether (1) the outlier occurred because of chance alone, and so should not trigger a change in fishery management policies (e.g., a change in control rules); or (2) the outlier is an indication that either the fish population or the fishery is changing, and that as a result, the probability distribution of catch is shifting, and so the outlier should trigger a change in fishery management policies. Typically, fishery managers would use a pre-specified level of statistical significance (say, 5 percent) to decide between (1) and (2). If the outlier exceeded the threshold value of catch based on the level of statistical significance, managers would decide that either the fish population or the fishery was changing, and that as a result, the probability distribution of catch was shifting, and so fishery management policies should be changed (or at least, further investigation was warranted).

It is important to note that because of MRIP's moderate sample size, it may not be possible to declare an individual estimate an outlier even when the underlying distribution has changed substantially. From the fishery manager's perspective, it is necessary to consider the spatial, temporal, and species dependence in the catch estimates to detect change more effectively. For example, an isolated large decrease in the catch estimate for one species in one 2-month wave in one region may well be due to sampling error, whereas several moderate decreases in consecutive 2-month waves or multiple adjacent regions can be stronger evidence that the probability distribution of catch has changed and should trigger management action. Properly vetted multivariate spatial-temporal models for the fish population and fishery effort are essential to assess the strength of the evidence for change detection.

The type of change detection relevant to in-season management is online change detection. Popular methods include the CUSUM approach (Page, 1954; Verdier, 2020), the autoregressive models approach (Gombay, 2008; Tsay, 1988), and the Bayesian approach (Adams and MacKay, 2007; Barry and Hartigan, 1993). The Bayesian approach for online change detection is recommended for in-season management, and a simplified example is described in detail under the Bayesian model example of in-season management in Appendix D. Given a triggering outlier, the outlier value of catch (and its variance) could be used to update the probability distribution of fish catch using Bayesian updating methodology as described under that

[61] The calibration methods used to correct for conversion of the CHTS to the FES, and the revised inclusion probabilities for the APAIS calibrations, could be sources of extreme values ("outliers") in the calibrated MRIP estimates. Both calibration approaches were peer-reviewed and found to be statistically sound. However, since the CHTS-FES calibrations resulted in varying increases in overall effort depending on year and region, and since the APAIS calibration also changed species-specific CPUE estimates, the chances of extreme values are increased. Hence, any extreme values in the calibrated estimates may be artifacts of the recalibration, despite their statistical rigor. Consideration of the joint effects of the methods used for CHTS-FES and APAIS calibrations on extreme value generation may be useful.

Bayesian model example. Other fisheries management policies (e.g., control rules) could then be updated based on the updated probability distribution of fish catch.

Order Statistics

In some cases, especially data-limited cases in which there are too few data points to develop a formal projection/forecasting model, fishing regulations have been based on ad hoc measures that attempt to find a balance between the "average" and the "variation" in the available MRIP catch estimates. An example of such a method is basing a catch forecast on "the third-largest of the five most recent MRIP catch estimates." To find the threshold for identifying an outlier in such cases, one first needs to derive the probability distribution of such statistics, and here the concept of "Order Statistics" might be useful. Order statistics provide a method for determining the probabilities that the first-largest, second-largest, third-largest, etc., number in a set of numbers will take on particular values. For example, the method can be used to answer such questions as, "What is the probability that the third-largest annual MRIP estimate for a particular fish species out of the last five annual MRIP estimates for that species will be greater than 3000 fish?" One possible definition of an outlier would be any such value with a chance of occurring that is less than the fishery managers' pre-selected level of statistical significance (say, 5 percent). Appendix H presents a brief review of order statistics with a few, simple fisheries management examples. Simulation studies should be used to compare alternative outlier detection methods before any particular method is adopted for a particular fishery.

Improved Partnerships and Collaborations

Effective and efficient coordination is of paramount importance given the range of federal, state, and regional organizations involved in surveys or analyses of recreational catch and effort. The MRIP Regional Implementation Teams and Interstate Fisheries Commission Fisheries Information Network (FIN) programs provide a valuable framework and structure for coordinating these interactions. For instance, Pacific RecFIN provides a good example of how a regional FIN system can facilitate successful coordination. Pacific RecFIN is led by the Pacific States Marine Fisheries Commission and involves coordinated sampling and data management across Washington, Oregon, and California. All three states implement locally tailored sampling programs to produce data on biological, social, and economic aspects of fisheries, and these data are ultimately contributed to a shared database. However, there are also recognized areas in which improvement is needed across all regions. For instance, the ACCSP Atlantic Coast Regional Implementation Plan stresses the importance of a continued emphasis on coordination as several state surveys that are not currently used in MRIP estimation could be used for this purpose later if MRIP certified. Another area for improvement involves the frequent need to calibrate recreational catch and effort estimates from various surveys. For instance, coordination is particularly critical in regions where survey methods may vary across states or specific fishery contexts, as well as when new survey programs are launched or modified. Finally, for all of these scenarios, effective and coordinated stakeholder engagement is critical for building and maintaining stakeholder trust and satisfaction in fisheries management. Chapter 5 builds upon these critical issues and looks at alternative surveys in the context of alternative management strategies.

CONCLUSIONS AND RECOMMENDATIONS

Conclusion: With strong support from fishery managers and stakeholders, MRIP and other recreational fisheries data collection programs have greatly improved the development and use of mobile apps and other electronic data collection and reporting platforms. While the use of these technologies can improve the efficiency of data collection, these technologies alone will not speed up the process if other systemic bottlenecks exist.

Conclusion: With additional resources, MRIP may be able to shorten by roughly 2 weeks the time between the end of its current bimonthly reporting period and the release of preliminary estimates. This change would put additional stress on existing MRIP staff and systems, and for purposes of in-season management, the benefits of a modest advance in the release of preliminary estimates for bimonthly waves would not be likely to justify the costs of accelerating the data processing and estimation phases of each bimonthly cycle. It is possible that the raw MRIP data streams could be used to inform more timely catch estimates through such approaches as nowcasting or other in-season projection methods.

> **Recommendation: MRIP should explore the costs and benefits of providing its partner fishery research and management programs in the regions and states with direct access to the continuous streams of raw MRIP data as they are being captured by the MRIP Access Point Angler Intercept Survey (APAIS) and For-Hire Survey (FHS) and the for-hire electronic logbook data programs (Vessel Trip Reporting [VTR], Southeast Regional Headboat Survey [SRHS], Southeast Region For-Hire Electronic Reporting [SEFHIER]). Legitimate and appropriate accessibility to these data should be coordinated through Regional Interstate Fishery Commission programs such as GulfFIN and the Atlantic Coastal Cooperative Statistics Program (ACCSP).**

Conclusion: Given an approximate doubling of the resources that could be allocated to its survey programs, MRIP could transition to monthly catch estimates that would have levels of precision comparable to those of the current estimates for bimonthly waves. For in-season management applications that rely on tracking MRIP estimates of cumulative catch against ACLs, the greatest advantage of moving to a 1-month cycle would lie in monitoring cumulative catch at the end of odd-numbered months. Other applications of MRIP data, including stock assessment and cross-year management of recreational fisheries (e.g., seasons, catch and size limits), would also benefit from an MRIP transition to larger sample sizes required to maintain precision for monthly estimation of catch.

Conclusion: It is impractical to further improve the precision and timeliness of MRIP catch estimates to levels that could be achieved in the near-census catch reporting schemes used for the commercial sector, such as the VTR and SEFHIER programs. Any further improvements in MRIP precision and timeliness are therefore unlikely to be sufficient in and of themselves to achieve more effective in-season management of recreational fisheries. However, the Committee identified a number of supplementary data sources and analytical approaches likely to improve the precision, timeliness, and adaptability of MRIP data for the purpose of improving catch forecasts for recreational fisheries subject to ACLs.

Conclusion: Further development of in-season management approaches utilizing novel statistical methods and additional data sources, such as state surveys, voluntary reporting, and analyses of social media posts, has the potential to improve incrementally the timeliness and precision of annual catch management. It is unlikely, however, that such approaches can replace MRIP as a source of spatially and temporally consistent catch information for monitoring and stock assessment of Council-managed stocks.

Conclusion: Since stock assessments rely on long time series of consistently collected data, and many federally managed stocks straddle state and survey boundaries, intercalibration of surveys is essential whenever a single survey is insufficient to support all assessment and management needs. Rigorous survey intercalibration requires temporal and spatial overlap between surveys. The need for intercalibration and the consequences of using different, uncalibrated surveys for various aspects of assessment and management are evident where different surveys provide very different estimates of the same unknown quantity (in the same units) and where the precision of surveys is perceived or known to differ.

> **Recommendation: Interstate Fisheries Commissions, States, NOAA Fisheries, and other members of MRIP Regional Implementation Teams should anticipate and take into account**

the need for intercalibration and continued survey development when new recreational fisheries surveys and survey methods are considered. These needs should also be clearly communicated to anglers, fishery managers, and other stakeholders.

Conclusion: Supplemental data in the form of state-specific recreational fishery surveys, species-specific surveys (e.g., Red Snapper), location-specific data, fishing tournament data, and voluntarily reported data (e.g., web portal– and smartphone-reported data) could be used in combination with MRIP estimates to improve in-season management. However, significant challenges would remain concerning the calibration and coordination of supplemental recreational catch and effort data with MRIP estimates. In addition to MRIP's existing programs to calibrate state survey data collection and estimates with MRIP data and estimates, some of the methods discussed in this chapter could facilitate the integration of data from multiple sources.

Conclusion: A great variety of ancillary variables in readily accessible electronic format exist and potentially could be combined with MRIP catch estimates to improve the annual and in-season catch forecasts made in support of fishery management. When choosing which of the variety of ancillary variables available to use, one can consider that a variable will be more useful when the correlation (either positive or negative) between that variable and the catch of one or more recreational species is high. Ancillary variables that are also correlated with survey response propensity may be useful for reducing nonresponse bias. Furthermore, a particular ancillary variable will be more useful for the specific purpose of deciding when to close a fishery within a fishing season when that variable is available electronically with high frequency (i.e., daily or weekly).

Recommendation: The National Marine Fisheries Service (NMFS) Regional Offices, Science Centers, and state agencies should explore and identify ancillary variables that have high correlations with the Fishing Effort Survey (FES) and Access Point Angler Intercept Survey (APAIS) response propensities, catch per unit effort (CPUE), and catch estimates and supplemental survey estimates for potential use in annual and in-season forecasting models. Ancillary variables available electronically with high frequency (i.e., daily or weekly) would be most useful for in-season management catch forecasts.

Conclusion: If fishery managers are willing to accept some amount of bias in catch forecasts, it may be possible to use "Stein rule"–related statistical estimation methods to reduce the variance (PSEs) of catch forecasts and lower the overall MSE of the estimates. If justifiable restrictions (either equality or inequality restrictions) on model parameters can be identified, then incorporating such restrictions into the estimation methodology may reduce the MSE of the estimates.

Recommendation: The National Marine Fisheries Service (NMFS) and Fishery Management Councils should discuss whether achieving perhaps substantial reductions in the percentage standard errors (PSEs) of catch forecasts is worth a moderate increase in the bias of catch forecasts. If so, then NMFS Regional Offices and state agencies should investigate whether Stein rule–related estimation methods can be developed that would achieve meaningful reductions in PSEs (with acceptably low increases in bias) and associated reductions in the mean square error of catch forecasts for fisheries with high PSEs.

Conclusion: Combining MRIP survey data with supplemental survey data using multiple-frame methods could decrease the variance (PSE) of catch estimates, depending on the relative sample sizes and catch variances of the combined surveys. Increasing the MRIP sample size decreases the value (in terms of variance reduction) of a supplemental survey. Increasing the sample size of a supplemental survey increases the value of that survey. An increase in the variance in catch within a supplemental survey increases the value of that survey. An increase in the variance in catch in the portion of the MRIP sample frame outside a supplemental survey sample frame decreases the benefit of that supplemental survey. As the size of a supplemental survey sample frame increases relative to the size of the MRIP sample frame, the benefit of that supplemental survey decreases.

Conclusion: Covariances between catch estimates from two different domains or between a catch estimate and an ancillary variable may be useful for reducing the variance and PSE of annual and in-season catch forecasts made by fishery managers who use MRIP output estimates in catch forecasting models. Conditional expectations of catch, conditional variances of catch, and the method of control variates may also be useful for improving catch forecasts.

Conclusion: Spatial-temporal forecasting models, such as time series cross-section models, SARIMA models, and SUR models, may be useful for developing catch forecasts for in-season management where data are sufficient. It may be necessary to combine MRIP catch estimates with data from supplementary surveys and on ancillary variables to achieve needed forecast accuracy and precision. These models can be used to address the statistical issues of heteroskedasticity, temporal autocorrelation, and contemporaneous correlation to improve the accuracy and precision of catch forecasts. The time series forecasting models of Farmer and Froeschke (2015) and Farmer and colleagues (2020) are good examples of the potential use of time series SARIMA methods for building applied, managerially relevant, in-season catch forecasting models. These models integrate MRIP and supplementary survey data as well as ancillary variables (stock status, weather, economic conditions, etc.) to forecast in-season catch, determine appropriate season length, and control the probability of exceeding an ACL.

Recommendation: The National Marine Fisheries Service (NMFS) Regional Offices and state agencies should explore the following to improve the accuracy and precision of catch forecasts:

- **The extent of autocorrelation in MRIP catch estimates across years and across waves within years, including seasonal patterns, should be investigated.**
- **The magnitude of any bias in the variance (percentage standard error [PSE]) of catch forecasts due to autocorrelation should be determined, and if necessary, projection/forecast models should be modified appropriately to address autocorrelation.**
- **The effects of ancillary variables (e.g., in the form of distributed lags) on catch should also be investigated to address autocorrelation. In particular, managers should explore refinement of the Farmer and Froeschke (2015) time series model and its application, along with similar models, to other fish species and geographic areas.**
- **The incorporation of similar time series models into a "Seemingly Unrelated Regression" (SUR) modeling framework that leverages contemporaneous correlation across species and/or areas should be considered.**
- **The development of similar time series models within a Bayesian modeling framework should be investigated.**

Conclusion: The SUR method may be useful for reducing the variance and PSEs of catch forecasts when the errors across domains (for example, across fish species) are contemporaneously correlated; that is, when the errors in different domains move together. When errors are contemporaneously correlated, it may be possible to improve forecasts by estimating systems of equations together, for example, by estimating together the forecasting models for multiple fish species. The SUR method can accommodate heteroskedasticity and temporal autocorrelation.

Conclusion: Bayesian modeling methodology may serve as a good overarching framework for regional federal and state fishery managers to use in integrating and updating MRIP catch estimates, supplemental survey data, and ancillary variables for the purpose of producing annual catch forecasts and in-season catch forecasts. Furthermore, many, if not all, of the other methodological approaches described in this report can be integrated within a Bayesian framework. The Bayesian methodology provides a consistent approach to handling uncertainty and risk and supporting probabilistic decision making, such as decisions about when to close seasonal fisheries to maintain the probability of exceeding ACLs below fishery managers' tolerance level. The existence of widely available software for implementing Bayesian models facilitates their use in fishery management.

Conclusion: For some rare-event species, the distribution of catch in catch forecasts may be better modeled using a probability distribution other than the normal distribution. Examples of such distributions include the Poisson, negative binomial, zero-inflated Poisson, and zero-inflated negative binomial. Statistical methods exist for determining when the use of one distribution would be better (lower error in catch forecasts) than another.

Conclusion: The method of inverse sampling may be useful for estimating the population or catch of some rare-event species, especially in situations in which the catch of the rare-event species is very low and sporadic, with zero catches in some locations and time periods.

Conclusion: For some rare-event species, especially newly discovered species or those with very little catch data, the combined use of uninformative priors, an assumption of catch proportional to abundance, and Bayesian updating may be useful for forecasting the catch of that species. When fishery-independent estimates of the total fish population (all species together) exist, the method may also be useful for estimating the population of the rare-event species as well. This method is a special case of the general Bayesian modeling framework discussed elsewhere in this report.

Conclusion: Traditional statistical methods can be used to define and identify outlier catch estimates in cases in which sufficient data are available. Order statistics may be useful for defining and identifying outliers in data-limited situations in which it may not be possible to apply the traditional methods. Change detection methods in time series data analysis, including Bayesian approaches, can be used to help answer the question of when an outlier should trigger management change.

Recommendation: The National Marine Fisheries Service (NMFS) Regional Offices and state agencies should explore the possibility of using the following statistical methods, parameters, and approaches as appropriate for the issue at hand (a more descriptive evaluation of these methods may be found in the Appendix):

- **multiple-frame methods and related methods to combine MRIP data with data from supplemental surveys to reduce the variance (percent standard errors [PSEs]) of catch estimates;**
- **covariances in catch estimates across MRIP domains, conditional expectations and conditional variances of catch (encompassing identification of the best conditioning variables, including ancillary variables), and the possible use of control variates, to reduce the PSE of catch forecasts;**
- **Bayesian modeling methods that could provide a consistent framework for updating annual and in-season catch forecasts and projections utilizing data streams of different precision and frequency, including MRIP estimates of given precision available by year and by 2-month wave, and estimates from other, supplemental sources that may have different precision and be available with different frequency;**
- **the combination of uninformative priors, an assumption of catch proportional to abundance, and Bayesian updating for forecasting the catch of rare-event species and possibly estimating the population sizes of such species;**
- **alternative statistical definitions of outlier catch estimates and the adoption of standard definitions to facilitate consistency in management actions;**

- **change in detection methods in time series data analysis to help answer the question of when an outlier should trigger management change; and**
- **contemporaneous correlation in the errors across MRIP domains (the Seemingly Unrelated Regression [SUR] method, its extension to situations with heteroskedasticity and autocorrelation, and its implementation within a Bayesian forecasting model could help reduce the variance and PSEs of catch forecasts).**

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5

Alternative Management Strategies for Recreational Fisheries

It is widely agreed that, thanks to implementation of the Magnuson-Stevens Fishery Conservation and Management Act (MSA) and its multiple reauthorizations, America's fisheries are among the best-managed in the world, and overfishing has been all but eliminated in U.S. waters. Federally managed fish stocks have established annual catch limits (ACLs) that cannot be exceeded, and fishery managers must employ accountability measures (AMs)—management controls that prevent ACLs from being exceeded or mitigate overages (NRC, 2014).

Historically, commercial and recreational fishers have largely supported implementation of the MSA because of the law's contributions to the long-term stability of fish stocks, a profitable fishing industry, and a vibrant coastal economy. However, in the midst of the nation's success in rebuilding marine fisheries and the growth in saltwater recreational fishing, some recreational fisheries advocates began expressing their perception that the U.S. federal fisheries management system has not adapted to meet the unique goals and needs of anglers. In spring 2014, the Commission on Saltwater Recreational Fisheries Management—better known as the Morris-Deal Commission (after its two initial chairs—Johnny Morris, CEO of Bass Pro Shops, and Scott Deal, president of Maverick Boats)—published *A Vision for Managing America's Saltwater Recreational Fisheries* (CSRFM, 2014), a landmark report providing a number of recommendations on potential strategies for improving saltwater recreational fisheries management. More recently, other recreational fisheries support organizations, such as the American Sportfishing Association (ASA) and the Theodore Roosevelt Conservation Partnership (TRCP), have conducted workshops, convened expert panels, and released a subsequent report providing additional recommendations for addressing recreational fisheries management issues (ASA and TRCP, 2018). The common thread in these recommendations is that recreational and commercial fishing are fundamentally different activities, and therefore require different management approaches.

ALTERNATIVE MANAGEMENT APPROACHES THAT COULD BE APPLIED TO RECREATIONAL FISHERIES

In light of the concerns raised by recreational fisheries industry organizations and in response to the recommendations provided by the expert panel and workshop reports referenced above, Section 102 of the MFA specifies that the National Oceanic and Atmospheric Administration's (NOAA's) National Marine Fisheries Service (NOAA Fisheries) and the Regional Fishery Management Councils (Councils) can implement alternative management approaches more suitable to the nature of recreational fishing as long as they still adhere to the conservation principles and requirements established by the MSA. An overview of the most common alternative management approaches that have been proposed by recreational fishing groups and that, in some cases, are under consideration by Councils is presented in Table 5.1. The approaches being proposed vary widely in nature and attempt to address different management challenges raised by the recreational fisheries sector. Although they are discussed here on an individual basis it is also possible to combine them in a variety of ways to form hybrid management options (CSRFM, 2014).

TABLE 5.1 Overview of the Most Common Alternative Management Approaches Being Discussed by Recreational Fisheries Support Organizations and Regional Fishery Management Councils

Management Strategy	Description	Data Needs or Gaps	Potential Benefits	Potential Challenges	Example Fisheries
Harvest rate management	Use of fishing mortality rate (F) as the main reference point for managing the fisheries Does not involve the use of an annual catch limit (ACL) or other landings- or quota-based hard catch limit	Annual measure of F; annual juvenile indices of abundance (to track annual recruitment, year-class strength)	Does not require the use of a hard catch limit; management adjusted in response to changes in F Perceived by anglers as better suited to recreational fisheries management (i.e., not a pounds-based quota)	Data-intensive. Requires annual assessment updates so estimate of current F can be obtained May not comply with the National Standards (NS) 1 requirement that fisheries under a Council Fishery Management Plan (FMP) be managed using ACLs Requires formal annual plan review	Atlantic striped bass (managed by the Atlantic States Marine Fisheries Commission [ASMFC])
Harvest tags	Tags are used to track harvest of individual fish. Similar to the process used to control harvest in wildlife game management (bear, elk, deer, etc.).	Recreational fisheries licensing and data collection systems capable of handling the harvest tags	Improve data collection or control effort Well suited for highly controlled, limited-harvest fisheries that are difficult to manage with traditional fisheries regulations (e.g., rare-event species or species under Endangered Species Act [ESA] recovery plans) Can provide greater flexibility for anglers to harvest when convenient	Fair distribution (open lottery vs. open access vs. allocation) Difficult to implement, administer, and enforce across federal–state jurisdictions Burdensome and prescriptive reporting requirements Requires compliance tracking effort Perceived by the recreational community as restricting access (i.e., the fisheries are no longer open-access)	Highly migratory species (HMS) fisheries in North Carolina and Maryland Salmon and Halibut in Oregon and Washington Tarpon in Florida and Alabama
Depth/distance-based management	Recreational fishing for single or multiple species is closed beyond a certain depth or distance from shore to allow higher production outside the fishing zone, potentially replenishing the fishing zone and reducing release mortality	Knowledge of the proportion of the stock's spawning-stock biomass (SSB) that occupies the deep/distant-from-shore area Connectivity between the two stock components (i.e., the deep/distant and the inshore/near-shore components)	Longer seasons, increased access in shallow/near shore areas Decreased fishing pressure and reduced release mortality by focusing fisheries in shallower areas	Viable only if portion of SSB in the deep/distant area is sufficient to replenish the near-shore area Reduced access to other, nonoverfished stocks in the deep/distant-from-shore area (can be perceived as turning the deep/distant-from-shore area into a large closed area) Federal–State coordination on managing the near-shore area Compliance and enforcement	Pacific rockfish conservation areas (RCAs) Considered by the South Atlantic Fishery Management Council (SAFMC) for South Atlantic Red Snapper

continued

TABLE 5.1 Continued

Management Strategy	Description	Data Needs or Gaps	Potential Benefits	Potential Challenges	Example Fisheries
Conservation equivalency	States can implement alternative management measures that are estimated to achieve the same conservation goals as those of the Councils	Recreational fisheries data appropriate to support necessary analyses (i.e., to assess whether state conservation equivalency measures achieve the conservation level required by the Council) States in the Council region need calibrated and compatible recreational fisheries data	Added flexibility to address differential management needs over broad Council region (e.g., state-by-state differences in fishing effort or species distribution) Improved angler trust, compliance, and cooperation	Requires sufficient recreational fisheries data at the state level to support development of conservation equivalency measures Inconsistent regulations across the region could be a challenge for the regional stock assessment Perceived inequities in management due to differing state-by-state regulations Conservation equivalency proposal approved annually	Atlantic Summer Flounder and Black sea bass (managed by ASMFC) State management of the private recreational component of Gulf of Mexico Red Snapper (Amendment 50 to the reef fish FMP)
Permits, endorsements, and stamps	Special permits, license endorsements, or stamps are required for possession or harvest of a species or group of species	Supplemental recreational fisheries data collection program Recreational fisheries licensing system capable of handling the additional permits, endorsement, and stamps	Better-defined universe of anglers, improved sampling frame for surveys Reduced scientific and management uncertainty (if better-defined universe of anglers leads to better surveys and improved quota monitoring) Increased access (if lower uncertainty leads to smaller buffers and thus higher ACLs)	Difficult to implement and administer from a federal–state licensing perspective Compliance and enforcement Cost (programs of this nature entail additional implementation, administrative, and enforcement costs)	Gulf of Mexico Red Snapper state programs (Florida State Reef Fish Survey, Alabama Snapper Check, Mississippi Tails 'n Scales, Louisiana LA Creel) Alaska king Salmon stamp Mid-Atlantic recreational Tilefish permit (Mid-Atlantic Fishery Management Council [MAFMC])

SOURCE: Gathered by the Committee.

Harvest Rate Management

The harvest rate management approach (HRM) centers around the use of target fishing mortality rates (F) to reach a desired level of removals and maintain sustainable spawning-stock biomass (SSB). The idea is that recreational fishing is not always based on harvest, and therefore not as suitable for the poundage-based hard quotas (i.e., ACLs) required by the current federal management system.

Although conceptually, managing fisheries based on harvest rates makes sense, the use of this approach faces multiple challenges. First, data and analytical requirements are extremely high (Table 5.1). Because under HRM fishery management is based on F values instead of landings, monitoring of stock status requires frequent (ideally annual) assessment updates so an estimate of current F can be obtained for comparison with target F. For example, to manage the Atlantic striped bass fishery using HRM, the Atlantic States Marine Fisheries Commission (ASMFC) uses a strategy that sets a threshold and target F that provides a desired level of SSB. Each year, landings and biological information, such as juvenile indices of abundance, are reviewed relative to trends and targets. Depending on this comparison, the ASMFC may direct states to adjust management measures. Approximately every 2 years, the stock assessment is updated, and the catch levels associated with the target harvest rate are adjusted. Management changes resulting from updated assessments are typically expressed as a percent change in harvest levels from the prior period, rather than as an ACL-style hard catch limit. There are fishing seasons but no in-season closures, and anglers in different states may be subject to more restrictive measures the following season if a reduction in landings in their state is required to meet the coastwide F-target. For example, a state may set a season length with associated size and bag limits that is predicted to constrain catch to a specific level, consistent with the coastwide target fishing mortality rate. However, if postseason evaluation determines that realized catch has exceeded expected catch, that state's fishery may be subject to a shorter season, lower bag limit, or higher size limit the following year. Monitoring of harvest for the purpose of closing the fishery early (should harvest exceed expectations) does not occur.

But perhaps the most severe challenge facing the use of HRM as an alternative management approach is that it may not comply with MSA mandates and National Standard (NS) 1 guidelines requiring that federally managed stocks (i.e., stocks in Councils' Fishery Management Plans [FMPs]) be managed with an ACL (NRC, 2014). Specifically, the MSA as amended in 2006 states that a Council will "develop annual catch limits for each of its managed fisheries that may not exceed the fishing level recommendations of its scientific and statistical Committee or the peer review process."[1] The act also requires FMPs to "establish a mechanism for specifying annual catch limits in the plan (including a multi-year plan), implementing regulations, or annual specifications, at a level such that overfishing does not occur in the fishery, including measures to ensure accountability."

Fundamentally, the current ACL-based catch specification system is already based on F values, as ACLs are obtained by multiplying the $F_{ABC/ACL}$ by the estimated annual stock biomass (B) over the projection period. It appears that the recreational fisheries sector's dissatisfaction with this approach (besides the use of pounds-based hard quotas) may be related to the inherent uncertainty of fishery projections. Annual estimates of stock biomass (B) are strongly dependent on estimated annual recruitment, a highly uncertain metric. Actual annual recruitment in a given year may end up being higher or lower than estimates used in projections and projected annual biomass, and therefore may not closely reflect what anglers are seeing out on the water. Compounding the issue is that previous years and MRIP waves are often not good predictors of current-year recreational landings because of significant interannual variability in such factors as fish availability, targeted fishing effort, and weather. This disconnect between stock assessment projections and more real-time perceptions of stock abundance experienced by fishermen out on the water represents one of the main challenges with which the current fisheries assessment–management system must contend when dealing with recreational fisheries.

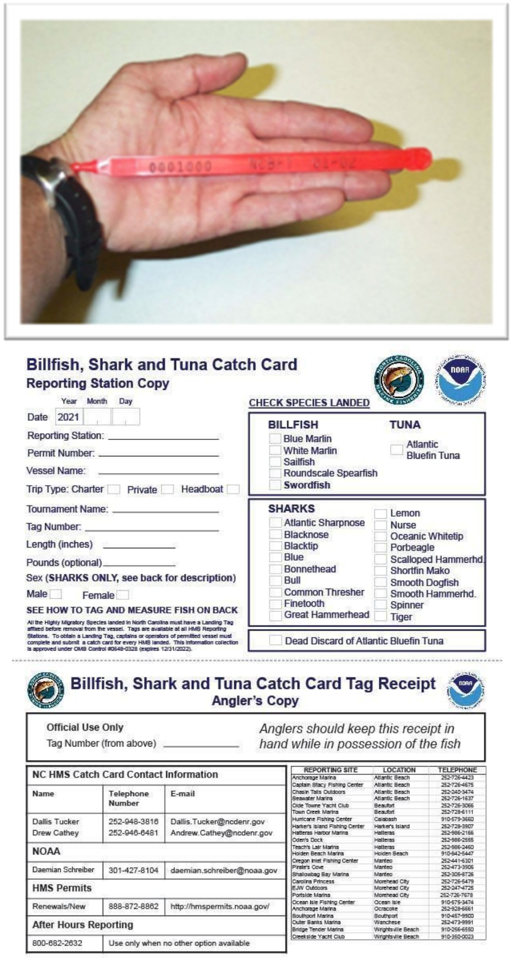
It is also important to note that HRM is a tool that may not be appropriate for all stocks. The ASMFC has 27 Fishery Management Plans (FMPs), including those covering, for example, coastal sharks and Shad and River Herring that include multiple species or stocks. Not all these stocks are managed the same as Striped Bass. Therefore, HRM should be considered another tool that the Councils could use in appropriate situations rather than a change in the management approach for all stocks.

Harvest Tags

This approach relies on the use of a physical tag to track the harvest of individual fish (Figure 5.1). Harvest tags are relatively common in wildlife management (e.g., bear, elk, deer), used to limit or account for animals harvested during hunting seasons. In marine fisheries, harvest tags have been used in some

[1] Magnuson-Stevens Fishery Conservation and Management Act, Pub. L. No. 109-479 §103(c)(3), 121 Stat. 3575, 3581 (2006).

highly controlled, limited harvest fisheries, such as tarpon in Florida and Alabama and salmon and Halibut in Oregon and Washington, as well as highly migratory species (HMS) (billfishes, sharks, and Tunas) in Maryland and North Carolina. In many cases, harvest tag programs also include a companion harvest or landing card used for reporting data associated with the harvest (Figure 5.1).



Billfish, Shark and Tuna Catch Card
Reporting Station Copy

Date: Year 2021 / Month / Day

Reporting Station: ______
Permit Number: ______
Vessel Name: ______
Trip Type: Charter ☐ Private ☐ Headboat ☐
Tournament Name: ______
Tag Number: ______
Length (inches) ______
Pounds (optional) ______
Sex (**SHARKS ONLY, see back for description**)
Male ☐ Female ☐

SEE HOW TO TAG AND MEASURE FISH ON BACK

All the Highly Migratory Species landed in North Carolina must have a Landing Tag affixed before removal from the vessel. Tags are available at all HMS Reporting Stations. To obtain a Landing Tag, captains or operators of permitted vessel must complete and submit a catch card for every HMS landed. This information collection is approved under OMB Control #0648-0328 (expires 12/31/2022).

CHECK SPECIES LANDED

BILLFISH
☐ Blue Marlin
☐ White Marlin
☐ Sailfish
☐ Roundscale Spearfish
☐ **Swordfish**

TUNA
☐ Atlantic Bluefin Tuna

SHARKS
☐ Atlantic Sharpnose
☐ Blacknose
☐ Blacktip
☐ Blue
☐ Bonnethead
☐ Bull
☐ Common Thresher
☐ Finetooth
☐ Great Hammerhead
☐ Lemon
☐ Nurse
☐ Oceanic Whitetip
☐ Porbeagle
☐ Scalloped Hammerhd.
☐ Shortfin Mako
☐ Smooth Dogfish
☐ Smooth Hammerhd.
☐ Spinner
☐ Tiger

☐ Dead Discard of Atlantic Bluefin Tuna

Billfish, Shark and Tuna Catch Card Tag Receipt
Angler's Copy

Official Use Only
Tag Number (from above) ______

Anglers should keep this receipt in hand while in possession of the fish

NC HMS Catch Card Contact Information		
Name	**Telephone Number**	**E-mail**
Dallis Tucker Drew Cathey	252-948-3816 252-946-6481	Dallis.Tucker@ncdenr.gov Andrew.Cathey@ncdenr.gov
NOAA		
Daemian Schreiber	301-427-8104	daemian.schreiber@noaa.gov
HMS Permits		
Renewals/New	888-872-8862	http://hmspermits.noaa.gov/
After Hours Reporting		
800-682-2632	Use only when no other option available	

REPORTING SITE	LOCATION	TELEPHONE
Anchorage Marina	Atlantic Beach	252-726-4423
Captain Stacy Fishing Center	Atlantic Beach	252-726-4675
Chasin Tails Outdoors	Atlantic Beach	252-240-3474
Seawater Marina	Atlantic Beach	252-726-1637
Olde Towne Yacht Club	Beaufort	252-726-3066
Town Creek Marina	Beaufort	252-728-6111
Hurricane Fishing Center	Calabash	910-579-3660
Harker's Island Fishing Center	Harker's Island	252-728-3907
Hatteras Harbor Marina	Hatteras	252-986-2166
Oden's Dock	Hatteras	252-986-2555
Teach's Lair Marina	Hatteras	252-986-2460
Holden Beach Marina	Holden Beach	910-842-5447
Oregon Inlet Fishing Center	Manteo	252-441-6301
Pirate's Cove	Manteo	252-473-3906
Shallowbag Bay Marina	Manteo	252-305-8726
Carolina Princess	Morehead City	252-726-5479
EJW Outdoors	Morehead City	252-247-4725
Portside Marina	Morehead City	252-726-7678
Ocean Isle Fishing Center	Ocean Isle	910-575-3474
Anchorage Marina	Ocracoke	252-928-6661
Southport Marina	Southport	910-457-9900
Outer Banks Marina	Wanchese	252-473-9991
Bridge Tender Marina	Wrightsville Beach	910-256-6550
Creekside Yacht Club	Wrightsville Beach	910-350-0023

FIGURE 5.1 Example of a landing tag (top) and catch card (bottom) used by the North Carolina Division of Marine Fisheries for recreational fisheries targeting highly migratory species (HMS). Atlantic bluefin Tuna, blue marlin, white marlin, sailfish, and swordfish landed recreationally in North Carolina must have a landing tag affixed before removal from the vessel. Captains or operators from trailered vessels must have the landing tag affixed before the vessel is removed from the water. Captains or operators of permitted vessels in North Carolina must use this method instead of the NOAA Fisheries call-in or website reporting process. HMS released alive are not required to be reported. SOURCE: North Carolina Division of Marine Fisheries, 2014.

In the context of fisheries managed with ACLs by Councils, harvest tags could provide a number of potential benefits. They are well suited to improving data collection or controlling harvest of species with low ACLs or rare-event species that are difficult to sample with traditional recreational fisheries surveys such as MRIP—for example, deepwater species managed by the South Atlantic Fishery Management Council (SAFMC), such as Snowy Grouper, Wreckfish, Golden Tilefish, and Yellowfin Grouper that regularly have percentage standard errors (PSEs) in excess of 50 percent. A stakeholder engagement process conducted by the American Sportfishing Association (ASA), Yamaha Marine Group, and the Coastal Conservation Association (CCA) in 2018–2019 to explore new ideas for management of the private recreational sector of the South Atlantic Snapper-Grouper fishery found that meeting participants were supportive of harvest tags for certain deepwater species (ASA, 2019). However, they noted that the number of anglers targeting these species is low compared with other Snapper-Grouper species, and most anglers would not be interested in obtaining a tag for species they do not usually target. This would make the allocation pool likely to be self-limiting, which could help address concerns raised during previous Council discussions about how to distribute tags fairly.

The use of harvest tags in recreational fisheries also presents a number of potential challenges (Johnston et al., 2007). Main concerns raised consistently by stakeholders have been (1) fair and equitable distribution among a diversity of angler interests, and (2) the potential to limit angler access, especially if the tag program is applied to higher-demand fisheries and causes the fisheries to no longer be open-access. For example, the ASA-CCA stakeholder engagement process in the South Atlantic (ASA, 2019) found that anglers felt tags should be available to all anglers, but some kind of extra effort should be required (e.g., calling to request the tag the day before a trip) to limit tag recipients to interested anglers. Similar angler engagement workshops (ASA and TRCP, 2018; GAFGI, 2017) focused on both the South Atlantic and Gulf of Mexico concluded that while harvest tags could be made available through an open lottery, depending on the popularity of the fisheries in question, an open lottery could create high demand whereby many anglers who entered the lottery would not win a tag and would not be allowed to harvest their preferred fish.

Some Councils have discussed potential use of harvest tags for certain recreational fisheries (e.g., SAFMC deepwater species). UnforTunately, it appears that a variety of concerns regarding how to handle implementation, administration, and enforcement of a program of this nature across federal–state jurisdictions inevitably bring these discussions to a halt. For example, the SAFMC explored the use of harvest tags for recreational harvest of Red Snapper, Snowy Grouper, Golden Tilefish, and Wreckfish in Snapper Grouper Amendment 22, but did not proceed with developing the amendment. NOAA General Counsel advised that a harvest tag program may need to meet the regulatory requirements for a limited access privilege program under the MSA, an issue also raised during the Gulf angler focus group discussions on tags for Gulf Red Snapper. Other concerns were also raised regarding how tags would be distributed and the effects of private and for-hire recreational participants not having access to a species if tags were made available to nonparticipants as well. The Council suspended development of Amendment 22 in March 2015. More recently, the joint working group formed by the SAFMC and Gulf of Mexico Fishery Management Council (GMFMC) in 2020 to discuss alternative management approaches under the MFA decided that, at least for now, they would not consider the use of harvest tags for improving data collection or controlling fishing effort or harvest. Collectively, these concerns highlight the many potential challenges associated with the development and implementation of harvest tags and suggest that realizing the advantages of harvest tag programs requires a well-conceptualized plan tailored to the specific fisheries involved and the preferences and attributes of different types of anglers.

Depth/Distance-Based Management

This approach involves closing recreational fishing harvest for single or multiple species beyond a certain depth or distance from shore. The basis for depth/distance-based management is that the portion of the stock in deeper waters would be protected from fishing pressure and experience reduced release mortality, leading to increased stock abundance and biomass and potentially helping replenish the shallower areas that remain open to harvest. Councils would need to coordinate with the states for a depth/distance approach to be successful since zones open to fishing are supposed to occur in areas that are shallower/closer to shore and are likely to be under state jurisdiction. Also, this approach appears to be difficult to apply in multispecies fisheries—if fishing for other, nonoverfished species in the deep/distant-from-shore area were permitted, there could be incidental catch of the species being managed, and the benefits of a closed, replenishment area would no longer be achieved.

Data needs for implementing this approach are not insignificant. For example, detailed data on fishing grounds are necessary to identify the boundaries of the spatial closure, along with information on the extent and composition of the portion of the stock that occupies the deep/distant-from-shore area. If these areas contain only a small portion of the stock or if they are occupied primarily by sexually immature fish that do not contribute to the stock's spawning biomass, the benefits of protection from fishing mortality and the probability that this portion of the stock could help replenish shallower/closer-to-shore areas would likely not be realized.

Another main challenge with this approach is that the expected reduction in fishing pressure may not occur if a large proportion of the harvest for the species in question already occurs nearer to shore, along with potential issues with compliance and enforcement of the fishing zone boundary. For example, a number of studies have documented that area closures (usually marine protected areas [MPAs]) focused on protecting fish-spawning aggregations can sometimes generate an "edge effect" whereby intense fishing activity becomes concentrated immediately outside of the MPA boundary where transient fish become vulnerable to harvest, thus compromising the conservation benefits of the closed area (Eklund et al., 2000; Ellis and Powers, 2012).

A version of the depth/distance-from-shore management approach has been implemented on the West Coast with some level of success, but in general its application has been limited. An example of its successful use is the implementation of rockfish conservation areas (RCAs), depth-based closed areas along the U.S. Pacific Coast set to minimize the bycatch of overfished Groundfish species or to protect Groundfish habitat.[2] RCAs extending along all or part of the U.S. Pacific Coast have been in place since September 2002. The RCA boundaries are lines that connect a series of latitude and longitude coordinates and are intended to approximate particular depth contours. RCA boundaries are set primarily to minimize incidental catch of overfished rockfish (*Sebastes* spp.) by eliminating fishing at locations and times when those overfished species are likely to co-occur with healthy target stocks of Groundfish. Boundaries can be different depending on what types of fishing gear are being used and are likely to differ between the northern and southern areas of the coast (Marks et al., 2015).

Conservation Equivalency

Conservation equivalency is a management approach that gives states the flexibility to develop alternative fishery regulations that address specific state or regional differences while achieving the same conservation goals as those described in FMPs. This allows states to tailor fisheries management to the preferences of their recreational fishing community and account for regional disparities in fish stock abundance or availability while still achieving equivalent conservation benefits to the resource (ASMFC, 2017). From an angler's perspective, having the same management measures across the broader geographic area managed by the Councils can be problematic. For example, anglers in some states may prefer to fish weekends, while anglers in other states may want a season that is open 7 days a week. Because of weather or school or work schedules, anglers in some states may prefer shortened seasons with larger creel limits over longer seasons with smaller creel limits. Or perhaps fishing seasons may be set for a migratory species in such a way that anglers in certain regions rarely get the chance to participate in the fishery (ASA and TRCP, 2018).

The ASMFC employs the concept of conservation equivalency in a number of interstate fishery management programs under its jurisdiction. However, in practice ASMFC frequently uses the term "conservation equivalency" in different ways depending on the language included in the plan in question. Also, approval of conservation equivalency as a valid management approach is contingent on a multistep approval process. During development of the management document, the Plan Development Team provides a determination as to whether conservation equivalency is an approved option for that specific fishery management plan since its use may not be appropriate or necessary for all management programs. This determination is based on predefined criteria that include stock status, stock structure, data availability, range of the species, socioeconomic information, and the potential for more conservative management when

[2] Magnuson-Stevens Act Provisions; Fisheries Off West Coast States; Pacific Coast Groundfish Fishery; Pacific Fishery Management Plan; Amendment 28 (https://www.federalregister.gov/documents/2019/11/19/2019-24684/magnuson-stevens-act-provisions-fisheries-off-west-coast-states-pacific-coast-Groundfish-fishery).

stocks are overfished or overfishing is occurring. Furthermore, states have the responsibility of developing conservation equivalency proposals for submission and review by a Plan Review Team (PRT), and the state submitting the proposal has the obligation to ensure that proposed measures are enforceable. If the PRT has a concern regarding the enforceability of a proposed measure, it can task the Law Enforcement Committee with reviewing the proposal. Upon approval of a conservation equivalency proposal, implementation of the program becomes a compliance requirement for the state. Each of the approved programs should be described and evaluated in the annual compliance review and included in annual FMP reviews. The ASMFC's interstate management program has a number of joint or complementary management programs with NOAA Fisheries, the U.S. Fish and Wildlife Service, and the Councils. ASMFC policies recognize that implementation of conservation equivalency measures places an additional burden on the Commission to coordinate with federal fishery management partners and recommends that to facilitate this coordination, a number of factors (e.g., stock status, stock structure, data availability, range of the species, and socioeconomic information) should be observed before a joint conservation equivalency plan can be approved.

In the context of fisheries managed by Councils, the use of this approach has been extremely rare. An exception is the GMFMC's implementation of a State Management Program for Recreational Red Snapper (Amendment 50 to the reef fish FMP). This amendment establishes the structure through which a Gulf state may establish a state management program that provides flexibility in the recreational management of Red Snapper for the state's private anglers. In recent years, the recreational fishing season for Red Snapper in Gulf of Mexico federal waters became progressively shorter despite regular increases in the recreational ACL. In response, recreational anglers asked for greater flexibility in the management of the recreational harvest of Red Snapper, including setting the fishing season. Amendment 50 to the GMFMC's reef fish FMP establishes the structure through which a Gulf state may establish a state management program that provides flexibility in the recreational management of Red Snapper for the state's private anglers (Fig. 5.2).

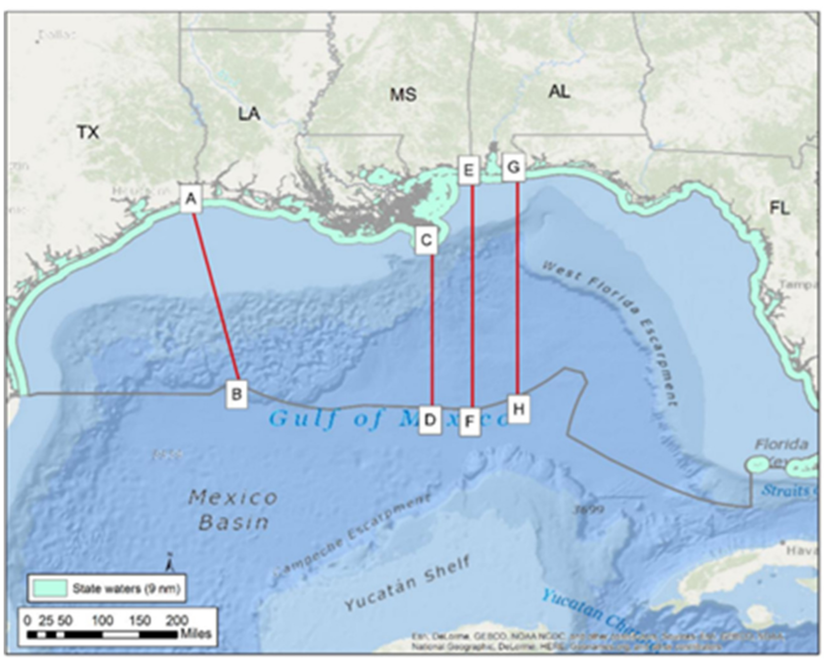


FIGURE 5.2 Map demarcating boundaries between state and federal jurisdictions in the management of the private recreational fishery for Red Snapper in the Gulf of Mexico. The area with green shading distinguishes reef fish management in state waters from that in federal waters. The gray line passing through points B, D F, and H indicates the outer boundary for federal waters. SOURCE: Final Amendment 50A to the Fishery Management Plan for the Reef Fish Resources of the Gulf of Mexico Including Final Programmatic Environmental Impact Statement, Fishery Impact Statement, Regulatory Impact Review, and Regulatory Flexibility Act Analysis (May 2019).

Giving states the flexibility to establish customized measures for managing their portion of the Red Snapper private recreational fishery has resulted in social and economic benefits, as it is assumed that each state provides fishing opportunities preferred by anglers landing Red Snapper in that state. Management measures under a state's approved state management program must achieve the same conservation goals as those of the current federal management measures—e.g., constrain harvest to the state's allocated portion of the recreational-sector ACL, and rebuild the Red Snapper stock. Nevertheless, under state management, Red Snapper remains a federally managed species. The GMFMC and NOAA Fisheries continue to oversee management of the stock in federal waters. This includes continuing to comply with the MSA's mandate to ensure that the recreational sector's Red Snapper stock ACL is not exceeded and that conservation objectives are achieved. The Council's Scientific and Statistical Committee (SSC) continues to determine the acceptable biological catch (ABC) for Red Snapper, while the Council determines the total recreational-sector ACL that is allocated among the states and the different recreational fisheries sector components.

Conceptually, adoption of a flexible management system like that provided by an approach such as conservation equivalency makes sense. When considering geographically distributed fisheries like those managed by most Councils, at least some stocks will show a fair degree of state-to-state variability in fish size, abundance, or availability. Consequently, groups of anglers in different parts of the range are likely to have different fishing experiences. However, the disadvantage is that if broadly implemented by Councils, conservation equivalency could generate a patchwork of fisheries regulations for each Council-managed stock, greatly increasing the complexity and inconsistency of regulations. For example, the GMFMC's Amendment 50 actually consists of six amendments: Amendment 50A consists of actions affecting all Gulf states and the overall federal management of Red Snapper, regardless of whether all states have a state management program, but in addition to Amendment 50A, each Gulf state has its own amendment (Amendments 50B–50F), consisting of management actions applicable to that state. A central assumption is that social benefits have been gained by allowing greater regional flexibility in the recreational harvest of Red Snapper because management measures are established in a way that better matches the preferences of local constituents. However, constraining landings to a greater number of smaller ACLs is more complex and could increase the likelihood of triggering a postseason overage adjustment.

Implementation of conservation equivalency can be problematic for other reasons. For example, by its very nature (i.e., the application of fisheries management at smaller spatial and temporal scales), this approach ends up having to rely on low-precision recreational fisheries estimates and inaccurate catch forecasting. Likewise, the difference between the current population structure (i.e., observed in real time) and the realized size or age composition induced by long-term adherence to the proposed regulations can be problematic. The perceived benefits (or "credits") are typically based on the long-term patterns rather than the transitional effects or influences of variable year classes. Finally, problems can arise when conservation equivalency measures are derived independently for different species commonly caught together. Adjustments for individual species may ignore the consequences of a misalignment of measures for species caught by the same group of anglers. For example, fishing rigs set up to catch black sea bass are likely to also catch Summer Flounder. However, if these species have different seasonal patterns of occurrence in the same area, overall discards could increase and diminish perceived conservation measures.

Permits, Endorsements and Stamps

This approach is based on adopting recreational fishing license registration measures (add-on permits, license endorsements, or stamps) to better define the universe of private anglers targeting Council-managed species, thereby providing improved sampling frames for recreational fisheries surveys. Although strictly speaking, development of a registry of offshore anglers targeting Council-managed species does not constitute a management approach per se, the use of this method is focused on addressing two main management issues: (1) the high uncertainty in MRIP data observed for federally managed stocks, and (2) development of a framework for implementation of specialized MRIP-supplemental surveys for Council-managed recreational fisheries.

There is general agreement that fishery scientists and managers face significant statistical limitations to their understanding of recreational impacts on federally managed species. One reason for these challenges is that saltwater recreational fishing licenses have not traditionally distinguished between anglers that fish inshore and/or offshore in federal waters. This limitation can make it more difficult to sample anglers accurately about their fishing activities, including the number of trips taken, fish discarded, and fish kept in federal waters. This higher level of uncertainty could cause catch limits to be set at unnecessarily low levels, thereby denying anglers sustainable access to the resource, or at unnecessarily high levels, thereby diminishing the long-term sustainability of the resource. Therefore, the need for spatial differentiation of recreational fisheries data—i.e., identifying the subset of recreational anglers targeting offshore, Council-managed species—has become an increasingly relevant topic in discussions of how to address uncertainties in determining sustainable fishing limits, as well as when dealing with multisector allocations in fisheries under multijurisdictional management (MAFAC, 2020).

The need for such an effort has been discussed by a variety of organizations interested in improving management of federally managed fisheries. One of the early calls to action in this regard came from the first of five GSMFC–NOAA Fisheries workshops on Red Snapper held in 2013. The report from that workshop (Opsomer et al., 2013) recognizes the need to better identify the universe of Red Snapper anglers as a required first step regardless of the survey method adopted by Gulf states:

> If participation in the Red Snapper fishery could be made permit-based, it would then be possible to design a targeted survey similar to the Large Pelagic Survey (LPS) along the Atlantic Coast. A sample of site-days would be selected for Red Snapper angler intercepts to estimate the Red Snapper catch/trip and obtain fish measurements, based on a sampling frame of fishing sites and time periods that encompass the Red Snapper fishing activity. The effort would then be estimated based on a survey of permit holders, both charter boat owners and individual anglers, using telephone or other modes as appropriate.

More recently, concerns raised by a number of recreational angler organizations, scientists, and managers regarding this issue prompted the Marine Fisheries Advisory Committee (MAFAC)[3] to examine whether there is an effective way to identify more precisely the universe of recreational anglers fishing in federal waters. The Gulf of Mexico recreational Red Snapper fishery was chosen as a case study for best practices (Chapter 3 describes Red Snapper surveys implemented by each Gulf state). However, the MACFAC study report (MAFAC, 2020) anticipates that results and recommendations are applicable to other coasts as well as other recreational fisheries. Key findings in the report include the following:

- There is broad consensus among fishery managers and scientists that there is value in better defining the universe of anglers that harvest and discard fish in the Exclusive Economic Zone (EEZ), and that may be a significant subset of the total population of saltwater license holders.
- Using the Gulf states as a case study, it appears that understanding the number of offshore anglers can be achieved through multiple approaches with varying levels of success:
  - using a direct, mandatory permit (free or fee-based) similar to those implemented by Alabama, Florida, and Louisiana; or

[3] The MAFAC is a federal advisory committee that advises the secretary of commerce on living marine resource matters under the jurisdiction of the U.S. Department of Commerce, primarily NOAA Fisheries. Comprising members from a diverse set of perspectives—including commercial, recreational, aquaculture, environmental, academic, state, tribal, seafood, and consumer fisheries interest groups—the committee has the unique role of working together across all of these sectors to make consensus-based recommendations to NOAA Fisheries.

- through a per–fishing trip system, such as that being used by Mississippi in requiring its offshore anglers to hail out before fishing for Red Snapper.

- Each of the programs using a formal or de facto permit was found to (1) provide more efficient targeting of surveys, or the development of future specialized surveys, as in Alabama's case; (2) reduce the uncertainty of data; and (3) facilitate improved transparency and communication with anglers that appears to have helped build confidence within that community. Under the fee-based version, benefits also included new funding streams to administer improvements to state data collection programs.
- To account for oversubscription rates in their systems, Mississippi, Louisiana, and Alabama all require an additional, separate step, such as an opt-in requirement. Concerns with the public burden of a separate step were minimized with communication and soft rollout in the first few years. Florida uses a statistical adjustment correction factor to address oversubscription.
- A single survey instrument[4] combined with a uniform sampling frame of the anglers fishing offshore can provide more consistent data across jurisdictions that are comanaging fisheries (such as a regional grouping of states or between a state and the federal government), thereby minimizing potential conflicts and improving trust levels among stakeholders.
- Significant differences in the estimates of catch for Red Snapper exist between the state and federal surveys; thus a more consistent survey method utilizing a transparent list of potential participants could be beneficial (MAFAC, 2020).

Finally, the MAFAC report provides the following recommendation:

> NOAA Fisheries should invite key state and regional Council fishery managers to evaluate the need for and potential benefits, if any, of layering in an offshore recreational permit to narrow the universe of anglers on a region-by-region basis. This novel approach will require additional scoping by NOAA Fisheries, in consultation with the states and Councils, to identify a comprehensive list of best practices that could help standardize data collection across multiple state jurisdictions to improve management and conservation. Some regions may prefer a standardized permit administered by NOAA. Other regions may prefer to implement a state-based system as in the Gulf. Some regions may prefer a permutation of the two, and some may not want to change their existing data collection. Taking regional needs and preferences into account will likely yield the highest opportunity for aggregate improvement. At the conclusion of this evaluation process, should NOAA find a need to proceed with a federal recreational offshore permit, the Secretary of Commerce should request Congressional authority for the agency to implement such a permit. NOAA's current authority to compel a federal recreational fishing registration is limited to anglers fishing in the EEZ and for anadromous or HMS species. Implementation on the ground could take many forms, ranging from a centralized approach (similar to the implementation of the current federal migratory bird stamp or "duck stamp,") to a decentralized approach that sets minimum standards as part of a Memorandum of Agreement such as the MOU currently in use under the National Saltwater Angler Registry. (MAFAC, 2020)

The Committee recommends further evaluation of this type of approach as a way to survey more effectively the subset of recreational anglers targeting offshore, Council-managed species. As a matter of fact, some Councils have already shown interest in adopting recreational fishing permits or endorsements that follow this basic model. For example, in response to input from stakeholders during development of its *2016-2020 Vision Blueprint for the Snapper Grouper Fishery in the South Atlantic* (SAFMC, 2015), the SAFMC has been formally considering implementation of reef fish permits, stamps, or endorsements,

[4] The term "survey instrument" is used to refer to the survey questionnaires that serve as the primary source of information on a given survey respondent. Traditionally, the primary variables found within the main dataset are derived directly from one or more survey instruments.

initially under Amendment 43 to the Snapper-Grouper FMP and subsequently under Amendment 46. Although the Council has paused development of this FMP amendment because of ongoing discussions by the GMFMC and SAFMC Joint Workgroup on Section 102 of the MFA, the workgroup is in the process of discussing the development of state-administered data collection and permitting programs for private recreational Snapper-Grouper fisheries. Another example of the interest in using this approach for Council-managed species is the MAFMC's adoption of a private recreational permit for Golden and Blueline Tilefish via Amendment 6 to the Tilefish FMP. Despite increasing popularity as targets for a subset of anglers, both Golden and Blueline Tilefish are species not commonly intercepted by MRIP because of the specialized nature (e.g., deepwater, far offshore) of the trips. The permit requires private recreational vessels that intend to target golden or blueline Tilefish north of the Virginia/North Carolina border to obtain a federal private recreational Tilefish vessel permit through an online application on the Greater Atlantic Regional Office website. Further, it requires private recreational Tilefish vessels to fill out and submit an electronic vessel trip report within 24 hours of returning to port for trips on which Tilefish were targeted and/or retained.

It is important, however, to emphasize that to a large degree, successful implementation of this approach—i.e., use of specialized MRIP-supplemental surveys to improve the quality and timeliness of recreational fisheries data for Council-managed species—relies on proper planning and good coordination with the MRIP Regional Implementation Team and all of its component partners in the region: the Interstate Fisheries Commission, the Fishery Management Council, and states in the region, as well as NOAA Fisheries (representatives from MRIP, the Regional Science Center, and the Regional Office). As indicated in Chapter 2, fisheries stock assessments are conducted at the unit stock level, and management benchmarks are estimated at that geographic scale. Consequently, for Council-managed species, the geographic scope for assessment and management occurs at the broad, regional scale, not on a state-by-state basis. Even in such cases as Gulf Red Snapper in which, through Amendment 50 to the reef fish FMP, individual states received delegated authority to manage their portion of the private recreational fisheries, management measures under a state's approved state management program must achieve the same conservation goals as those of the current federal management measures—i.e., constrain harvest to the state's allocated portion of the recreational-sector ACL and continue contributing to rebuilding the region-wide Red Snapper stock. In other words, even under the state management program provided by Amendment 50, Red Snapper remains a federally managed species. If this same principle is applied to other Council-managed species, it is clear that implementation of supplemental recreational fisheries surveys *solely at the state level* and not closely coordinated with the full suite of regional partners—i.e., state-specific surveys that are not fully compatible across the region—is likely to create difficulties for regional, Council-based assessment and management.

This is not a new conclusion. Two previous National Academies studies focused on the Marine Recreational Fishery Statistical Survey (MRFSS)/MRIP (NASEM, 2017; NRC, 2006) identified the need for a higher level of multiagency, interjurisdictional coordination in the development and implementation of recreational fisheries surveys. The 2006 study explicitly makes the following recommendation:

> A much greater degree of standardization among state surveys, and between state surveys and the central MRFSS, should be achieved. This will require a much greater degree of cooperation and coordination among the managers of the various surveys.

The Committee emphasizes this point here once again and stresses that, when focused on regional or Council-managed species, development and implementation of MRIP-supplemental surveys needs to be accomplished in close coordination with the Interstate Fisheries Commissions, NOAA Fisheries, and other members of the MRIP Regional Implementation Teams.

HOW CURRENT MANAGEMENT STRATEGIES COULD BE MODIFIED TO ALIGN BETTER WITH EXISTING SURVEYS OR SUGGESTED IMPROVEMENTS

Generalized Carry-Over of Recreational Catches

The need for timeliness of recreational catch information is driven in large part by the fact that ACLs are set and monitored on a strictly annual basis. If the ACL is not met, part of the allowable catch is forgone, at least in the short term (until a new stock assessment accounts for the fish left in the sea and their reproductive contributions). If the ACL is exceeded, AMs may force payback to occur more immediately, in the following year. These asymmetric, short-term consequences result in a high value being placed on meeting the ACL exactly every year. A simple and inexpensive solution to this problem may be the introduction of carryover provisions, allowing ACL underages to be carried over and added to or subtracted from the following year's ACL. Such carryover provisions have been allowed since the revision of NS 1 guidelines in 2016 (81 FR 71858; October 18, 2016). The guidelines specify that carryover is allowed as long as overfishing is prevented every year—i.e., the ACL, including carryover, remains below the overfishing limit (OFL). Such carryover provisions must be integrated into the Council's ABC control rule. In applying carryover, Councils should consider the likely reason for underages. Underages likely caused by management uncertainty (e.g., closing the season too early) are appropriate to carry over, whereas underages likely caused by poor stock condition are less so. Simulation studies show that in the long term, carryover within the rules set by the revised NS 1 guidelines tends to increase the yield of the fishery, but also increases the risk of overfishing and low stock size and the interannual variability of catches (Wiedenmann and Holland, 2020). Risks of adverse outcomes increase with the amount of carryover allowed. Capping the allowable carryover, for example at 15 percent of the OFL could be considered to keep these risks low. Risks can also be reduced by carrying over both underages and overages (generalized carryover). Without this generalization, AMs require payback of overages only when a fishery has been determined to be overfished.

Carryover provisions have been implemented or considered for multiple fisheries (Holland et al., 2020). However, the potential for such provisions to address the specific management issues resulting from data limitations for in-season management of recreational fisheries has not been systematically explored. In their simplest form, carryover provisions do not require modifications to catch monitoring or stock assessment procedures and can therefore be implemented with minimal effort and cost. It is likely that more sophisticated carryover procedures can be developed in conjunction with a new interim assessment, thereby updating stock abundance and catch information simultaneously and reducing subjectivity in the assessment of underlying reasons for underages.

Both the SAFMC and GMFMC have explored carryover provisions in fisheries with significant recreational components. Prior to the October 2016 publication of the revisions to the NS 1 guidelines that provided for carryover of unused quota, the SAFMC considered options for implementing carryover of unused ACL by a sector from the current year to the subsequent year in both the Dolphin and yellowtail Snapper fisheries.[5] While the Council initially structured the carryover or "unused ACL credit" actions to be applicable to either sector, early closures of the commercial sector of both fisheries in 2015 (due to the sector ACL's being met) prompted their development. At the time, the recreational sector of each fishery had substantially underharvested its respective ACL for at least the previous 10 years. The carryover actions were originally developed with multiple conditions for use (e.g., a cap on the proportion of unused sector ACL to be carried over in a single year; a threshold proportion of the total ACL remaining unharvested; a maximum cap on the ACL "credit" that could accrue to a sector). Subsequently, they were simplified to allow carryover of a specific proportion of the sector ACL to the next fishing year only, and moved into a

[5] SAFMC Meeting September 2016 Briefing Materials, Tab 8, Attachment 4, Dolphin Wahoo Amendment 10 Snapper Grouper Amendment 44 Scoping Document: https://safmc.net/download/Briefing%20Book%20September%202016/TAB%20008_Jt%20Dolphin%20Wahoo%20Snapper%20Grouper%20Mackerel%20Cobia/JtDW-SG-MC_A3_DW10-%20SG44ScopingDocument071516.pdf.

Comprehensive ABC Control Rule Amendment to address the use of carryover and phase-in provisions across all of the Council's fisheries.[6] Development of the amendment was paused pending publication of NOAA Fisheries' guidance on the use of carryover and phase-in provisions. In December 2020, the SAFMC resumed consideration of the amendment, and it plans to address carryover provisions and other ABC control rule modifications during 2021.[7]

Similarly, the GMFMC developed a comprehensive amendment in 2018 to address carryover provisions across FMPs,[8] but paused development in 2019 to consider other approaches, such as interim assessment analyses, that might offer a more efficient alternative.[9] Both SAFMC and GMFMC amendments include comparable actions to establish criteria for the use of carryover, as well as limits on the amount of unused ACL or ABC that could be carried forward. The Committee believes further evaluation of such approaches is warranted, which could allow the recreational sector to achieve a high level of ACL utilization while reducing risks of extreme overages and subsequent payback in a way that would be both practical and cost-effective. It is noteworthy that, while there are many examples of carryover in U.S. commercial fisheries, there are no existing examples of carryover provisions in U.S. recreational fisheries.

Carryover provisions are often viewed primarily as a means of achieving a high level of ACL utilization. As such, carryover provisions could exacerbate year-to-year variation in recreational season lengths or bag limits. However, it is also conceivable that carryover could be used to smooth out interannual variation while allowing a higher level of utilization than could be achieved with constant seasons and no carryover (in which case season lengths would have to be set conservatively to avoid overages). Stability of regulations is frequently mentioned as a goal by stakeholders, and should be considered in the design of carryover provisions for the recreational sector.

Other options that have been considered by Councils to address optimal use of ACLs have included a "common pool" quota accessible to either sector, as well as conditional, temporary transfers of unused ACL between sectors. The SAFMC contemplated both approaches for the Dolphin fishery, while the GMFMC examined conditional transfers of unused ACL for the Gulf migratory stock of king mackerel.[10] The MAFAC has had a long-standing conditional ACL transfer provision in its bluefish FMP since 2000. This allows for a transfer of quota to the commercial sector (above its 17 percent sector allocation) should harvest projections indicate that the recreational sector will not achieve its harvest limit. A transfer cap is imposed, such that the commercial sector's total allowable landings may not exceed 10.5 million pounds, which is the average of commercial landings during the period 1990–1997. Evaluation of whether a transfer is warranted occurs during the annual specifications process. This provision is currently being reviewed in the Council's Bluefish Allocation and Rebuilding Amendment and includes an option to allow bidirectional transfers, i.e., from the commercial sector to the recreational sector and vice versa.[11] Many recreational

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[6] SAFMC Meeting June 2017 Briefing Materials. Tab 10, Attachment 11: https://safmc.net/download/Briefing%20Book%20Jun%202017/10%20Snapper%20Grouper/A11_SG_ABCBackgroundDoc_062017.pdf.

[7] SAFMC Meeting March 2019 Briefing Materials. Final Committee Reports, Council Session II: https://safmc.net/download/BB%20Council%20Meeting%20Dec%202020/Committee%20Reports%20FINAL/CouncilSessionII_FINALReport_12_2020.pdf.

[8] GMFMC Amendments on Hold, Comprehensive Generic Amendment on Carryover Provisions and Framework Modifications: https://gulfCouncil.org/wp-content/uploads/E-6a-Draft-Generic-Amendment-for-Quota-Carryover-and-Framework-Modification.pdf.

[9] GMFMC June 2019 Meeting Motions Report: https://gulfCouncil.org/wp-content/uploads/Full-Council-Motions-Report_June-2019_Final.pdf.

[10] The SAFMC developed actions in Dolphin Wahoo Amendment 10 to allow transfer of unused ACL between either sector (see March 2017 Briefing Materials, Tab 6, Attachment 2), while the GMFMC considered a unidirectional transfer from the recreational king mackerel sector to the commercial sector (see August 2016 Briefing Materials, Tab C, Attachment 4a: Allocation Sharing and Accountability Measures for the Gulf Migratory Group of King Mackerel https://gulfCouncil.org/Council_meetings/BriefingMaterials/BB-08-2016/C%20-%204(a)%20%20Options%20Paper%20-%20CMP%20Amendment%2029%20072516%20-%20Stock%20Version.pdf).

[11] MAFMC Meeting February 2021 Briefing Materials. Tab 4, Bluefish Allocation and Rebuilding Amendment Public Hearing Draft: https://www.mafmc.org/s/Tab04_Bluefish-Amendment_2021-02.pdf.

stakeholders do not support the current unidirectional transfer provision, and have expressed concerns regarding its impact on the abundance of fish available to the recreational sector. While cross-sector transfer provisions have the potential to assist either sector in achieving fishery objectives, and could possibly offset management uncertainty associated with the implementation of recreational management measures (i.e., whether or not such measures have the intended impact on harvest), the Committee favors the development and/or consideration of criteria for when transfers are advisable.

Modifications to Recreational Accountability Measures

Depending on the fishery, the uncertainty and time lag associated with MRIP estimates can make implementation of AMs, particularly in-season AMs (e.g., closure when the recreational ACL is met or projected to be met, adjustments to bag limits, area closures), challenging. High PSEs may lead to early in-season closures or unnecessary triggering of postseason measures (e.g., application of restrictive management measures the following season or overage paybacks). Conversely, high PSEs may also result in failure to apply AMs (whether in season or postseason) when needed to ensure that recreational harvest remains at sustainable levels. Additionally, the release of MRIP harvest estimates 45 days after the end of a 2-month wave may lead to in-season closures that occur well after an ACL has been met or exceeded. In either case, recreational fishing opportunities may be negatively impacted, with anglers feeling as though they are being unnecessarily punished for the perceived shortcomings of both data collection and management. In some instances, geographic differences in species seasonality may result in greater adverse impacts to fishing opportunities in one part of a region compared with another. While the NS 1 guidelines recommend the use of in-season AMs "whenever possible," they provide a range of examples beyond an in-season fishery closure, and recommend the use of an annual catch target (ACT) (a level of catch set below the ACL) for fisheries without in-season AMs. However, the guidelines contain no specific provisions with respect to the appropriateness of certain approaches for either recreational or commercial fisheries.

Recreational fisheries managed by the Northeast Fishery Management Council (NEFMC) and the Mid-Atlantic Fishery Management Council (MAFMC) do not have in-season AMs (i.e., fishery closures or other adjustments) for the reasons noted above, in addition to the seasonal nature of their fisheries. Instead, both Councils use proactive AMs in which recreational measures are evaluated prior to the upcoming fishing season to determine whether adjustments are necessary to ensure that recreational ACLs are not exceeded. Additionally, both Councils apply reactive (postseason) AMs in which recreational catch is compared with the recreational ACL; if the ACL has been exceeded, adjustments are made to prevent an overage from occurring in the subsequent season. For recreational Groundfish fisheries in New England, a 3-year moving average of recreational harvest is compared with the 3-year average of the recreational sub-ACL to determine whether reactive AMs need to be applied.[12] These may include modifications to the season length, size limit, and/or bag limit, but there are no paybacks of recreational ACL overages. This approach relies on past fishery performance's being representative of future year's harvest, which can be impacted by such external factors as fish availability.

Since 2013, a bioeconomic model developed by the Northeast Fisheries Science Center (NEFSC) has been used annually to set recreational measures. The model takes into account how changes in management measures may impact recreational fishing effort, angler welfare, fishing mortality, and stock levels (Gulf of Maine cod and haddock only), although it is constrained by uncertainties associated with data inputs (e.g., preliminary MRIP data, terminal year stock assessment information). Broadly, the economic subcomponent is a recreational demand model that was parameterized using a choice experiment survey administered via MRIP (Lee et al., 2017). It accounts for changes in recreational effort based on trip cost and duration, as well as participation choices that vary according to angler expectations of landings and discards. This is linked to a biological submodel that incorporates stock dynamics (based on the peer-reviewed population assessment), but has been modified to run on a bimonthly time step that matches the

[12] NEFMC Amendment 16 to the Multispecies FMP: https://www.nefmc.org/library/amendment-16.

2-month periodicity of an MRIP wave. The biological submodel also converts fish ages from the stock assessment model to fish lengths. This allows for modeling of the impacts of length-based regulations, as well as angler selectivity and targeting. While model projections have been mixed with respect to under- or overpredicting harvests, the model is a tool that incorporates empirically derived relationships among angler effort, stock size, and management measures.

For recreational fisheries managed by the MAFMC, a postseason process similar to that in New England is used to determine whether reactive AMs are necessary. A 3-year moving average of recreational catch is compared with the 3-year average of the recreational ACL to determine whether an overage has occurred and whether adjustments to recreational management measures are needed. However, the reactive or postseason AMs in the Mid-Atlantic do include provisions for payback of recreational overages only in certain circumstances that are tied to stock status (e.g., whether a stock is overfished) and biomass level. In such instances, the payback is not a strict pound-for-pound payback, but it is scaled to the condition of the stock. These postseason, reactive AMs were implemented in 2013 through the MAFMC's Omnibus Recreational Accountability Amendment, which also removed in-season closure authority for recreational fisheries.[13] While a bioeconomic model has not been developed and/or applied to the MAFMC's recreational fisheries, the Council has supported the development of several management strategy evaluations (MSEs) for the recreational Summer Flounder fishery to address trade-offs and impacts of different suites of recreational management measures (see the section on MSE development later in this chapter).

The South Atlantic Marine Fishery Council (SAFMC) began development of an amendment in 2018 to review and revise the recreational AMs in its Snapper-Grouper and Dolphin-Wahoo FMPs. The purpose was to address uncertainties in MRIP data, improve stability, and allow more flexibility in the management of recreational fisheries. The amendment was revised to address only the recreational Snapper-Grouper fishery, and was paused in December 2019 because of concerns regarding the impact of revised MRIP estimates on allocations and existing ACLs.[14] Most of the 55 species in the Snapper-Grouper FMP have never been assessed, and ACLs for those species have been set using landings-based and other data-limited approaches. This limits the ability to establish consistent AMs that are tied to stock status across all species. While the majority of species in the FMP have in-season closures, several have extremely low recreational ACLs and/or short seasons that make implementation of in-season AMs challenging. For many others, MRIP estimates are very imprecise, even at the annual level, and low intercepts of trips harvesting Snapper-Grouper (typically offshore) tend to turn these into rare-event species. Since 2016, only eight in-season AMs (i.e., closures) have been applied to Snapper-Grouper species. However, several of these closures have not been implemented until December because of the timing of MRIP estimates, while the ACLs were met in July–August (and subsequently exceeded).[15] The SAFMC amendment examines the possible removal of recreational in-season closures for species with consistently high PSEs across a range of thresholds.

Similar to the NEFMC and MAFMC, the SAFMC is also considering postseason AM triggers that would attempt to address the uncertainty in estimates of recreational harvest. These include, among others, a 3-year moving geometric mean of recreational harvest exceeding the recreational ACL, a 3-year sum of recreational harvest exceeding the 3-year sum of recreational ACLs, recreational harvest exceeding the recreational ACL in two out of three years, and total (commercial plus recreational) harvest exceeding the total ACL, among others. Should a trigger be reached, postseason AMs that could be implemented include adjustments to season length and payback of overages. The SAFMC reviewed the amendment in November 2020 and declined to take further action at that time because of ongoing discussion of recreational AMs by

[13] MAFMC Omnibus Recreational Accountability Amendment: https://www.mafmc.org/actions/omnibus-recreational.

[14] SAFMC Snapper Grouper Regulatory Amendment 31(Recreational Accountability Measure Modifications): https://safmc.net/download/BB%20RecTopics%20Council%20Meeting%20Nov2020/A2a_Rec%20Topics_SG%20Reg%2031%20DD_Dec%202019.pdf.

[15] John Carmichael, SAFMC Executive Director. Committee presentation, September 8-9, 2020.

the GMFMC and SAFMC Joint Workgroup on Section 102 of the Modernizing Recreational Fisheries Management Act of 2018, or Modern Fish Act (MFA), which may inform future options.[16]

In contrast to the U.S. East Coast Councils, the primary AM for recreational fisheries under Pacific Fishery Management Council (PFMC) management is the extensive in-season monitoring conducted by the states.[17] This is used to adjust management measures to maintain harvest within established limits. If necessary, AMs may also include in-season closures. It should be noted that the states expend significant resources to monitor these fisheries, and that recreational effort (angler trips) in the Pacific region is two orders of magnitude less than that in the Atlantic region (New England, Mid-Atlantic, South Atlantic). Similarly, the State of Alaska also conducts in-season monitoring and management of most recreational fisheries (with the exception of Pacific Halibut, which is shared with NOAA Fisheries and the International Pacific Halibut Commission [IPHC]).

In conclusion, the committee acknowledges the challenges associated with the development and application of AMs in large recreational fisheries given the precision and timing of MRIP estimates. Exploration of such tools as bioeconomic models and consideration of multiyear approaches as highlighted above could minimize the need for in-season AMs or enable refined application of postseason AMs, and could mitigate uncertainty. NOAA Fisheries also would be well advised to review the National Standard 1 guidelines to ensure that agency guidance with respect to recreational AMs, particularly the use of in-season AMs, aligns with the timeliness and precision of harvest estimates produced by MRIP.

Voluntary Catch Reporting By Anglers

In most marine fisheries, recreational anglers do not report their catches or related information unless they are approached as part of a survey. However, there has been substantial interest in recent years in encouraging voluntary angler data programs or in some cases, mandatory reporting schemes. Voluntary reporting in particular has been widely suggested as a way of supplementing or even replacing survey-based data collection programs. The aims of such programs may include (1) obtaining more data, better data, or data that are impractical to obtain in other ways; (2) engaging stakeholders in decision making, education, and trust building; and (3) potentially reducing the effort and cost of data collection.

There is a great diversity of such voluntary programs, described by such terms as “angler apps,” “citizen science,” and “voluntary angler data.” To assess the potential of a particular program, it is important to understand its characteristics in multiple dimensions, including objectives, types of data collected, reporting technology, sampling design, data analysis, and dissemination and use of the information generated. As mentioned above, most voluntary programs have multiple objectives involving collecting various types of data as well as engaging and possibly educating stakeholders. The latter is addressed below in the section on managing for angler satisfaction. Voluntary data programs involving anglers may aim to gather information on, for example, species occurrence; catches; fishing effort; catch per unit of effort (CPUE); discards; size composition of catches and discards; fishing gear use; fish handling, including use of barotrauma mitigation; or observations or perceptions of stock abundance trends. In terms of reporting technology, options include traditional paper-based forms and logbooks, web portals, and smartphone apps.

Apps have received particular attention because of their potential to facilitate two-way information flow; near-real-time data entry; and integration of information about anglers, trips, effort, and catch on a single platform (Venturelli et al., 2017). However, other reporting options, such as web portals, remain important and may in fact be preferred by participants because use of apps on the water can distract from the fishing activity (Crandall et al., 2018). Possible sampling designs include entirely voluntary reporting, universal mandatory reporting to create a census, or survey sampling approaches whereby representative samples of participants are surveyed. In some cases, such as the Mississippi Tails n’ Scales or the Alabama

[16] SAFMC November 2020 Meeting Transcript: https://safmc.net/download/FullCouncilMin_Nov20RecTopics.pdf.

[17] See PFMC Groundfish Amendment 23 (https://www.pcouncil.org/documents/2010/09/Groundfish-fmp-amendment-23-environmental-assessment.pdf).

Snapper Check programs, voluntary reporting has been expanded and eventually made mandatory for an increasing number of species. Analysis of data collected from angler reporting often uses approaches similar to those used for survey data. However, additional considerations and novel analyses may be necessary to address biases that may arise from the selective nature of voluntary reporting, particularly if participation is low (implying high potential for bias). Collecting data to characterize such characteristics of volunteers as motivation, skill, and behavior is important to understand and quantify biases. Voluntary reporting and citizen science programs often place great emphasis on disseminating data publicly as a way of maintaining participation and serving broader education and engagement objectives.

Fisheries data provided by voluntary reporting have proven highly informative in some cases; for example, data on the occurrence of "unusual" species have been used to track climate-related changes in species ranges (Pecl et al., 2019), while data on the size composition of discards have proven important to some stock assessments, such as the snook stock assessment conducted by the Florida Fish and Wildlife Conservation Commission (FWC). Catch and effort data collected using voluntary angler data programs have been shown to yield CPUE estimates consistent with those obtained from such surveys as MRIP (Jiorle et al., 2016). However, as a result of low participation in voluntary catch-effort reporting, such data have not meaningfully augmented or replaced large-scale surveys to date. A variety of approaches have been established for addressing data quality issues in citizen science programs, including voluntary angler data programs (Bird et al., 2014; McKinley et al., 2017). Skills requirements for basic catch reporting are relatively moderate, but participants still need to be able to identify common species, conduct any size measurements that may be requested, and understand the importance of reporting trips on which no fish were caught. Often, participants have a wide range of skill levels (sustained participants may be skilled amateurs), and citizen science programs have found that accounting for assessed or self-assessed skill levels in analyses can improve data quality.

The greatest, fundamental challenge with voluntary angler data programs is their almost universally low participation (and even lower sustained participation). The long-running Florida FWC Snook Logbooks program had 122 participants overall, of whom about 30 participated in any one year between 2002 and 2014. The Angler Action program had 600 participating anglers between 2012 and 2016, but fewer than 10 major contributors (Crandall et al., 2018). The Texas iSnapper program had 95 anglers reporting a total of 163 trips in the 2015 Red Snapper season. Despite low participation, the Snook Logbook and Angler Action programs produced important information on the size composition of snook discards that was used in the snook stock assessments, illustrating that even limited voluntary reporting can be useful if it provides crucial information that is difficult to obtain in other ways. On the other hand, as mentioned above, low participation in voluntary catch-effort reporting means that such data are unlikely to substantially augment, let alone replace large-scale catch-effort surveys. In addition to limiting the precision of estimates, very low levels of reporting imply a very high potential for bias. Low participation has been a near-universal challenge for voluntary angler data programs despite substantial efforts to recruit and retain participants. Reasons for low participation include that most anglers are likely to be driven by motivations other than observing and recording data, and many are positively reluctant to share information on their fishing spots or catch rates. Of course, some anglers do like to record and share data for the sake of science. Crandall and colleagues (2018) found that sustained participants in a voluntary angler data program had motivations similar to those associated with participants in other citizen science programs.

Even though voluntary data programs use unpaid volunteers, they require substantial efforts and financial investments to recruit, retain, and train volunteers; analyze and report data; etc. They should not therefore be considered low-cost alternatives to more formal surveys or research programs (McKinley et al., 2017). Moreover, many volunteer data programs lack a sampling frame and therefore do not support probability-based estimates of catch and effort. This issue can be addressed in well-designed logbook and other citizen science programs, such as by establishing an angler panel.

Volunteer data/citizen science programs offer multiple opportunities to better engage the public in fisheries management decision making. Such programs can facilitate the bidirectional flow of information. Volunteers, through training and experience, can better understand the ability of science to provide answers. They may also appear at public meetings and provide constructive input and spread information through social networks, helping scientists and managers better understand the perspectives of stakeholders. Volunteer data/citizen science programs therefore can provide benefits far beyond the data collected, and in many cases those broader benefits may in fact be the most important.

Mandatory Catch Reporting By Anglers

Mandatory reporting and integration with other approaches (e.g., dockside intercepts) may alleviate many of the problems associated with voluntary reporting. Such approaches may achieve near-census levels of coverage akin to those achieved in many commercial catch reporting programs. An example of such a program is the Mississippi Tails n' Scales Red Snapper catch monitoring program. Not only is reporting mandatory, but the survey designs for both charter and private boat fishing consist of two complementary components: an electronic reporting system and a dockside access point intercept survey. Through a capture–recapture survey design, catch and effort information reported electronically by anglers is validated and corrected using information from the dockside intercept survey. While the program benefits from Mississippi's geography and relatively small recreational fishing sector, similar programs can potentially be effective with lower levels of dockside sampling and enforcement. Further development and testing of such approaches is necessary—for example, with respect to the coverage of private docks that are unavailable to access point intercepts and can account for a substantial share of fishing activity. With widespread availability of electronic reporting tools, objections to mandatory reporting are often more philosophical than practical. Concerns that some anglers may not have access to such tools, thereby introducing coverage bias, have been voiced but are unlikely to be borne out in federal fisheries that often require substantial investment in boats and equipment from private recreational anglers to participate. However, the committee believes that mandatory catch reporting programs have the potential to improve the accuracy and timeliness of recreational data collection and encourages further exploration of such approaches.

Recreational Reform Initiative

The Recreational Reform Initiative is a joint effort of the MAFMC and Atlantic States Marine Fisheries Commission (ASMFC) to improve management of the recreational fisheries for Summer Flounder, scup, black sea bass and bluefish. All four species are jointly managed by the MAFMC and ASMFC, which requires that both entities jointly approve ACLs and most management strategies, although there may be differences between recreational management measures for state and federal waters. The initiative was launched in 2019 with the following goals: provide stability in management measures (e.g., size limit, bag limit, season), increase flexibility in the management process, and ensure accessibility to fishery resources that is aligned with availability and stock status. The intent is to develop alternative approaches to working with existing MRIP data while meeting the mandates of the MSA.[18]

A suite of topics have been identified to address the goals of the initiative, several of which fall within the objective of better incorporating MRIP uncertainty into management. One of these is development of a process for identifying and smoothing outlier MRIP estimates. The ASMFC Summer Flounder, Scup, and Black Sea Bass Technical Committee previously identified two outlier MRIP estimates of black sea bass (2016 New York Wave 6 for all modes and 2017 New Jersey Wave 3 private/rental mode) using a modified Thompson's tau approach and replaced them with smoothed estimates for use in the development of state waters recreational measures. Generally, nonstatistical methods, such as multiyear averaging, have been used by both the ASMFC's Technical Committee and the MAFMC's Monitoring Committee to address uncertainty in MRIP data when trying to project future harvest under various management measures. Development of a standardized approach for identifying and adjusting outliers (both

[18] For a complete history of the development of the Recreational Reform Initiative, see https://www.mafmc.org/actions/recreational-reform-initiative.

high and low) would be beneficial for setting harvest specifications or evaluating the application of AMs, as noted above.

Other topics under this objective include evaluating the pros and cons of using preliminary current-year MRIP data, and developing an "envelope of uncertainty" approach for determining when changes to recreational management measures are needed. Typically, MAFMC staff use preliminary current-year Wave 1–4 data for Summer Flounder, scup, and black sea bass combined with the proportion of harvest in one or more past years (as recommended by the MAFMC Summer Flounder, Scup, and Black Sea Bass Monitoring Committee) to develop harvest projections for comparison against the following year's recreational harvest limit. The MAFMC and ASMFC are considering the development of guidelines for the appropriate use of preliminary MRIP data in making harvest projections. Use of an "envelope of uncertainty" approach would involve employing a predefined range above and below the projected current-year estimate of harvest (e.g., based on PSE) for comparison against the upcoming year's recreational harvest limit. Should the following year's harvest limit fall within this "envelope," no changes would be made to management measures (size, bag, season), presumably providing additional stability to the recreational fishery. While the MAFMC Monitoring Committee and ASMFC Technical Committee have recommended status quo management measures (see the next paragraph for additional discussion) based on PSE in the past, the intent is to create a standardized and repeatable process for use of an envelope of uncertainty approach through an FMP framework amendment or possibly a guidance document. As this is currently under development, metrics other than PSE may end up being considered by the ASMFC and MAFMC.

There are several other topics under consideration beyond improving how MRIP uncertainty is accounted for in the management process. One is the development of guidelines for when to maintain status quo recreational management measures based on comparison of harvest with such stock metrics as biomass, fishing mortality, and recruitment. These guidelines could also incorporate the envelope of uncertainty approach and other topics related to MRIP uncertainty described above. Another topic being explored to provide regulatory stability is the development of a process for setting multiyear recreational management measures, i.e., maintaining the same management measures for a 2-year period with no adjustments. This would require a commitment by both management bodies not to react to new information indicating that management measures could be liberalized, or conversely that they might need to be more restrictive. Recommendations are to align this approach with the stock assessment schedule so that updated scientific information would be available during the review of a 2-year management cycle.

Another topic of discussion is the timing of when recreational measures for federal waters are adopted, which could be combined with the 2-year management cycle described above to enhance fishery stability. Currently, final adoption of federal recreational measures for Summer Flounder, scup, and black sea bass does not occur until December of each year. This has resulted in regulations not being effective until late spring (April–May) of the following year, i.e., the year in which changes are needed, because of the federal rulemaking process. This poses challenges for coordinating the implementation of state waters management measures and impacts for-hire captains trying to plan trips for the following year. While moving the approval of federal waters measures earlier could allow for earlier implementation, it would also result in less information being available from the current year for evaluating fishery performance (and is therefore closely tied to the issue of use of preliminary current-year data).

An additional approach under consideration as part of this initiative is a "harvest control rule" proposed by multiple recreational fishing organizations under which predetermined sets of management measures would be applied at different stock biomass levels.[19] Significant stakeholder input would be required to develop the upper and lower bounds of the management "steps," but in general, higher levels of biomass would be associated with more liberal management measures and greater fishery access, while lower levels of biomass would result in more restrictive measures and less fishery access. The assumption is that there is a level of access at high stock biomass above which anglers do not need higher bag limits or

[19] The full proposal can be found at https://www.mafmc.org/s/SFSBSB-ComRec-AllocationAmd_2020-05.pdf (pp. 147–152).

lower size limits, and that restrictive measures imposed at low biomass levels are those that could be tolerated without major loss of business. While such an approach using predetermined management measures would provide fishery stability, the measures implemented at each management step would need to be translated into a level of catch to comply with MSA mandates. One concern raised by staff is the ability to project the catch associated with a set of management measures. Total recreational catch has varied significantly in years when management measures were relatively consistent, and can be impacted by a variety of external factors.

Two final topics under consideration are recreational catch accounting and recreational sector separation. The former includes such items as mandatory private angler reporting, required recreational tournament reporting, use of harvest tags, and enhanced Vessel Trip Reporting (VTR) requirements for for-hire vessels, all of which were suggested during public scoping processes. Mandatory reporting for private anglers harvesting Golden and Blueline Tilefish in the Mid-Atlantic became effective in August 2020; however, the scale of participation in the Summer Flounder, Scup, Black Sea Bass, And Bluefish fisheries could pose a challenge to the implementation of recreational reporting. Similar considerations apply to the use of harvest tags in these fisheries. The level of tournament harvest of all four species has not been evaluated, although tournament harvest is currently incorporated in MRIP estimates. Suggestions for enhanced for-hire vessel trip reporting included that vessels without federal permits (i.e., operating only in state waters) be required to report, as well as reinstatement of no-fishing reports.

Recreational-sector separation includes several options that range from developing separate management measures for the for-hire vs. private-angler sectors to establishing completely separate for-hire and private recreational allocations. There is a perception among for-hire stakeholders that the federal vessel trip report data are more accurate than the MRIP private/shore-mode data. However, only vessels operating in federal waters are required to obtain permits and submit VTRs, so total for-hire catch is underrepresented. This poses a challenge for determining which dataset (VTR vs. MRIP) to use when considering the development of separate ACLs or sub-ACLs for each sector.

The MAFMC and ASMFC will be considering priorities and next steps for all Recreational Reform Initiative topics in February 2021, including the most appropriate and expedient vehicles (e.g., guidelines, framework, full amendment) for implementation.[20] The committee supports such efforts to examine different approaches for the use of MRIP data in management, as well as the exploration of how management processes can be better aligned with the current limitations of MRIP.

EVALUATING TRADE-OFFS OF PAIRING SURVEY METHODS WITH ACL MANAGEMENT STRATEGIES USING MANAGEMENT STRATEGY EVALUATION

Gulf of Mexico Red Snapper Fishery Management Strategy Evaluation (MSE)

MSE is often used to test the robustness of various management strategies and regulations against uncertainty associated with fish population dynamics, fisheries monitoring and stock assessment, and fisheries management (De Lara and Martinet, 2009; Jones et al., 2009). MSE uses a series of simulation models to quantify the risk associated with potential fisheries management actions (Punt and Hobday, 2009; Kraak et al., 2010; Milner-Gulland et al., 2011). For alternative management strategies and regulations, potential impacts must be carefully evaluated prior to their implementation, and ineffective or risk-prone management procedures should be excluded before they cause ecological harm (Butterworth 2010; Murua et al. 2010).

MSE can include both long-term management strategies and short-term regulations. It can account for different fishery sectors by simulating expected monitoring data programs, fishing season length, and regulations associated with a given allocation of the total allowable catch across a fishery.

[20] February 2021 MAFMC and ASMFC Joint Meeting materials pertaining to Recreational Reform: https://www.mafmc.org/s/Tab01_Rec_reform_memo_Feb2021_v2.pdf.

An MSE framework is currently under development to help quantify the risks and trade-offs among the various alternative long-term management strategies and potential short-term regulations that might be used for the rebuilding and sustainable management of the Gulf of Mexico Red Snapper resource. This Red Snapper MSE sets a 9 percent buffer for the federal for-hire component and 20 percent for the private angling component. The default bag limit is set at two fish per bag. Based on the historical length of the fishing season and the landings, the catch rate can be estimated. Two management options are provided in the MSE for regulating the recreational fishery: the season length is determined by the ACT, or the ACT is determined by the input season length* catch rate (which means no buffer). The MRIP data are not explicitly used in the current Red Snapper MSE.

The Red Snapper MSE is still under construction. The committee encourages the incorporation of the MRIP data in the MSE, and suggests that machine learning methods be used to analyze the MRIP data to better predict the catch rate and season length. This would make it possible to estimate spatial and temporal dynamics of Red Snapper, which could then be used to reestimate the recreational landings as well as the discards. The detection probability that anglers encounter Red Snapper could also be estimated. The factors influencing landing could be evaluated and identified, and the quantity of recreational landings could be predicted for possible in-season management. Such a machine learning method has the potential to overcome the problem associated with current time lags of mailing/phone surveys and improve estimates of angler landings.

Mid-Atlantic Fishery Management Council Summer Flounder MSE

The MAFMC first explored the use of MSE for management of the recreational Summer Flounder fishery in 2013. The recreational fishery had been subject to increasingly restrictive measures (e.g., higher size limits, lower bag limits, shorter seasons) to avoid exceeding harvest limits, resulting in almost 90 percent of total recreational catch being discarded because of regulations. Concerns were raised about the biological and fishery impacts of high discards, as well as the disproportionate harvest of female fish due to increasing minimum size limits. The model examined the ability of current and alternative approaches to maintaining recreational harvest within catch limits, as well as the effects of different combinations of recreational regulations (size limits, slot limits, bag limits) on both the population and the fishery. It evaluated the impact of ACTs set at various buffers from the ACL, and incorporated seasonal and regional (north/south) differences in both fishery and Summer Flounder population dynamics (Wiedenmann et al., 2013).

Overall, there were few differences in population biomass among all regulatory options examined, although such performance measures as recreational harvest, discards, size of landed fish, and harvest per angler varied according to the regulatory scenario. Coastwide, scenarios in which only the bag limit was adjusted resulted in the lowest number and proportion of discards, as well as the lowest proportion of female fish harvested. Regionally, these options also resulted in a higher harvest per angler. Further, the MSE illustrated the utility of ACTs as a management approach, with larger buffers between the ACT and ACL resulting in less frequent and smaller overages, although this varied regionally.

In 2018, the MAFMC supported the development of an additional recreational MSE for Summer Flounder that expanded the previous work of Wiedenmann and colleagues (2013). This MSE evaluated the current harvest-based management procedure (catch adjustments based on MRIP point estimates of harvest compared with the recreational harvest limit) and a (F)-based approach (catch adjustments based on actual vs. target F), and included options that incorporated uncertainty into the estimates of harvest and F. One of the objectives was to determine whether an F-based management approach might allow for greater stability of recreational regulations from year to year. The performance of these different management approaches was evaluated relative to harvest limits and stock reference points. One component of the MSE was development of a recreational fleet dynamics model to simulate the impact of various combinations of regulatory measures (e.g., minimum size, bag limit, season length) and such variables as wave and state on recreational harvest and discards. While this model informed the other components of the MSE (i.e., the harvest-based and F-based catch adjustments under the various management procedures evaluated), it was also designed to be used as a stand-alone tool for evaluating short-term impacts of regulatory changes at a coastwide, regional, or state-specific scale (Fay and McNamee, 2019).

The results of the 2018 MSE demonstrated very little difference among the harvest-based vs. F-based management approaches with regard to total catch, biomass, and status determination criteria (i.e., overfished/overfishing). However, the harvest-based management procedure that incorporated uncertainty had a greater likelihood of recreational regulatory stability. The fleet dynamics model showed impacts of regulatory changes on harvest and discards that were consistent with historical data. Harvest increased with increases in bag limit and season length, while increasing minimum size resulted in increased harvest to a peak followed by a decrease. While discards decreased with increasing bag limits, increases in season length caused discards to initially increase and then plateau. Wave had a parabolic impact on harvest and discards, reflecting the seasonal nature of the fishery that peaks in or near Wave 4 (Fay and McNamee, 2019). Additionally, the MAFMC Summer Flounder, Scup, and Black Sea Bass Monitoring Committee reviewed the MSE and was able to use the fleet dynamics model to evaluate the nonpreferred Summer Flounder coastwide recreational measures in November 2019 as part of the 2020 fishery specifications.[21]

The MAFMC's Ecosystem Approach to Fisheries Management (EAFM) Guidance Document established a structured framework process for the Council to use in incorporating ecosystem considerations and trade-offs into its policy choices. As part of this process, the Council is undertaking another MSE[22] to "evaluate the biological and economic benefits of minimizing discards and converting discards into landings in the recreational [Summer Flounder] sector. Identify management strategies to effectively realize these benefits." Selection of this issue was informed by previous steps in the structured framework process to conduct a risk assessment and complete development of a Summer Flounder conceptual model to prioritize and refine high-risk ecosystem interactions. Unlike the previous two MSEs, this MSE will make use of an extensive stakeholder input process to inform model development and is not expected to be completed until 2022. While this MSE is being developed in an ecosystem context, it provides the MAFMC the opportunity to align its EAFM process with its standard recreational management review process, and will address an issue of concern to the Council and stakeholders.

BEYOND RETAINED CATCH: MANAGING RECREATIONAL FISHERIES FOR ANGLER SATISFACTION AND ECONOMIC OUTCOMES

While this report is concerned primarily with technical problems in the monitoring and in-season management or recreational catches, it is helpful to place these problems in the broader context of recreational fisheries management and the factors influencing angler satisfaction and economic outcomes. This context is important for two reasons. First, satisfaction with their fishing experience may vary considerably among different anglers fishing under the same conditions and regulations, and may be highly sensitive to specific attributes of the latter. Second, angler satisfaction with management is influenced by a variety of procedural factors such as perceived fairness or the ability to take meaningful action in the management process in addition to the satisfaction associated with a specific regulatory outcome. Indeed, dissatisfaction expressed about specific regulatory outcomes or their technical basis may be a reflection of much deeper frustrations about the management process.

Recreational anglers are diverse in terms of such aspects as their fishing motivations and ways of attaining satisfaction. Key concepts for segmenting recreational anglers include catch orientation (I go fishing because catching fishes is very enjoyable for me); consumptive orientation (to obtain fresh fish for a meal with family/friends); voluntary release orientation (I release most of the fish that I catch); trophy/size orientation (I prefer to catch one or two big fishes instead of catching ten smaller ones); sector/domain (shore, charter, private boat); avidity and specialization (essentially the level of commitment to and

[21] MAFMC Meeting December 2019 Briefing Materials, Tab 12, page 6: https://www.mafmc.org/s/Tab12_Summer-Flounder-Rec-Measures_2019-12.pdf.

[22] MAFMC Meeting October 2020 Briefing Materials, Tab 6 (EAFM Activities Update): https://www.mafmc.org/s/Tab06_EAFM-Update_10_2020.pdf.

attainment of mastery in recreational fishing); club/group membership (often associated with avidity/specialization but also wealth, class, and demographics); and demographics (age, wealth, gender, race, ethnicity, language, etc.). Angler satisfaction with the fishing experience can be defined as "the difference between the outcomes an angler desires or thinks should be received and the perceived fulfillment of the desired outcomes" (Ditton and Fedler, 1989).

Angler satisfaction has both activity-general elements (e.g., relaxing outdoors, in pleasant company, natural environment) and activity-specific elements (e.g., number of consumable fish caught, number of fish bites, fishing regulations) (Arlinghaus, 2006). Anglers in different segments attain satisfaction from quite different experiences. For instance, anglers with a strong catch-and-release orientation, such as many of those fishing for largemouth bass in freshwaters, snook and certain other coastal species, or billfishes offshore, may derive satisfaction from good opportunities to catch large fish of their target species. Having to release the fish they caught is unlikely to reduce their satisfaction, and may indeed enhance it (with a catch-and-release ethic being seen as a hallmark of an accomplished angler in this segment). On the other hand, anglers with a consumptive orientation derive a large part of their satisfaction from being able to take a nice fish home to eat, and may be dissatisfied when regulations require them to release all fish caught.

The two example types of anglers also have very different implicit perceptions of fishery access. For the catch-and-release–oriented angler, being able to practice catch-and-release fishing year-round, combined with an abundant population of target fish, would be very satisfactory fishing access. For the consumption-oriented angler, the same fishery would be perceived to provide no access if releasing caught fish were mandatory, even though the angler could engage in catching fish year-round. Both extremes, and various intermediate situations, arise in recreational marine fisheries with ACLs. Many of these fisheries, such as the Snapper-Grouper fisheries in the Southeast or the rockfish fisheries on the West Coast, however, are characterized by a strong consumptive orientation among participating anglers. Moreover, postrelease mortality may limit the sustainability of catch-and-release fishing, particularly for species caught in great depths, even when barotrauma mitigation and best release practices are used. In these cases, perceived fishing access is closely related to the recreational ACL and the specific regulations governing recreational harvest. It should be noted also that these recreational fisheries, therefore, are not as fundamentally different from commercial fisheries in their management objectives as are the catch-and-release–oriented recreational fisheries mentioned previously. Nonetheless, as is the case in commercial fisheries, the specific regulations used to maintain catches within the ACL can have major implications for angler satisfaction and the economic performance of the fishery. For instance, such implications may differ between a short season with high bag limits and a longer season with low bag limits. Predictability and consistency in season length may increase satisfaction even if it comes with a small trade-off in terms of accessing the full ACL in every year. Allocation of harvest tags to individual anglers may bring maximum flexibility in terms of when fish can be taken, but may raise concerns about perceived access and fairness of distribution.

Angler satisfaction with the fisheries management system is influenced not only by management outcomes but also by attributes of the management process. One important aspect of this is trust. There are four key types of trust relevant to fisheries management: dispositional "general trust"; rational trust based on "reciprocity" or "perceived utility" (informed by prior performance and predictions of likely future outcomes); affinitive trust based on perceived "benevolence, integrity, and social factors" (assumptions of shared values, social connectedness, shared positive experiences); and procedural trust based on perceptions of legitimacy, transparency, and effectiveness of implementation (Stern and Coleman, 2015). It is apparent that trust in the management system is low among recreational stakeholders in at least some marine recreational fisheries managed with ACLs. This general lack of trust is likely due to a deficit in more than one of the above mentioned types: it is based on past experiences of poor outcomes (e.g. very short seasons); lack of affinity for federal management agencies (recreational stakeholders often profess greater affinity for state management agencies); and perceptions that federal management lacks transparency and effectiveness. An important corollary of this is that addressing certain technical aspects of management, such as further improving the MRIP survey, are likely to be neither necessary nor sufficient to increase trust in federal management of recreational fisheries.

Another aspect of management satisfaction is related to the perception among stakeholders of being able to take meaningful action to affect management. Research suggests that while most marine recreational fishing stakeholders feel that public input should be included in decision making, few agree that it is or that managers listen to public input. Crandall and colleagues (2019) found a significant correlation between respondents' perception that they could take meaningful action to influence management and their overall satisfaction with management. Overall, this suggests that the perception that opportunities for participation are limited and not genuine is associated with overall dissatisfaction with marine recreational fisheries management. Various measures could be taken to increase awareness of participation opportunities; in particular, transparent and effective use of stakeholder input in decision making would ensure that engagement opportunities were viewed as meaningful.

A particular challenge for better engaging recreational anglers in the management of recreational marine fisheries subject to ACLs is that it is rare for individual anglers to participate actively in the management process and effective angling management organizations remain largely absent. The role of advocating for the recreational fishing sector is often taken up by recreational marine industry groups, such as the American Sportfishing Association and its Center for Sportfishing Policy, or by organizations with strong industry ties, such as the Coastal Conservation Association. While industry organizations are important stakeholders in their own right, they cannot fully address the need for engagement and representation of recreational anglers into the fisheries management process. New approaches and organizational structures may be needed to fully integrate recreational fisheries in the fisheries management process. Some pointers can be drawn from the work of Sutinen and Johnson (2003), Abbott and colleagues (2018), and Arlinghaus and colleagues (2019). Key elements of such approaches include implementing management measures that provide a high degree of control over recreational fishing mortality; creating strong angling rights that can be assigned to organizations or other groups as well as individuals in recreational fisheries; decentralized management with limited management authority devolved to and shared with local organizations and governing institutions; and cost recovery for such programs, since it is expected to strengthen accountability and improve the overall performance of the management program. For example, Sutinen and Johnson (2003) suggest the creation of community-based so-called angling management organizations (AMOs) combining aspects of management devolution, strengthened harvest rights, and comanagement. Current management arrangements for marine recreational fisheries fall short of most of these principles.

A framework for discussing how better to integrate angler satisfaction and other social and economic fishery management outcomes in the management of recreational fisheries appears to be provided by the concept of optimum yield (OY). As discussed in Chapter 2, OY is defined by the MSA as the amount of fish harvest that will provide the greatest overall benefit to the nation with respect to food production, recreational opportunities, and protection of marine ecosystems. Although still derived from MSY, OY is defined to explicitly take into account relevant social, economic, and ecological factors. Therefore, OY offers the framework and context for evaluation of fisheries management models and policies that go beyond the biological aspects of stock sustainability (Arlinghaus et al., 2019; Patrick and Link, 2015). Indeed, several recreational fisheries support organizations, such as the American Sportfishing Association, the Theodore Roosevelt Conservation Partnership, and the Center for Sportfishing Policy, have identified OY as the management reference point they believe, when appropriately applied, could help NOAA Fisheries and the Regional Fishery Management Councils address what they perceive as a fisheries management system that is still too focused on yield-based management goals more appropriate for managing commercial fisheries, and therefore inadequate to meet the needs of anglers (ASA and TRCP, 2018; CSRFM, 2014). Further, in the context of in-season management of recreational fisheries, the question of whether the investment needed for in-season ACL monitoring is warranted from a cost/benefit perspective could be discussed within the management framework provided by OY. The committee agrees that OY (as defined by the MSA) offers opportunities for exploring ways to better integrate human dimensions and other social and economic factors into the management of recreational fisheries. Therefore, the committee believes that further work is warranted to engage recreational fisheries stakeholders in a more in-depth discussion of OY and how it can be used to identify and prioritize management objectives that are better suited to the cultural, economic, and conservation goals of the angling community.

CONCLUSIONS AND RECOMMENDATIONS

> **Recommendation: NOAA Fisheries and MRIP should work in coordination with the Regional Fishery Management Councils, Interstate Fisheries Commissions, and states to, on a region-by-region basis, test the feasibility and potential benefits of alternative management approaches for some recreational fisheries. The committee recommends pilot testing of the following approaches:**
> - **The use of harvest tags for low-ACL, rare-event species; species of concern; species under Endangered Species Act (ESA) recovery plans; or other species that may not be well suited for sampling by a general recreational fisheries survey like MRIP.**
> - **Implementation of a private recreational fisheries license endorsement (or permitting program) focused on identifying the subset of licensed anglers that target Council-managed species (e.g., offshore components of the fisheries). This license registry could then be used to assist in the development of specialized surveys that could improve recreational fisheries data collection for sampling domains that are challenging for MRIP.**

> **Recommendation: Implementation of MRIP-supplemental surveys focused on regional or Council-managed species should be accomplished in close coordination with the Interstate Fisheries Commissions, NOAA Fisheries, and other members of the MRIP regional implementation teams.**

Conclusion: A generalized carry-over provision for recreational ACL underages and overages attributable to implementation error would reduce the need for precise catch management on an annual basis by allowing deviations to be corrected in the following year. Such carry-over approaches have been evaluated and found to be generally sustainable.

> **Recommendation: NOAA Fisheries and the Councils should further evaluate approaches to establishing criteria for the use of carry-over provisions, as well as limits on the amount of unused ACL or acceptable biological catch that could be carried forward. Implementation of such carry-over approaches could allow the recreational sector to achieve a high level of ACL utilization in a way that would be both practical and cost-effective while reducing risks of extreme overages and subsequent payback.**

Conclusion: The committee acknowledges the challenges associated with the development and application of AMs in recreational fisheries given the precision and timing of MRIP estimates.

> **Recommendation: NOAA Fisheries should review the National Standard 1 guidelines to ensure that agency guidance with respect to recreational accountability measures aligns with the timeliness and precision of harvest estimates produced by MRIP.**

Conclusion: The adoption of mandatory, electronic catch reporting schemes combined with intercept sampling for verification has the potential to bring recreational catch monitoring to a level of precision and timeliness comparable to that achieved in commercial catch monitoring programs. Implementing such mandatory reporting schemes could be considered for some recreational fisheries where precise monitoring and management are considered crucial.

Conclusion: Precise monitoring, such as that which may be achieved by using mandatory reporting, may also allow, and be further enhanced by, the adoption of rights-based management approaches in recreational fisheries.

> **Recommendation: NOAA Fisheries and the Councils should develop a process for engaging recreational fisheries stakeholders in a more in-depth discussion of optimum yield and how it can be used to identify and prioritize management objectives that are better suited to the cultural, economic, and conservation goals of the angling community.**

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Appendix A

Multiple-Frame Methods

The example below illustrates the application of Hartley's (1962, 1974) basic dual-frame estimator to the case of combining MRIP survey data with supplemental survey data for the purpose of reducing the variance of a total catch estimate.

Consider two intersecting survey sample frames, M and S, where M is the MRIP sample frame, and S is the supplemental survey sample frame (e.g., a supplemental state survey frame). N_M is the target population covered by M, N_S is the target population covered by S, N_{ms} is the population covered by the intersection of M and S, N_m is the population in M that is not in S, and N_s is the population in S that is not in M.

A random sample of individuals is taken from each sample frame. n_M is the sample from M, n_S is the sample from S, n'_{ms} is that part of n_M in the intersection of M and S, n''_{ms} is that part of n_S in the intersection of M and S, n_m is that part of n_M that is not in S, and n_s is that part of n_S that is not in M. One potential challenge of using multiple-frame methods is identifying individuals in the intersection of the sample frames (NASEM, 2017, p. 48). Some type of identifying information, such as angler license number or address, might need to be collected by both surveys in order to identify anglers occurring in both frames (NASEM, 2017, p. 50). However, if the supplementary survey frame is a subset of the MRIP sample frame (for example, if a state conducts a supplementary mail survey of a subset of the FES sample frame for that state), then all of the observations from the supplementary survey are in the intersection of M and S (that is, $n_S = n''_{ms}$ and $n_s = 0$), and additional identifying information may not need to be collected by the supplementary survey.

Suppose that variable y is measured for each individual i sampled in each survey. For the case of combining MRIP with a supplemental survey, let y_i = fish catch of individual i, $\bar{y}_m$ = sample mean fish catch for individuals in sample frame M who are not in sample frame S, $\bar{y}_m$= sample mean fish catch for individuals in sample frame S who are not in sample frame M, $\bar{y}_s$ = sample mean fish catch for individuals from sample frame M in the intersection of sample frames M and S, $\bar{y}''_{ms}$ = sample mean fish catch for individuals from sample frame S in the intersection of sample frames M and S, p = a weighting variable to be determined later below, and Y_{MS} = total fish catch for all individuals in the population targeted by the combined sample frames. Assuming sufficient sample sizes so that finite population corrections can be ignored, the "dual-frame" post-stratified estimator $\hat{Y}_{MS}$ of total Y_{MS} is (Hartley, 1962):

$$\hat{Y}_{MS} = N_m\bar{y}_m + N_{ms}(p\bar{y}'_{ms} + (1-p)\bar{y}''_{ms}) + N_s\bar{y}_s$$

with variance:

$$var(\hat{Y}_{MS}) = \frac{N_M^2}{n_M}\left[\sigma_m^2\left(1-\frac{N_{ms}}{N_M}\right) + p^2\sigma_{ms}^2\frac{N_{ms}}{N_M}\right] + \frac{N_S^2}{n_S}\left[\sigma_s^2\left(1-\frac{N_{ms}}{N_S}\right) + (1-p)^2\sigma_{ms}^2\frac{N_{ms}}{N_S}\right]$$

where σ_m^2 is the population variance of y for individuals in sample frame M who are not in sample frame S, σ_s^2 is the population variance of y for individuals in sample frame S who are not in sample frame M, and σ_{ms}^2 is the population variance of y for individuals in the intersection of sample frames M and S.

"MRIP Alone" Estimator

For the purpose of comparing the estimators of catch and variance when MRIP is used alone with the estimators of catch and variance when MRIP is used together with a supplemental survey, the "MRIP alone" catch estimator $\hat{Y}_M$ in the notation above is:

$$\hat{Y}_M = N_m \bar{y}_m + N_{ms}(p\bar{y}'_{ms})$$

The "MRIP alone" estimator above is a special case of the general dual-frame estimator in which $N_s = 0$, p = 1, and (1-p) = 0. Similarly, the variance of the "MRIP alone" estimator is a special case of the variance of the general dual-frame estimator in which $N_S = 0$:

$$var(\hat{Y}_M) = \frac{N_M^2}{n_M}\left[\sigma_m^2\left(1 - \frac{N_{ms}}{N_M}\right) + p^2\sigma_{ms}^2\frac{N_{ms}}{N_M}\right]$$

"MRIP with Supplemental Survey" Dual-Frame Estimator

Assuming that the MRIP sample frame has 100% coverage of the population of interest (licensed recreational saltwater anglers in the region of interest), sample frame S is a subset of sample frame M, and so $N_s = 0$ in the general dual-frame estimator, yielding the "MRIP with Supplemental Survey" estimator:

$$\hat{Y}_{MS} = N_m \bar{y}_m + N_{ms}(p\bar{y}'_{ms} + (1-p)\bar{y}''_{ms})$$

When sample frame S is a subset of sample frame M, it follows that $N_{ms} = N_S$ and $\sigma_{ms}^2 = \sigma_S^2$, and so the variance of the general dual-frame estimator simplifies to:

$$var(\hat{Y}_{MS}) = \frac{N_M^2}{n_M}\left[\sigma_m^2\left(1 - \frac{N_S}{N_M}\right) + p^2\sigma_{ms}^2\frac{N_S}{N_M}\right] + \frac{N_S^2}{n_S}\left[(1-p)^2\sigma_{ms}^2\right]$$

The optimal value of the weighting variable p minimizes $var(\hat{Y}_{MS})$. The optimal value of p is found by setting the partial derivative of $var(\hat{Y}_{MS})$ with respect to p equal to zero and solving for p (note that $var(\hat{Y}_{MS})$ is convex in p):

$$p = \frac{\frac{N_S}{n_S}}{\frac{N_M}{n_M} + \frac{N_S}{n_S}}$$

Reduction in Variance of Catch Estimate Due to Supplemental Survey

The variance of the catch estimate using the dual-frame estimator as a proportion of the variance of the catch estimate using MRIP alone is given by:

$$\frac{var(\hat{Y}_{MS})}{var(\hat{Y}_M)}$$

For example, if the ratio above is 0.75, then the variance of the catch estimate based on the dual-frame estimator is only 75 percent as large as the variance of the catch estimate based on MRIP alone; that is, using the dual-frame estimator has reduced the variance of the catch estimate by 25 percent compared to what the variance would be using MRIP alone.

Inserting the values of $var(\hat{Y}_M)$ and $var(\hat{Y}_{MS})$ into the variance ratio above, and after some algebraic manipulation, the ratio can be shown to be:

$$\frac{var(\hat{Y}_{MS})}{var(\hat{Y}_M)} = \frac{(N_M - N_S)\sigma_m^2 + p(N_S\sigma_S^2)}{(N_M - N_S)\sigma_m^2 + N_S\sigma_S^2}$$

where $0 < \frac{var(\hat{Y}_{MS})}{var(\hat{Y}_M)} < 1$ for $N_M > N_S > 0$ and $0 < p < 1$. Hence, for sufficiently large sample sizes n_M and n_S, combining MRIP survey results with those from a supplemental survey with sample frame S that is a subset of the MRIP sample frame M always reduces the variance of the catch estimate.

Sensitivity Analysis

Increasing the MRIP survey sample size n_M increases the value of p, increases the variance ratio $\frac{var(\hat{Y}_{MS})}{var(\hat{Y}_M)}$, and hence reduces the benefit (in terms of variance reduction) of a supplemental survey.

Increasing the supplemental survey sample size n_S decreases the value of p decreases the variance ratio, and hence increases the benefit (in terms of variance reduction) of conducting a supplemental survey.

An increase in the variance of y within the supplemental survey (that is, an increase in σ_S^2) decreases the variance ratio, and hence increases the benefit (in terms of variance reduction) of conducting a supplemental survey.

An increase in the variance of y in the portion of the MRIP sample frame outside the supplemental survey sample frame (that is, an increase in σ_m^2) increases the variance ratio, and hence decreases the benefit (in terms of variance reduction) of conducting a supplemental survey.

As the size of the supplemental survey sample frame increases relative to the size of the MRIP sample frame (that is, as N_S/N_M increases), the variance ratio increases, and hence the benefit (in terms of variance reduction) of conducting a supplemental survey decreases.

The sensitivity analysis results, taken together, provide guidance on how best to target supplemental surveys for the goal of variance reduction within a dual-frame estimation framework. To provide the most benefit in terms of variance reduction, supplemental surveys should be targeted on MRIP domains with relatively low MRIP sample sizes (small nM) and with high variance in y. Within the MRIP domain, the subset population targeted by the supplemental survey should be relatively small (small NS), but the sample size within the subset should be relatively large (nS large relative to NS).

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Appendix B

Leveraging Covariances and Conditionals

The Covariance of Catch Estimates Across MRIP Domains

MRIP provides estimates of fish catch and its variance by *domain*, where a domain is defined as a combination of: fish species, 2-month wave time period, geographic state or sub-state location, fishing area (inshore, state ocean waters, or federal ocean waters), and fishing mode (private boat, shore-based, charter, or head boat). Typically, information from only one domain is used by fishery managers to forecast catch for that domain. This neglects information in patterns that may exist in the data *across domains* that might be useful for increasing the precision (decreasing the PSEs) of catch and effort *forecasts*, such as those made for the purpose of in-season management by fishery managers using the MRIP output estimates.

MRIP produces a catch estimate for a given domain by multiplying an estimate of fishing "effort" (i.e., fishing trips) for the domain obtained from FES by an estimate of the "catch per unit effort" (i.e., catch per fishing trip), or CPUE, obtained from APAIS for the domain. The MRIP estimates are weighted such that the effort estimate from FES is statistically independent of the CPUE estimate from APAIS *within a domain*. However, the effort estimate in one domain may not be statistically independent of the effort estimate in another domain. Similarly, the CPUE estimate in one domain may not be statistically independent of the CPUE estimate in another domain.

As an example, consider MRIP catch estimates for two domains, where estimated catch in the first domain is C1, and estimated catch in the second domain is C2. For example, C1 might be the catch of a particular species in a particular location in a particular wave, and C2 might be the catch of a different species in that same location and wave. The MRIP estimates of these catches are estimated by multiplying together weighted estimates of effort (trips) in each domain, E1 and E2, with weighted catch per unit effort in each domain, U1 and U2:

$$C1 = T1 \cdot U1$$

$$C2 = T2 \cdot U2$$

When fish catch in one domain moves in the same direction as the fish catch in the other domain, the *covariance* between the two fish catches is positive. When the catches move in opposite directions, the covariance between the catches in the two domains is negative. The general definition of the covariance between the catches across the two domains, cov(C1,C2), is:

$$\text{cov}(C1,C2) \quad = \text{cov}(T1 \cdot U1, T2 \cdot U2)$$

By the definition of covariance:

$$= E[(T1 \cdot U1) \cdot (T2 \cdot U2)] - E[T1 \cdot U1] \cdot E[T2 \cdot U2]$$

$$= E[(T1 \cdot T2) \cdot (U1 \cdot U2)] - E[T1 \cdot U1] \cdot E[T2 \cdot U2]$$

By the independence of T and U within a domain:

$$= E[(T1\cdot T2)\cdot(U1\cdot U2)] - E[T1]\cdot E[U1]\cdot E[T2]\cdot E[U2]$$

By the definition of cov[(T1·T2),(U1·U2)]:

$$= cov[(T1\cdot T2),(U1\cdot U2)] + E[T1\cdot T2]\cdot E[U1\cdot U2] - E[T1]\cdot E[U1]\cdot E[T2]\cdot E[U2]$$

$$= cov[(T1\cdot T2),(U1\cdot U2)] + \{cov[T1\cdot T2]+E[T1]\cdot E[T2]\} \cdot \{cov[U1\cdot U2]+E[U1]\cdot E[U2]\} - E[T1]\cdot E[U1]\cdot E[T2]\cdot E[U2]$$

$$\begin{aligned}= {} & cov[(T1\cdot T2),(U1\cdot U2)] + cov(T1,T2)\cdot cov(U1,U2) \\ & + cov(T1,T2)\cdot E[U1]\cdot E[U2] + cov(U1,U2)\cdot E[T1]\cdot E[T2] \\ & + \cancel{E[T1]\cdot E[U1]\cdot E[T2]\cdot E[U2]} - \cancel{E[T1]\cdot E[U1]\cdot E[T2]\cdot E[U2]}\end{aligned}$$

or, finally:

$$\begin{aligned}cov(C1,C2) = {} & cov[(T1\cdot T2),(U1\cdot U2)] + cov(T1,T2)\cdot cov(U1,U2) \\ & + cov(T1,T2)\cdot E[U1]\cdot E[U2] + cov(U1,U2)\cdot E[T1]\cdot E[T2]\end{aligned}$$

Therefore, the covariance between catches across domains, or cov(C1,C2), could be non-zero when any of the following is non-zero:

- covariance in the product of effort (T1·T2) and the product of CPUE (U1·U2) across domains (that is, cov[(T1·T2),(U1·U2)])
- covariance in effort across domains, cov(T1,T2), or
- covariance in CPUE across domains, cov(U1,U2).

The examples below illustrate how non-zero covariances could occur in many situations.

The covariance in the product of effort (T1·T2) and the product of CPUE (U1·U2) across domains (that is, cov[(T1·T2),(U1·U2)]) could be non-zero in some situations. For example, Gillig et al. (2000) investigated the effect of Red Snapper CPUE (from MRFFS) on fishing effort (trips per angler) targeting Red Snapper for reef fish anglers in the Gulf of Mexico in 1991. In this cross-section study, these investigators found that CPUE was correlated with fishing effort. Specifically, the authors found that "a 10% increase in catch rate [CPUE] will result in a 14.6% increase in the number of recreational Red Snapper trips [T]." This implies that the covariance between fishing effort and CPUE across locations is not zero; for example, if CPUE is high in two locations in a particular time period, then, all else equal, one would expect fishing effort to be high in those two locations in the same time period. Similarly, the covariance between fishing effort and CPUE across time periods may be non-zero; for example, if CPUE is relatively high in a particular location for two time periods, then, all else equal, one might expect that fishing effort would be relatively high in that location for those two time periods.

In the example where C1 is the catch of a particular species targeted in a particular location in a particular time period, and C2 is the catch of a different species targeted in that same location and time period, then cov(T1,T2) is clearly positive, as both species experience the same number of trips in a particular location and time period. If the FES-estimated number of trips for species 1 in a particular location and time, namely T1, were larger (say, in a different, hypothetical, FES sample drawn at that same location and time—a FES re-sampling experiment), then the FES-estimated number of trips for species 2 in the same location and time, namely T2, would also be larger, and by the same amount, because the FES estimate of the number of trips for that location and time is applied to both species.

Positive cov(T1,T2) for two targeted species at same location and time

	Species 1	Species 2
	Effort (T1)	Effort (T2)
Sample 1	8	8
Sample 2	10	10
Sample 3	6	6
Sample 4	7	7
cov(T1,T2)	2.9167	

Similarly, suppose the two species are found in the same locations and are typically caught together (on a given trip). In this case, if the APAIS estimate of the catch rate for the first species, U1 increases (say, due to a different, hypothetical, APAIS sample being drawn from the anglers present at that location and time—an APAIS re-sampling experiment), then the APAIS estimate of the catch rate for the second species, U2, would also increase, because U1 and U2 are calculated from the same sample of APAIS anglers, and species 1 and species 2 are caught together; in this case, cov(U1,U2) would be positive. On the other hand, if species 1 and species 2 were typically not caught together (on a given trip), then APAIS samples (hypothetically, drawn from the same population of anglers at a given location and time) resulting in a higher estimate of U1 might result in a lower estimate of U2, and cov(U1,U2) would be negative.

Positive cov(U1,U2) for two species typically caught together

	Species 1	Species 2
	CPUE (U1)	CPUE (U2)
Sample 1	3	5
Sample 2	5	7
Sample 3	10	15
Sample 4	2	3
cov(U1,U2)	18.6667	

Negative cov(U1,U2) for two species typically <u>not</u> caught together

	Species 1	Species 2
	CPUE (U1)	CPUE (U2)
Sample 1	3	10
Sample 2	8	2
Sample 3	10	2
Sample 4	1	6
cov(U1,U2)	-12.6667	

Comparing catches of a *single* species at two different locations over time (either across years, or across waves within a year), where C1 is the catch of the species in one location and C2 is the catch of the same species in a different location, cov(C1,C2) would be positive if the abundance of the species is similar at both locations at the same time. On the other hand, cov(C1,C2) would be negative if high abundance at one location was typically paired with low abundance at the other location at a given time. The value of cov(C1,C2) where C1 and C2 represent catches in different locations could be due to covariance in trips across locations, cov(T1,T2), covariance in CPUE across locations, cov(U1,U2), or both.

Positive cov(C1,C2) for a single species across Location 1 and Location 2

	Catch C1	Catch C2
	Location 1	Location 2
Time 1	3	3
Time 2	5	5
Time 3	10	10
Time 4	2	2
cov(C1,C2)	12.66667	

Negative cov(C1,C2) for a single species across Location 1 and Location 2

	Catch C1	Catch C2
	Location 1	Location 2
Time 1	3	5
Time 2	5	3
Time 3	10	2
Time 4	2	10
cov(C1,C2)	-10	

Comparing catches of a *single* species at two different times (either two different years or two different waves) for a set of locations, where C1 is the catch of the species at time 1, and C2 is the catch of the same species at a later time 2, cov(C1,C2) would be positive if the size of the catch is similar at both times for a given location. On the other hand, if a large catch in one time period is associated with a small catch in the other time period at the same location, then cov(C1,C2) would be negative. The value of cov(C1,C2) where C1 and C2 represent catches in different time periods could be due to covariance in trips across time periods, cov(T1,T2), covariance in CPUE across time periods, cov(U1,U2), or both.

Positive cov(C1,C2) for a single species across Time 1 and Time 2

	Catch C1	Catch C2
	Time 1	Time 2
Location 1	3	3
Location 2	5	5
Location 3	10	10
Location 4	2	2
cov(C1,C2)	12.66667	

Negative cov(C1,C2) for a single species across Time 1 and Time 2

	Catch C1	Catch C2
	Time 1	Time 2
Location 1	3	5
Location 2	5	3
Location 3	10	2
Location 4	2	10
cov(C1,C2)	-10	

Using Conditioning to Reduce Catch Variance and PSEs

In some situations, the probability distribution of one variable, say fish catch in a particular MRIP domain, C, may depend in part on the value of another variable, say X. In such cases, we say that the probability distribution of C is *conditional* on the value of X, expressed as: P(C|X), and we say that X is a *conditioning variable* for C. For example, suppose the catch of Wahoo off the coast of North Carolina in June, C, depends in part on the water temperature off the coast of North Carolina in May, X. In this case, P(C|X) says that the probability of catching various numbers of Wahoo off the coast of North Carolina in June depends on the water temperature off the coast of North Carolina in May.

The conditioning variable X could be anything that affects the probability distribution of C. For example, X could be the catch of the same fish species in some other place or season, or X could be the catch of some *other* species in a particular place or season, or X could be a weather variable (air temperature or precipitation), or an ocean conditions variable (wave height, seawater temperature, current, tide, El Nino, etc.), or an economic conditions variable (unemployment rate, fuel price, etc.), or a cultural variable (holidays, hunting season, etc.), or a fishery regulation variable (length of fish season, bag limit, size limit, etc.), etc.

There can be more than one conditioning variable (more than one X) for C. For example, the probability of catching various numbers of Wahoo of the coast of NC in June might depend on the weather (which affects angler effort), the estimate of the Wahoo stock size (from a stock assessment), and an estimate of the abundance of Wahoo prey (which attract Wahoo to this particular area), as well as water temperature. In this case, C might be conditional on all of these variables. In practice, fishery managers would want to focus on the conditioning variables that have the largest effect on C, and those variables for which data are readily available or cheap to collect.

For the purposes of this discussion, focus on a single conditioning variable, X, say water temperature.

In practice, the probability distribution of C conditional on X, that is, P(C|X), is calculated by looking back in time at the MRIP catch estimates of C and comparing them with the various values of X. For example, when water temperature is 75°F, then the probabilities of catching various numbers of Wahoo would be P(C|X=75), but when water temperature is 80°F, then the probabilities of catching various numbers of Wahoo would be P(C|X=80), and so on.

The *expected value of C conditional of X*, that is, the average value of C for a particular value of X, is denoted E[C|X]. If fishery managers look back at the MRIP estimates of C when X=75, and then take the average of the MRIP estimates of C when X=75, this would give E[C|X=75]. The same could be done for other values of X (e.g., E[C|X=65], E[C|X=85], etc.).

Note that the *expected value of the conditional expectation of C*, given X, that is E[E[C|X]], is an unbiased estimate of E[C] (Ross, 1988, p. 286):

$$E[\ E[C|X]\ ] = E[C]$$

For example, the formula above says that if you take E[C|X=75], E[C|X=80], E[C|X=85], etc., for all of the different values of water temperature X, and then you average them all together, then you get the average value of C averaged across all of the different, possible values of water temperature X.

The *conditional variance* of C with respect to X, Var (C | X), is defined as (Ross, 1988, p. 292):

$$\mathrm{Var}\ (C \mid X)\ =\ E[\ [C - E(C \mid X)]^2 \mid X]\ =\ E[C^2 \mid X]\ -\ (\ E[C \mid X]\ )^2$$

The formula above gives the variance of catch for a particular value of X, say the variance in Wahoo catch for a particular water temperature.

By taking the expectation of Var (C | X) and combining the result with the definition of Var (E [C|X]), the *Conditional Variance Formula* (Ross 1977, p. 292) below can be derived:

$$\mathrm{Var}(C) = E\ [\ \mathrm{Var}(C|X)\ ]\ +\ \mathrm{Var}\ (\ E[C|X]\ )$$

Rearranging:

$$\mathrm{Var}\ (\ E[C|X]\ ) = \mathrm{Var}(C) - E\ [\ \mathrm{Var}(C|X)\ ]$$

By the definition of variance, $\mathrm{Var}(C) > 0$, $\mathrm{Var}\ (C \mid X) \geq 0$ and, hence, $E\ [\ \mathrm{Var}\ (C \mid X)\ ] \geq 0$.

Thus:

$$\mathrm{Var}\ (\ E[C|X]\ ) \leq \mathrm{Var}(C).$$

The last formula above is a very important result. It says, for example, that the variance in Wahoo catch at a particular water temperature is less than the variance of Wahoo catch across all water temperatures. The formula implies that if we know (or can estimate/forecast) a good conditioning variable X (such as water temperature in the present example), then *we can reduce the variance in our forecast of C (Wahoo catch) below the variance estimate provided by MRIP by taking the conditioning variable, such as water temperature, into account.* If fishery managers can find a good conditioning variable X, then they could use it to reduce the variance (and PSE) of the catch forecast, which would allow more precise in-season management--fishery managers could “manage closer to the ACL.”

In summary, the method of conditioning might be useful to fishery managers because E[E[C|X]] is an unbiased estimate of E[C], and Var(E[C|X]) is smaller than Var(C).

Covariances, Conditional Expectations and Forecasts

Suppose that fishery managers wish to forecast the catch C of a species in a particular location and wave/season (i.e., in a particular MRIP domain), and information is available on a good *conditioning variable*, X (see the Appendix section above). The conditioning variable X could be the catch of the *same* species in a different location or wave/season, or the catch of a *different* species in the same (or different) location or wave/season, or X could be some ancillary variable, such as water temperature, wind speed or fuel price. Suppose managers wish to use the value of X to help forecast the value of C.

Let f(X) be a "prediction function" that attempts to predict C based on X. The "best" prediction function, defined as the (unbiased) prediction function that minimizes the variance of the prediction, is the *expected value of C conditional on X*, that is, E(C|X).

Note that the best predictor E[C|X] is an unbiased estimator of E[C]:

$$E[E[C|X]] = E[C]$$

and note that the *variance* of of the best predictor E[C|X] is less than the variance of *any other* predictor f(X) based on X, that is:

$$E[(C - E[C|X])^2] \leq E[(C - f(X))^2] \quad \text{for all } f(X) \qquad \text{(proof: Ross, 1988, p. 294)}$$

If the joint probability distribution of C and X is not completely known, or the analytical calculation of E[C|X] is mathematically difficult, then E[C|X] could be simulated, or the discussion could be limited to a common class of prediction functions, such as linear prediction functions, f(x) = a + bX. The <u>best</u> *linear* prediction function E[C|X] (that is, the function that results in an unbiased prediction with minimum variance within the class of linear prediction functions), is (proof, Ross, 1988, p.298):

$$E[C|X] \;=\; E[C] + [\mathrm{cov}(C,X) / \mathrm{var}(X)\,] \cdot (X - E[X])$$

where E[E[C|X]] = E[C], that is, the predictor is unbiased, and where the mean square error (MSE) of the conditional prediction is (proof, Ross, 1988, p.298):

$$\mathrm{MSE}(E[C|X]) \;=\; E[(C - E[C|X])^2] \;=\; \mathrm{var}(C) \;-\; [\mathrm{cov}(C,X)^2 / \mathrm{var}(X)]$$

For the special (but common) case in which C and X jointly have a bivariate normal distribution, the expectation of C conditional on X, that is, E(C|X), is, in fact, linear in X, and so the results above give the best possible predictor for C and its MSE among *all possible* predictors (not just within the class of linear predictors) (proof: Ross, 1988, p. 299).

Notice the importance of the covariance between C and the conditioning variable X, that is cov(C,X), in the formula for MSE. The larger the covariance, cov(C,X), the smaller the MSE of the conditional prediction. In fact, the MSE decreases with the *square* of the covariance between C and X. Also, the smaller the value of var(X), the smaller the MSE. *Hence, when attempting to identify good candidates for a conditioning variable X, fishery managers should search for X variables that have a large value of cov(C,X) and a small value of var(X).*

Software Implementation

MRIP uses SAS Proc Survey means to conduct its data analysis, and Proc Survey means can calculate conditional means and variances. If the variable X were identified by fishery managers, and fishery managers provided MRIP with data on X, then MRIP could add the data on variable X to the MRIP dataset, and then E(C|X), cov(C,X), and MSE(E[C|X]) could be calculated easily by SAS Proc Survey means and released by MRIP for subsequent use by fishery managers.

The Role of Covariance When Fishery Managers Aggregate or Disaggregate MRIP Catch Estimates

The covariance between fish catch X in one MRIP domain and fish catch Y in a different MRIP domain can affect the variance (and PSE) of a catch forecast in situations where fishery managers aggregate or disaggregate the domain-level fish catch estimates X and Y provided by MRIP. In the discussion below, we are *not* referring to the methodology that MRIP uses to calculate the catch estimates X and Y and the variances (and PSEs) of X and Y; instead, we are referring to fishery managers' *subsequent* use of MRIP estimates to produce catch forecasts using the catch estimates and PSEs that have been produced and disseminated by MRIP.

1. Aggregating Fish Catches Across Domains:

Covariance can be important when aggregating fish catches across domains, such as aggregating the catch of a particular species across geographic regions, or aggregating the catch of a particular species across time periods (i.e, across waves or across years), or aggregating the catch of a particular species across fishing modes, or aggregating the catch of related species into a species-group total (such as aggregating the catches of various Grouper species into total catch of all Groupers), or aggregating the catch across all species to obtain the "total catch of all fish" at a given location and time period.

In general, the variance of the aggregated fish catch X + Y depends on the variance of X, the variance of Y, and the covariance of X and Y, as given by (Ross, 1988, p. 276):

$$\mathrm{var}(X + Y) = \mathrm{var}(X) + \mathrm{var}(Y) + 2\mathrm{cov}(X,Y)$$

If the fish catches X and Y are independent, then cov(X,Y) is zero, and the variance of the aggregated fish catch is correctly calculated by simply summing the variances of X and Y provided by MRIP:

$$\mathrm{var}(X + Y) = \mathrm{var}(X) + \mathrm{var}(Y)$$

However, suppose that fishery managers *assume* that the fish catches X and Y are independent and that cov(X,Y) is zero when in fact the catches are dependent and $\mathrm{cov}(X,Y) \neq 0$. If catches X and Y are dependent and cov(X,Y) is not zero, then omitting the covariance may lead to over- or underestimation of the variance (and PSEs) of the aggregated catch.

If cov(X,Y) is in fact *negative*, and if it is omitted from the calculation of var(X+Y), then var(X+Y) and PSEs of the forecast will be *over*estimated. PSEs will appear larger than they actually are, resulting in fishery regulations that are more stringent than they need to be in order to avoid catches that exceed an ACL. Thus, correctly including cov(X,Y) in the calculation of var(X+Y) will reduce var(X+Y) and PSEs, allowing less stringent fishery regulations.

Perhaps equally important, if cov(X,Y) is in fact *positive*, and if it is omitted from the calculation of var(X+Y), then var(X+Y) and PSEs of the forecast will be *under*estimated. In this case, fishery regulations based on the PSEs may be too lax, resulting in catches that exceed ACLs more often than fishery managers expect. In this case, correctly including cov(X,Y) in the calculation of var(X+Y) will increase var(X+Y) and PSEs, resulting in stricter fishery regulations that keep catches below the ACL as often as fishery managers.

2. Disaggregating Fish Catches Across Domains:

Recognizing the importance of covariances is also important when disaggregating fish catches across domains, for example, when disaggregating total regional fish catch into catches by sub-regions, or when disaggregating total fish catch into catches by fishing mode, or when disaggregating total catch of a species group into catches by species (such a disaggregating total Grouper catch into catches by species of Grouper).

In general, the variance of the disaggregated catch X depends on the variance of the aggregated fish catch X + Y, the variance of Y, and the covariance of X and Y:

$$\mathrm{var(X) = var(X + Y) - var(Y) - 2cov(X,Y)}$$

If the fish catches X and Y are independent, then cov(X,Y) is zero, and the variance of the disaggregated fish catch var(X) is correctly calculated by simply subtracting MRIP-supplied var(Y) from the MRIP supplied variance of the aggregated catch var(X+Y):

$$\mathrm{var(X) = var(X + Y) - var(Y)}$$

However, suppose that fishery managers *assume* that the fish catches X and Y are independent and that cov(X,Y) is zero when in fact it is not. If catches X and Y are dependent and cov(X,Y) is not zero, then omitting the covariance may lead to over- or underestimation of the variance (and PSEs) of the disaggregated catch.

If cov(X,Y) is in fact *negative*, and if it is omitted from the calculation of var(X), then var(X) will be *under*estimated. In this case, fishery regulations based on the mistakenly small PSEs may be too lax, resulting in catches that exceed ACLs more often than managers expect. In this case, correctly including cov(X,Y) in the calculation of var(X) will increase var(X) and PSEs, resulting in stricter fishery regulations that keep catches below the ACL as often as managers expect.

On the other hand, if cov(X,Y) is in fact *positive*, and if it is omitted from the calculation of var(X), then var(X) and PSE will be *over*estimated. PSEs will appear larger than they actually are, resulting in fishery regulations that are more stringent than they need to be in order to avoid catches that exceed an ACL. Thus, correctly including cov(X,Y) in the calculation of var(X) will reduce var(X) and PSE, allowing fishery regulations to be relaxed.

Extension to More Than Two Domains

The issues discussed in this section extend to aggregation or disaggregation of catches across more than two domains (i.e., more than two time periods, more than two species, etc.). When more than two domains are involved, the covariances between *all pairs* of domains can affect the variance of the result.

The general variance formula for aggregating across n domains, $X_1, X_2, \ldots, X_n$, is given by (Ross, 1988, p. 276):

$$var\left(\sum_{i=1}^{n} X_i\right) = \sum_{i=1}^{n} var(X_i) + 2\sum_{i=1}^{n}\sum_{j=1}^{i} cov(X_i, X_j)$$

and the formula for the variance of X_i disaggregated from $X_{j\neq i}$ is given by:

$$var(X_i) = var\left(\sum_{j=1}^{n} X_j\right) - \sum_{j\neq i} var(X_j) - 2\sum_{j=1}^{n}\sum_{k=1}^{j} cov(X_j, X_k)$$

Covariances Are Likely Negative Among Species in a Multi-Species Fishery Constrained by a Binding ACL

In a multi-species fishery constrained by a binding ACL, such as perhaps the South Atlantic Snapper/Grouper fishery, we might expect covariances across catches to be negative among species in the fishery. One possible reason for this is illustrated by the following example.

Suppose there are r species in the multi-species fishery, indexed i = 1 to r. Suppose the proportion of each species i in the multi-species population is P_i, such that $\sum_i P = 1$, and suppose that fish are caught in proportion to their prevalence in the multi-species population; that is, the probability that a fish caught by an angler is of species i is given by P_i. Suppose that each cast by an angler is independent of every other cast by that angler and is also independent of the casts made by other anglers (the example could be modified to include correlation among casts, but that is not the primary point here). Suppose the N_i is the catch of species i by all anglers in the fishery in a specified time period. Let C be the total catch of all species in a multi-species fishery constrained by an annual catch limit (ACL), such that $C = \sum_i N_i = 1 = ACL$. In this situation, the joint probability of all the anglers together catching the combination of fish $(N_1, N_2, \ldots, N_r)$ is given by the multinomial distribution (Ross, 1988, p. 282):

$$P(N_1, N_2, \ldots, N_r) = \left(\frac{ACL!}{N_1! N_1! \cdots N_r!}\right) (P_1)^{N_1} (P_2)^{N_2} \cdots (P_r)^{N_r}$$

and the covariance between the catch of species i, N_i, and species j, N_j, is:

$$\mathrm{cov}(N_i, N_j) = -\ ACL \cdot P_i \cdot P_j$$

The covariance above is negative, and it is larger in magnitude for larger values of the ACL and for species pairs that are larger proportions P_i and P_j of the total multi-species population.

Using Control Variates to Reduce the Variance of Catch Forecasts

Covariances across MRIP domains might also be used to reduce catch variances through the use of *control variates*. For example, suppose that fish catch in domain i is X_i, and fishery managers are interested in reducing the variance (and PSE) of X_i. Suppose further that catch X_i can be aggregated with fish catch in domain j, X_j, to produce aggregated catch $(X_i + X_j)$, where the aggregated catch has mean $E(X_i + X_j) = \mu$.

Construct the artificial "control variate" variable, W:

$$W = X_i + a \cdot [(X_i + X_j) - \mu], \qquad \text{where “a” is a constant to be determined.}$$

Note that the mean value of W, E[W], is the same as the mean value of X_i, $E[X_i]$.

The variance of W is given by:

$$\mathrm{var}(W) = \mathrm{var}(X_i) + a^2 \cdot \mathrm{var}(X_i + X_j) + 2 \cdot a \cdot \mathrm{cov}[X_i, (X_i + X_j)]$$

The value of "a" that minimizes var(W) can be determined by taking the partial derivative of var(W) with respect to a, setting the partial derivative equal to zero, and solving for a to find:

$$a = -\ \frac{cov[X_i, (X_i + X_j)]}{var(X_i + X_j)}$$

Substituting the value of "a" into var(W) and simplifying:

$$\text{var}(W) = \text{var}(X_i) - \frac{[cov(X_i,(X_i+X_j))]^2}{var(X_i+X_j)}$$

Since it is always the case that $\text{var}(X_i + X_j) > 0$ and $[cov(X_i, (X_i + X_j))]^2 \geq 0$, it is always the case that:

$$\text{var}(W) \leq \text{var}(X_i)$$

and as long as $\text{cov}[X_i,(X_i + X_j)]$ is not zero, whether positive or negative, it is the case that:

$$\text{var}(W) < \text{var}(X_i)$$

Thus, the fishery in domain i could be managed by tracking the control variate W rather than catch X_i, where W has the same mean (expected value) as X_i, but the variance (and PSE) of W is smaller than the variance (PSE) of X_i.

Note that degree of variance reduction increases with the *square* of $\text{cov}[X_i,(X_i + X_j)]$, the covariance between X_i and $(X_i + X_j)$.

Note that the control variate technique might be useful across various types of domains. For example, X_i and X_j could be the catches of two species in a multi-species fishery, or X_i and X_j could be the recreational and commercial catch of the same species, or X_i and X_j could be the catches of the same species in two different geographic regions, or X_i and X_j could be the catches of the same species at two different time periods. The control variate technique might be especially useful for the catch of a rare-event species X_i that is correlated with the total catch $(X_i + X_j)$ of a fishery of which the rare-event species is a part (e.g., a particular rare-event species of Grouper that is part of the total catch of all Grouper species in a particular location).

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Appendix C

Contemporaneous Correlation SUR Model

This Appendix presents Zellner's "Seemingly Unrelated Regression" (SUR) model and several extensions (Zellner 1962, Judge et al., 1985, pp. 28-29, 465-471). The SUR method might help fishery managers improve the precision (reduce the PSEs) of annual or in-season catch forecasts made using MRIP output estimates of catch and associated PSEs. The SUR method would likely be most useful when there are relatively large correlations in the catch errors of forecasting models across MRIP domains.

The SUR model is a type of Generalized Least Squares (GLS) regression model (Aitken 1936, Hansen 2007). An SUR model consists of a set of regression models, estimated jointly. In general, consider a system of M "stacked" linear regression forecasting models corresponding to M domains. The M domains could be M states, M sub-state regions, M species, M fishing modes, etc., or *any combination of these domains*.

The M models are indexed i = 1, 2, . . . , M.

For each of the M models, there are T observations (corresponding to T time periods) on dependent variable y_i, a matrix of non-stochastic independent variables X_i, a column vector of parameters β_i to be estimated, and a column vector of errors e_i. Each X_i matrix has K_i independent variables (columns). (Note that the numbers of, and the identities of, the independent variables may differ across the M models.)

$$y_i = X_i\beta_i + e_i, \quad i = 1, 2, \ldots, M$$

where y_i and e_i are each of dimension (T*1), X_i is (T*K_i) and β_i is (K_i*1).

The M models can be written together in "stacked" matrix form as:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix} = \begin{bmatrix} X_1 & & & \\ & X_2 & & \\ & & \ddots & \\ & & & X_M \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_M \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_M \end{bmatrix}$$

or, the set of M models can be written more compactly as simply:

$$y = X\beta + e, \text{ where}$$

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix} \quad X = \begin{bmatrix} X_1 & & & \\ & X_2 & & \\ & & \ddots & \\ & & & X_M \end{bmatrix} \quad \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_M \end{bmatrix} \quad \text{and} \quad e = \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_M \end{bmatrix}$$

and where

- in a fisheries application, $\mathbf{y}_i$ is catch of species i, and $\mathbf{y}$ is a random vector of the $\mathbf{y}_i$,
- $\boldsymbol{\beta}_i$ is the column vector of parameters for equation i, and $\boldsymbol{\beta}$ is the concatenated vector of all the $\boldsymbol{\beta}_i$ vectors,
- $E(y) = X\beta_0$ for some β_0,
- and variance-covariance matrix, $var(y) = \Omega$, is a positive definite matrix.

In fishery applications, the matrix X could include variables such as:

- MRIP domain indicator ("dummy") variables: geographic region, wave, fishing location (in/offshore, EEZ), fishery (recr/comm), mode (shore, private boat, charter),
- ancillary variables: weather, ocean conditions, unemployment rate, fuel prices, dummy variables for alternative fishing regulations, etc,
- the lagged values of the X variables listed above.

In the basic SUR model, the error in each equation (each domain) in the model is allowed to have a different variance; that is, the model accommodates heteroskedasticity across domains (Duncan 1983).

In addition, the errors are allowed to be "contemporaneously correlated" across the equations (across domains) in the model; that is, the errors are correlated across domains at a given point in time. (In the basic SUR model, the errors are not autocorrelated across time; however, as mentioned below, extensions of the basic model allow the errors to be autocorrelated across time as well as contemporaneously.) Hence, the covariance matrix of the joint fish catch distribution vector **y** in the basic SUR model is given by:

$$E[e_i] = 0 \quad \text{and} \quad E[e_i e_j'] = \Omega = \Sigma \otimes I,$$

where $\otimes$ is the Kronecker product operator, **I** is the identity matrix, and where:

$$\Sigma = \begin{bmatrix} \sigma_{11}^2 & \sigma_{12} & \cdots & \sigma_{1M} \\ \sigma_{21} & \sigma_{22}^2 & & \vdots \\ \vdots & & \ddots & \vdots \\ \sigma_{M1} & \cdots & \cdots & \sigma_{MM}^2 \end{bmatrix}$$

where σ_{ii}^2 is the error variance of model equation i, σ_{ij} is the covariance in errors between model equations i and j at a given point in time (representing the contemporaneous correlation between domains i and j at a given point in time), and where $\sigma_{ij} = \sigma_{ji}$.

It is important to recognize that fishery managers can obtain the elements of the matrix from MRIP; σ_{ii}^2 is the variance of the catch estimate for equation i (i.e., for domain i), and σ_{ij} is the covariance in the catch errors across equations i and j (i.e., across domains i and j).

The best (minimum variance) linear unbiased estimator (BLUE) for $\boldsymbol{\beta}$ is (Aitken 1936):

$$\hat{\beta}_{GLS} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}y$$

with variance-covariance matrix: $var(\hat{\beta}_{GLS}) = (X'\Omega^{-1}X)^{-1}$

SUR Methods Can Lower the PSEs of Catch Forecasts

Joint estimation of systems of multiple equations using SUR methods will in general lead to efficiency gains (greater precision, lower PSEs) relative to single equation estimation (Zellner 1962). Judge et al., et al. (1985, p. 468) describe the types of situations in which the SUR method is likely to provide efficiency gains: “efficiency gains from joint estimation tend to be higher when the explanatory variables in different equations are not highly correlated but the disturbance terms corresponding to different equations are highly correlated.”

Hypothesis Tests for Contemporaneous Correlation

Hypothesis tests exist for determining whether contemporaneous correlation is present and the SUR model may be warranted (e.g., Breusch and Pagan, 1980; Judge et al., 1985, p.476).

SUR Model with Autocorrelation (Judge et al., 1985, p. 518)

Note that the SUR model can be extended to include autocorrelation in the errors over time within a domain (e.g., autoregressive, AR-1 models) (Kmenta and Gilbert 1970; Judge et al., 1985, p.483). The autocorrelation specification may be extended further to include higher order autocorrelation (AR models), moving average errors (MA models), and autoregressive moving-average models (ARMA models) of the errors within each domain (Judge et al., 1985, p. 496). If the autoregressive specification is extended still further such that the error in a given domain is allowed to depend on the errors in previous time periods *in all domains* included in the model, the vector autoregressive model (VAR) results (Judge et al., 1985, p. 484).

To fix these ideas, consider an example with just two domains (M = 2, m = 1, 2) and two time periods (T = 2, t = 1, 2). In this case we have:

$$\mathrm{e} = \begin{bmatrix} e_{m=1,t=1} \\ e_{m=1,t=2} \\ e_{m=2,t=1} \\ e_{m=2,t=2} \end{bmatrix} \quad \text{and} \quad \mathrm{e}' = [e_{m=1,t=1}, e_{m=1,t=2}, e_{m=2,t=1}, e_{m=2,t=2}]$$

and hence variance-covariance matrix (Judge et al., 1985, p. 581):

$$\mathrm{E}[\mathrm{ee}'] = \Omega = \begin{bmatrix} \frac{\sigma_{11}^2}{1-\rho_1\rho_1} & \frac{\sigma_{11}^2\rho_1}{1-\rho_1\rho_1} & \frac{\sigma_{12}}{1-\rho_1\rho_2} & 0 \\ \frac{\sigma_{11}^2\rho_1}{1-\rho_1\rho_1} & \frac{\sigma_{11}^2}{1-\rho_1\rho_1} & 0 & \frac{\sigma_{12}}{1-\rho_1\rho_2} \\ \frac{\sigma_{21}}{1-\rho_2\rho_1} & 0 & \frac{\sigma_{22}^2}{1-\rho_2\rho_2} & \frac{\sigma_{22}^2\rho_2}{1-\rho_2\rho_2} \\ 0 & \frac{\sigma_{21}}{1-\rho_2\rho_1} & \frac{\sigma_{22}^2\rho_2}{1-\rho_2\rho_2} & \frac{\sigma_{22}^2}{1-\rho_2\rho_2} \end{bmatrix}$$

where, in the variance-covariance matrix above:

- σ_{11}^2 is the variance for domain m = 1
- σ_{22}^2 is the variance for domain m = 2
- σ_{12} (same as σ_{21}) is the covariance between domain m = 1 and domain m = 2
- ρ_1 is the first-order autocorrelation coefficient for domain m = 1
- ρ_2 is the first-order autocorrelation coefficient for domain m = 2

The variance-covariance matrix above allows for:

- different variance for different domains (heteroskedasticity), that is, $\sigma_{11}^2 \neq \sigma_{22}^2$
- autocorrelation across time within each domain, that is, $\rho_1 \neq 0$ and $\rho_2 \neq 0$
- different autocorrelation for different domains, that is, $\rho_1 \neq \rho_2$
- contemporaneous correlation across domains, that is, $\sigma_{12} \neq 0$ (same as $\sigma_{21} \neq 0$)

Autocorrelation coefficients can then be obtained by taking ratios of the appropriate elements of the variance-covariance matrix, for example:

$$\rho_1 = \frac{\left[\dfrac{\sigma_{11}^2 \rho_1}{1 - \rho_1 \rho_1}\right]}{\left[\dfrac{\sigma_{11}^2}{1 - \rho_1 \rho_1}\right]}$$

VAR specification

With the last autocorrelation specification above, the error within a domain at one point in time is affected by the error within that same domain from the previous point in time, but it is not affected by the error in *the other domain* at the previous point in time. If we allow the error within a domain at one point in time to be affected by the error within that same domain from the previous point in time *and the error in the other domain* at the previous point in time, then we have the *vector autoregressive (VAR) specification* for the variance-covariance matrix:

$$E[ee'] = \Omega = \begin{bmatrix} \dfrac{\sigma_{11}^2}{1-\rho_1\rho_1} & \dfrac{\sigma_{11}^2\rho_1}{1-\rho_1\rho_1} & \dfrac{\sigma_{12}}{1-\rho_1\rho_2} & \dfrac{\sigma_{12}\rho_2}{1-\rho_1\rho_2} \\ \dfrac{\sigma_{11}^2\rho_1}{1-\rho_1\rho_1} & \dfrac{\sigma_{11}^2}{1-\rho_1\rho_1} & \dfrac{\sigma_{12}\rho_1}{1-\rho_1\rho_2} & \dfrac{\sigma_{12}}{1-\rho_1\rho_2} \\ \dfrac{\sigma_{21}}{1-\rho_2\rho_1} & \dfrac{\sigma_{21}\rho_1}{1-\rho_2\rho_1} & \dfrac{\sigma_{22}^2}{1-\rho_2\rho_2} & \dfrac{\sigma_{22}^2\rho_2}{1-\rho_2\rho_2} \\ \dfrac{\sigma_{21}\rho_2}{1-\rho_2\rho_1} & \dfrac{\sigma_{21}}{1-\rho_2\rho_1} & \dfrac{\sigma_{22}^2\rho_2}{1-\rho_2\rho_2} & \dfrac{\sigma_{22}^2}{1-\rho_2\rho_2} \end{bmatrix}$$

Again, the example above is for the case of two domains and two time periods. However, the matrix equations above readily extend to any number of domains and time periods.

Further Extensions of the Basic SUR Model

The SUR model can also be extended to include unequal numbers of observations across equations (Judge et al., 1985, p.480), as might be the case when combining information from multiple surveys that collect data with different frequencies, or surveys that started or stopped at different points in time , or bad weather interrupts data collection in a particular location and time period.

Wang et al. (1980) show how the SUR model can be extended to include lagged dependent variables (such as past values of catch and effort) and autocorrelated errors. So, for example, past values of catch and effort (along with other variables) could be included in the model to help predict current and future values of catch.

Ozuna and Gomez (1994) provide an example of using SUR to estimate fishing effort using a Poisson model of angler fishing effort.

The SUR model may also be implemented within a Bayesian modeling framework (Zellner 1971, Chapter 8; Judge et al., 1985, p. 478).

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Appendix D

Bayesian Methods

This Appendix presents an example of a Bayesian model that could be used by fishery managers to set season lengths and decide on season closure dates under an ACL. The example presented here is a modified version of the Clark (1990) model. The example focuses on the management of a single-species fishery located in a particular geographic region, but the approach can be extended to multiple-species and/or multiple-region fisheries.

Consider a single-species fishery with an annual catch limit (ACL) that is set for the upcoming year by a stock assessment process. On any given fishing day, all anglers together in the fishery engage in a number “n” of fishing “attempts” (think of a fishing attempt as a single cast of a fishing line), each of which results in either a legally-caught fish with average probability “p” or a failure with probability “1-p”. The Binomial probability distribution gives the probability of X successes (that is, X fish caught) in n fishing attempts. If the number of fishing attempts n is large, and the probability of success p on any individual fishing attempt is low, as would typically be the case, then the Binomial probability distribution is well-approximated by the Poisson distribution with parameter $\lambda = n*p$, where λ is the expected (mean) number of successes per time period (that is, λ = the average daily total catch of all fishermen together). The Poisson distribution is widely used to model the probability distribution of any discrete random variable arising from a Binomial probability process (Ross 2010). Hence, following Clark (1990), we assume that total fish catch per day, X, in the fishery follows a Poisson process with parameter λ:

$$\text{Prob}(X) = \frac{\lambda^X e^{-\lambda}}{X!}, \text{ where } X \geq 0, \lambda > 0. \qquad \text{(E1)}$$

Parameter λ is a random variable that may vary from season-to-season and, indeed, may vary within the season due to factors such as varying fishing effort (which may, in turn, depend on varying weather conditions and economic factors, such as fuel costs and the unemployment rate, etc.), varying catch per unit effort (CPUE) (which may, in turn, depend on varying stock sizes of legally-harvestable fish (within size limits, etc.), varying gear types employed, varying vessel size, etc.), and other factors. Fishery managers do not know the precise value of λ on any particular day, but they can estimate the expected, or mean value of λ, denoted μ_{prior}, and its variance, denoted σ^2_{prior}, based on prior historical data, such as data from MRIP. For example, MRIP FES data from the prior years could be used to estimate the mean and variance of the number of angler trips per day from the previous fishing season, and MRIP APAIS data from the prior year could be used to estimate the mean and variance of catch per trip from the previous fishing season, and the two estimates could be combined to yield estimates of μ_{prior} and σ^2_{prior} for mean (total for the fishery) catch per day, λ. If some other method is judged (by an SSC, for example) to give better estimates of the mean and variance of λ, the alternative method could be used instead. For example, the mean and variance of λ could be estimated from a time series of MRIP data, rather than data from only the prior year, or data from the “previous 3 years” could be used, or the “the previous 5 years minus the highest and lowest years,” etc. Any of these methods could be used to obtain the best estimates of μ_{prior} and σ^2_{prior}.

Because λ can vary, it has a probability distribution. Following Clark (1990), we assume that the probability distribution of λ can be approximated by a Gamma distribution[1] with parameters α and ν:

[1] Note, if the data indicate that a normal distribution fits λ better than a gamma distribution, there is an alternative version of this model that uses a normal distribution for λ.

$$\text{Prob}(\lambda) = \frac{\alpha^{\nu}\,\lambda^{\nu-1}\,e^{-\alpha\lambda}}{\Gamma(\nu)} \;, \qquad \text{(E2)}$$

where Γ(ν) is the gamma *function*, and where parameters α and ν are determined by the mean and variance of λ as:

$$\alpha = \mu_{prior} / \sigma^2_{prior} \quad \text{and} \quad \nu = (\mu_{prior})^2 / \sigma^2_{prior}. \qquad \text{(E3 and E4)}$$

(That is, the parameters α and ν come from estimates of the mean and variance of λ.)

For use further below, note that the mean and variance of λ can be expressed in terms of the parameters of the gamma function:

$$\mu_{prior} = \nu / \alpha \quad \text{and} \quad \sigma^2_{prior} = \nu / \alpha^2 \,. \qquad \text{(E5 and E6)}$$

The Gamma distribution is commonly used to approximate the empirical distribution of any continuous, non-negative random variable because it can represent a variety of distributional shapes, as illustrated in Figure A.1.

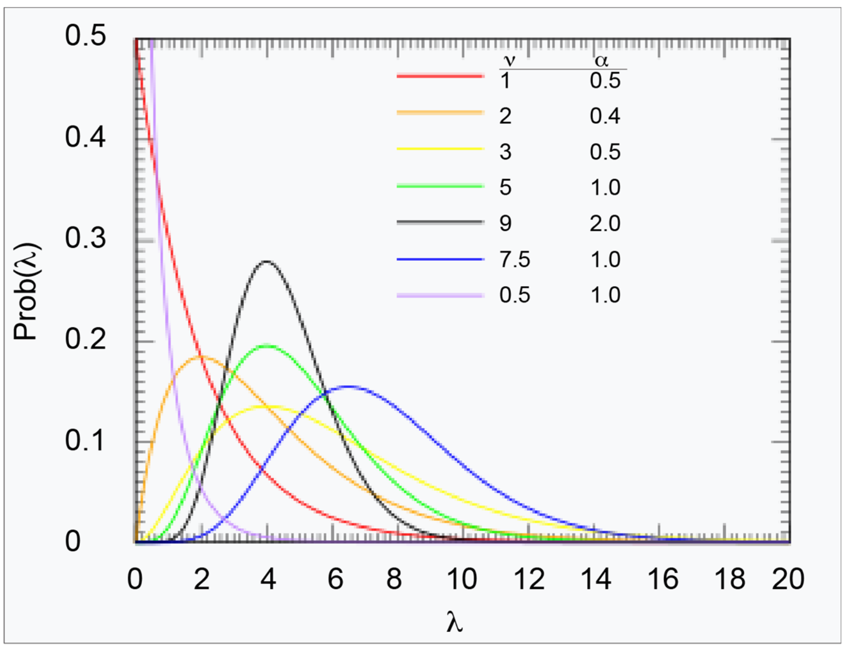

FIGURE A.1 Shapes of the Gamma Distribution for Various Values of α and ν. SOURCE: Modified from: Wikipedia.org, see https://en.wikipedia.org/wiki/Gamma_distribution.

The Prior Probability Distribution of Catch per Day (X) Given Uncertainty in Mean Catch per Day (λ)

Given Prob(X) and Prob(λ), we can combine the two distributions to calculate the "prior" probability distribution of total catch per day (X). When Prob(X) and Prob(λ) are combined, it turns out that the resulting prior probability distribution is a Negative Binomial distribution with parameters α and ν, denoted NegBin_{prior} (X | α_{prior}, ν_{prior}), as specified below:

$$\text{NegBin}_{prior}\,(X \mid \alpha_{prior}, \nu_{prior}) = \frac{\Gamma(X+\nu_{prior})}{X!\cdot\Gamma(\nu_{prior})} \cdot \frac{(\alpha_{prior})^{\nu_{prior}}}{(\alpha_{prior}+1)^{X+\nu_{prior}}} \;, \qquad \text{(E7)}$$

where Γ is the gamma *function* (as opposed to the gamma *distribution*) and ! is the factorial operator.

Interpretation: $NegBin_{prior}$ ($X \mid \alpha_{prior}, \nu_{prior}$) gives the probability distribution of total catch *per day* for the fishery as a whole (X) for the upcoming fishing season based on the uncertainty (as measured by μ_{prior} and σ^2_{prior}) in mean total catch per day (λ) as best estimated using MRIP data from the previous fishing season(s).

The Negative Binomial parameters α_{prior} and ν_{prior} are determined by the underlying parameters μ_{prior} and σ^2_{prior} as follows:

$$\alpha_{prior} = \mu_{prior} / \sigma^2_{prior} \quad \text{and} \quad \nu_{prior} = (\mu_{prior})^2 / \sigma^2_{prior} \qquad \text{(E8 and E9)}$$

For the $NegBin_{prior}$ ($X \mid \alpha_{prior}, \nu_{prior}$) distribution,

$$\text{mean } X = \nu_{prior} / \alpha_{prior} = \mu_{prior} \quad \text{and} \quad \text{variance } X = \frac{\nu_{prior} \cdot (1+\alpha_{prior})}{(\alpha_{prior})^2} = \mu_{prior} + \sigma^2_{prior}. \qquad \text{(E10 and E11)}$$

$NegBin_{prior}$ is the "prior" probability distribution of total catch per day (X) for the upcoming fishing season in the sense that it is the best estimate that can be made before (that is, "prior" to) the beginning of the upcoming fishing season. This prior distribution is based on the best estimates of μ_{prior} and σ^2_{prior} that can be made using MRIP data from past/previous/historical fishing seasons, before the arrival of any new MRIP data from the upcoming fishing season.

Estimating the Optimal Fishing Season Length Using the Prior Distribution

We assume that the fishery managers' objective is to maximize the fishing season length (measured here in days) while holding the risk (as measured by probability P) of exceeding the ACL below some target level, denoted P^*. The prior probability distribution can be used to determine the fishing season length that meets this objective.

At the beginning of the fishing season, before any new information arrives, the prior probability distribution $NegBin_{prior}$ ($X \mid \alpha_{prior}, \nu_{prior}$) gives the best estimate of the probability distribution of fish catch X *per fishing day* in the season. If "t" days are contemplated for the fishing season, and the probability distribution of fish catch X on each day is negative binomial $NegBin_{prior}$ ($X \mid \alpha_{prior}, \nu_{prior}$), and we assume that the daily catches are independent of one another,[2] then using statistical formulas for the sums of random variables (see, for example, Mendenhall et al., 1990, p. 242), we find that the probability distribution of *cumulative* fish catch at the end of t fishing days, X_t, (that is, at the end of the contemplated fishing season) is also a negative binomial distribution with parameters α and t·ν, that is, $NegBin_{prior}$ ($X_t \mid \alpha_{prior}, t \cdot \nu_{prior}$), and we find that:

$$\text{mean } X_t = (t \cdot \nu_{prior})/\alpha = t \cdot \mu_{prior} \quad \text{and}$$

$$\text{variance } X_t = [t \cdot \nu_{prior} \cdot (1+\alpha_{prior})]/\alpha_{prior}^2 = t \cdot (\mu_{prior} + \sigma^2_{prior}).$$

To determine the probability P that total fish catch at the end of the season exceeds a given target, say the ACL, we simply sum the values of $NegBin_{prior}$ ($X_t \mid \alpha_{prior}, t \cdot \nu_{prior}$) from $X_t = 0$ to X_t = ACL and subtract the sum from one, that is:

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[2] If the daily catches are *not* independent, that is, if the daily catches are correlated with one another, either positively or negatively, then alternative formulas (Mendenhall et al., 1990, p. 242) that take this correlation into account can be employed to calculate the mean and variance of total season catch X_t.

$$\text{Prob}\ (X_t > \text{ACL}) = 1 - \left[\sum_{X_t=0}^{X_t=ACL} NegBin_{prior}\ (X_t \mid \alpha_{prior}, t \cdot \nu_{prior})\right]$$

If fishery managers wish to keep this probability below some target level, say P*, then managers should vary the length of the fishing season t until they find the season length t^* where Prob (X_t > ACL) = P*; a fishing season of length t^* is the maximum season length that maintains Prob (X_t > ACL) below P*. Note that this gives an "optimal stopping rule:" stop the season at t^* days.

Note that Excel has a built-in function, NEGBINOM.DIST, that can be used to calculate cumulative negative binomial probabilities (that is, the negative binomial cumulative distribution function). Using this function:

$$\text{Prob}\ (X_t > \text{ACL}) = 1 - \text{NEGBINOM.DIST}(t \cdot \nu_{prior}, \text{ACL}, 1/(1+\alpha_{prior}), \text{cumulative})$$

and the season length t can be adjusted (using the Solver feature of Excel, for example) until t^* is found where Prob (X_t > ACL) = P*.

Using Bayesian Updating to Incorporate New Information, Obtain the Posterior Probability Distribution of Catch per Day (X), and Update the Fishing Season Length

As new data arrive during the fishing season, the prior probability distribution of catch per day, $NegBin_{prior}$ (X | α_{prior}, ν_{prior}) can be "updated" to take the new data into account. The "updated" probability distribution of catch per day is called the "posterior" distribution because it is "posterior to" (i.e., "after") the arrival of the new data. Bayes' Rule gives a formula for combining the prior distribution of catch per day, $NegBin_{prior}$ (X | α_{prior}, ν_{prior}), with new data to obtain the posterior, "updated," distribution of catch per day, denoted $NegBin_{post}$(X | α_{post}, ν_{post})

New data can arrive in different forms. We consider two likely forms of new data arrival below, but other forms of new data arrival could be analyzed using a similar procedure. For each of the two examples below, we give the posterior distribution of catch per day derived using Bayes' Rule.

Example 1 – New data arrive in the form "all anglers together caught n fish over d days"

In Example 1, after the fishing season begins, managers receive new data that all anglers in the fishery together caught n fish over d days. In Example 1, there is no uncertainty about the number of fish caught, n. Think of Example 1 as a situation of "perfect catch reporting" or "perfect monitoring." (Example 2 below considers the more likely case of "imperfect catch reporting" with uncertainty in n.)

Using Bayes' Rule, the new data (n, d) can be combined with the prior probability distribution of catch per day, $NegBin_{prior}$ (X | α_{prior}, ν_{prior}), to derive the new, updated, posterior probability distribution of catch per day for each day of the fishing season, $NegBin_{post}$(X | α_{post}, ν_{post}), which is also a negative binomial distribution, but with updated parameters α_{post} and ν_{post}:

$$NegBin_{post}(X \mid \alpha_{post}, \nu_{post}) = \frac{\Gamma(X+\nu_{post})}{X! \cdot \Gamma(\nu_{post})} \cdot \frac{(\alpha_{post})^{\nu_{post}}}{(\alpha_{post}+1)^{X+\nu_{post}}},$$

where: $\alpha_{post} = \alpha_{prior} + d$ and $\nu_{post} = \nu_{prior} + n$

$\mu_{post} = \nu_{post} / \alpha_{post}$ and $\sigma^2_{post} = \nu_{post} / (\alpha_{post})^2$.

For the $NegBin_{post}$(X | α_{post}, ν_{post}) distribution:

$$mean_{post}\ X = \nu_{post} / \alpha_{post}$$

$$= (\nu_{prior} + n) / (\alpha_{prior} + d)$$

$$= [((\mu_{prior})^2 / \sigma^2_{prior}) + n] / [(\mu_{prior} / \sigma^2_{prior}) + d] \quad \text{and}$$

$$\text{variance}_{post}\ X = \frac{\nu_{post}(1+\alpha_{post})}{(\alpha_{post})^2}$$

$$= (\nu_{prior} + n)(1 + \alpha_{prior} + d) / (\alpha_{prior} + d)^2$$

$$= [((\mu_{prior})^2 / \sigma^2_{prior}) + n][1 + (\mu_{prior} / \sigma^2_{prior}) + d] / [(\mu_{prior} / \sigma^2_{prior}) + d]^2$$

(Note that the updated distribution $NegBin_{post}(X \mid \alpha_{post}, \nu_{post})$ is an update of the distribution of catch per day for *all* days of the fishing season and, as such, will be applied to *all* days of the fishing season, including the days that occurred before the arrival of the new information and the days that occur after the arrival of the new information.)

The updated probability distribution of catch per day, $NegBin_{post}(X \mid \alpha_{post}, \nu_{post})$, is then used to update the estimate of the probability distribution of *cumulative* fish catch at the end of the fishing season, X_t, given by $NegBin_{post}\ (X_t \mid \alpha_{post}, t{\cdot}\nu_{post})$, where:

$$\text{mean}_{post}\ X_t = (t{\cdot}\nu_{post})/\alpha_{post} = t{\cdot}\mu_{post} \quad \text{and}$$

$$\text{variance}_{post}\ X_t = [t{\cdot}\nu_{post}{\cdot}(1+\alpha_{post})]/\alpha_{post}^2 = t{\cdot}(\mu_{post} + \sigma^2_{post}).$$

To determine the updated estimate of the probability P that total fish catch at the end of a fishing season of length t exceeds the given ACL target, we sum the values of $NegBin_{post}\ (X_t \mid \alpha_{post}, t{\cdot}\nu_{post})$ from $X_t = 0$ to X_t = ACL and subtract the sum from one, that is:

$$\text{Prob}\ (X_t > \text{ACL}) = 1 - \left[\sum_{X_t\,=\,0}^{X_t\,=\,ACL} NegBin_{post}\ (X_t \mid \alpha_{post}, t\cdot\nu_{post})\right]$$

If fishery managers wish to keep this probability below some target level, say P*, then managers should update the length of the fishing season t until they find the updated season length t_{post}^* where Prob (X_t > ACL) = P*. A fishing season of length t_{post}^* is the maximum season length that maintains Prob (X_t > ACL) below P*.

Again, Excel has a built-in function, NEGBINOM.DIST, that can be used to calculate cumulative negative binomial probabilities (that is, the negative binomial cumulative distribution function). Using this function:

$$\text{Prob}\ (X_t > \text{ACL}) = 1 - \text{NEGBINOM.DIST}(t{\cdot}\nu_{post}, X_t, 1/(1+\alpha_{post}), \text{cumulative})$$

and the season length t can be adjusted (using the Solver feature of Excel, for example) until t_{post}^* is found where Prob (X_t > ACL) = P*.

Note that t_{post}^* is the total season length. To find the length of the *remaining* fishing season, $t_{remaining}^*$, any fishing days that have already occurred in the current season, $t_{occurred}$, should be subtracted from the total season length, that is, $t_{remaining}^* = t_{post}^* - t_{occurred}$.

For each new data update that arrives, the α_{post}, ν_{post} values from the earlier data update become the new α_{prior}, ν_{prior} values that are used with the newly arriving data, and the updating process described above is repeated.

Note that because the arrival of new data will generate new estimates of $t_{remaining}^*$, from the fisherman's point of view, the remaining length of the fishing season is uncertain—fishery managers might need to increase or decrease $t_{remaining}^*$ as more data arrive. How confident should fishermen be in the estimate of $t_{remaining}^*$ at any point in time? At any point in time, the probability that the length of the fishing season will need to be decreased/shortened to avoid exceeding ("going over") the ACL is given by probability P^*, and the probability that the length of the fishing season can be increased/lengthened in the future to "fish as close as we safely can" to the ACL is $(1 - P^*)$. So, fishery managers can tell fishermen: "Based on the data that we have so far this season, our best estimate of the remaining length of the season is $t_{remaining}^*$, and the probability that the season will need to be shortened is P^*, but the probability that the season can be extended is $(1 - P^*)$."

Fishery managers should note that choosing a smaller value for P^* reduces the chances of exceeding the ACL but also reduces the length of the remaining fishing season $t_{remaining}^*$. However, choosing a smaller P^* also increases the chances $(1 - P^*)$ that the remaining fishing season can be increased/lengthened as new data arrive. So, choosing a small value for P^* is a "good news—bad news—good news" type of decision: good news—the chances of exceeding the ACL are small, bad news—we have to (at this moment) set a short fishing season, good news—there is a high chance $(1 - P^*)$ that the fishing season will be extended.

On the other hand, if fishery managers choose a larger value for P^*, this would increase the chances of exceeding the ACL but also increase the length of the remaining fishing season $t_{remaining}^*$. However, choosing a larger P^* also increases the chances (P^*) that the remaining fishing season will need to be decreased/shortened as new data arrive. So, choosing a larger value for P^* is a "bad news—good news—bad news" type of decision: bad news—the chances of exceeding the ACL are larger, good news—we can (at this moment) set a longer fishing season, bad news—the chances are high (P^*) that the fishing season will need to be shortened.

Example 2 – New data arrive in the form of new estimates for the mean (μ) and variance (σ^2) of catch per day (λ)

In Example 2, managers do not benefit from "perfect catch reporting" or "perfect monitoring" during the fishing season, as was assumed in Example 1. Instead, after the fishing season begins, managers receive new, but uncertain, estimates of the mean and variance of total catch per day within the fishery. Denote the new estimate of mean catch per day as μ_{new}, and the new estimate of the variance of catch per day as σ_{new}^2. These new estimates could come from a new wave of MRIP data, a state data collection program, etc.

Using Bayes' Rule, the new information $(\mu_{new}, \sigma_{new}^2)$ can be combined with the prior probability distribution of catch per day, $\text{NegBin}_{prior}(X \mid \alpha_{prior}, \nu_{prior})$, to derive the new, updated, posterior probability distribution of catch per day for each day of the fishing season, $\text{NegBin}_{post}(X \mid \alpha_{post}, \nu_{post})$, which is also a negative binomial distribution, but with updated parameters α_{post} and ν_{post}:

$$\text{NegBin}_{post}(X \mid \alpha_{post}, \nu_{post}) = \frac{\Gamma(X+\nu_{post})}{X! \cdot \Gamma(\nu_{post})} \cdot \frac{(\alpha_{post})^{\nu_{post}}}{(\alpha_{post})^{X+\nu_{post}}},$$

where: $$\alpha_{new} = \mu_{new} / \sigma_{new}^2 \quad \text{and} \quad \nu_{new} = (\mu_{new})^2 / \sigma_{new}^2$$

$$\alpha_{post} = \alpha_{prior} + \alpha_{new} \quad \text{and} \quad \nu_{post} = \nu_{prior} + \nu_{new} - 1$$

$$\mu_{post} = \nu_{post} / \alpha_{post} \quad \text{and} \quad \sigma^2_{post} = \nu_{post} / (\alpha_{post})^2.$$

For the $\text{NegBin}_{post}(X \mid \alpha_{post}, \nu_{post})$ distribution:

$$\text{mean}_{post}\, X = \nu_{post} / \alpha_{post}$$

$$= (\nu_{prior} + \nu_{new} - 1) / (\alpha_{prior} + \alpha_{new})$$

$$= [((\mu_{prior})^2 / \sigma^2_{prior}) + ((\mu_{new})^2 / \sigma_{new}^2) - 1] / [(\mu_{prior} / \sigma^2_{prior}) + (\mu_{new} / \sigma_{new}^2)] \quad \text{and}$$

$$\text{variance}_{post}\ X = \frac{\nu_{post}(1+\alpha_{post})}{(\alpha_{post})^2}$$

$$= (\nu_{prior} + \nu_{new} - 1)(1 + \alpha_{prior} + \alpha_{new}) / (\alpha_{prior} + \alpha_{new})^2$$

$$= [((\mu_{prior})^2 / \sigma^2_{prior}) + ((\mu_{new})^2 / \sigma_{new}^2) - 1][1 + (\mu_{prior} / \sigma^2_{prior}) + (\mu_{new} / \sigma_{new}^2)] / [(\mu_{prior} / \sigma^2_{prior}) + (\mu_{new} / \sigma_{new}^2)]^2$$

(Note that the updated distribution $NegBin_{post}(X \mid \alpha_{post}, \nu_{post})$ is an update of the distribution of catch per day for *all* days of the fishing season and, as such, will be applied to *all* days of the fishing season, including the days that occurred before the arrival of the new information and the days that occur after the arrival of the new information.)

The updated probability distribution of catch per day, $NegBin_{post}(X \mid \alpha_{post}, \nu_{post})$, is then used to update the estimate of the probability distribution of *cumulative* fish catch at the end of the fishing season, X_t, given by $NegBin_{post}(X_t \mid \alpha_{post}, t \cdot \nu_{post})$, where:

$$\text{mean}_{post}\ X_t = t \cdot (\nu_{post} / \alpha_{post}) \quad \text{and}$$

$$\text{variance}_{post}\ X_t = [t \cdot \nu_{post} \cdot (1+\alpha_{post})] / \alpha_{post}^2 .$$

From this point, the procedure used to update the total fishing season length, t_{post}^*, and fishing season length remaining, $t_{remaining}^*$, follow the procedure used in Example 1. To determine the updated estimate of the probability P that total fish catch at the end of a fishing season of length t exceeds the given ACL target, we sum the values of $NegBin_{post}(X_t \mid \alpha_{post}, t \cdot \nu_{post})$ from $X_t = 0$ to $X_t = ACL$ and subtract the sum from one, that is:

$$\text{Prob}\ (X_t > ACL) = 1 - \left[\sum_{X_t = 0}^{X_t = ACL} NegBin_{post}\ (X_t \mid \alpha_{post}, t \cdot \nu_{post})\right]$$

If fishery managers wish to keep this probability below some target level, say P*, then managers should update the length of the fishing season t until they find the updated season length t_{post}^* where Prob (X_t > ACL) = P*. A fishing season of length t_{post}^* is the maximum season length that maintains Prob (X_t > ACL) below P*.

Again, Excel has a built-in function, NEGBINOM.DIST, that can be used to calculate cumulative negative binomial probabilities (that is, the negative binomial cumulative distribution function). Using this function:

$$\text{Prob}\ (X_t > ACL) = 1 - \text{NEGBINOM.DIST}(t \cdot \nu_{post}, ACL, 1/(1+\alpha_{post}), \text{cumulative})$$

and the season length t can be adjusted (using the Solver feature of Excel, for example) until t_{post}^* is found where Prob (X_t > ACL) = P*.

Note that t_{post}^* is the total season length. To find the length of the *remaining* fishing season, $t_{remaining}^*$, any fishing days that have already occurred in the current season, $t_{occurred}$, should be subtracted from the total season length, that is, $t_{remaining}^* = t_{post}^* - t_{occurred}$.

As in Example 1, for each new data update that arrives, the α_{post}, ν_{post} values from the earlier data update become the new α_{prior}, ν_{prior} values that are used with the newly arriving data, and the updating process described above is repeated.

Similarly, the remarks made in the discussion at the end of Example 1 concerning the confidence that fishermen should have in $t_{remaining}^{*}$ and the pros and cons of fishery managers setting higher or lower values of P^{*}apply to Example 2, as well.

Extensions and Applications of the Basic Bayesian Model

Given the Basic Bayesian Model outlined above, several extensions and applications of the model can be made to address additional questions relevant to in-season management of fisheries under an ACL. For example, the Bayesian Model can be used to:

- Compare fishery management outcomes under a fixed season length ("Predictability") to outcomes under a flexible season length ("Flexibility") by running simulations that calculate season length based on prior data only (fixed season length) vs. based on updating season length based on Bayesian updating and new data that arrive throughout the season (flexible season length).
- Demonstrate how Bayesian updating can extend season length by reducing the variance of estimated catch per day, even if the estimated mean catch per day stays constant across the season.
- Assess the value of increasing the frequency of data collection, such as going from a 2-month MRIP wave to a 1-month MRIP wave. Increasing the frequency of MRIP waves allows more rapid Bayesian updating, which can affect season length, total catch, etc. These outcomes can then be compared to cost of collecting more frequent data.
- Assess the value of improvements in data quality (improvements in precision, reductions in variance and PSEs). Improvements in data quality would reduce σ_{new}^2, which in turn affects season length and catch. These outcomes can then be compared with cost of a program to improve data quality.
- Compare the fishery management outcomes (via simulations) of using MRIP estimates of given frequency (e.g., bi-monthly), bias and precision with estimates from other surveys of potentially different frequency, bias and precision.
- Combine MRIP estimates with estimates from supplementary surveys that may have frequencies, means and variances that differ from those produced by MRIP to use the information from both surveys to update the Bayesian model throughout the fishing season. This would entail two estimates λ entering the updating process, one from each survey (the estimates of λ could be independent or correlated). Through the Bayesian updating process, survey estimates that are less precise receive less weight in the updating process. This process could be used to simulate "adding a state survey to MRIP," such as adding Tales 'n Scales to MRIP. Or, the process could be used to simulate "adding MRIP to a state survey," such as extending MRIP to Texas.
- Accommodate both autocorrelation and contemporaneous correlation in the forecasting process.
- Accommodate correlation in catch across days within a season. For example, if it is known that catch per day decreases (or decreases) as a season progresses, this can be taken into account in the Bayesian updating model.
- Accommodate differences in effort between weekend days and weekdays (Powers and Anson 2016) as catch is accumulated across the days within a season.
- Accommodate changes in fishing season length that result from changes in fishing effort per day (Powers and Anson 2016, 2019).
- Accommodate separate Bayesian models for recreational sector catch and commercial sector catch that can be combined to assess probabilities of meeting sector-specific ACLs and a sector-combined total catch ACL.
- Accommodate separate Bayesian models for different geographic regions that can be combined to assess probabilities of meeting region-specific ACLs and a combined-region total catch ACL.

- Make the best use of any available information in data poor fisheries. Any available data from prior years could be used to form priors, or a non-informative prior could be used. Simulations could be used to assess the implications of alternative priors and the length of time it would take for any differences in outcomes, based on differences in the priors, to become negligible. As another alternative, expert opinion on maximum and minimum catch per day values could be used with a uniform distribution (a non-informative prior, conditional on the maximum and minimum values) to obtain a mean and variance for a prior.
- Assess the differences in proposed catch "carry-over" ("overage" and "underage") policies across years via simulation. For example, when an underage increases ACL in the subsequent year, or an overage decreases the ACL in the subsequent year, the model can be used to estimate the effects on the probability distribution of season length in the subsequent year.
- Assess via simulation whether particular ancillary variables (e.g., weather, water temperature, fuel prices, unemployment rate, etc.) (Powers and Anson 2016) could potentially reduce uncertainty in priors by reducing σ_{prior}^2 or reduce uncertainty in new or updated data by reducing σ_{new}^2.
- Assess via simulation how new technologies (e.g., dockside cameras) that increase data collection frequency (thereby increasing the frequency of Bayesian updating within a season) or improve data quality (and thereby reduce σ_{new}^2) would affect expected fishery management outcomes. The simulations could also be used to investigate the use of more frequent but lower quality data on expected fishery management outcomes.

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Appendix E

Rare-Event Species—Normal or Poisson?

This Appendix provides an example of the type of analysis that can be used to identify the appropriate catch probability distribution for the purpose of catch forecasting in the case of a rare-event species. For the purpose of calculating the probability that the catch of a rare-event species will exceed a given ACL, the analysis answers the question: Which is better, the Normal distribution or the Poisson distribution?

The Probability of Rare-Event Species Catch--The Binomial Distribution

In theory, the probability of catching various numbers of rare-event species fish in a given fishery is given by the Binomial distribution, and the Normal Distribution and Poisson Distribution are just approximations to the underlying Binomial Distribution. This Binomial Distribution is discussed first, followed by discussions of the Normal and Poisson Distributions. To relate the Binomial Distribution to the catch of rare-event species in a fishery, suppose that in a given fishery, p gives the proportion of rare-event fish in the population of all fish caught by the fishery (the value of p could be estimated by the method of inverse sampling or by some other method). Now, in a given time period, suppose that n fish are caught in the fishery (including both rare-event species fish and common species fish). The value of n is the estimated catch provided by MRIP (or some projection/forecast of n based on MRIP data, perhaps in combination with ancillary data). The probability that the number of rare-event fish caught, r, will be less than a pre-specified Allowable Catch Limit (ACL) of rare-event fish is given by the Binomial cumulative distribution function (Binomial CDF) (Ross, 1988):

$$\text{Binomial CDF: } P(r \le ACL) = \sum_{r=0}^{ACL} \binom{n}{r} p^r (1-p)^{n-r}$$

mean = np
variance = np(1-p)

Approximations to the Binomial Distribution

Because calculating the Binomial CDF can be difficult when n is very large and p is small (precisely the conditions describing the catch of a rare-event species), two probability distributions, the Poisson CDF and the Normal CDF, are often used to approximate the Binomial CDF (Ross, 1988).

The Poisson distribution has the advantage of being a discrete distribution, like the Binomial; however, the mean and the variance of the Poisson are the same, whereas the mean and the variance of the Binomial are different. Another difference is that the Poisson attributes some probability to all positive values of r, regardless of the value of n, whereas the Binomial attributes probability to only those positive values of r up to n.

$$\text{Poisson CDF: } P(r \le ACL) = \sum_{r=0}^{ACL} e^{-np} \cdot \frac{(np)^r}{r!}$$

mean = np
variance = np (note: variance is equal to the mean for the Poisson)

It can be shown that, for large n, as p approaches zero, the Poisson Distribution approaches the Binomial Distribution. Thus, the Poisson approximation improves for large n and very small p.

The Normal distribution has the advantage that the mean can be different from the variance, like the Binomial; however, the Normal distribution is continuous, whereas the Binomial distribution is discrete. Another difference is that the Normal distribution attributes some probability to all positive and negative values of r, regardless of the value of n, whereas the Binomial attributes probability to only those positive values of r up to n.

$$\text{Normal CDF: } P(r \leq ACL) = \int_{-\infty}^{ACL} \frac{1}{\sqrt{2\pi[np(1-p)]}} e^{-\left(\frac{(r-(np))^2}{2[np(1-p)]}\right)}$$

$$\text{mean} = np$$
$$\text{variance} = np(1-p)$$

Calculating the Probability of Exceeding the ACL

For each CDF, to find the probability that the catch of rare fish (r) exceeds the ACL, that is P(r > ACL), we simply calculate:

$$P(r > ACL)_{\text{Binomial}} = 1 - P(r \leq ACL)_{\text{Binomial}}$$

$$P(r > ACL)_{\text{Poisson}} = 1 - P(r \leq ACL)_{\text{Poisson}}$$

$$P(r > ACL)_{\text{Normal}} = 1 - P(r \leq ACL)_{\text{Normal}}$$

The Error of Using An Approximation

The error associated with using either the Poisson or the Normal distribution to approximate the probability of exceeding the ACL as given by the Binomial distribution can be found by subtraction:

$$\text{Error of Using Poisson} = P(r > ACL)_{\text{Poisson}} - P(r > ACL)_{\text{Binomial}}$$

$$\text{Error of Using Normal} = P(r > ACL)_{\text{Normal}} - P(r > ACL)_{\text{Binomial}}$$

Here, a *positive* error measures the number of percentage points by which the approximation *over*estimates the probability that the catch of rare fish (r) exceeds the ACL, whereas a *negative* error indicates the number of percentage points by which the approximation *under*estimates the probability.

Poisson Approximation to a Binomial Distribution

The Binomial CDF with mean = np and variance = np(1-p) is given by (Ross, 1988, p. 129):

$$\text{Binomial } P(r \leq ACL) = \sum_{r=0}^{ACL} \binom{n}{r} p^r (1-p)^{n-r}$$

$$= \sum_{r=0}^{ACL} \left(\frac{n!}{(n-r)r!}\right) p^r (1-p)^{n-r}$$

$$= \sum_{r=0}^{ACL} \left(\frac{n!}{(n-r)r!}\right) \left(\frac{np}{n}\right)^r (1-\frac{np}{n})^{n-r}$$

$$= \sum_{r=0}^{ACL} \left(\frac{n(n-1)\cdots(n-r+1)}{n^r}\right)\left(\frac{(np)^r}{r!}\right)\left(\frac{(1-(np/n))^n}{(1-(np/n))^r}\right)$$

for large values of n, $\left(\frac{n(n-1)\cdots(n-r+1)}{n^r}\right)$ --> 1

Hence, for large n:

$$\text{Binomial CDF: } P(r \le ACL) = \sum_{r=0}^{ACL} \left(\frac{(np)^r}{r!}\right)\left(\frac{(1-(np/n))^n}{(1-(np/n))^r}\right)$$

Recall that the Poisson CDF is given by:

$$\text{Poisson CDF: } P(r \le ACL) = \sum_{r=0}^{ACL} \frac{(np)^r}{r!} \cdot e^{-np}$$

The error (in percentage points) of using the Poisson to approximate the Binomial probability of exceeding an ACL is given by:

$$\text{Error} = P(r > ACL)_{\text{Poisson}} - P(r > ACL)_{\text{Binomial}}$$

$$= [1 - P(r \le ACL)_{\text{Poisson}}] - [1 - P(r \le ACL)_{\text{Binomial}}]$$

$$= \left(1 - \sum_{r=0}^{ACL} \frac{(np)^r}{r!} \cdot e^{-np}\right) - \left(1 - \sum_{r=0}^{ACL} \left(\frac{(np)^r}{r!}\right)\left(\frac{(1-(np/n))^n}{(1-(np/n))^r}\right)\right)$$

$$= \sum_{r=0}^{ACL} \left(\frac{(np)^r}{r!}\right)\left(\frac{(1-(np/n))^n}{(1-(np/n))^r}\right) - \sum_{r=0}^{ACL} \frac{(np)^r}{r!} \cdot e^{-np}$$

$$= \sum_{r=0}^{ACL} \left(\frac{(np)^r}{r!}\right)\left[\left(\frac{(1-(np/n))^n}{(1-(np/n))^r}\right) - e^{-np}\right]$$

where, for large n, as p approaches zero:

$$(1-(np/n))^n \approx e^{-np} \quad \text{and} \quad (1-(np/n))^r \approx 1$$

Thus, for large n, as p approaches zero, the Poisson Distribution approaches the Binomial Distribution. The Poisson is a good approximation for the Binomial for large n and small p such that np is moderate in size and np ≈ np(1-p) (Ross, 1988, p. 129).

Normal Approximation to a Binomial Distribution

The Binomial CDF with mean = np and variance = np(1-p) is given by (Ross, 1988, p. 129):

$$\text{Binomial CDF: } P(r \le ACL) = \sum_{r=0}^{ACL} \binom{n}{r} p^r (1-p)^{n-r}$$

By the DeMoivre-Laplace Limit Theorem (Ross, 1988, p. 170), as n grows large, the Binomial CDF P(r ≤ ACL) with mean np and variance np(1-p) converges to the Normal CDF P(r ≤ ACL + 0.5) with mean np and variance np(1-p):

$$\text{Binomial CDF } P(r \le ACL) \quad n \to \infty \to \quad \text{Normal CDF } (r \le ACL + 0.5)_{\text{mean = np, variance = np(1-p)}}$$

where:

$$\text{Normal CDF } (r \le ACL + 0.5)_{\text{mean = np, variance = np(1-p)}} = \int_{-\infty}^{(ACL\,+\,0.5)} \frac{1}{\sqrt{2\pi[np(1-p)]}}\, e^{-\left(\frac{(r-(np))^2}{2[np(1-p)]}\right)}$$

The Normal Distribution may not be a good approximation to the Binomial Distribution for values of n and p satisfying np(1-p) < 10, that is, when the variance of the Binomial Distribution is less than 10 (Ross, 1988, p.l71).

The error (in percentage points) of using the Normal distribution to approximate the Binomial probability of exceeding an ACL is given by:

$$\text{Error} = P(r > ACL+0.5)_{\text{Normal}} - P(r > ACL)_{\text{Binomial}}$$

$$= [1 - P(r \leq ACL+0.5)_{\text{Normal}}] - [1 - P(r \leq ACL)_{\text{Binomial}}]$$

$$= [1 - \text{Normal CDF } (r \leq ACL + 0.5)_{\text{mean = np, variance = np(1-p)}}] - [1 - \text{Binomial CDF } P(r \leq ACL)]$$

$$= \sum_{r=0}^{ACL} \binom{n}{r} p^r (1-p)^{n-r} - \int_{-\infty}^{(ACL + 0.5)} \frac{1}{\sqrt{2\pi[np(1-p)]}} e^{-\left(\frac{(r-(np))^2}{2[np(1-p)]}\right)}$$

Choosing Between the Normal and the Poisson

For likely values of n (for example, estimates of n based on past catches in the fishery), an estimate of p, and a given value of the ACL for the rare-event species, the distribution (Poisson or Normal) with the smaller error, as calculated above, should be used.

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Appendix F

Rare-Event Species—Inverse Sampling

Haldane (1945) (see also Cochran, 1977, section 4.5) developed the *inverse sampling* method to estimate the proportion of individuals with a rare characteristic in a population. In a fisheries context, fish that are members of a so-called “rare-event” fish species could be considered members of a population (the population of all fish) with a rare characteristic (namely, belonging to the rare species). This Appendix presents Handane’s method with applications to the management of rare fish species.

Methodology

Handane (1945) considers a situation in which there are two classes of sample elements, for example, a “rare-event” species of fish and other, “common” species of fish. Fish are sampled (harvested) until m rare-event species fish are caught. Suppose it is the case that n fish (including both rare-event and common species together) must be caught in order to obtain m rare-event fish. Haldane (1945) shows that:

$$p = (m - 1) / (n - 1)$$

is an unbiased estimate of the true proportion P of rare-event fish in the population. Furthermore, by way of an infinite series expansion, Haldane shows to a very good approximation that the variance of p is given by:

$$\mathrm{var}(p) \approx \frac{m(n-m)}{n^2(n-1)}$$

which Cochran (1977, section 4.5) shows is equivalent to:

$$\mathrm{var}(p) \approx \frac{mp^2(1-p)}{(m-1)^2}$$

which, unfortunately, depends on the unknown value of p.

However, the PSE of p is given by:

$$\mathrm{PSE}(p) = \frac{s.e.(p)}{p} \cdot 100 = \frac{\sqrt{var(p)}}{p} \cdot 100 = \frac{\sqrt{m}}{(m-1)} \cdot \sqrt{(1-p)} \cdot 100$$

which approaches the upper limit $\frac{\sqrt{m}}{(m-1)} \cdot 100$ as p approaches zero.

Hence, by choosing m in advance, an upper limit on the value of PSE(p) can be obtained, and the value will be a very good approximation of PSE(p) for small values of p, which is the case for rare-event species. Examples of values of m and corresponding PSE(p) are presented in the table below:

m	PSE (pct)	m	PSE (pct)
1	-----	20	23.54 %
2	141.42 %	30	18.89 %
3	86.60 %	40	16.22 %
4	66.67 %	50	14.43 %
5	55.90 %	60	13.13 %
6	48.99 %	70	12.13 %
7	44.10 %	80	11.32 %
8	40.41 %	90	10.66 %
9	37.50 %	100	10.10 %
10	35.14 %	110	9.62 %

Thus, to obtain an estimate of p with a PSE(p) < 50%, we must wait for 6 rare-event species fish to be caught in a given fishery, then p = (m - 1) / (n - 1) can be used to estimate the proportion of rare event species in the population. For a PSE(p) < 30%, we must wait for 20 rare-event species fish to be caught.

Applied Example – Estimating the Proportion of a Rare-Event Species in a Population

For example, suppose, at the beginning of the fishing season, we choose m = 20 in order to achieve PSE(p) = 23.54%. Then, we wait until 20 rare-event fish are caught by the fishery and, at that point in time, we note the total catch of the fishery, n. Suppose n = 10,000 fish. Then, the unbiased estimate of the proportion of rare-event fish in the population is:

$$p = (m - 1) / (n - 1) = 19/9{,}999 = 0.0019$$

with a PSE(p) of 23.54%

Extension – Estimating the Total Population of a Rare-Event Species

In cases where there is an unbiased estimate t (e.g., from a stock assessment) of the total number of fish (both rare-event and common species together) T in the population exploited by the fishery, and the variance of the estimate is var(t), then an unbiased estimate r of the total *number* of rare-event fish r in the population is given by:

$$r = p \cdot t$$

with variance var(r) obtained from Goodman's (1960) formula:

$$\mathrm{var}(r) = p^2 \cdot \mathrm{var}(t) + t^2 \cdot \mathrm{var}(p) - \mathrm{var}(t) \cdot \mathrm{var}(p)$$

and

$$\mathrm{PSE}(r) = \frac{\sqrt{var(r)}}{r} \cdot 100$$

Extension – Multiple Types of Rare-Event Species

The formulas above can be generalized (Haldane, 1945) to the case of multiple types of rare-event species within the same population (e.g., multiple types of rare Grouper or Snapper species within a Grouper-Snapper complex).

Extension – Cluster Sampling

For application to MRIP data, it may be necessary to extend Haldane's method to situations involving cluster sampling (Cochran, 1977, section 3.12). For example, a fishing trip may be considered a sample unit, and individual fish caught on the trip may be considered sample elements within a sample unit. Each fishing unit (trip) is a cluster of elements (fish). The elements (fish) are classified into two cases, rare-event species and "common" species. Elements are likely to be clustered by unit in cases where the spatial distribution of rare-event species is patchy, such that some units (trips) collect elements from locations where rare-event species are present while other units (trips) collect elements from locations where such species are absent.

Extension – Sampling Without Replacement

If the population of the rare species is thought to be so small that sampling without replacement might be appropriate, Espejo et al. (2008) provide some initial results toward extending Haldane's method in this direction.

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Appendix G

Rare-Event Species—Uninformative Priors and Bayes' Rule

Suppose that in a particular time period and in a particular geographic location/area/region, fishermen catch r fish of a particular rare species and c fish of other species (including both common species and other rare species). Suppose that this is all the information that fishery managers have about the particular rare species in that location/area/region—that is, fishery managers are starting from almost nothing.

Assume that the distribution of catch across species is proportional to the abundance of each species in the fish population at the fishing location; that is, the probability P of catching a fish of the particular rare species is the same as the proportion P of that particular species of rare fish in the general fish population at that location. For example, if five percent of the fish in the fish population in that location are of the particular rare species, then a fisherman has a five percent chance that any fish caught will be of that rare species. (Note that the discussion presented below can be modified to account for the "selectivity-adjusted" probabilities of catching the various fish species.)

Suppose now, as is likely to be the case, that the proportion P of the particular rare fish species in the general fish population at the location is unknown. A common definition of an "unknown" proportion is that the proportion is *equally likely* to be any value between 0 and 1; this excludes 0 and 1, because we know that some rare fish exist, because we caught r of them, but we know that not all of the fish are rare, because we also caught c fish of other species. This definition of "unknown" is modeled using a uniform statistical distribution for P with parameters a = 0 and b = 1. (This is known as an "uninformative prior" distribution in a Bayesian modeling framework.) That is, P ~ Uniform(a = 0, b = 1).

Given only one time period of catch information (r and c), what is the probability distribution of the proportion P of the particular species of rare fish in the general fish population in the location of interest? Furthermore, what is the expected (mean) catch of the particular species of rare fish, and the variance of the catch of this rare species? If a fishery-independent estimate is available for the total fish population (including all species, both rare and common, together) caught by the fishery at the location, what is the expected total population (and variance) of the particular rare species at the location?

Finding the Probability Distribution of the Proportion of Rare Fish in the Fish Population

Suppose that, from time period to time period, R + C is the total number of fish caught at the location of interest, where R is the number of fish of the particular rare species that is caught, and C is the number of fish of other species that is caught. Both R and C can vary from time period to time period. Fishery managers have catch information from only one time period, and for that time period, R = r and C = c (that is, r and c are the numbers of fish that were caught in the one time period for which we have catch data).

Each time period, the probability that anglers will catch R = r rare fish in a batch of size r + c, given that the probability of a caught fish being rare is p, where p is a particular value of P, is given by the binomial probability distribution:

$$\text{Probability } (\mathrm{R} = \mathrm{r} \mid \mathrm{P} = \mathrm{p}) = \binom{r+c}{r} p^r (1-p)^c$$

The probability distribution of P, given that r rare fish were actually caught (that is, the conditional probability distribution of P, given R = r), is found via Bayes' rule:

$$\text{Probability } (P = p \mid R = r) = \frac{\mathit{Probability}\ (R = r \mid P{=}p) * \mathit{Probability}\ (P{=}p)}{\mathit{Probability}\ (R = r)}$$

Given that, initially, P ~ Uniform(a=0,b=1), it follows that Probability (P = p) = 1 / (b - a) = 1/(1 - 0) = 1 in the numerator of the expression above.

Substituting the expressions for Probability (R = r) and Probability (P = p) into the expression for Probability (P = p | R = r):

$$\begin{aligned}
\text{Probability } (P = p \mid R = r) &= \frac{\mathit{Probability}\ (R = r \mid P{=}p) * \mathit{Probability}\ (P{=}p)}{\mathit{Probability}\ (R = r)} \\
&= \frac{\binom{r+c}{r} p^r (1-p)^c * (1)}{\int_0^1 \binom{r+c}{r} p^r (1-p)^c dp} \\
&= \frac{\binom{r+c}{r} p^r (1-p)^c}{\binom{r+c}{r} \int_0^1 p^r (1-p)^c dp} \\
&= \frac{p^r (1-p)^c}{\int_0^1 p^r (1-p)^c dp}
\end{aligned}$$

The last expression above is a Beta (1 + r, 1 + c) distribution, hence:

Probability (P =p | R = r) ~ Beta (1 + r, 1 + c)

where, from the definition of a Beta distribution with parameters (1+r) and (1+c), it follows that:

$$\text{mean (P)} = E[P] = \frac{(1+r)}{(1+r) + (1+c)}$$

$$\text{variance (P)} = \text{var}[P] = \frac{(1+r)(1+c)}{[(1+r)+(1+c)]^2 \cdot [(1+r)+(1+c)+1]}$$

The probability that the proportion of rare fish P is less than a particular value, say "a," can be found using the cumulative distribution function of the Beta distribution:

$$\text{CDF } (P < a) = \frac{\int_0^a p^r (1-p)^c dp}{\int_0^1 p^r (1-p)^c dp}$$

For example, the probability that the proportion of rare fish P is less than 7 percent (0.07) would be:

$$\text{Probability } (P < 0.07) = \text{CDF } (P < 0.07) = \frac{\int_0^{0.07} p^r (1-p)^c dp}{\int_0^1 p^r (1-p)^c dp}$$

Similarly, to calculate the probability that the proportion of rare fish is between 5 percent and 10 percent:

Probability (0.05 < P < 0.10)

$$= \text{CDF } (P < 0.10) - \text{CDF } (P < 0.05) = \frac{\int_0^{0.10} P^r(1-p)^c dp}{\int_0^1 P^r(1-p)^c dp} - \frac{\int_0^{0.05} P^r(1-p)^c dp}{\int_0^1 P^r(1-p)^c dp}$$

Likewise, the probability that the proportion of rare fish is greater than 3 percent is:

$$\text{Probability } (0.03 < P) = 1 - \text{CDF } (P < 0.03) = 1 - \frac{\int_0^{0.03} P^r(1-p)^c dp}{\int_0^1 P^r(1-p)^c dp}$$

Estimating the Mean and Variance of the Catch of a Rare Species

Suppose fishery managers have an estimate of the average (mean) total fish catch (both rare and common fish species combined), E[R + C]), for the location of interest, and the variance of total fish catch, var[R+C], for the location of interest. For example, these values could come from past MRIP estimates for the location. Fishery managers also have the number of rare fish, r, and the number of other fish, c, caught at the location of interest for only one time period. If it is reasonable to assume that the proportion of rare fish in a particular location P is independent of the total fish catch (R+C) in that location[1], and that fish are caught in proportion to their prevalence in the population (that is, the rare fish are not being "selected for" or "selected against"), then the expected value (mean) number of rare fish caught, E[R], is given by:

$$E[R] = E[P\cdot(R+C)]$$

$$= E[P]\cdot E[(R+C)] \quad \text{by independence of P and (R+C)}$$

$$= \frac{(1+r)}{(1+r) + (1+c)} \cdot E[(R+C)]$$

where E[(R+C)] is the MRIP estimate of mean catch of all fish in the location.

The variance in the number of rare fish caught, var(R), is given by Goodman's (1960) formula for the variance of the product of two independent variables:

$$\text{var}(R) = \text{var}\,[P\cdot(R+C)] = (E[P])^2\cdot\text{var}[(R+C)] + (E[R+C])^2\cdot\text{var}[P] + \text{var}[(R+C)]\cdot\text{var}[P].$$

Estimating the Mean and Variance of the Population of a Rare Species

Suppose the total fish population (both rare and common fish species combined) in the location of interest is X, of which the number of rare fish is N, such that $N = P\cdot X$. Suppose, too, that fishery managers have a fishery-independent estimate of the expected (mean) total fish population, E[X], and the variance of total fish population, var[X]. For example, the estimates E[X] and var[X] could come from a stock assessment. If it is reasonable to assume that the proportion of rare fish in the location of interest P is independent[2] of the total fish population in that location X, then the expected number of rare fish in the population, E[N], is given by:

$$E[N] = E[P\cdot X]$$

$$= E[P]\cdot E[X] \quad \text{by independence of P and X}$$

[1] If P and (R+C) are not independent, then $E[R] = E[P\cdot(R+C)] = E[P]\cdot E[(R+C)] + \text{cov}(P,(R+C))$, and $\text{var}(R) = \text{var}\,[P\cdot(R+C)]$ is given by Equation 18 in Goodman (1960), where x = P and y = (R+C).

[2] If P and X are not independent, then $E[N] = E[P\cdot X] = E[P]\cdot E[X] + \text{cov}(P,X)$, and $\text{var}(N) = \text{var}\,[P\cdot X]$ is given by Equation 18 in Goodman (1960), where x = P and y = X.

$$= \frac{(1+r)}{(1+r) + (1+c)} \cdot \mathrm{E}[X]$$

where E[X] is the fishery-independent estimate of expected population of all fish at the location, and the variance in the number of rare fish in the population, var(N), is given by Goodman's (1960) formula for the variance of the product of two independent variables:

$$\mathrm{var}(N) = \mathrm{var}\,[P \cdot X] = (\mathrm{E}[P])^2 \cdot \mathrm{var}[X] + (\mathrm{E}[X])^2 \cdot \mathrm{var}[P] + \mathrm{var}[X] \cdot \mathrm{var}[P].$$

Regarding software implementation of this approach, both Microsoft Excel and R have functions for the Beta distribution.

In summary, the method uses the mean and variance (from MRIP) of the catch of all fish (both rare and common) in the region of interest, and the mean and variance (from a stock assessment) of the population of all fish (both rare and common) in the region of interest.

The mean and variance of the rare species catch estimates based on the catch data from the initial time period could serve as the initial estimates for a Bayesian updating model of rare species catch.

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Appendix H

Defining and Managing "Outliers" in MRIP Output—An Order Statistics Approach

The MRIP program produces estimates of recreational fish catch and variance of catch by 2-month wave and by year. These estimates are produced by domain, such as by species, by geographic region, or by fishing mode. Fishing regulations are typically based on recent MRIP catch estimates or statistics derived from MRIP catch estimates, such as "the third-largest of the five most recent MRIP catch estimates." In such derived statistics, the influence of so-called "outlier" estimates on the derived statistics is an important issue. The questions of how to define an "outlier," how to decide whether an outlier of a given magnitude should trigger a change in management policy, and how to update management policy given a "triggering" outlier, are important questions for fishery managers. This Appendix presents a method to answer these questions based on the statistical concept of "order statistics."

Order Statistics

The statistical concept of "order statistics" offers one approach to defining, identifying and measuring "outliers." Order statistics provide a method for determining the probabilities that the first-largest, second-largest, third-largest, etc., in a set of ordered numbers will take particular values.

For example, denote the i = 1 n annual MRIP catch estimates for a particular fish species as X_1, $X_2, \ldots, X_n$. Assuming no change in the fish population or fishery from year to year (an assumption that can be tested later), the X_i are independent, and identically-distributed random variables having a common probability density f(X) and a common cumulative distribution function F(X). For non-rare fish species, f(X) is typically the density function for the normal distribution and F(X) is the cumulative distribution function for the normal distribution. (For rare fish species, f(X) and F(X) could be the probability mass function and cumulative distribution function for the Poisson or negative binomial distribution.)

Arrange the $X_1, X_2, \ldots, X_n$ values in order from smallest to largest, and use subscripts j = 1 to n in parentheses to denote the order of the values as shown below:

$X_{(1)}$ = the smallest of the set $X_1, X_2, \ldots, X_n$.
$X_{(2)}$ = the second smallest of the set $X_1, X_2, \ldots, X_n$.
⋮
$X_{(j)}$ = the jth smallest of the set $X_1, X_2, \ldots, X_n$.
⋮
$X_{(n-1)}$ = the second largest of the set $X_1, X_2, \ldots, X_n$.
$X_{(n)}$ = the largest of the set $X_1, X_2, \ldots, X_n$.

Probability Distributions of Order Statistics

It can be shown (Ross, 1988, p. 225) that the joint density function f_{joint} of the order statistics is given by:

$$f_{joint}(X_{(1)}=x_1, X_{(2)}=x_2, \ldots, X_{(n)}=x_n) \quad = \quad n!\cdot f(X=x_1)\cdot f(X=x_2)\cdot\ldots\cdot f(X=x_n)$$

The density function $f(X_{(j)} = x)$ of the jth order statistic $X_{(j)}$ can be obtained by integrating the joint density function above to find (Ross, 1988, p. 227):

$$f(X_{(j)} = x) = \frac{n!}{(n-j)!(j-1)!}[F(x)]^{j-1}[1 - F(x)]^{n-j} f(x)$$

The cumulative distribution function $F(X_{(j)} \leq b)$ of the jth order statistic $X_{(j)}$ can be obtained by integrating the density function $f(X_{(j)} = x)$ of the jth order statistic to find (Ross, 1988, p. 227):

$$F(X_{(j)} \leq b) = \frac{n!}{(n-j)!(j-1)!}\int_{-\infty}^{b}[F(x)]^{j-1}[1 - F(x)]^{n-j} f(x)\, dx$$

For example, $F(X_{(n-2)} \leq 3000)$ gives the probability that the third-largest catch out of n catches is less than or equal to 3000.

Similarly, $1 - F(X_{(n-2)} \leq 3000)$ gives the probability that the third-largest catch out of n catches is greater than 3000.

Fisheries Applications: Defining an Outlier

First, consider the problem of trying to determine whether the largest value of catch in n time periods is an outlier. Assume that i = 1 to n time periods of catch data are available for a non-rare fish species, where fish catch in each time period i, X_i, follows a normal distribution $f(X_i)$ with the same mean μ and variance σ^2 for all i, and where $F(X_i)$ is the cumulative normal distribution function of X_i. Suppose fishery managers are trying to decide whether the largest value of catch from the n time periods, namely $X_{(j = n)}$, is an outlier.. One possible definition of "outlier" would be any value of $X_{(j = n)}$ with a chance of occurring that is less than the fishery managers' pre-selected level of statistical significance (say, a 5 percent). The "threshold" value of catch denoted b for this definition of outlier would be the value of b that is the solution to:

$$1 - F(X_{(j=n)} \leq b) = 0.05.$$

Hence, if the "largest catch" X(j = n) in the n time periods is greater than b, then it would be considered an outlier because it has a less than 5 percent probability of occurring by chance alone. Similarly, if a fishery regulation were based on the "third largest of the five most recent MRIP catch estimates," then the threshold value c for the third largest catch estimate in n = 5 catch estimates to have a 5 percent chance of occurring is the solution to:

$$1 - F(X_{(j = n-2 = 5-2 = 3)} \leq c) = 0.05,$$

where any value for the "third largest catch" greater than c would be considered an outlier.

Fisheries Applications: Deciding Whether an Outlier Should Trigger a Management Change

If an outlier were to occur, fishery managers would first check to ensure that the outlier was not due to an error in the data or an error in data processing. If the outlier was not due to an error, then managers would need to decide whether (i) the outlier occurred due to chance alone, and so the outlier should not trigger a change in fishery management policies (e.g., a change in control rules), or (ii) the outlier is an indication that either the fish population or the fishery is changing, and that, as a result, the probability distribution of X is shifting, and so the outlier should trigger a change in fishery management policies. Typically, fishery managers would use their pre-specified level of statistical significance (say, 5 percent) to decide between (i) and (ii). If the outlier exceeded the threshold value of catch (such as "b" or "c" in the examples above), then managers would decide that either the fish population or the fishery is changing, and that, as a result, the probability distribution of X is shifting, and so fishery management policies should be changed (or, at least, further investigation is warranted).

Fisheries Applications: How to Update Management Policy Given a "Triggering" Outlier

Given a "triggering" outlier, the outlier value of catch would be used to update the probability distribution of fish catch using Bayesian updating methodology as described under the Bayesian model of in-season management outlined in this report. Other fisheries management policies (e.g., control rules) could then be updated based on the updated probability distribution of fish catch.

REFERENCES

Ross, S. 1988. *A First Course in Probability, 3rd Edition*. Macmillan Publishing Co., New York.