Marine Recreational Information Program
FY-2013

Assessing and refining the collection of app-based angler information in relation to stock assessment

Project: Internet based angler logs as a source of fishery dependent data

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1. Executive Summary

Fisheries professionals need to collect data on and manage recreational fisheries more effectively, so different organizations and agencies have begun utilizing electronic, self-reporting platforms to supplement current sampling programs. We assess the utility of the iAngler smartphone "app"—one such sampling program—for recreational fisheries stock assessment by characterizing the dataset and comparing specific metrics to those of NOAA's Marine Recreational Information Program (MRIP). Note that access to data from other apps was not possible for the projects. Metrics compared were the spatial distribution of trips by county, frequency of catch for the ten most commonly reported species, and species-specific catch rates. We conducted "catch frequency" and catch rate comparisons for different spatial designations in Florida and catch rate comparisons for different fishing modes. Data from iAngler exhibits a strong spatial bias toward southeast Florida and a bias toward three common inshore species: Common Snook (*Centropomus undecimalis*), Spotted Seatrout (*Cynoscion nebulosus*), and Red Drum (*Sciaenops ocellatus*). However, iAngler catch rates for these three species were similar to those of the MRIP. Because a majority of trips reported to iAngler came from a relatively small number of anglers, we used a simulation to develop a proper weighting for angler avidity. Using a geometric mean that accounted for zero-catch fishing trips and angler avidity, we recalculated catch rates for Common Snook, Spotted Seatrout, and Red Drum and found avidity to have a variable yet noticeable impact on catch rates. This study shows the potential for electronic, self-reporting programs to provide reliable recreational fisheries data, as long as spatial coverage is sufficient, and avidity is accounted for.

1 Objectives Summary

Phase 1

1.1 Description of stock assessment needs and evaluation of the potential for angler e-logs to provide information that is usable in stock assessments. The initial description will include at least two angler based electronic reporting/logging systems in addition to the iAngler application developed by the Snook and Gamefish Foundation.

There are three main needs for conventional stock assessments in relation to the qualification recreational fisheries that can potentially be met by angler e-logs 1) The quantification of catch rates with greater accuracy so that the estimation of total harvest (retained, live and dead discards) can be estimated with percent standard errors (PSE) within an acceptable range (generally <30%); 2) The quantification of size frequencies for all catch components (retained, live and dead discards). 3) Improving the understanding of the spatial distribution of fishing effort. Currently the MRIP program does not provide sufficient spatial or temporal coverage to accurately estimate catch at the state resolution for species that are infrequently encountered resulting in PSE >>30%. In addition, currently the MRIP program does not quantify the size distribution or depth of discards. For a number of species (e.g., Red Snapper), mortalities from discards can represent a large proportion of the allowable catch. Given the size and depth dependency in discard mortality rates, the ability to more accurately quantify this component of the catch is necessary. In addition, MRIP quantifies the spatial distribution of effort at a coarse resolution such as state or federal waters and at the county of intercept. Such information is insufficient to quantify the potential effect of depth on discard mortality rates.

From the analysis presented in this document (sections 3 and 4) it is apparent that e-logs have the potential to provide this information but because that are still in their infancy and lack the spatial coverage to augment the MRIP data except in areas where participation is high. Unfortunately, areas of high participation, at least for the iAngler app, are currently too localized to be considered an accurate reflection of the angling community even though the catch rates and length frequencies are comparable to MRIP. Unless there is more ubiquitous adoption of e-logs such as iAngler it is unlikely that they will provide the necessary spatial and temporal resolution to augment the MRIP data for the purpose to stock assessment at more localized (eg., regional or state) levels.

The data availability and geographic scope of the iAngler data are limited and the initial intent of the iAngler app was not to collect information that could be used in stock assessment. Our intent with the study was to present an apples to apples comparison between the available data in iAngler and the current best available data which is the MRIP to demonstrate that where comparisons were possible the data were similar. The analysis indicated that if such a program could be scaled up in participation rate and geographic coverage, data from such a program would potentially be similar to MRIP (such a broad scale comparison is not possible since an app with such coverage does not exist). These results were positive and suggest that even with all the concerns of potential biases that could be introduced by a rotating panel of participants, the data told the same story. There are two critical points that should be made here. 1) The ability to subset and alter the app data at the level of the individual gives any analysis a high degree of flexibility in defining the sampling probabilities and the potential to reduce biases that result from avidity etc. This only becomes a problem if the participant pool is reduced to a limited number of individuals. 2) MRIP was designed to answer questions at the national level and given the potential hit and miss nature of the sampling from the MRIP program at finer spatial scales, app data, provided it is available in an area may provide a better depiction of the catch and composition information. We have also done some length-frequency comparison that also show a similar pattern in the data from iAngler and MRIP which suggest a potential to use apps to collect more detailed discard information (this is not currently done with the iAngler app). The potential for apps like iAngler to provide supplementary information exists: the two data sources match but data such as the size distribution of discards is currently not collected. With no further modification to the type of data collected in the iAngler app it would be possible to use the data to supplement MRIP catch rates and length frequency of retained catch information but only at the limited spatial scale over which iAngler data are collected. Further modification of the app would be required to collect data on the location and size structure of discards and a much broader geographic scope of use would be needed before data could be used for most stock assessments.

1.2 Description of minimum data elements and standards for inclusion of angler e-log data in stock assessments.

Venturelli et al. (2016) provide a list of potential data elements to be included at a minimum for any e-log entry. Fishing trips should be georeferenced with the intended target species acknowledged. The length of time fishing should be recorded. Catch data should include at a minimum, the species, number and fate (e.g., retained, released). Additional information for each fish regardless of fate such as length and weight can provide valuable information for assessments. Information on angler demographics and behavior can also be essential for defining the sampling frame and evaluation of data for potential biases.

From the analysis performed in this report a number of recommendations can be made with respect to the minimum data requirements for the inclusion of e-log data. Currently very little demographic information is collected by e-logs. This is in part due to privacy issues and not wanting to overburden users with lengthy registration. This lack of demographic information makes it challenging to directly compare the composition of anglers using e- logs to those included in the MRIP intercept survey or phone/mail survey. While there is no guarantee that demographic data is a logical comparison to make to validate effort and catch information it would be an additional check and allow for comparison with intercept or license data. The minimum requirements for this data would likely be age, sex, race. A number of app developers have indicated that such data can be mined from social media sources. For e-log data to be useful for the estimation of total harvest in conjunction with the MRIP program catch rate data collected from an e-log must be compatible with MRIP data streams. This requires that catch by trip by location (kept, releases alive, released dead) by species can be attributed to an individual angler so that catch rate can be calculated. One of the challenges integrating e-log data with MRIP to estimate total catch is attributing e-log catch to MRIP locations. For e-log data to be useful in improving estimates of discard mortality for live discards requires at a minimum that in addition to catch information, length and ideally depth of capture be reported.

Provided sufficient demographic information can be collected the data provided from an app can be readily subsampled to match the demographics of the data it is supplementing. As identified, the ability to subset is completely dependent on the nature of the data collected. Sufficient demographic data would need to be collected to align any data from an app to the categories in the MRIP effort survey or at least to the level used in the MRIP intercept survey. Unlike angler license databases, the effort and intercept surveys are not dependent on the license database. App data on user demographics is a critical development that will be needed for app data to be useful in stock assessment. Should sufficient data be available then apple to apple comparisons would be made for data validation though it would be necessary to perform appropriate QAQC on app reported data. This is potentially the greatest cost associated with the use of app data. While adjustments to application design is straight forward and cost effective, database alignment and validation between applications and MRIP may require modifications to both data collection methods.

1.3 Development of protocols for ranking or evaluating angler e-Logs based on data requirements.

The following list of angler apps is listed in Venturelli et al. (2016) Fangstdatabanken, Fangstjournalen, FishBrain, Great Lakes Fish Finder, iAngler, iFish Forever, IGFA, iSnapper, Mijn VISmaat, Snapper Check. All of these apps record the minimum data listed above and more producing data that is on par with traditional creel programs at a greater spatial and temporal resolution. All of these apps are adequate in regards to the information collected. The analysis that follow in this report clearly indicated that the information collected using the iAngler app is similar to that collected in the MRIP program suggesting little difference between the data sources when and where comparison were made. Some general recommendations can be put forward in terms of developing a ranking/evaluation scheme:

· Periodically data from e-logs should be compared to other programs such as traditional logbook or creel programs. If no significant differences are found between the distributions it would seem reasonable to use the e-log data for application at the spatial extent of the data.

· Data should not be used if sample sizes are insufficient to define the statistical distribution of the data. In the analyses presented in this report direct comparisons between the statistical distribution of catch rate data were made between e-log and MRIP. A formal power analysis should be done to determine the minimum sample size when comparisons are made.

· An understanding between angler behavior as it relates to app use is essential for understanding reporting bias and to ultimately use e-log data to estimate effort. Very little work had been done to understand: the relationship between app users and the general angling population (demographics, angling avidity, angling skill), the relationship between angling avidity and reporting avidity, as well as the nature of reported trips relative to other trips.

· Data validation and alignment will be an ongoing cost of any app program but would not be cost prohibitive given the potential data gaps that could be covered by app data (e.g., greater sampling of species specific catch rates at finer spatial scales and the sampling of discard size and locations.). The cost (i.e., incentives) of maintaining a rotating panel of sufficient size and geographic scope is currently unknown given the lack of demographic information associated with app data. Maintenance of what would likely need to be a large pool of users over a broad geographic range would likely require an expansive advertising campaign and incentives. Such programs could be maintained at a state level provided there was data harmonization between applications.

1.4 Evaluation of the potential for certification standards as determined by compliance with minimum data standards.

Given the specialized nature of many e-logs and the nature of free market enterprise it is unlikely that a single app or set of apps will have sufficient coverage to meet the requirements for all but highly localized assessments. This reality requires the development of a centralized information system to which app developers can upload data collected from users. As outlined in Venturelli et al (2016) for data collected from apps to be of use in assessment there is a need to (i) identify a minimum data set that the majority of app developers are willing to share for scientific or management purposes; (ii) adopt formal, internationally recognized, and general standards for metadata and data collection that can be applied to any angler app; (iii) identify those apps that meet some or all of these standards; and (iv) conduct research to evaluate standards. This will require the establishment of a standards council at national and international levels. Minimum data requirements have been identified above and every app would need to be certified by the council. The harsh reality is that research will need to be funded continually determine the reliability of the data provided.

1.5 Evaluation of the iAngler log devised by the Snook and Gamefish Foundation in its current form for use as a potential source of data for stock assessments. The evaluation will include:

1.5.1 Evaluation of the panel in terms of selection bias and volume of information obtained.

In general app user retention is low and the same is true for fishing apps. Generally, there is only 5% retention after 5 months. The iAngler app has a 10% retention rate after 1 year. Most users report only a single trip and a very small percentage of the users report a high volume of trips (Figure 1-1). It is reasonable to quantify the panel that participates in the iAngler app as highly variable and rapidly rotating. How some of this bias can be addressed is dealt with in section 3. No demographic data is available for the users except location.

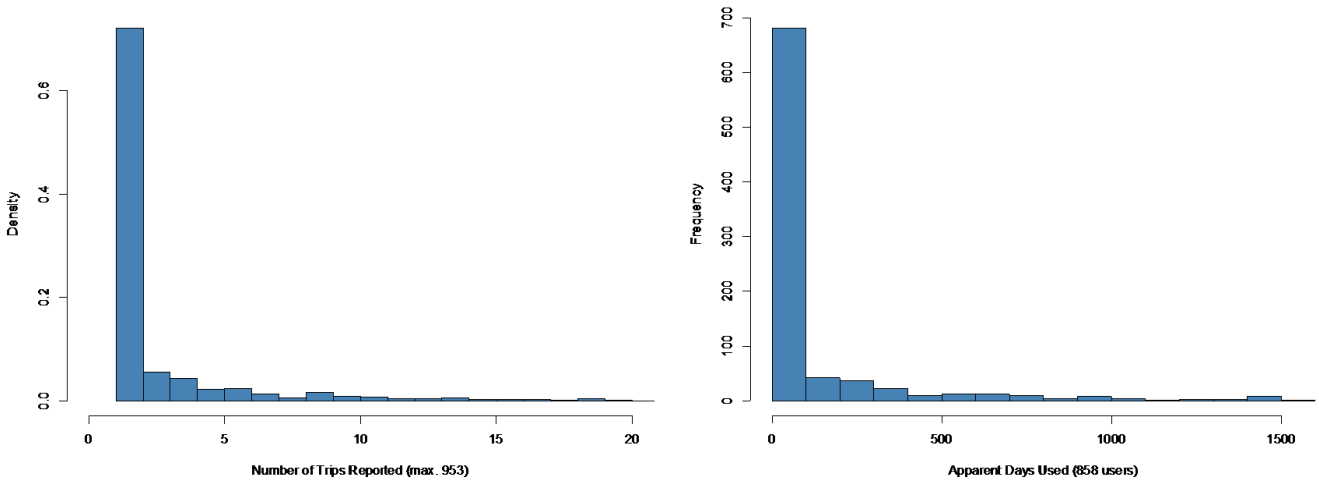

Figure 1-1 Left Panel – Number of trips reported by users of the iAngler app. Right Panel - Apparent number of days users used the iAngler app

1.5.2 Description and critique of the survey instrument and information components.

See section 3

1.5.3 Description and evaluation of data elements in terms of formatting, minimum data requirements, data quality and participant behavior (reporting patterns).

See section 3

1.5.4 Outline of improvements necessary for inclusion of iAngler data in stock assessment process.

See section 3

1.5.5 Description of practical improvements to the iAngler system that will address sources of bias in terms of data usability.

See section 3

1.5.6 Set expectations for the inclusion of iAngler data at the assessment level based on criteria for:

a. scientific defensibility – must be able to identify and/or account for bias.

b. compatibility with existing data.

c. stock assessment needs.

1.6 Assessment of recommended improvements to the iAngler system. Recommended improvements will form the basis for a set of recommended practices and minimum data requirements to be made available to entities interested in providing data for stock assessment purposes.

See section 3

Summary

The high degree of similarity between the catch rate data from the iAngler smartphone app and the MRIP survey suggests an electronic, self-reporting framework can provide information that is usable for the assessment of recreational fisheries. Thus, for fish species where iAngler has adequate sample size (e.g., common snook, spotted seatrout, red drum), the data should be useful for fishery-dependent uses in stock assessment. Although the spatial bias of iAngler makes it inappropriate for usage on a statewide level, this study used only the first two years of the app, when knowledge of the app was spread exclusively by “word-of-mouth” (Brett Fitzgerald, personal communication). The fact that the iAngler and MRIP catch/trip values were similar when compared at an appropriate spatial resolution (i.e. the county clusters) shows the ability of an electronic, self-reporting program to provide representative catch rate data. While it was clear that the avidity bias was present for some of these species in certain spatial regions, the application of a relatively elegant weighting factor can adjust for these biases provided they are understood.

A smartphone app used for collecting recreational fisheries data can be thought of as an angler diary, which has been useful for recreational fisheries managers. For example, paper-based diaries have been used to track relative abundance over time (Kerr 1996; Sztramko et al. 1991) , compare a fishery before and after a change in regulation (MacLennan 1996) , provide biological data (Ebbers 1987) , and correct for the recall bias (Tarrant et al. 1993) . Now that there is evidence of the reliability of a smartphone app framework, programs like iAngler can be used for most, if not all, of these issues—at a much smaller cost and in a form anglers appear to prefer (Baker and Oeschger 2009; Stunz et al. 2014) . This type of program could even be applied to situations often addressed with a telephone survey, such as the elimination of the public access bias, which arises in creel surveys when many trips are taken from private access points (Ashford et al. 2010) . Electronic, self-reporting platforms have the potential to become a valuable data collection method for many different types of questions in fisheries management.

In certain management scenarios, a fisheries manager may want to know individual catch rates, and a smartphone app such as iAngler may be reliable if the data is properly treated for angler avidity. For example, if an agency desires a certain percentage of the angling population to have a certain catch rate, this information cannot be obtained from a population-level mean CPUE. Here, it is likely best to weight each angler’s contributions to the overall dataset by using the inverse of his or her avidity as the weight. Further, as Thomson (1991) showed, this type of bias can even exist in carefully implemented creel surveys. Thus, the weighting developed in this work has applications not only to electronic, self-reporting programs, but other types of surveys as well.

One of the main strengths an app like iAngler has is the ability to provide comprehensive data on individual fish (e.g. lengths of fish, both retained and discarded), but unfortunately, such information was not submitted in high enough sample sizes in the first two years to be useful. Having information on the size structure of fish can help provide size-based indicators of the fishery’s health (Shin et al. 2005) . While the MRIP survey collects the lengths of retained catch, many fisheries regulated by a minimum size limit have high discard rates. In this event, a program like the iAngler app has the potential to be the main contributor of length data, as it

provides the opportunity for anglers to record lengths of released fish. The importance of understanding discarding cannot be emphasized enough, as the success of the commonly applied minimum size limit regulation is hinged upon the fate of undersized discards (Coggins et al. 2007) . Future studies should attempt to perform length comparisons between the MRIP survey and the iAngler dataset. For released fish, a possible avenue of research could be to compare iAngler's length distribution of discards to that of a fisheries independent survey.

Some other possibilities for future research include repeating these same analyses with a longer time series of data from the app as well as developing an understanding of the demographics and behavior of the app's users. The question of whether or not electronic, self-reporting data collection programs can provide a relative index of abundance for stock assessment would be better supported with data that comes from more than two years, as was the case with this study. By understanding the different types of anglers that contribute to the program, the data from an app like iAngler could be more appropriately utilized. For instance, changes in individual catch rates could not be safely attributed to a change in stock status if it is not known whether avidity has changed. Also, a survey could be distributed to the users of the app to determine what percentage of each angler's total number of trips were reported through the app. Many studies emphasize the impact that variable reporting rates can have on measures of effort/participation {Absher, 1987, Southern Lake Michigan sportfishery: angler profiles and specialization index for Illinois and Indiana} (Absher and Collins 1987; Connelly and Brown 1995; Connelly et al. 2000; Harris and Bergersen 1985; Lowry 1978; Tarrant et al. 1993) .

This research has shown that electronic, self-reporting smartphone apps can provide data for recreational fisheries management that is comparable to the programs already in place. Although the spatial coverage and overall usage is insufficient for iAngler to stand alone as a primary data source, its most useful attribute will be its ability to provide novel types of data (e.g. discard data, lengths, increased spatial resolution) that will supplement recreational fisheries management.

2 Detailing the impact of under sampling of recreational catch estimation

Accurate and precise estimation of the composition and magnitude of harvest and discards from the recreational fishing sector, in particular the private recreational fishing sector, is a deficiency in many quantitative stock assessments. Most assessments rely on information from the national MRIP survey to quantify harvest and discard removals. However, the MRIP and its predecessor MRFSS were intended to quantify recreational fisheries at the national level and as a result can lead to inaccurate and imprecise estimates at the spatial scale considered for many species due to sparse sampling at finer spatial scales.

Within this section we develop a simple simulation model to demonstrate how the precision and bias of catch estimates from stratified random sampling programs such as MRIP changes as a function of the proportion of the angling population sampled. Our intent is to demonstrate that sparse sampling has the potential to severely bias catch estimates to the point of them being potentially misleading in terms of dynamic changes in the fishery. We will further demonstrate that small increases in sampling coverage can result in large improvements in estimates and that there is a potential for electronic forms of catch reporting to provide the necessary coverage to achieve the desired level of accuracy and precision for quantitative assessments.

Model Structure

To simulate data collection from a coastal fishery, 3 population centers were established along the coastline with 10 potential access points. Population density around each center was modeled as a normal distribution and distributions were combined to determine the coast wide population density. Access points were distributed in relation to modeled population density so that areas with higher population density contained more access points. A single target species distribution was modeled as a normal distribution along the coastline.

The recreational angling population was modeled by assigning each individual to a location along the coast in proportion to the simulated population density. This was necessary so that the travel cost to each access point could be calculated for each angler. Each angler was then assigned a skill level from a lognormal distribution which determined their individual expected catchability. Individual were then assigned a total number of trip taken within a season using a negative binomial distribution. Trips were assumed independent of skill level. Expected catch rate was then calculated for each angler/access point combination by averaging the target species population density over 10 spatial areas around each access point. The value of an access point was then calculated for each angler as the difference between expected catch rate and scaled travel distance. For each angler/trip combination, an access point was selected as a weighted random draw and the exact spatial location near the access point selected for fishing was assumed in proportion to the expected local catch rates with some random variation added. This process resulted in a potential sampling frame of trips as the associated catch to be potentially sampled by an MRIP type program.

To determine the weights assigned to each access point for the stratified random sampling program, expected effort at each ramp was determined assuming the value associated with the average angler. The number of samples taken was then distributed at each ramp based on the expected effort levels. The number of trips sampled varied between 1-20% of the trips taken.

Average expected catch rate and the associated standard error was calculated assuming stratified random sampling and expanded to total catch assuming the total number of trips taken was assessed accurately. Estimated total catch from sampling was then compared to the actual total catch for the simulated population. To map out the potential bias a precision of estimate of 2000 simulations were run.

Assessment of accuracy and bias

Simulation indicate that bias and precision both improve as the proportion of the total number of trips sampled increases (Figure 1-1). Standard error declined rapidly with little change in the estimate after 10% of the trips sampled. Gains in bias were less rapid but simulations suggest there are little gains beyond sampling 20% of the population. There is the potential for very large positive and negative bias in estimated catch a low proportion sampled.

These simulation results suggest that the low number of records for a number of species in the MRIP is likely to result in biased and imprecise estimates of total catch as the spatial coverage of the data is refined these biases are likely to be exacerbated. With large fluctuation in the estimated catch resulting from the sampling process and not the fishery. However, large improvement can be gained with increasing the number of trips sampled, provided these samples are representative of the potential sampling frame of trips. These results suggest that validated records from electronic reporting platform such as phone apps can increase the proportion of trips sampled and have the potential to improve the estimates of recreational catch

utilized in stock assessment.

2. Background

One of the recommendations made in the National Research Council's 2006 review of recreational survey methodology was to explore the potential for using panel survey methodology to obtain fisheries information (NRC, 2006)[1]. Currently, numerous examples exist of informal volunteer panel based electronic angler reporting systems that allow recreational anglers to record catch and fishing trip information. These panels take the form of web-based electronic logbooks that make use of smart phone as well as other forms of mobile technology targeting similar types of information. There can be distinct differences in how panel participants are recruited, and panels maintained. Individual angler logs may vary by length of the recall period, the resolution and quality of catch and effort information obtained and angler incentives to report trip information. The motivation for the creation of a web-based angler survey or log may be out of concern for a particular stock or just a desire to provide a way for anglers/members a means to more accurately track their fishing trips. Whatever the rationale, there are some minimum data needs that must be addressed if the logs are to provide meaningful data for stock assessment purposes. How the data can be used will depend on how well they represent fishing activity and behavior (i.e., panel recruitment and maintenance and identification of potential sources of reporting bias among panel participants). Statistical considerations concerned with panel recruitment and maintenance were discussed recently at an MRIP funded workshop on "Opt-In" angler panels (Didden, 2012)[2]. Currently there are no minimum standards for how panels are constructed (i.e., recruited), the types of data collected or for the units reported. There may be an expectation among well-meaning panel participants and organizers that their data be used, and a tendency to presume foul play when they are not used as expected to inform stock assessments. Ironically, one of the cautions included in the NRC review was that stock assessment biologists were made aware of the data limitations (NRC, 2006). That caution could certainly be extended to participant anglers in electronic logbook programs and organizations that may have unrealistic expectations for how their data may be used. The defense of any decision to include or exclude data from this increasingly popular source is greatly facilitated through a well-designed set of criteria that outlines minimum requirements for data types and quality as well as for the selection process used to recruit panel members. By setting criteria or standards and making those standards available to angling groups, who wish to avail of electronic reporting, decisions to include or exclude logbook data in the stock assessment process can be defended at data workshops. Guidance to angler groups and organizations wishing to establish electronic reporting systems or improve existing reporting systems, needs to take the form of a set of recommended practices that includes recommendations for minimum data elements and standards. By providing a template that ranks usability of data provided in e-logs in terms of data needs (including adaptability to future data needs), data quality, ability to account for potential sources of bias, and meet minimum standards for consideration as valid data sources, angler expectations for data use are clearly defined, and the potential of angler e-logs to augment state and federal data collection programs can be explored. The process may allow for integration of an increasingly visible potential source of data under the MRIP umbrella.

Project Description

University of Florida will partner with Florida Fish and Wildlife Conservation Commission (FWC) to evaluate angler e-log programs. Initially this evaluation will be done on data from the iAngler application developed by the Snook and Gamefish Foundation (SGF) but may be extended to the International Game Fish Association (IGFA) application as well as Greg Stunz's iSnapper application at Texas A&M. Application data and panels will be compared to information collected by MRIP. The evaluation of e-log data will be run in two phases. Phase 1, in consultation with FWC and SGF, will evaluate the utility of e-log data to help inform stock assessment and its potential as a fishery dependent data source. The expected outcomes of phase 1 are outlined below. Phase 2 will reevaluate the utility and scope of e-log data once recommendations from phase 1 are implemented.

Description of Goods and Services

Phase 1

1.1 Description of stock assessment needs and evaluation of the potential for angler e-logs to provide information that is usable in stock assessments. The initial description will include at least two angler based electronic reporting/logging systems in addition to the iAngler application developed by the Snook and Gamefish Foundation

1.2 Description of minimum data elements and standards for inclusion of angler e-log data in stock assessments.

1.3 Development of protocols for ranking or evaluating angler e-Logs based on data requirements.

1.4 Evaluation of the potential for certification standards as determined by compliance with minimum data standards.

1.5 Evaluation of the iAngler log devised by the Snook and Gamefish Foundation in its current form for use as a potential source of data for stock assessments. The evaluation will include:

1.5.1 Evaluation of the panel in terms of selection bias and volume of information obtained.

1.5.2 Description and critique of the survey instrument and information components.

1.5.3 Description and evaluation of data elements in terms of formatting, minimum data requirements, data quality and participant behavior (reporting patterns).

1.5.4 Outline of improvements necessary for inclusion of iAngler data in stock assessment process.

1.5.5 Description of practical improvements to the iAngler system that will address sources of bias in terms of data usability.

1.5.6 Set expectations for the inclusion of iAngler data at the assessment level based on criteria for:

a. scientific defensibility – must be able to identify and/or account for bias.

b. compatibility with existing data.

c. stock assessment needs.

1.6 Assessment of recommended improvements to the iAngler system. Recommended improvements will form the basis for a set of recommended practices and minimum data requirements to be made available to entities interested in providing data for stock assessment purposes.

Phase 2

2.1 Re-evaluation of e-log data following recommendation from 1.6

2.2 Re-evaluation (year 2) of e-log data following recommendation from 1.6 and recommendation from

Goods and Services reported on in this final report.

This summary report combines information in previous reports for phases 1 and 2 with the addition of a simulation clarifying the potential impacts of under sampling recreational participants in terms of its impact on the potential bias and precision of catch estimates as well as a final recommendations section.

List of abbreviations

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[1] National Research Council (2006). Review of Recreational Fisheries Survey Methods. National Academy of Sciences, Washington, D.C. 187pp.

[2] Didden, J. (2012). Summary of Feb 2, 2012 Workshop on Opt-In Angler Panels. MRIP Report 10pp.

3.1 Phase 1 evaluation of iAngler

Background

Recreational fishing has high economic importance in the United States, with over 33 million participants nationwide, taking approximately 455 million fishing trips in 2011 (US Department of the Interior et al. 2011) . This—combined with the fact that recreational fisheries can cause overfishing (Coleman et al. 2000; Post et al. 2002) —means there is a need to evaluate the recreational fishing sector during the stock assessment process. In the Gulf of Mexico, recreational landings have often exceeded commercial landings for high-profile stocks such as Red Snapper *Lutjanus campechanus* (Coleman et al. 2000) and Gag *Mycteroperca microlepis* (NOAA 2014) . Other stocks such as Common Snook *Centropomus undecimalis* and Red Drum *Sciaenops ocellatus* no longer have a commercial sector, so stock assessments require data from the recreational fisheries. In order to ensure long-term sustainability of such stocks, scientists and managers need a process for gathering reliable information from recreational anglers.

Sampling recreational anglers is a challenging process that depends on the willingness of

anglers to participate in data collection and the quality of data provided. A creel survey is one of the most commonly utilized methods, where interviewers are hired to collect catch and trip information from anglers. If surveys are not properly designed (e.g., stratified or random sampling), biases will occur (NRC 2006) . Further, obtaining precise estimates is difficult given the broad spatial and temporal extent of recreational fishing.

Self-reported angler catches can be obtained through a variety of mechanisms. Angler diaries are a common reporting tool, where anglers record their own trip and catch information and submit it to managers. While these are less expensive to employ than creel surveys, they often suffer from poor participation rates (Cooke et al. 2000) . Angler diaries also depend on the ability of anglers to accurately identify species and record information. Some organizations and agencies are attempting to take advantage of burgeoning mobile electronic technologies to address the challenges of sampling recreational anglers. Software has been designed for smartphones and digital tablets (SDTs) that allow anglers to self-report data from all aspects of their fishing trips, effectively taking the form of an electronic angler diary. One example of this is the iSnapper program piloted by a Stunz et al. (2014) , which recruited for-hire boat captains to volunteer their catch information for Gulf of Mexico Red Snapper fishing trips through a smartphone/tablet app. The Snook & Gamefish Foundation has developed the Angler Action Program (AAP), which is used primarily in Florida and the Chesapeake Bay area. The original smartphone app under the AAP is known as iAngler, which began in 2012.

There is concern among most fisheries scientists that the data provided by self-reporting platforms cannot provide accurate recreational fisheries data (Didden 2012) , although electronic programs specifically had not yet been tested for data reliability. The chief concern arises out of the fact that these programs do not randomly select their participants, so the data provided could be coming from a nonrepresentative portion of the angling population. If this is the case, there is a chance that such a program could produce biased estimates of metrics like catch per unit effort (CPUE) and participation (Didden 2012) . It has also been shown that, for traditional paper-based angler diaries, there is a bias created by the disproportionately higher diary usage by the more avid anglers in a fishery (Absher and Collins 1987; Connelly and Brown 1995; Connelly et al. 2000; Harris and Bergersen 1985; Lowry 1978; Tarrant et al. 1993) . Thus, in order for fishery managers to be able to trust that smartphone app datasets are useful for recreational fisheries assessment, it must be shown that metrics such as angler catch rate are similar to what is seen in randomly sampled surveys, such as the Marine Recreational Information Program (MRIP) intercept survey performed by the National Oceanic and Atmospheric Administration (NOAA). These programs must also be tested for the avidity bias among its participants, and if it should be present, corrected for such a bias.

The goal of this study was to determine the utility of an electronic, self-reporting smartphone app for the purposes of recreational fisheries assessment and management. I chose the iAngler smartphone app as an example of one of these programs because of its multiple years of implementation. The two main goals of this project were 1) to determine the validity of its catch information by comparing it to the MRIP survey; and 2) to develop a method for correcting for an avidity bias. In order to assess the reliability of its catch information, I first found appropriate species and spatial resolutions for comparison and then determined whether or not the catch/trip data provided were similar to those of the MRIP survey. For the avidity bias correction, I used a simulation model to determine the best possible weighting factor and then applied it to certain stocks' catch/trip estimates in the iAngler dataset. The results of this research show the ability

of electronic, self-reporting programs to contribute to the management of recreational fisheries.

The economic importance of recreational fishing in the United States engenders the need to adequately assess stocks and manage for sustainability. The conclusion that recreational fisheries have the potential to cause overfishing (Coleman et al. 2004; Post et al. 2002) means that, by law, this sector must be included in a fisheries management plan under the Magnuson-Stevens Act if the fishery exists in federal waters (generally, beyond three miles from shore). In the Gulf of Mexico, recreational landings have often exceeded commercial landings for high-profile stocks such as Red Snapper *Lutjanus campechanus* (Coleman et al. 2004) and Gag *Mycteroperca microlepis* (NOAA 2014) . Other stocks such as Common Snook *Centropomus undecimalis* and Red Drum *Sciaenops ocellatus* no longer have a commercial sector, so stock assessments require data from the recreational fisheries. In order to ensure long-term sustainability of such stocks, scientists and managers need a process for gathering reliable information from recreational anglers.

Sampling and assessing the marine recreational sector is challenging. Recreational fisheries are diverse and dispersed, and monitoring on this scale becomes costly (Pereira and Hansen 2003) . In addition to collecting data on the biological aspects of the stock in question, recreational fisheries scientists must also understand the vastly different attributes of the anglers themselves. For example, anglers that are highly specialized (i.e., skill, commitment) have a higher willingness-to-pay when it comes to fishing as an activity (Oh et al. 2005) . More and less specialized anglers also differ in the types of fishing (e.g., high catch rates of small fish versus exclusively large fish) they prefer (Chipman and Helfrich 1988) . This information, although potentially critical, can be difficult to accurately collect.

Even when programs are implemented to sample recreational anglers, potential biases exist. Malvestuto *et al.* (1978) provided an overview of creel surveys (specifically, roving creel surveys) and developed methods for obtaining catch and effort estimates from incomplete trips. However, biases in creel survey data still exist due to limited spatial coverage of surveys (NRC 2006) , as well as heterogeneous probabilities of contacting various angler types. For example, Thomson (1991) discussed how the increased sampling of more avid anglers has the potential to bias total participation estimates and economic analyses. Another potential problem exists when a fishery features users that have private access to the resource because interviewers have no way of intercepting them at a public access point (Ashford et al. 2010) .

Angler logbooks, or diaries, are an alternate data source to traditional creel surveys and allow anglers to record their own fisheries data to later submit to managers. While this format theoretically eliminates the public access bias, it can still suffer from other potential problems. For instance, like intercept surveys, logbooks could have biases arising from an angler's prestige bias, or the tendency to inflate the number and/or sizes of catches. Some new sources of biases can arise with this type of program, such as nonresponse bias, poor identification of species, and inaccurate measurement. However, with proper support from an administrative body, angler diaries can provide valuable fisheries data at a much lower cost (Cooke et al. 2000) .

Since 1979, the National Oceanic and Atmospheric Administration (NOAA) has been employing an access-point intercept survey combined with a telephone survey to estimate catch and effort

of marine recreational fisheries. Originally known as the Marine Recreational Fishery Statistics Survey (MRFSS), it began an effectively continuous revision process in 2006 following a critique by the National Research Council; now it is known as the Marine Recreational Information Program (MRIP). The system uses telephone surveys of coastal residents for estimation of recreational fishing effort and a stratified, multi-stage cluster sample for the intercept surveys to estimate catch per unit effort (NRC 2006) . Although the survey design is now believed to be largely unbiased, the fundamental challenges of sampling recreational anglers continues to provide challenges, even for such a carefully constructed process.

Recent attention has been given to developing methods of real-time data collection for fast, adaptive forms of fisheries management. This idea has become more palpable as smartphones and digital tablets have become more powerful and versatile. Because they can have built-in GPS, photography, and temperature-measuring capabilities (among many others), they have become attractive tools for data collection (Gutowsky et al. 2013) . Despite concerns of durability and convenience, it is becoming more common for smartphones and digital tablets to be waterproof, physically resistant, and have solar charging and "cloud," or back-up software capabilities (Gutowsky et al. 2013) . A few fisheries data collection programs of this nature have already been piloted for the recreational sector. Baker and Oeschger (2009) implemented a text-message-based program to collect trip and catch information from for-hire captains (charter and headboats), using a compact syntax called RECTEXT. Stunz *et al.* (2014) had for-hire captains use an iPhone/iPad application (or "app") called "iSnapper" in lieu of physical papers for their mandatory reporting of Red Snapper trips. In both studies, feedback was solicited from the users of the programs, and mainly positive reviews were received, even from those who were not initially familiar with text messaging or smartphone technology. One program that has been in usage since 2012 is the Snook and Gamefish Foundation's iAngler app, yet it has not been characterized or analyzed. One main advantage these electronic self-reporting apps have over traditional sampling programs such as the MRIP is the ability to collect comprehensive information on discarded fish and improved spatial information. Given the existence of programs like these and the ever-increasing prevalence and capabilities of smartphones, electronic, self-reporting fisheries data collection programs are expected to increase in popularity in the future.

There is a need to evaluate the validity of angler-reported catches from smartphone apps with respect to traditional creel survey data. In this study, I conducted a comparative study between iAngler—a smartphone app for angler-reported trip and catch information—and NOAA's MRIP survey, with a focus on its access-point intercept survey. The objective of this study was two-fold: 1) to summarize the basic characteristics of the iAngler data set with respect to its extent of usage and participants; and 2) to make direct comparisons between iAngler and MRIP for spatial distribution of effort, most commonly caught species, and mean catch-per-trip of selected species. By determining whether or not the dataset provided by iAngler is of a similar quality to that of MRIP, I can suggest the appropriate contexts for using this self-reported data for future recreational fisheries management. This general methodology can also be used for the purposes of assessing the data quality of other opt-in, self-reporting fisheries sampling programs, which will likely become more common in the future.

3.2 Assessment of potential angler avidity bias correction

Introduction

Florida contains the largest recreational fisheries in the USA, and in some cases, recreational catches have surpassed the landings of Florida's commercial fisheries (Coleman et al. 2004) . One of the recommendations made in the National Research Council's 2006 review of recreational survey methodology was to explore the potential for using panel survey methodology (i.e. survey with specific pool of potential recipients) to obtain fisheries information to help meet the data demands required for adequate assessment of the population impacted (NRC 2006) . These panel programs are intended to inform data deficiencies in current sampling methods such as access-point angler-intercept surveys (e.g. National Oceanic and Atmospheric Administration's [NOAA] MRIP dockside survey) and telephone surveys (e.g. NOAA's MRIP phone survey). These panels can take the form of mail-in surveys, angler diaries/logbooks, and more recently, electronic self-reporting angler logbooks in the form of smartphone and digital tablet (SDT) "apps." Statistical considerations concerned with panel recruitment and maintenance were discussed recently at an MRIP-funded workshop on "Opt-In" angler panels (Didden 2012) . Currently there are no minimum standards for how panels/survey participants are constructed (i.e., recruited), the types of data collected, or the units reported.

One reason SDTs have become platforms for fisheries reporting is because of their growing reliability and technical capabilities (Gutowsky et al. 2013) . Another advantage is that they have the potential to provide real-time data to fisheries managers. One such example was an SMS text-message-based program that was piloted to allow for-hire captains in North Carolina to send shorthand reports of their catch information to an online database (Baker and Oeschger 2009) . Another program is an iPhone/iPad "app" called "iSnapper" that for-hire captains in the Gulf of Mexico can use instead of traditional logbooks to report their trip and catch information (Stunz et al. 2014) . Both of these studies note generally positive reviews from the users of the pilot studies, even those who were not initially familiar with the platform that was used. One program that is available to all recreational anglers is the Snook and Gamefish Foundation's "iAngler" smartphone app. Originally developed as the Angler Action Program for the Common Snook *Centropomus undecimalis* fishery, it has since been expanded to include all species and areas, both freshwater and saltwater. The iAngler app is one such platform under the Angler Action Program, which features other specialized apps, such as Chesapeake Catch (for recreational fishing trips in the Chesapeake Bay area).

Each type of sampling scheme has its own set of strengths and weaknesses, and the challenge for fisheries professionals is to identify these weaknesses and correct for them. Some common biases in recreational fisheries sampling programs are prestige bias, public access bias for intercept surveys (Ashford et al. 2010) , recall bias, nonresponse bias, and avidity bias. The nonresponse bias occurs when participants in a program exhibit different fishing behavior from those who choose not to participate in the program. For example, when comparing a 12-month mail survey with a phone follow-up for the nonrespondents and a quarterly phone survey, Connelly et al. (2000) found that estimates of mean number of days fished were higher among respondents than nonrespondents—leading to an inflated estimate of fishing effort. Tarrant et al. (1993) used a phone survey to contact nonrespondents of mail surveys and angler diaries and found that initial respondents reported fishing nearly twice as many days as those who did not respond. In fact, the nonresponse of less avid anglers generally leads to estimates of total participation that are too high (Absher and Collins 1987; Connelly and Brown 1995; Connelly et al. 2000; Harris and Bergersen 1985; Lowry 1978) . Managers who want to perform economic analyses might then overestimate the value a fishery has if effort is artificially inflated. Likewise, if fisheries scientists combine total effort with CPUE estimates derived from creel surveys, the

inflated estimates of total effort could lead to biased estimates for total catch for the fishery.

Using multiple studies to validate each other is the most common way to address these biases. For example, phone surveys are an effective way to correct for nonresponse and public access bias (Ashford et al. 2010; Connelly et al. 2000; Tarrant et al. 1993) . Angler diaries can be used to address the recall bias inherent in mail surveys (Connelly and Brown 1995) . Thus, while every method has a vulnerability to certain biases, each can often be used to fill the gaps of another tool. Because electronic, self-reporting platforms, such as those on apps and tablets, are analogous to angler diaries, they are likely prone to suffer from similar biases. However, it also means they could serve as a validation tool if distributed appropriately.

Despite the growing popularity of using smartphones and digital tablets as tools for fisheries data collection (Gutowsky et al. 2013) , it remains unclear to what extent these biases are present in self-reporting, electronic sampling platforms. While it is generally assumed these same biases exist as in other self-reporting programs such as angler diaries (Didden 2012) , a smartphone app has potentially important differences from its paper counterpart. The real-time capability of a smartphone- or digital tablet-based logbook theoretically reduces or eliminates the effect of the recall bias, assuming anglers report in real-time. An unanswered question is then whether or not a nonrespondent or avidity bias is present. It is possible that the decreased time investment of an electronic reporting system would make all users more likely to use the platform, especially since there is nothing to be physically mailed out or further reported after the data is entered.

The propensity of anglers to self-report data can vary within an angling population, and this can bias catch rate estimates if those reporting more frequently have different catch rates than those reporting less. For example, anglers submitting information through a mail-based survey exhibited a mean CPUE twice as high as the estimate obtained from a creel survey (Carline 1972) . However, angler avidity does not bias catch rate data in a stratified random creel survey because the probability of being sampled is naturally tied to one’s contribution to the overall angling population. The relative number of trips reported by each user in a program such as iAngler does, in fact, have the potential to bias catch rates.

In this paper, we look to explore the effect of angler avidity in the iAngler smartphone app data for two reasons. First, this dataset has not been piloted or critically assessed in relation to the characteristics of its users, so any assumptions of avidity bias for such a program do not yet have scientific backing. Second, citizen science recreational fisheries sampling programs such as this require evaluation of potential biases in angler catch rates, and avidity may be the most likely bias. Our objectives are to 1) determine if the iAngler dataset contains avid reporters; 2) use a simulation-evaluation framework to determine the proper treatment of self-reported data for calculating mean catch rates; and 3) see how much the avidity bias impacts mean catch rates estimates in the iAngler dataset.

3. Methods

MRIP

The MRIP data used in this study come from NOAA's online, publicly accessible database (http://www.st.nmfs.noaa.gov/recreational-fisheries/access-data/data-downloads/index), which contains the raw data collected in the access-point angler intercept surveys. The access-point intercept survey is hereafter referred to as the "MRIP survey," as I did not include data from the MRIP telephone survey for our analysis. Each interview is given a unique "ID code" and covers one interview, which could represent one or multiple anglers in a trip. Catch is divided into three categories and identified by species: 1) "claim" refers to all of the fish that were caught, retained, and available for the interviewer to inspect for lengths and weights; 2) "harvest" refers to all unavailable, retained catch (i.e., those filleted or used as bait and any catch that was discarded dead); and 3) "release" refers to all fish discarded alive. Spatial data include the state and county of the trip as well as how far from shore (generally, greater or less than 3 miles, but 10 miles for the gulf coast of Florida). The mode of the fishing trip is recorded (e.g., private/rental boat, shore/beach, man-made structure, charter boat).

I specifically worked with data from 2012-2013 in the state of Florida (the first two years of the iAngler app's operation), and in some cases, worked with data by county. The species were chosen based on those that had sufficient data in iAngler (for comparisons), and those were Common Snook *Centropomous undecimalis*, Spotted Seatrout *Cynoscion nebulosus*, and Red Drum *Sciaenops ocellatus*. I then compared the data by mode (private boat mode, single-angler private boat trips, shore trips, and charter boat trips) and spatial designation (both statewide and smaller scale, "county clusters"). The "single-angler private boat" mode refers to a specific subset of the full private boat mode, and it contains trips with only a single angler in the fishing party. For trips with multiple anglers in the boat, it is difficult to allocate the retained catches between the anglers (Meaghan Bryan, personal communication). Thus, the single-angler mode was considered separately because it has the potential to provide data on an individual-angler catch rate. The county clusters were chosen based on representation in the iAngler data set and are as follows: Atlantic (Brevard, Indian River, St. Lucie, Martin, Palm Beach, and Broward counties); Ft. Myers (Charlotte, Lee, Sarasota, and Collier counties); and Tampa (Hillsborough, Pinellas, and Manatee counties).

For the purposes of counting trips, the number of trips was considered the number of "ID codes" that met the desired criteria. Whenever catch is mentioned, this refers to the total catch of all fish of a given species—for the MRIP survey, the value for total catch=claim+harvest+release. In the MRIP survey, if a trip has no catch for the given species, the interviewer can still note the primary and secondary species targeted, if applicable. In this event, I considered only the primary species sought for the purposes of calculating species-specific catch rates.

iAngler

One opt-in, electronic, self-reporting fisheries data collection program that has not been piloted or critically assessed is the Snook and Gamefish Foundation's iAngler smartphone app, which exists under its Angler Action Program (AAP). Originally implemented in 2010 as a program for collecting physical logbook data on Common Snook and uploading to a computer at home, the AAP was expanded in 2012 to smartphones, included all freshwater and marine species, and became known as iAngler (Brett Fitzgerald, personal communication). Through this app, users can submit relevant information regarding a recreational fishing trip, such as time fished, number

of fish caught/released, length, weight, GPS location of fishing spots, and even a photograph of the fish. What makes it different than the programs referenced in Baker and Oeschger (2009) and Stunz et al. (2014) is the ability to collect information from all fishing modes and not just for-hire captains. However, because iAngler has not been critically assessed, its validity is in question, even though its discard information for Common Snook has already been included in state stock assessments (Muller and Taylor 2013) .

All of the iAngler data were retrieved with the permission of the Snook and Gamefish Foundation. The iAngler data differs from MRIP in that, users of the iAngler smartphone app choose to participate by their own decision, and they report all of the data through the app's interface. These data are then automatically collected and stored in the Angler Action Program database.

The number of trips in the iAngler database was considered as the number of unique "Trip IDs." Because iAngler only distinguishes between fish kept versus fish released, catch here implies total catch, which is represented by the sum of iAngler's "Quantity Caught" and "Quantity Released."

The data consisted of MRIP surveys and iAngler submissions (self-reported fishing trips, saltwater only) for the entire state of Florida from 2012 through 2013. Between these two databases, I made comparisons of number of reported trips by county, most commonly caught species, number of fish caught per trip, catch and lengths of fish caught. The number of trips will also be referred to as "effort," and the number of fish caught in a trip will be referred to as "catch/trip" or simply catch rate. Because the MRIP data are divided into catch, trip, and size (of each fish) data, I used Microsoft Access to merge relevant information pertaining to catch, location and duration of trips, and lengths of the fish caught. Likewise, I used a similar method in Access for bringing iAngler's spatial information and lengths for individual fish into the main catch dataset.

General Data Comparison

I created effort distribution maps showing each county's percent of total effort for the state of Florida for both the iAngler and MRIP datasets and compared these relative proportions using a chi-square goodness of fit test. Because MRIP surveys are weighted according to expected fishing effort, the MRIP theoretically provides an unbiased spatial distribution of effort throughout the state. Thus, any differences in spatial fishing effort distribution between iAngler and the MRIP likely indicated a bias in spatial coverage of iAngler data.

I tabulated the total number of each dataset's unique trip/intercept-survey identifier. In iAngler, there would be separate entries not only for separate species in a given trip, but also if the angler fished at different locations within that trip. For the purpose of determining the number of trips per county, I pooled the species and fishing-spot identifiers and considered them one trip. I also extracted the number of iAngler users contributing to each county to calculate a mean "submissions-per-user." In iAngler, a county that had a large number of reported trips would not be considered well-represented if they all came from a small number of anglers.

I evaluated the percentage of trips where the most common species were caught (includes kept and released fish) in each of the two datasets. This was estimated as the total number of trips and counting the top ten most commonly caught species. These percentages represented trips

where a given species was caught, and thus, the sum of these values across species would exceed 100% because it is common to catch multiple species per trip. To avoid confusion with the composition of catch, this metric will be referred to as “catch frequency.”

Species-Specific Comparisons

The specific subsets for species, fishing mode, and spatial location were obtained by filtering according to state, county (when necessary), and then by species and fishing mode. All of the combinations of species (Common Snook, Spotted Seatrout, and Red Drum), mode (private boat; single-angler private boat; shore; and charter), and spatial designation (statewide, Atlantic cluster, Ft. Myers cluster, and Tampa cluster) were considered, for a total of 48 comparisons of mean catch/trip between iAngler and MRIP reported trips.

To compare the catch/trip estimates between the iAngler app and MRIP survey, I compared the mean and dispersion of each data set’s catch records. A distribution of catch/trip was created by plotting the catches for a given scenario; because each catch value came from the trip level, this represented a frequency distribution of catch/trip for a species, mode, and spatial combination for the years 2012-2013. Because of the distributions’ shapes, I fitted the data using a negative binomial distribution, with the mean (μ) and size (n, i.e. dispersion) parameterization (Figure 3-1; a complete list of catch/trip plots is shown in Appendix A).

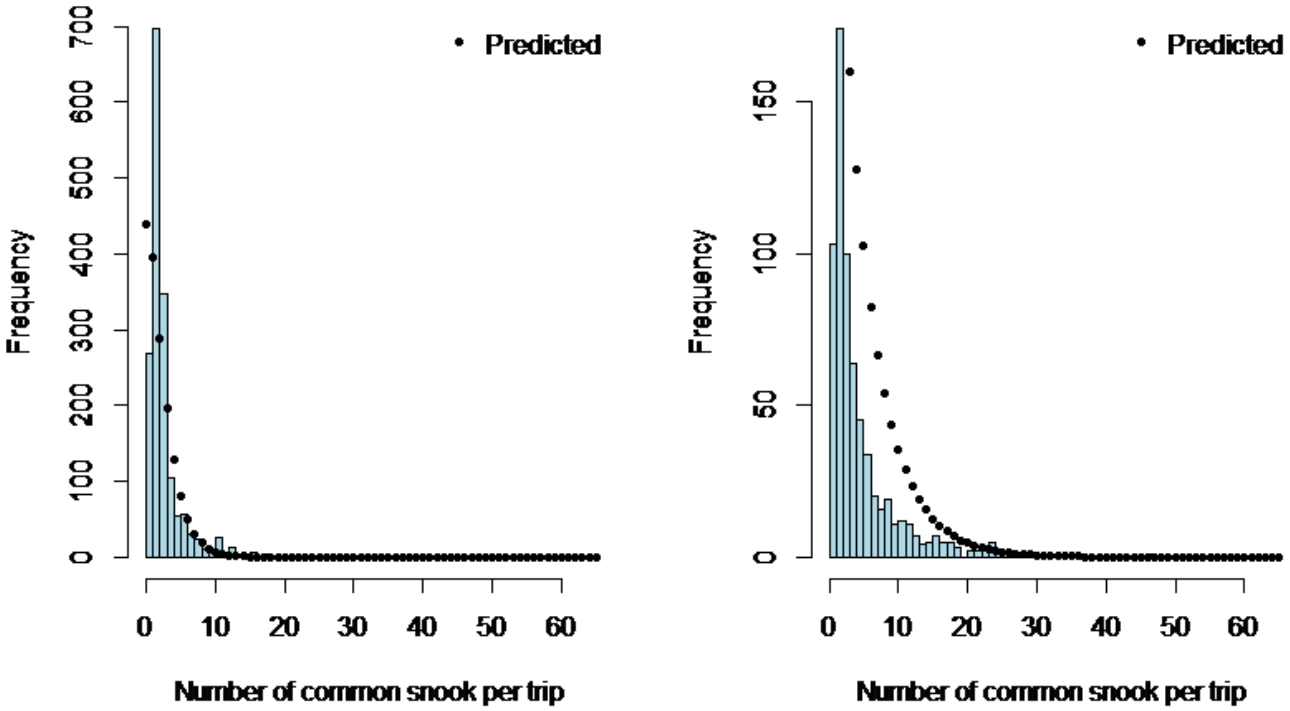


Figure 3-1. Sample plots showing the frequency distributions of number of common snook caught per trip in the private boat mode of the MRIP (left) and iAngler (right) datasets in the Atlantic county cluster, years 2012-2013. Black dots are the predicted values obtained from the fitted negative binomial distribution.

That is, I used the negative binomial distribution parameters to predict the behavior of the catch/trip values (Equation 3-1).

$$Predicted\ catch/trip = [(x+n-1)!/(n-1)!x!](n/n+\mu)^{n}[1-(n/n+\mu)]^{x}$$

(3-1)

Here, *x* indicates a reported catch/trip value for that given scenario (species, mode, spatial designation). I only compared data sources if both the iAngler and MRIP subsets of data had at least 30 records of catch. Each distribution was fitted using a Markov-chain Monte Carlo simulation (100,000 runs, 5,000-run burn-in period) with a Metropolis-Hastings algorithm. This created estimates for the mean and dispersion parameters of the negative binomial distribution. Using these parameters, I drew 10,000 random samples from the parameters' posterior distributions to create simulated catch/trip distributions for each species-mode-spatial combination. Then, by subtracting the MRIP distribution from the corresponding iAngler distribution, I obtained a "difference distribution" and observed the degree of overlap between them. I presented the 80% and 20% quantiles as well as the median for this resulting distribution. The 80% is included because in a likelihood ratio test framework, the 80% quantile would give an indication of the 95% confidence interval (Anderson 2007) . Thus, if the 80% quantiles of a difference distribution included zero, the corresponding iAngler and MRIP catch/trip distributions were considered "similar."

I also compared length distributions of fish caught with each database using the same species, fishing mode, and spatial designation combinations as in the catch/trip analysis. Catches were divided into similar length bins (for a given iAngler-MRIP pair) and compared using a chi-square goodness of fit test. Comparisons were not made if 20% of the length bins had expected frequencies less than 5. In general, there are fewer length records than the total number of fish caught. In MRIP, only fish that are retained and whole are available for length measurements, leaving out discarded fish and those already filleted. In iAngler, due to the voluntary nature of the app, not every fish that is caught and kept is measured for length. However, this information is still important because, if the length distributions of caught fish in iAngler can be shown to be similar to those of MRIP, then a length distribution of discarded fish from iAngler might be reliable—a metric not provided by the MRIP survey.

Assessment of potential angler avidity bias correction

Methods

Data

We received data from the Angler Action Program's iAngler database, courtesy of the Snook and Gamefish Foundation. This consisted of recreational fishing trips from 2012-2013, and we focused this analysis on three clusters of adjacent counties in the state of Florida because the iAngler dataset has a spatial bias in effort on the statewide level (Jiorle et al). These clusters are indicated as follows: the "Atlantic" cluster (Brevard, Indian River, St. Lucie, Martin, Palm Beach, and Broward counties); "Ft. Myers" cluster (Charlotte, Lee, Sarasota, and Collier counties); and "Tampa" cluster (Hillsborough, Pinellas, and Manatee counties). By tabulating the number of records associated with each user, we determined the number of reported trips per angler as well as an angler-specific mean catch rate ("catch/trip" or catch rate) for each species. The

number of trips per angler indicates how dispersed the data are among the users, and if these users with an above-average reporting rate have different mean catch rates, then an avidity bias will be present. Whether or not the avid reporters have a higher, lower, or similar catch rate to the rest of the users will determine the presence and extent of the bias itself.

-

Simulation-Evaluation

We developed a simulation to compare methodologies aimed at estimating overall angler-CPUE, recognizing that both zero-catch trips and angler avidity will introduce bias. To generate trip-level data, we first assumed that angler avidity was proportional to an individual angler's mean expected catch rate. Angler mean expected catch rate over the angling population of 100 anglers was assumed to follow a log-normal distribution with a population mean and standard deviation (Figure 3-9).

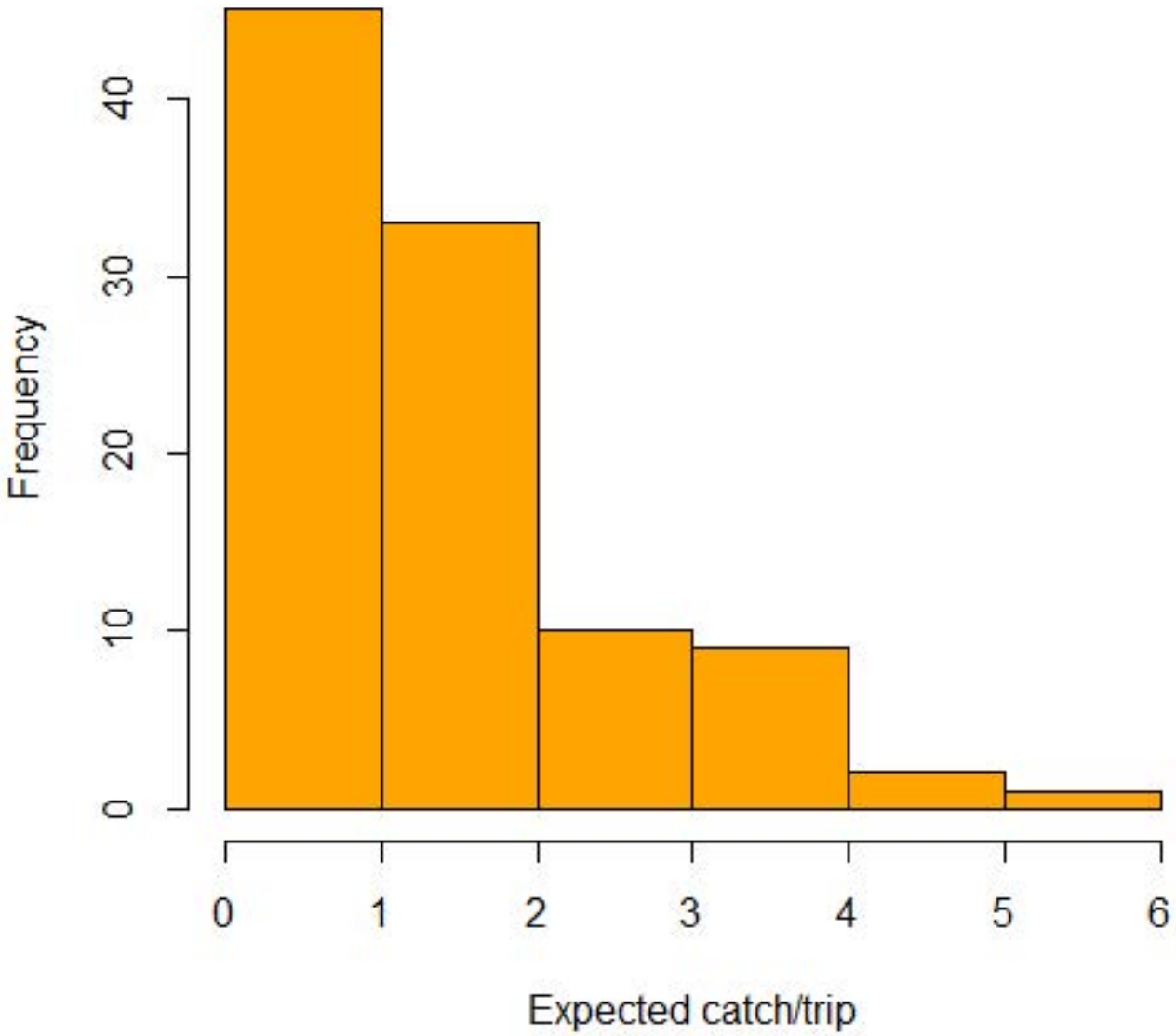


Figure 3-9. Simulated individual-angler expected mean catch rate, log-normally distributed.

Bootstrap sampling of the angler population with replacement in proportion to their avidity generated 1,000 trip records. For an individual trip record from an individual angler, reported catch rate was randomly drawn from a Poisson distribution with a mean equal to the individual angler's expected catch rate. This process resulted in a distribution of reported catch rates that can be described by a negative binomial distribution (Figure 3-10).

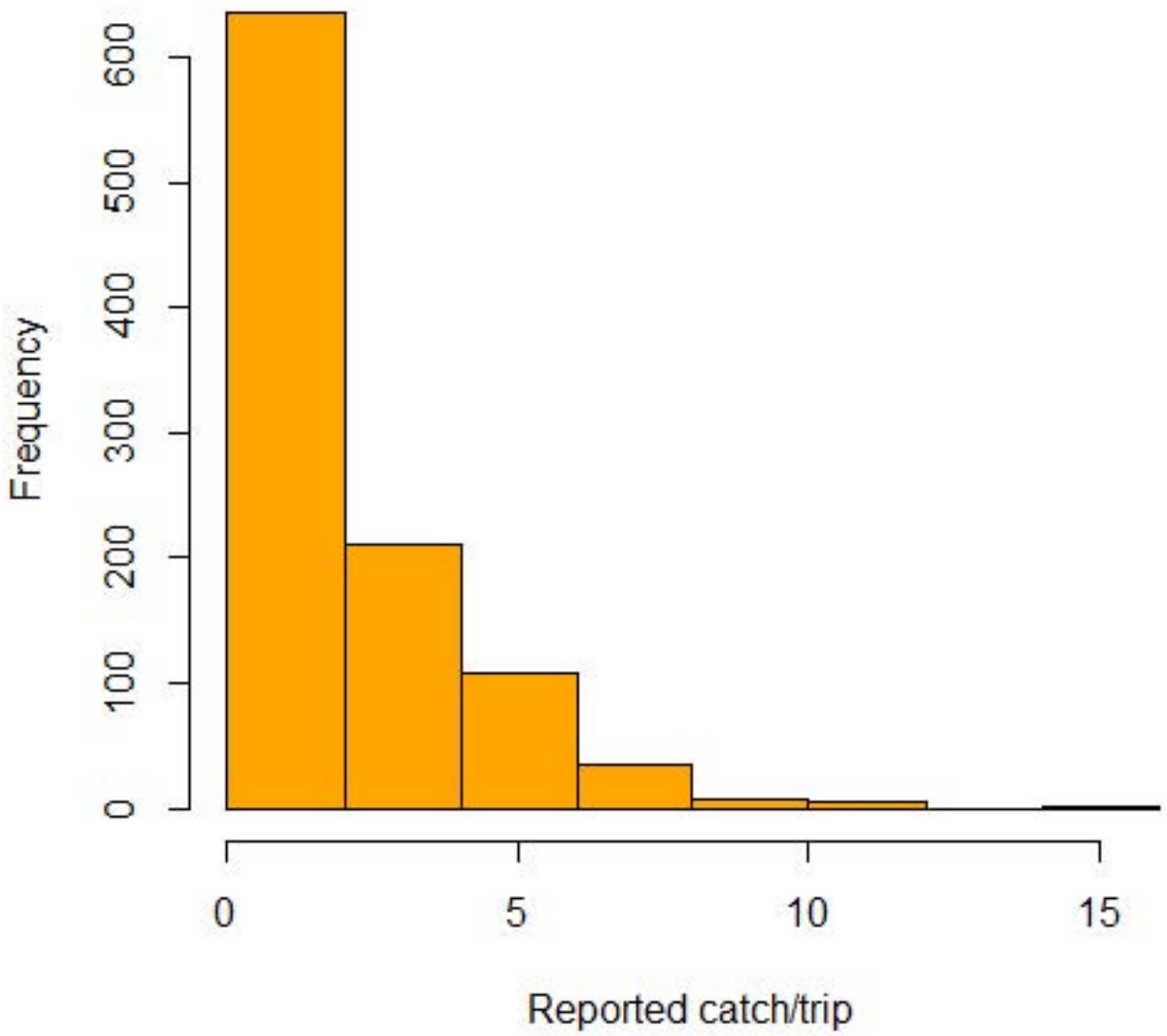


Figure 3-10. Simulated reported catch/trip obtained by sampling from a Poisson distribution, where the trips are drawn according to each angler's avidity. An angler's avidity is based on log-normally distributed expected catch rates (see Figure 3-9).

Working under the assumption that average angler catch rate is likely to follow a log-normal distribution and reported catch rates are over-dispersed relative to this distribution, five models were evaluated to determine the most appropriate method for recovering the overall population mean expected catch rate. When calculating the adjusted mean catch/trip, we used a geometric mean (as opposed to the arithmetic mean) that more accurately reflects the central tendency when the distribution is skewed (Smothers et al. 1999) . Also, because real-world fisheries data

has many zero-catch trips, it is necessary to treat the positive-catch and zero-catch trips separately, as the logarithm function cannot be applied to zero. Habib (2012) derives geometric mean calculations for data that includes zeros:

$$g = \left(n_t g_t + n_0 g_0\right)/n = \left(n_t/n\right) g_t \qquad (3\text{-}2)$$

We assumed that the reporting rate (i.e. number of trips reported) of a given angler was a measure of the angler's avidity, and weighted the geometric mean using avidity as a "penalty." Thus, in our simulation, anglers who reported more trips had their average catch rate weighted less than a less avid angler to correct for potential avidity bias. First, we accounted for the avidity related to non-zero-catch trips withwhere g is the weighted average geometric mean, n is the total number of samples, g_+ and g_0 are the geometric means of the positive and zero values, respectively (note $g_0=0$), and n_+ and n_0 are the numbers of positive- and zero-catch trips, respectively. This method more explicitly accounts for the presence of zero-catch trips when calculating mean catch rates.

$$W_t = 1/v \qquad (3\text{-}3)$$

where $W+$ is the weight for a given non-zero-catch trip and v is the associated avidity (equivalent to that angler's reporting rate, or number of trips reported). To create the overall weighting factor W, which accounts for all trips, we used

$$W = W_t / \left(\Sigma_{i=1}^{k}\right)\left(1/v_i\right) \qquad (3\text{-}4)$$

where v_i is the avidity associated with all trips, and k is the number of reported trips. Thus our equation for calculating avidity-adjusted geometric mean G for the angling population's catch/trip was

$$G = \left[\left(n_t/n\right) e\ \Sigma_{j=1}^{k}\right] w \log r_j \qquad (3\text{-}5)$$

where r_j is the reported catch/rate for a given report. This geometric mean calculation that accounts for zero-catch trips and avidity was compared against a geometric mean accounting for zeros but not angler avidity and a geometric mean from only positive records. Two negative binomial models were also fit to the data, one accounting for angler avidity and the other with no weighting. This simulation was conducted for three levels of variability within individual-angler expected catch rates. Because angler ability was distributed log-normally, this variability was determined by the distribution's standard deviation, which we assigned =0.2, 0.5, and 0.8. Overall, the method that came closest to match the true mean (i.e. reduced the avidity we introduced) was considered the best for treating real data that may suffer from this type of bias.

Application to iAngler Data

Using the zero-adjusted, avidity-adjusted geometric mean from the simulation-evaluation, we calculated adjusted catch/trip estimates for three inshore species—Common Snook *Centropomus undecimalis*, Spotted Seatrout *Cynoscion nebulosus*, and Red Drum *Sciaenops*

ocellatus—that had sufficient records in the iAngler dataset. While this process is similar to the process used in simulation described above, one difference is that we had no need to derive our reporting from the angler's mean catch rate since the number of trips per user is given by the dataset. We considered the subset of the private boat fishing mode trips that only consisted of a single angler to avoid complications regarding the allocation of fish among multiple members of a fishing party. These geometric means, adjusted for zero-catch trips and angler avidity, were compared to geometric mean catch/trip estimates that only accounted for zero-catch trips (a "raw" geometric mean). We also calculated raw arithmetic means as well as avidity-adjusted arithmetic means. The comparison of an arithmetic versus geometric mean allowed us to determine whether expected angler catch rates were log-normally distributed. The comparison of raw to avidity-adjusted means allowed us to determine whether or not angler avidity was biasing the data set.

4. Results

General Data Comparisons

One important feature of the iAngler data is that submissions are highly variable throughout the state of Florida. From 2012-2013, the distribution of trips by county was significantly different from that of MRIP (^{2}=7,609, df=34, p<0.0001), with a strong bias toward counties along the south-central Atlantic coast (Figure 3-2).

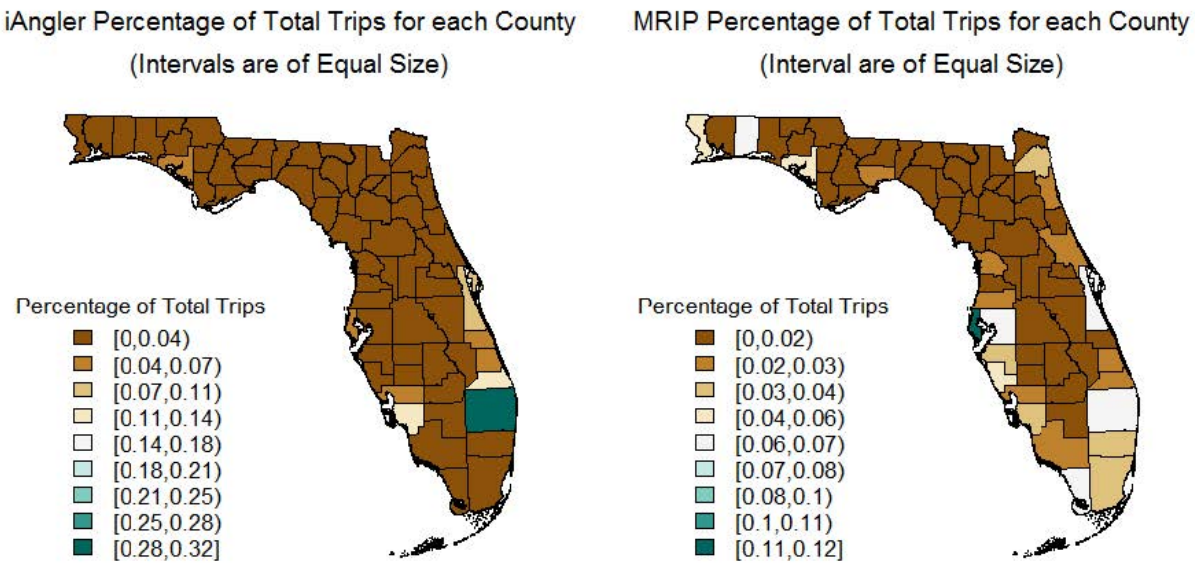


Figure 3-2. Maps comparing the distribution of trips by county between iAngler (left) and MRIP (right).

The number of reported saltwater angling trips ranged from 0 (Clay, Jefferson, and Nassau counties) to 1,115 (Palm Beach), with a total of 3,572 trips (Table 3-1).

Table 3-1. A summary of number of angling trips per county and users reporting these trips. MRIP does not distinguish its reports by user, so there is not a column for number of users or

trips/user.

		iAngler			MRIP	
County	No. Trips	Proportion	No. Users	Trips/User	Trips	Proportion
Bay	127	0.035	20	6.350	3019	0.047
Brevard	316	0.088	65	4.862	3926	0.061
Broward	31	0.009	17	1.824	1725	0.027
Charlotte	170	0.047	16	10.625	1077	0.017
Citrus	22	0.006	9	2.444	1192	0.019
Clay	0	0.000	0	0.000	50	0.001
Collier	43	0.012	17	2.529	1376	0.021
Dixie	27	0.008	1	27.000	285	0.004
Duval	11	0.003	8	1.375	2265	0.035
Escambia	1	0.000	1	1.000	3392	0.053
Flagler	2	0.001	1	2.000	371	0.006
Franklin	4	0.001	1	4.000	443	0.007
Gulf	20	0.006	6	3.333	414	0.006
Hernando	3	0.001	3	1.000	804	0.013
Hillsborough	99	0.028	31	3.194	3679	0.057
Indian River	124	0.035	16	7.750	828	0.013
Lee	381	0.106	39	9.769	2160	0.034
Levy	10	0.003	2	5.000	777	0.012
Manatee	29	0.008	10	2.900	2555	0.040
Martin	398	0.111	52	7.654	1475	0.023
Miami-Dade	21	0.006	14	1.500	2213	0.034
Monroe	100	0.028	34	2.941	4263	0.066
Nassau	0	0.000	0	0.000	471	0.007
Okaloosa	10	0.003	6	1.667	3875	0.060
Palm Beach	1115	0.311	50	22.300	3896	0.061
Pasco	10	0.003	6	1.667	1130	0.018
Pinellas	177	0.049	55	3.218	7686	0.120
Santa Rosa	4	0.001	2	2.000	604	0.009
Sarasota	101	0.028	21	4.810	3061	0.048
St. Johns	3	0.001	1	3.000	894	0.014
St. Lucie	125	0.035	33	3.788	1169	0.018
Taylor	6	0.002	3	2.000	674	0.010
Volusia	73	0.020	24	3.042	1548	0.024
Wakulla	1	0.000	1	1.000	952	0.015
Walton	1	0.000	1	1.000	40	0.001

For the MRIP, the number of access-point interviews by county ranged from 40 (Walton county) to 7,686 (Pinellas county), with a mean of 1,837 and a median of 1,192 interviews. Of the counties that reported trips to iAngler, the mean number of trips was 90, while the median was 16. For those same counties, the number of different users of the app ranged from 1 (Baker, Dixie, Escambia, Flagler, Franklin, Putnam, St. Johns, Wakulla, and Walton counties) to 65 (Brevard), with a mean of 14 and a median of 6. The iAngler dataset is characterized by high

spatial variability, which could make it problematic if used for state-level assessment purposes.

The statewide values for catch frequency in the iAngler dataset showed a high percentage of Common Snook (*Centropomus undecimalis*), Spotted Seatrout (*Cynoscion nebulosus*), and Red Drum (*Sciaenops ocellatus*) when compared to the MRIP dataset. This is a trend throughout the data, as the iAngler app was initially created to supplement the state stock assessments with data on Common Snook and later expanded to include other species. Common Snook were caught on more than one-third of the trips reported to the iAngler app, which is more than ten times the percentage of MRIP trips reporting Common Snook catches (Table 3-2).

Table 3-2. Comparing the percentage and number of trips where each species was caught on the state level.

iAngler (3,573 total trips)			MRIP (64,289 total trips)		
Species	Percentage of trips caught	Number of trips caught	Species	Percentage of trips caught	Number of trips caught
Common Snook	38%	1372	Spotted Seatrout	14%	9029
Spotted Seatrout	25%	891	Pinfish	9%	5976
Red Drum	18%	628	Gray Snapper	7%	4647
Crevalle Jack	10%	342	Ladyfish	7%	4428
Gray Snapper	6%	218	Red Drum	7%	4239
Ladyfish	6%	217	Crevalle Jack	6%	3737
Spanish Mackerel	3%	121	Hardhead Catfish	5%	3415
Yellowtail Snapper	3%	120	Spanish Mackerel	5%	3136
Tarpon	2%	87	Red Snapper	5%	3012
Red Snapper	2%	72	Blue Runner	4%	2693

Out of the top ten most commonly reported species from each data set, seven species were shared between the two, with only Common Snook, Yellowtail Snapper (*Ocyurus chrysurus*), and Tarpon (*Megalops atlanticus*) being unique to iAngler and Pinfish (*Lagodon rhomboides*), Hardhead Catfish (*Ariopsis felis*), and Blue Runner (*Caranx crysos*) being unique to MRIP. When the data from each sampling program were re-normalized to include only trips that reported catches of the seven shared species, there was still a significant difference between the percentages of each species in the catch (^{2}=372.070, df=6, $p<0.0001$). The presence of seven shared species suggests there is some degree of overlap between the trips being reported by iAngler and the trips being interviewed by the MRIP survey.

The catch frequencies for the county clusters were similar to that of the statewide scale, but with a few differences in species. In the Atlantic county cluster (southeast Florida), there were five species shared in the top ten list of most commonly caught species (Table 3-3), and when they were re-normalized and compared, their relative proportions were also significantly different (^{2} =177.69, df=4, p<0.0001).

Table 3-3. Comparing the percentage and number of trips where each species was caught for the Atlantic county cluster.

iAngler (2,107 total trips)			MRIP (13,019 total trips)		
Species	Percentage of trips caught	Number of trips caught	Species	Percentage of trips caught	Number of trips caught
Common Snook	44%	929	Crevalle Jack	10%	1318
Spotted Seatrout	20%	430	Spotted Seatrout	7%	931
Crevalle Jack	11%	226	Little Tunny	7%	894
Red Drum	9%	199	Blue Runner	7%	858
Gray Snapper	6%	116	Gray Snapper	6%	760
Yellowtail Snapper	5%	101	Hardhead Catfish	5%	670
Tarpon	2%	44	Ladyfish	5%	591
Mutton Snapper	4%	80	Dolphin (Mahi)	4%	483
Ladyfish	4%	77	Bluefish	3%	436
Blue Runner	2%	52	Pinfish	3%	428

This is the only case where Red Drum was not the third most reported catch in the iAngler dataset (Crevalle Jack). In the Ft. Myers county cluster, there were six species shared among the top ten species (Table 3-4), and their re-normalized relative proportions were significantly different (^{2}=75.778, df=5, p<0.0001).

Table 3-4. Comparing the percentage and number of trips where each species was caught for the Ft. Myers county cluster.

iAngler (694 total trips)			MRIP (6,928 total trips)		
Species	Percentage of trips caught	Number of trips caught	Species	Percentage of trips caught	Number of trips caught
Common Snook	37%	258	Spotted Seatrout	22%	1387
Spotted Seatrout	33%	230	Gray Snapper	15%	921

Red Drum	26%	183	Red Drum	12%	749
Ladyfish	13%	89	Ladyfish	11%	716
Crevalle Jack	11%	74	Pinfish	11%	685
Spanish Mackerel	7%	51	Common Snook	9%	537
Gray Snapper	4%	29	Hardhead Catfish	8%	523
Tarpon	3%	21	Sheepshead	8%	477
Gulf Flounder	3%	18	Red Grouper	7%	447
Florida Pompano	2%	17	Crevalle Jack	7%	430

This was the only instance where Common Snook were among the top ten most reported catches for the MRIP dataset. Finally, in the Tampa county cluster, there were 7 species shared in the top ten (Table 3-5), and their re-normalized relative proportions were significantly different (^{2}=76.309, df=6, p<0.0001).

Table 3-5. Comparing the percentage and number of trips where each species was caught for the Tampa county cluster.

iAngler (304 total trips)			MRIP (13,920 total trips)		
Species	Percentage of trips caught	Number of trips caught	Species	Percentage of trips caught	Number of trips caught
Common Snook	44%	133	Spotted Seatrout	21%	2958
Spotted Seatrout	43%	132	Pinfish	19%	2603
Red Drum	37%	111	Ladyfish	10%	1451
Gray Snapper	9%	26	Red Grouper	9%	1319
Spanish Mackerel	7%	22	Spanish Mackerel	9%	1253
Crevalle Jack	7%	21	White Grunt	8%	1146
Ladyfish	6%	18	Red Drum	8%	1124
Gulf Flounder	6%	18	Gag	7%	957
Gag	4%	11	Gray Snapper	7%	909
Tarpon	3%	8	Crevalle Jack	6%	899

This cluster had the highest proportion of Common Snook, Spotted Seatrout, and Red Drum when they are considered together. For all three county clusters, as well as at the state level, four species that were consistently shared in the top ten list of most commonly reported catches were Spotted Seatrout, Crevalle Jack (*Caranx hippos*), Gray (Mangrove) Snapper (*Lutjanus griseus*), and Ladyfish (*Elops saurus*). The differing catch frequencies in the iAngler and MRIP datasets suggests that, while there is some degree of overlap in the trips reported through each program, the relative proportions of trips targeting the various species are different. However, this does not negate the value of making comparisons on a species-by-species basis.

Because iAngler showed a strong bias toward Common Snook, Spotted Seatrout, and Red Drum—popular inshore species in Florida—these three fish were used for further comparisons with the MRIP data. Red Snapper (*Lutjanus campechanus*), Red Grouper (*Epinephelus morio*), and Gag Grouper (*Mycteroperca microlepis*) were three other species also used to assess the status of iAngler with regards to important offshore stocks.

Species-Specific Comparisons

Angler catch/trip data for all private boat mode trips showed similar means in all cases between iAngler and the MRIP (Appendix B). There were enough trips (n>30) to make catch/trip comparisons for all of the inshore species-mode combinations for all spatial designations, as well as the three offshore species at the state level (Figure 3-3).

State	666/ 1930	633/ 9846	546/ 7093	71/ 1198	35/ 1427	44/ 1632
Atlantic	434/ 409	321/ 1143	259/ 883	25/ 35	7/ 62	5/ 53
Ft. Myers	91/ 684	115/ 1356	122/ 1244	0/ 9	2/ 367	4/ 219
Tampa	107/ 703	113/ 3082	105/ 1953	0/ 33	5/ 576	7/ 679
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor

MRIP poor

Both poor

Both sufficient

Figure 3-3. Summary of data quality in relation to comparing the catch/trip distributions for all private boat mode trips. Each cell contains the number of trips for iAngler (top) and MRIP (bottom), where n=30 is the minimum number of samples required to fit to a negative binomial distribution. Each color indicates which, if either, dataset had enough records.

This fishing mode is the most comprehensive in the iAngler dataset. No other fishing mode had enough data from both iAngler and the MRIP to perform catch/trip comparisons for the offshore

species, and so they are not further discussed. For the inshore species, all comparisons of catch/trip between iAngler and the MRIP for the private boat mode resulted in similar distributions (Figure 3-4).

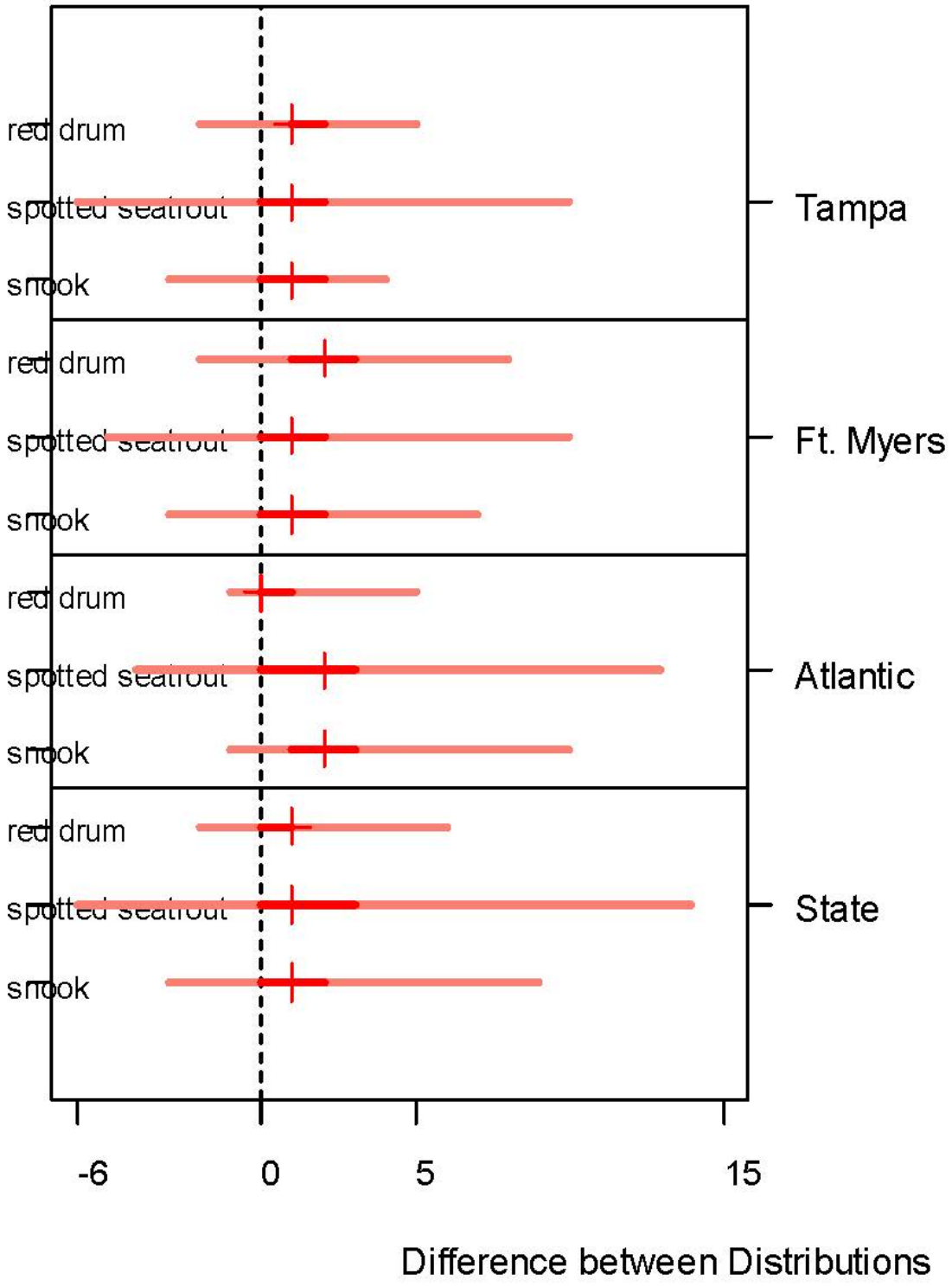


Figure 3-4. Difference between iAngler and MRIP simulated catch/trip distributions for the private boat mode. Crosses represent the median, dark red bars represent the 20% quantiles,

and the light red bars represent the 80% quantiles.

In all scenarios, the 20% quantiles lay to the right of zero; because I subtracted the simulated MRIP catch/trip values from the iAngler catch/trip values, this suggests the iAngler values were consistently larger across species and spatial designations. This could be due to a smaller proportion of zero-catch trips in iAngler as opposed to that of the MRIP data. Still, Common Snook in the Atlantic county cluster, and Red Drum in the Ft. Myers and Tampa clusters were the only instances where the 20% quantile did not include zero, so there was ultimately a high degree of similarity between the two data sets' catch/trip estimates. This tendency toward zero for the 20% quantiles was seen even in some of the cases where the 80% quantiles were skewed farther to the right, which suggests the central tendency of these difference distributions was near zero regardless of the degree of overdispersion seen in the catch/trip data. Overall, the iAngler dataset provides very similar catch/trip data to the MRIP for these three inshore species.

I also evaluated the private boat mode for trips that only consisted of one angler in the party, and the catch/trip values were also similar for the three species in question. However, as mentioned before, no offshore species had enough records to fit with parameters and make a comparison. All of the inshore species had sufficient data at the various spatial designations (Figure 3-5).

State	333/ 280	325/ 1280	287/ 1108	2/ 32	1/ 59	4/ 100
Atlantic	204/ 61	165/ 144	136/ 94	0/ 0	0/ 6	0/ 2
Ft. Myers	37/ 82	68/ 163	58/ 177	0/ 2	0/ 17	1/ 18
Tampa	82/ 111	79/ 422	78/ 341	0/ 0	1/ 24	1/ 48
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor

MRIP poor

Both poor

Both sufficient

Figure 3-5. Summary of data quality in relation to comparing the catch/trip distributions for single-angler private boat mode trips only. Each cell contains the sample size for iAngler (top) and MRIP (bottom), where n=30 is the minimum number of samples required to fit a negative binomial distribution. Each color indicates which, if either, dataset had enough records.

It appears iAngler captures proportionately more of these single-angler private boat trips than does MRIP, as evidenced by the fact that the discrepancy between the numbers of records between these two programs is generally smaller than with the whole private boat mode. The

80% quantiles of the difference distributions for this mode suggest that all corresponding catch/trip distributions are similar (Figure 3-6).

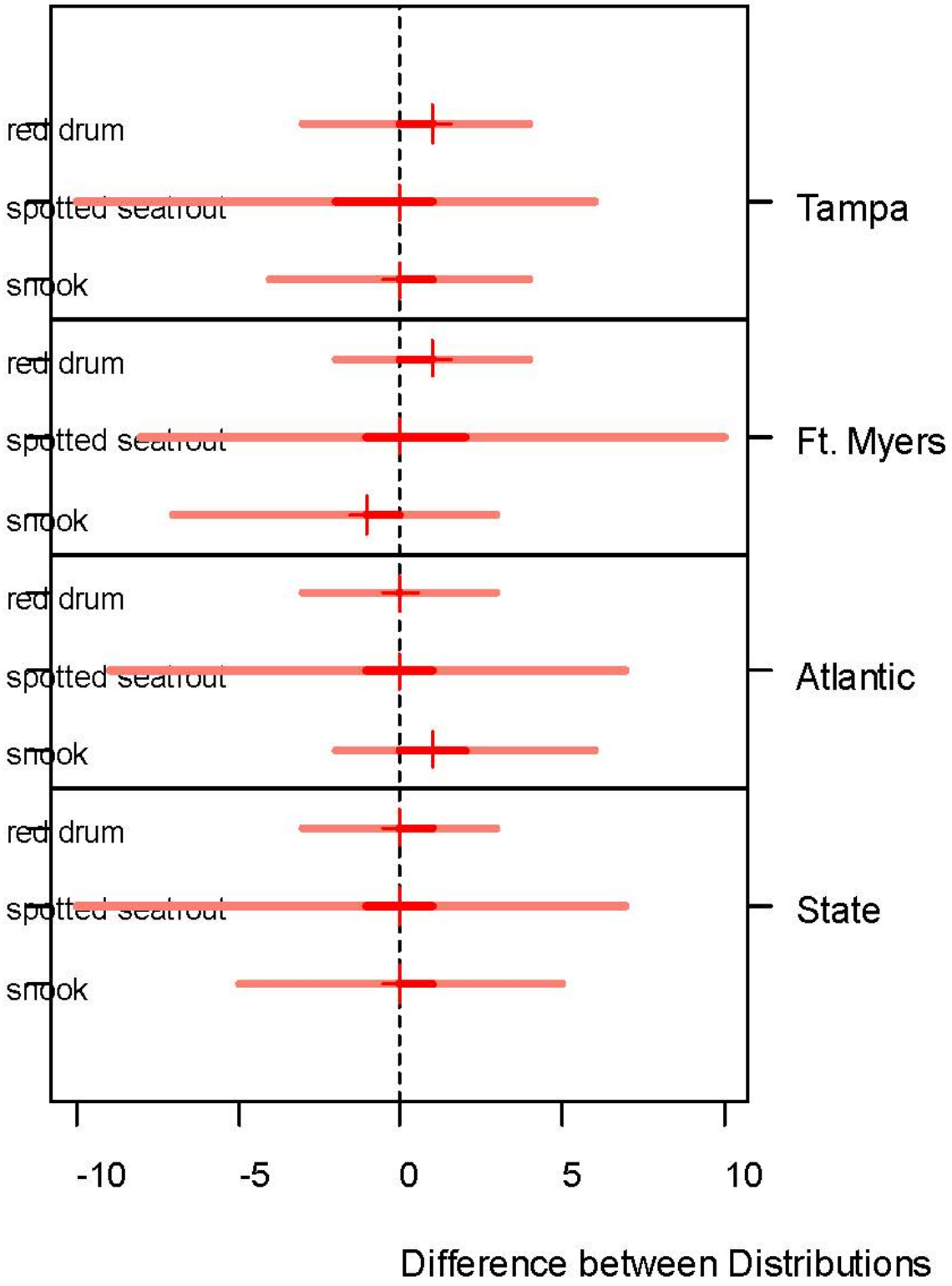


Figure 3-6. Difference between iAngler and MRIP simulated catch/trip distributions for the

single-angler private boat mode trips only. Crosses represent the median, dark red bars represent the 20% quantiles, and the light red bars represent the 80% quantiles.

Overall, the catch/trip comparisons for this mode provided a higher degree of agreement than for the entire private boat mode. The intervals are not consistently skewed toward the right, and for 8 of the 12 comparisons, the median value was zero. In light of the spatial bias on the statewide scale, it is important that the data are similar on the level of the county clusters—especially for the counties near Tampa, which have the highest effort according to the MRIP survey. The overall similarity across species and spatial designations shows that iAngler can provide catch/trip data that are comparable to that of the MRIP survey for single-angler trips taken on a private boat.

Despite having some gaps in the data for both iAngler and the MRIP survey, the shore mode catch/trip values were similar when comparisons were possible. Comparisons were not possible for any of the species in the Tampa cluster or Spotted Seatrout in the Atlantic cluster, but sufficient data existed for the other spatial designations (Figure 3-7).

State	921/ 361	362/ 559	246/ 558			
Atlantic	573/ 22	123/ 29	59/ 112			
Ft. Myers	326/ 81	217/ 58	105/ 69			
Tampa	14/ 48	13/ 243	10/ 88			
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor
MRIP poor
Both poor
Both sufficient

Figure 3-7. Summary of data quality in relation to comparing the catch/trip distributions for shore mode trips. Each cell contains the sample size for iAngler (top) and MRIP (bottom), where n=30 is the minimum number of samples required to fit to a negative binomial distribution. Each color indicates which, if either, dataset had enough records. Red snapper, red grouper, and gag are not considered because they are not inshore species, where shore trips occur.

For the rest of the scenarios, all comparisons suggest the iAngler and MRIP catch/trip data to be similar (Figure 3-8).

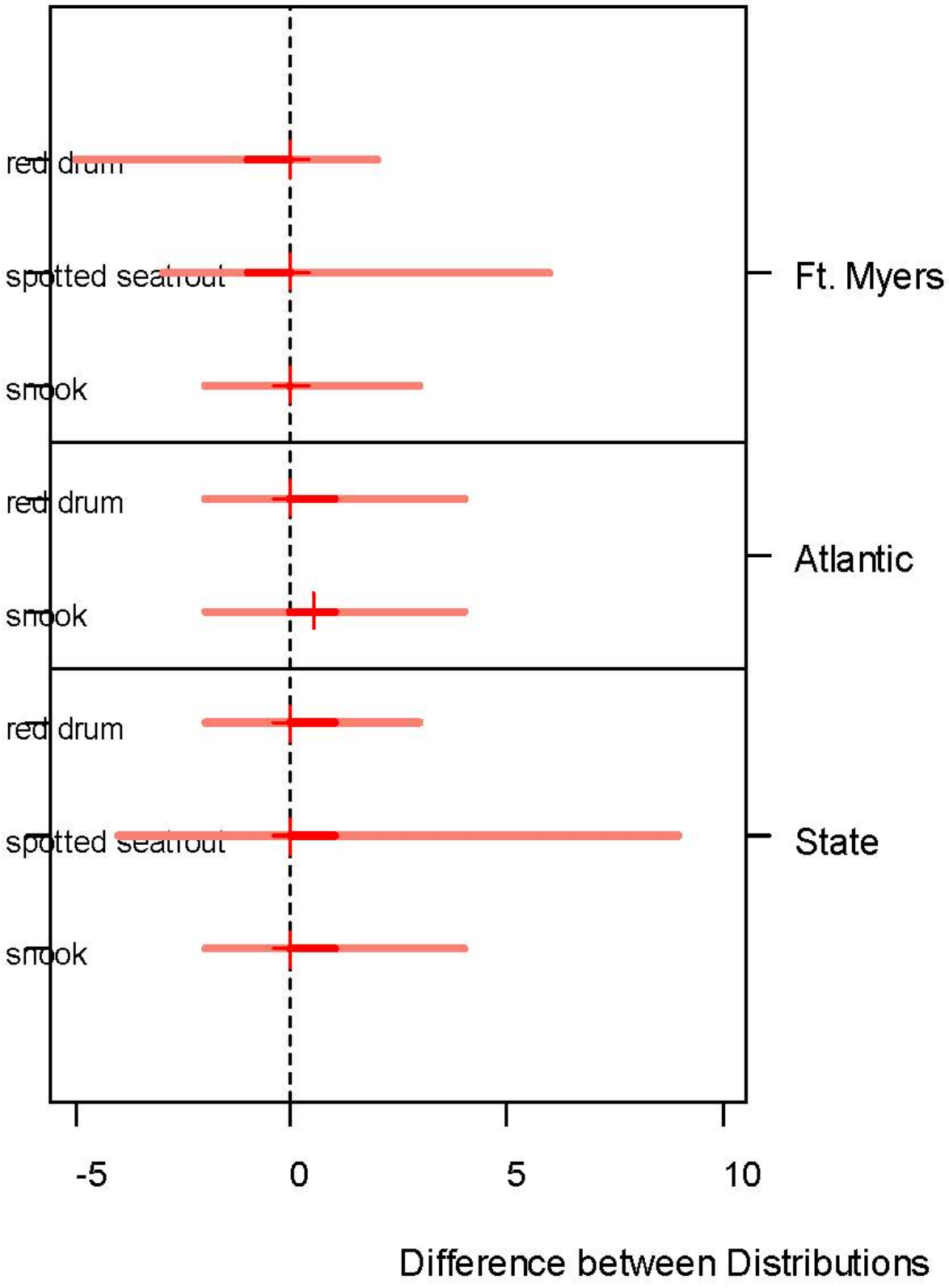


Figure 3-8. Difference between iAngler and MRIP simulated catch/trip distributions for the shore mode. Crosses represent the median, dark red bars represent the 20% quantiles, and the light red bars represent the 80% quantiles.

In 7 out of the 8 comparisons, the median catch/trip value was zero. Also, when compared to the private boat mode, the 80% quantiles for the shore mode comparisons are tighter. Taken together, these two points indicate the iAngler and MRIP data have not only similar central tendencies, but similar dispersions as well. The shore mode of iAngler has considerably fewer trips in the Tampa cluster, but actually exceeds the total number of MRIP trips for nearly all cases in the other two clusters (especially Common Snook). In these events, the mean catch rate data for iAngler are very similar to those of the MRIP survey.

Species-specific data for the charter boat mode was extremely deficient in the iAngler dataset and so are not included in the analysis. Likewise, iAngler's length data for retained catch were insufficient for the chi-square goodness-of-fit test. Thus, the length data for retained catch for iAngler are at least insufficient to test, even for the popular inshore species—if not altogether different.

Assessment of potential angler avidity bias correction

Results

Summary of iAngler Data

For all saltwater trips in the state of Florida from 2012-2013, there were 402 users of the app, who reported a total of 3,573 trips, but just 56 of the users reported 77.5% of all the trips. The mean number of reports for each user was 8.89 trips, yet the median was only 2 trips. For Common Snook trips that fell under the private boat, single-angler designation, there were 69 users who reported 330 total trips, and 12 of the users accounted for 66.1% of those trips. Likewise, for Spotted Seatrout trips that fell under the private boat, single-angler designation, there were 60 users who reported 323 trips, yet 7 of the users reported 72.1% of the trips. Finally, for Red Drum trips that fell under the private boat, single-angler designation, there were 59 users who reported 283 trips, and 8 of those users reported 72.1% of the trips. All of these data suggest there are a small number of avid anglers using the iAngler app that account for a majority of the trips. As a result, there is a need to investigate to what extent this fact might be impacting the mean catch rate for these three species.

Simulation-Evaluation

The simulation-evaluation determined that the zero-adjusted, avidity-adjusted geometric mean has the most potential to approximate a true mean catch rate when avidity is present. In the low variability case (=0.2), all of the estimation methods fall primarily within 20% of the true mean, with the exception of the unadjusted (non-zero-catch trips only) geometric mean (Figure 3-3). In fact, for the avidity-adjusted negative binomial mean, the first and third quartiles contain zero, where 0% deviation indicates the true mean was fully recovered. The regions of 1.5 times the interquartile ranges for the zero-adjusted geometric mean and the unadjusted negative binomial mean include the 0% deviation. Overall, at this low amount of variability in angler ability, the negative binomial fitting process appears to approximate the true mean better than the geometric mean processes.

In the moderate variability case (=0.5), the zero-adjusted, avidity-adjusted geometric mean best

approximated the true mean catch/trip, although the zero-adjusted geometric mean and avidity-adjusted negative binomial mean also performed well (Figure 3-4). Once again, the unadjusted geometric mean provided the poorest approximation for the true mean catch rate. This suggests that, at low and moderate variability in expected angler catch rates, the number of zero-catch trips has a large impact on the estimated mean. Meanwhile, adjusting for avidity does not lead to as large of a change.

In the high variability case (=0.8), the zero-adjusted, avidity-adjusted geometric mean was the best approximation for the true mean catch/trip, with 1.5 times the interquartile range including the 0% deviation (Figure 3-5). The avidity-adjusted negative binomial mean was a reasonable approximation, but the other three techniques featured deviations of 100% or more. In this instance, the addition of adjustments for zero-catch trips did not have as much of an effect as the other two cases, while adjusting for avidity led to a more noticeable drop in percent deviation. This is likely a result of avidity being a more powerful effect with more variable (i.e. higher) catch rates that are being reported by the avid anglers.

The standard deviations from the zero-adjusted, avidity-adjusted geometric means flip from a positive deviation in the low variability scenario (=0.2) to negative deviations in the moderate (=0.5) and high (=0.8) variability scenarios (Figure 3-6). In other words, as the expected catch rates of anglers become more dispersed, this particular geometric mean technique predicts proportionately less variation in reported catch/trip values—going from overestimating the variance to underestimating it.

Application to the iAngler Dataset

Overall, the effect of zero-catch trips and avidity in the iAngler dataset influenced mean catch rate estimates for all three species considered. In all situations, the raw geometric mean provided a lower value than the raw arithmetic mean. In nearly all regions and years, the addition of the zero-adjusted, avidity-adjusted geometric mean (as compared to a raw geometric mean) resulted in smaller catch/trip estimates, suggesting that the avid anglers in the dataset had higher catch rates than the rest of the users. For example, in the Common Snook data, all scenarios except Ft. Myers in 2012 and Tampa in 2013 had lower mean catch rates after avidity weighting was introduced (Table 3-6).

Table 3-6. Mean catch/trip (in fish-per-trip) estimates for Common Snook using four different calculations. "Raw" refers to an unweighted (zero-adjusted for geometric means) mean, while "avidity-adjusted" refers to avidity weighting (and zero-adjusted for geometric means).

	Raw				Avidity-adjusted			
	Arithmetic mean	Arithmetic variance	Geometric mean	Geometric variance	Arithmetic mean	Arithmetic variance	Geometric mean	Geometric variance
Atlantic 2012	3.1	14	2.2	1.2	2.8	11	1.6	1.6
Atlantic 2013	2.7	11	1.9	1.4	2.0	7.3	1.5	1.5
Ft. Myers	1.6	1.2	1.4	1.3	2.0	1.5	1.7	1.3

2012								
Ft. Myers 2013	2.5	7.6	2.0	0.67	2.9	9.0	1.6	1.2
Tampa 2012	2.3	4.7	1.8	1.4	1.8	3.6	1.4	1.4
Tampa 2013	1.6	1.4	1.4	1.0	2.1	1.4	1.6	1.0

Likewise, for Spotted Seatrout, the avidity weighting led to smaller mean catch rates in five of six cases; in the event where the weighted catch rate was higher (Tampa 2013), this suggests the avid anglers had lower catch rates than the rest of the app's users (Table 3-7).

Table 3-7. Mean catch/trip (in fish-per-trip) estimates for spotted seatrout using four different calculations. "Raw" refers to an unweighted (zero-adjusted for geometric means) mean, while "avidity-adjusted" refers to avidity weighting (and zero-adjusted for geometric means).

	Raw				Avidity-adjusted			
	Arithmetic mean	Arithmetic variance	Geometric mean	Geometric variance	Arithmetic mean	Arithmetic variance	Geometric mean	Geometric variance
Atlantic 2012	4.3	35	2.8	1.8	6.0	130	2.5	2.9
Atlantic 2013	2.9	6.7	2.4	1.1	2.6	3.4	1.9	1.1
Ft. Myers 2012	4.8	39	2.9	2.4	2.9	15	1.8	2.2
Ft. Myers 2013	4.0	17	3.0	1.6	3.9	9.2	2.7	1.3
Tampa 2012	4.1	35	2.5	1.8	3.9	37	2.0	1.9
Tampa 2013	3.6	10	2.6	1.8	6.0	11	4.4	1.5

For Red Drum, the avidity weighting decreased the mean catch rate in four cases, increased it in one case, and had roughly no difference for one case (Table 3-8).

Table 3-8. Mean catch-trip (in fish-per-trip) estimates for red drum using four different calculations. "Raw" refers to an unweighted (zero-adjusted for geometric means) mean, while "avidity-adjusted" refers to avidity weighting (and zero-adjusted for geometric means).

	Raw				Avidity-adjusted			
	Arithmetic mean	Arithmetic variance	Geometric mean	Geometric variance	Arithmetic mean	Arithmetic variance	Geometric mean	Geometric variance
Atlantic 2012	1.0	3.8	0.79	0.35	1.0	1.6	0.62	0.67
Atlantic	1.1	1.3	0.94	0.52	1.4	2.3	0.88	0.83

2013								
Ft. Myers 2012	2.8	5.7	2.1	1.7	3.1	8.5	2.2	1.9
Ft. Myers 2013	2.1	3.3	1.7	1.3	2.2	2.8	1.6	1.2
Tampa 2012	2.1	8.2	1.5	1.0	1.7	4.5	1.2	1.2
Tampa 2013	1.9	3.0	1.5	0.92	2.2	1.6	1.5	0.89

The fact that Red Drum was affected differently (to a lesser extent) than Common Snook and Spotted Seatrout shows that the impact of avidity is not necessarily constant across species in the iAngler dataset.

Phase 2 evaluation

See phase 1 for methods

2.1 Re-evaluation of e-log data following recommendation from 1.6. Phase 2 compares iAngler with MRPI using an additional 3 years of data for a total for 5 years (2012-2016) to determine if the two data collection methods are comparable. In addition, Phase two present a comparison between iAngler and MRIP length frequencies for species where sufficient data was available. For relevant figures and table a side by side comparison of results from 2012-13 and 2012-16 are presented.

Results

General Data Comparisons

One important feature of the iAngler data is that submissions are highly variable throughout the state of Florida. From 2012-2016, the distribution of trips by county was significantly different from that of MRIP (^{2}=7,719, df=34, p<0.0001), with a strong bias toward counties along the south-central Atlantic coast (Figure 4-1).

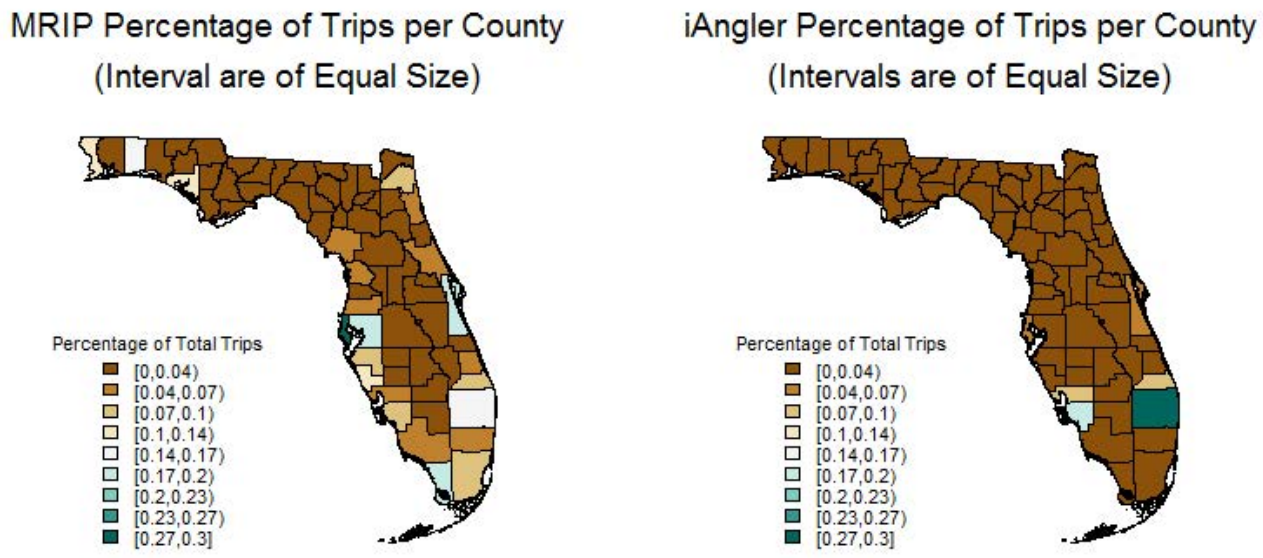


Figure 4-1. Maps comparing the distribution of trips by county between iAngler (left) and MRIP (right).

The number of reported saltwater angling trips ranged from 0 (Clay, Jefferson, and Nassau counties) to 2,030 (Palm Beach), with a total of 6,111 trips (Table 4-1). For the MRIP, the number of access-point interviews by county ranged from 63 (Clay county) to 15,365 (Pinellas county), with a mean of 3,716 and a median of 2,843 interviews. Of the counties that reported trips to iAngler, the mean number of trips was 116, while the median was 12. For those same counties, the number of different users of the app ranged from 1 (Baker, Dixie, Escambia, Flagler, Franklin, Putnam, St. Johns, Wakulla, and Walton counties) to 76 (Brevard), with a mean of 16 and a median of 7. The iAngler dataset is characterized by high spatial variability, which could make it problematic if used for state-level assessment purposes.

The statewide values for catch frequency in the iAngler dataset showed a high percentage of Common Snook (*Centropomus undecimalis*), Spotted Seatrout (*Cynoscion nebulosus*), and Red Drum (*Sciaenops ocellatus*) when compared to the MRIP dataset. This is a trend throughout the data, as the iAngler app was initially created to supplement the state stock assessments with data on Common Snook and later expanded to include other species. Common Snook were caught on nearly one-third (31%) of the trips reported to the iAngler app, which is more than ten times the percentage of MRIP trips reporting Common Snook catches (Table 4-2).

Table 4-2. Comparing the percentage and number of trips where each species was caught on the state level.

iAngler (6,111 total trips)			MRIP (130,063 total trips)		
Species	Percentage of trips caught	Number of trips caught	Species	Percentage of trips caught	Number of trips caught

Common Snook	31%	1915	Spotted Seatrout	13%	17437
Spotted Seatrout	21%	1294	Gray Snapper	9%	11957
Red Drum	13%	815	Pinfish	8%	10287
Crevalle Jack	11%	690	Red Drum	7%	9187
Ladyfish	9%	520	Ladyfish	7%	8475
Gray Snapper	6%	373	Hardhead Catfish	6%	7919
Yellowtail Snapper	4%	240	Crevalle Jack	6%	7849
Spanish Mackerel	4%	217	Red Grouper	5%	5940
Tarpon	2%	140	Spanish Mackerel	4%	5731
Red Snapper	2%	93	White Grunt	4%	5658

Out of the top ten most commonly reported species from each data set, six species were shared between the two, with Common Snook, Yellowtail Snapper (*Ocyurus chrysurus*), Red Snapper (*Lutjanus campechanus*), and Tarpon (*Megalops atlanticus*) being unique to iAngler and Pinfish (*Lagodon rhomboides*), Hardhead Catfish (*Ariopsis felis*), White Grunt (*Haemulon plumierii*), and Blue Runner (*Caranx crysos*) being unique to MRIP. When the data from each sampling program were re-normalized to include only trips that reported catches of the six shared species, there was still a significant difference between the percentages of each species in the catch (^{2} =347.1, df=5, p<0.0001). However, the presence of six shared species suggests there is some degree of overlap between the trips being reported by iAngler and the trips being interviewed by the MRIP survey.

The catch frequencies for the county clusters were similar to that of the statewide scale, but with a few differences in species. In the Atlantic county cluster (southeast Florida), there were five species shared in the top ten list of most commonly caught species (Table 4-3), and when they were re-normalized and compared, their relative proportions were also significantly different (^{2} =171.69, df=4, p<0.0001).

Table 4-3. Comparing the percentage and number of trips where each species was caught for the Atlantic county cluster.

iAngler (2,676 total trips)			MRIP (26,314 total trips)		
Species	Proportion of trips caught	Number of trips caught	Species	Proportion of trips caught	Number of trips caught
Common Snook	0.46	1214	Crevalle Jack	0.08	2201
Spotted Seatrout	0.38	984	Spotted Seatrout	0.06	1690

Crevalle Jack	0.15	401	Little Tunny	0.05	1233
Red Drum	0.13	334	Blue Runner	0.05	1201
Gray Snapper	0.07	186	Gray Snapper	0.04	1080
Yellowtail Snapper	0.06	159	Hardhead Catfish	0.04	989
Tarpon	0.05	132	Ladyfish	0.03	908
Mutton Snapper	0.05	123	Dolphin (Mahi)	0.03	865
Ladyfish	0.05	121	Bluefish	0.03	762
Blue Runner	0.03	86	Pinfish	0.03	678

In the Ft. Myers county cluster, there were six species shared among the top ten species (Table 4-4), and their re-normalized relative proportions were significantly different (^{2}=77.79, df=5, p<0.0001).

Table 4-4. Comparing the percentage and number of trips where each species was caught for the Ft. Myers county cluster.

iAngler (1,386 total trips)			MRIP (14,797 total trips)		
Species	Proportion of trips caught	Number of trips caught	Species	Proportion of trips caught	Number of trips caught
Common Snook	0.32	445	Spotted Seatrout	0.20	2893
Spotted Seatrout	0.31	432	Gray Snapper	0.12	1711
Red Drum	0.26	365	Red Drum	0.12	1703
Ladyfish	0.09	123	Ladyfish	0.11	1565
Crevalle Jack	0.09	119	Pinfish	0.08	1121
Spanish Mackerel	0.07	98	Common Snook	0.05	777
Gray Snapper	0.04	56	Hardhead Catfish	0.05	768
Tarpon	0.02	25	Sheepshead	0.05	705
Gulf Flounder	0.02	22	Red Grouper	0.05	677
Florida Pompano	0.02	22	Crevalle Jack	0.04	609

This was the only instance where Common Snook were among the top ten most reported catches for the MRIP dataset. Finally, in the Tampa county cluster, there were 7 species shared

in the top ten (Table 4-5), and their re-normalized relative proportions were significantly different (^{2}=71.34, df=6, p<0.0001).

Table 4-5. Comparing the percentage and number of trips where each species was caught for the Tampa county cluster.

iAngler (698 total trips)			MRIP (21,349 total trips)		
Species	Proportion of trips caught	Number of trips caught	Species	Proportion of trips caught	Number of trips caught
Common Snook	0.35	242	Spotted Seatrout	0.32	6788
Spotted Seatrout	0.33	232	Pinfish	0.23	5004
Red Drum	0.29	199	Ladyfish	0.13	2877
Gray Snapper	0.06	45	Red Grouper	0.10	2090
Crevalle Jack	0.06	41	Spanish Mackerel	0.09	1890
Spanish Mackerel	0.06	40	White Grunt	0.09	1888
Ladyfish	0.05	36	Red Drum	0.08	1760
Gulf Flounder	0.05	34	Gag	0.08	1734
Gag	0.03	18	Gray Snapper	0.08	1654
Tarpon	0.02	14	Crevalle Jack	0.08	1634

This cluster had the highest proportion of Common Snook, Spotted Seatrout, and Red Drum when they are considered together. For all three county clusters, as well as at the state level, four species that were consistently shared in the top ten list of most commonly reported catches were Spotted Seatrout, Crevalle Jack (*Caranx hippos*), Gray (Mangrove) Snapper (*Lutjanus griseus*), and Ladyfish (*Elops saurus*). The differing catch frequencies in the iAngler and MRIP datasets suggests that, while there is some degree of overlap in the trips reported through each program, the relative proportions of trips targeting the various species are different. However, this does not negate the value of making comparisons on a species-by-species basis.

Because iAngler showed a strong bias toward Common Snook, Spotted Seatrout, and Red Drum, popular inshore species in Florida, these three fish were used for further comparisons with the MRIP data. Red Snapper (*Lutjanus campechanus*), Red Grouper (*Epinephelus morio*), and Gag Grouper (*Mycteroperca microlepis*) were three other species also used to assess the status of iAngler with regards to important offshore stocks.

Species-Specific Comparisons

Catch per Trip

Angler catch/trip data for all private boat mode trips showed similar means in all cases between iAngler and the MRIP. There were enough trips (n>30) to make catch/trip comparisons for all of the inshore species-mode combinations for all spatial designations, as well as the three offshore species at the state level (Figure 4-2).

2012-2013

State	666/ 1930	633/ 9846	546/ 7093	71/ 1198	35/ 1427	44/ 1632
Atlantic	434/ 409	321/ 1143	259/ 883	25/ 35	7/ 62	5/ 53
Ft. Myers	91/ 684	115/ 1356	122/ 1244	0/ 9	2/ 367	4/ 219
Tampa	107/ 703	113/ 3082	105/ 1953	0/ 33	5/ 576	7/ 679
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor
MRIP poor
Both poor
Both sufficient

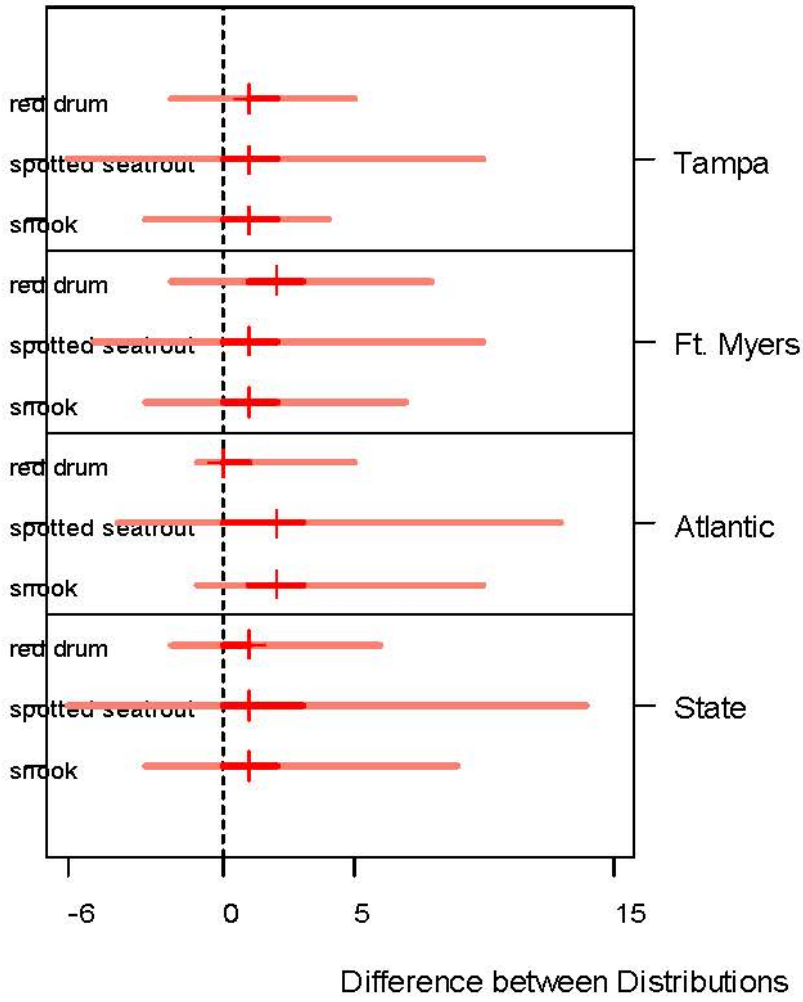
2012-2016

State	864/ 5362	807/ 18932	672/ 15289	88/ 2764	39/ 3300	47/ 3293
Atlantic	532/ 246	399/ 2035	318/ 1638	26/ 210	9/ 101	5/ 103
Ft. Myers	136/ 1557	138/ 2625	158/ 2316	0/ 28	2/ 839	5/ 501
Tampa	136/ 2359	150/ 5970	114/ 4247	0/ 72	6/ 1523	9/ 1407
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor
MRIP poor
Both poor
Both sufficient

Figure 4-2. Summary of data quality in relation to comparing the catch/trip distributions for all private boat mode trips. Each cell contains the number of trips for iAngler (top) and MRIP (bottom), where n=30 is the minimum number of samples required to fit to a negative binomial distribution. Each color indicates which, if either, dataset had enough records.

This fishing mode is the most comprehensive in the iAngler dataset. No other fishing mode had enough data from both iAngler and the MRIP to perform catch/trip comparisons for the offshore species, and so they are not further discussed. For the inshore species, all comparisons of catch/trip between iAngler and the MRIP for the private boat mode resulted in similar distributions (Figure 4-3).


red drum
spotted seatrout
snook
Tampa
red drum
spotted seatrout
snook
Ft. Myers
red drum
spotted seatrout
snook
Atlantic
red drum
spotted seatrout
snook
State
-6
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5
15
Difference between Distributions

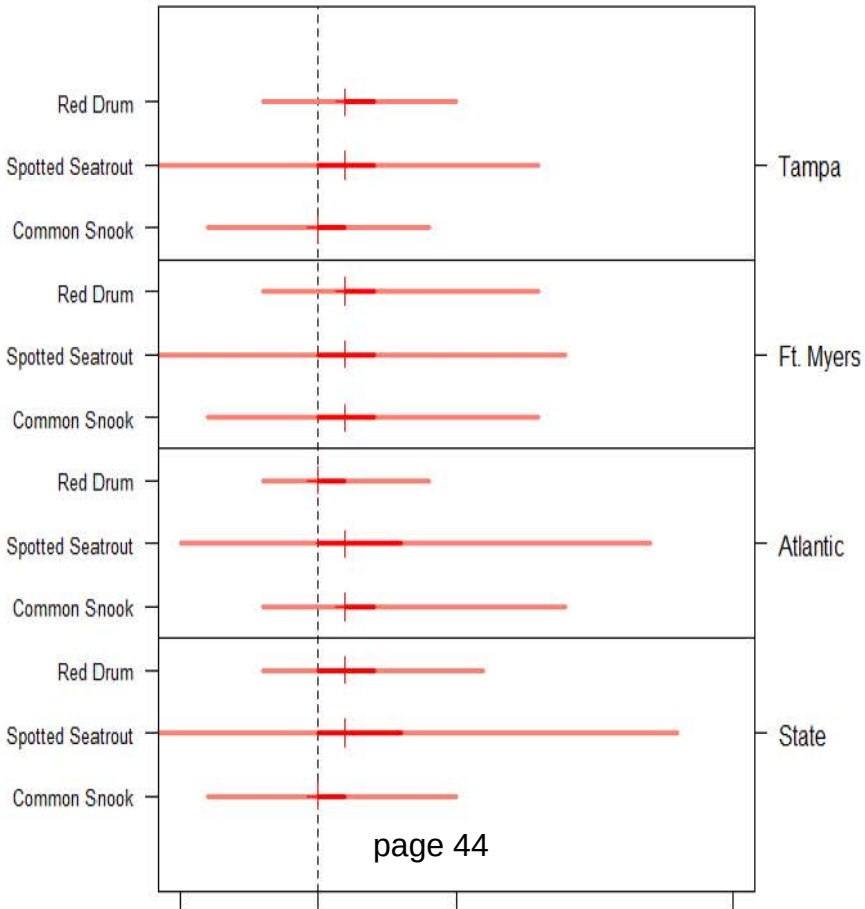

Red Drum
Spotted Seatrout
Common Snook
Tampa
Red Drum
Spotted Seatrout
Common Snook
Ft. Myers
Red Drum
Spotted Seatrout
Common Snook
Atlantic
Red Drum
Spotted Seatrout
Common Snook
State

Figure 4-3. Difference between iAngler and MRIP simulated catch/trip distributions for the private boat mode. Crosses represent the median, dark red bars represent the 20% quantiles, and the light red bars represent the 80% quantiles. 2012-2013 top, 2012-2016 bottom.

In all scenarios, the 20% quantiles lay to the right of zero; because we subtracted the simulated MRIP catch/trip values from the iAngler catch/trip values, this suggests the iAngler values were consistently larger across species and spatial designations. This could be due to a smaller proportion of zero-catch trips in iAngler as opposed to that of the MRIP data. Still, Common Snook in the Tampa county cluster and Red Drum in the Atlantic cluster were the only instances where the 20% quantile did not include zero, so there was ultimately a high degree of similarity between the two data sets' catch/trip estimates. This tendency toward zero for the 20% quantiles was seen even in some of the cases where the 80% quantiles were skewed farther to the right, which suggests the central tendency of these difference distributions was near zero regardless of the degree of overdispersion seen in the catch/trip data. Overall, the iAngler dataset provides very similar catch/trip data to the MRIP for these three inshore species.

Private boat mode was evaluated for trips that only consisted of one angler in the party, and the catch/trip values were also similar for the three species in question. However, as mentioned before, no offshore species had enough records to fit with parameters and make a comparison. All of the inshore species had sufficient data at the various spatial designations (Figure 4-4).

2012-2013

State	333/ 280	325/ 1280	287/ 1108	2/ 32	1/ 59	4/ 100
Atlantic	204/ 61	165/ 144	136/ 94	0/ 0	0/ 6	0/ 2
Ft. Myers	37/ 82	68/ 163	58/ 177	0/ 2	0/ 17	1/ 18
Tampa	82/ 111	79/ 422	78/ 341	0/ 0	1/ 24	1/ 48
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor
MRIP poor
Both poor
Both sufficient

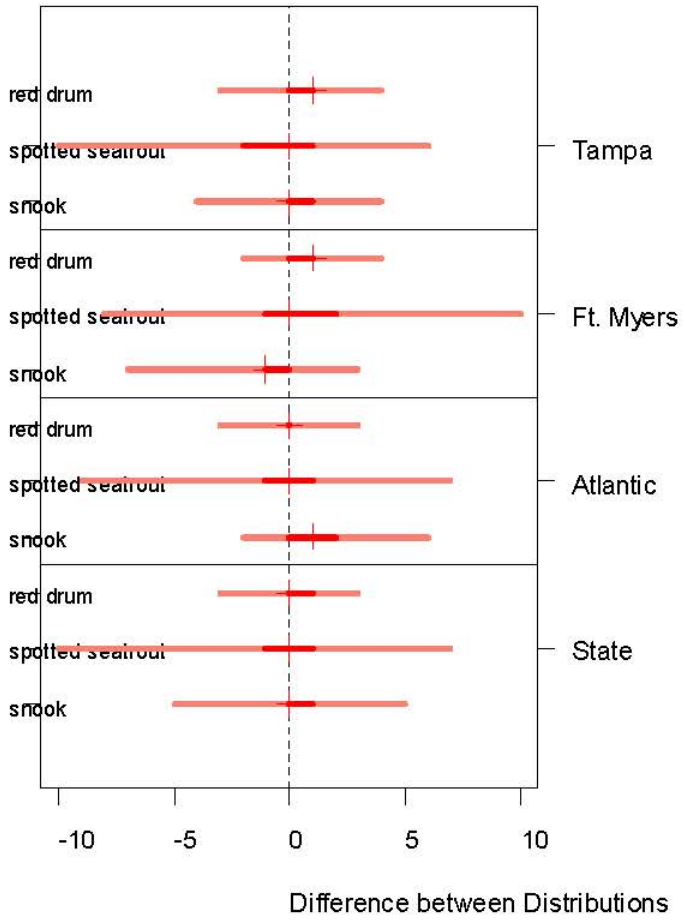
2012-2016

State	455/ 862	392/ 2550	348/ 2470	4/ 70	2/ 131	5/ 222
Atlantic	265/ 170	209/ 264	177/ 219	0/ 0	0/ 6	0/ 2
Ft. Myers	63/ 216	80/ 343	71/ 357	0/ 3	0/ 17	1/ 18
Tampa	102/ 382	89/ 859	81/ 748	0/ 0	1/ 24	2/ 48
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor
MRIP poor
Both poor
Both sufficient

Figure 4-4. Summary of data quality in relation to comparing the catch/trip distributions for single-angler boat mode trips only. Each cell contains the sample size for iAngler (top) and MRIP (bottom), where n=30 is the minimum number of samples required to fit to a negative binomial distribution. Each color indicates which, if either, dataset had enough records.

It appears iAngler captures proportionately more of these single-angler private boat trips than does MRIP, as evidenced by the fact that the discrepancy between the numbers of records between these two programs is generally smaller than with the whole private boat mode. The 80% quantiles of the difference distributions for this mode suggest that all corresponding catch/trip distributions are similar (Figure 4-5).


red drum
spotted seatrout
snook
Tampa
red drum
spotted seatrout
snook
Ft. Myers
red drum
spotted seatrout
snook
Atlantic
red drum
spotted seatrout
snook
State
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Difference between Distributions

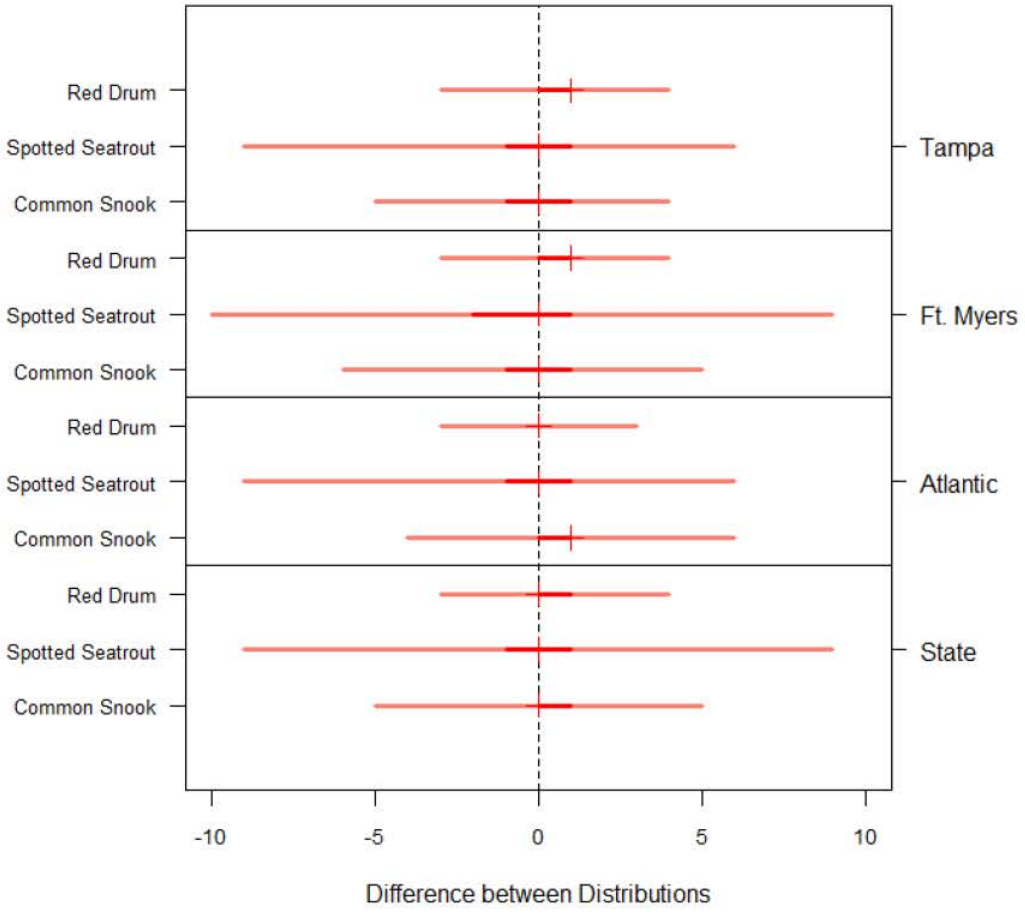

Red Drum
Spotted Seatrout
Common Snook
Tampa
Red Drum
Spotted Seatrout
Common Snook
Ft. Myers
Red Drum
Spotted Seatrout
Common Snook
Atlantic
Red Drum
Spotted Seatrout
Common Snook
State
-10
-5
0
5
10
Difference between Distributions

Figure 4-5. Difference between iAngler and MRIP simulated catch/trip distributions for the single-angler private boat mode trips only. Crosses represent the median, dark red bars represent the 20% quantiles, and the light red bars represent the 80% quantiles. 2012-2013 top, 2012-2016 bottom.

Overall, the catch/trip comparisons for this mode provided a higher degree of agreement than for the entire private boat mode. The intervals are not consistently skewed toward the right, and for 9 of the 12 comparisons, the median value was zero. In light of the spatial bias on the statewide scale, it is important that the data are similar on the level of the county clusters—especially for the counties near Tampa, which have the highest effort according to the MRIP survey. The overall similarity across species and spatial designations shows that iAngler can provide catch/trip data that are comparable to that of the MRIP survey for single-angler trips taken on a private boat.

Despite having some gaps in the data for both iAngler and the MRIP survey, the shore mode catch/trip values were similar when comparisons were possible. Comparisons were not possible for any of the species in the Tampa cluster, but sufficient data existed for the other spatial designations (Figure 4-6).

2012-2013

State	921/ 361	362/ 559	246/ 558			
Atlantic	573/ 22	123/ 29	59/ 112			
Ft. Myers	326/ 81	217/ 58	105/ 69			
Tampa	14/ 48	13/ 243	10/ 88			
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor
MRIP poor
Both poor
Both sufficient

2012-2016

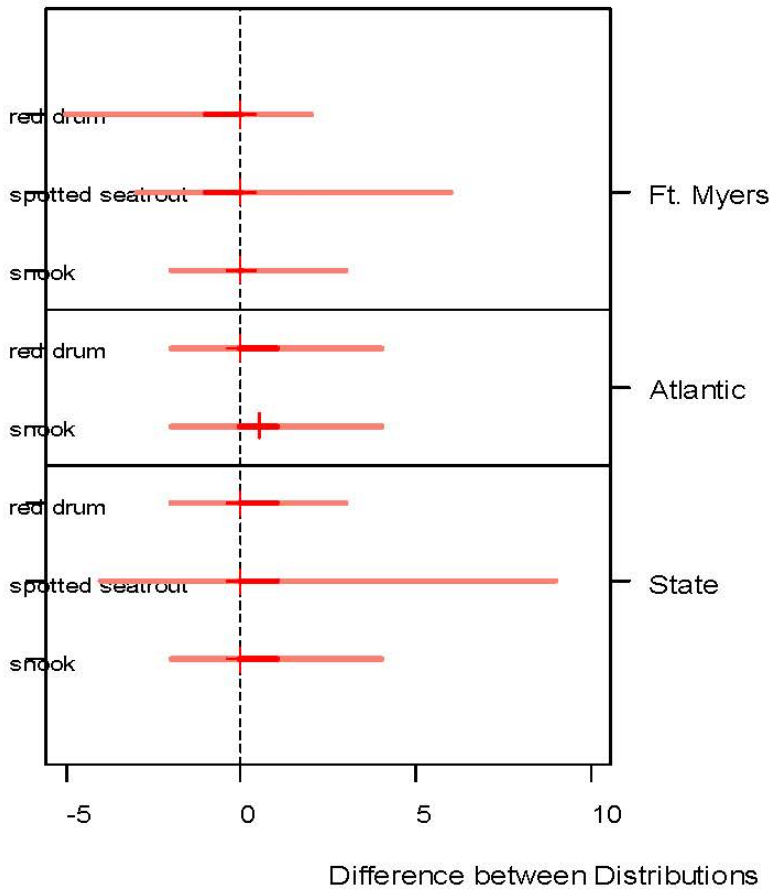
State	1680/ 830	665/ 866	348/ 1025			
Atlantic	769/ 570	134/ 45	81/ 246			
Ft. Myers	865/ 151	503/ 88	178/ 97			
Tampa	28/ 93	14/ 292	10/ 134			
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor
MRIP poor
Both poor
Both sufficient

Figure 4-6. Summary of the data quality in relation to comparing the catch/trip distributions for shore mode trips. Each cell contains the sample size for iAngler (top) and MRIP (bottom), where n=30 is the minimum number of samples required to fit to a negative binomial distribution. Each

color indicates which, if either, dataset had enough records. Red snapper, red grouper, and gag are not considered because they are not inshore species, where shore trips occur.

For the rest of the scenarios, all comparisons suggest the iAngler and MRIP catch/trip data to be similar (Figure 4-7).



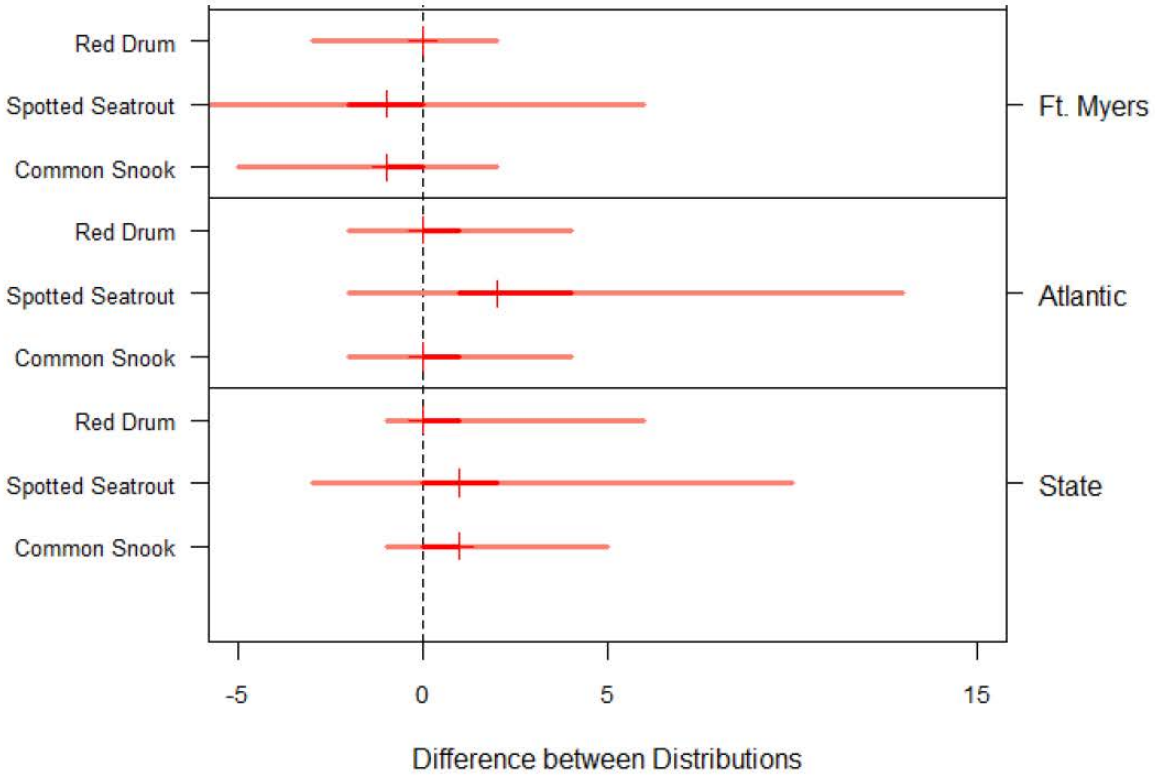


Figure 4-7. Difference between iAngler and MRIP simulated catch/trip distributions for the shore mode. Crosses represent the median, dark red bars represent the 20% quantiles, and the light red bars represent the 80% quantiles. 2012-2013 top, 2012-2016 bottom.

In 4 out of the 9 comparisons, the median catch/trip value was zero. Also, when compared to the private boat mode, the 80% quantiles for the shore mode comparisons are tighter. Taken together, these two points indicate the iAngler and MRIP data have not only similar central tendencies, but similar dispersions as well. The shore mode of iAngler has considerably fewer trips in the Tampa cluster, but actually exceeds the total number of MRIP trips for nearly all cases in the other two clusters (especially Common Snook). In these events, the mean catch rate data for iAngler are very similar to those of the MRIP survey.

Species-specific data for the charter boat mode was extremely deficient in the iAngler dataset and so are not included in the analysis. Likewise, iAngler's length data for retained catch were insufficient for the chi-square goodness-of-fit test. Thus, the length data for retained catch for iAngler are at least insufficient to test, even for the popular inshore species, if not altogether different.

Length Data

In the iAngler data set from 2012-2016 there were 103 Common Snook reported harvested ranging from 711 to 819 with a mean size of 776.1 mm (Total Length; TL). From 2012-2016 there were 132 Common Snook sampled for the MRIP survey ranging from 711 to 834 with a mean size of 763.4 mm TL. The length frequency distributions (Figure 4-7) were significantly different (^{2}=45.79, df=4, p<0.0001). The iAngler data set contained 2,914 Common Snook that were released from 2012-2016 that ranged from 71 to 963 mm and a mean of 462.5 TL (Figure 4-8).

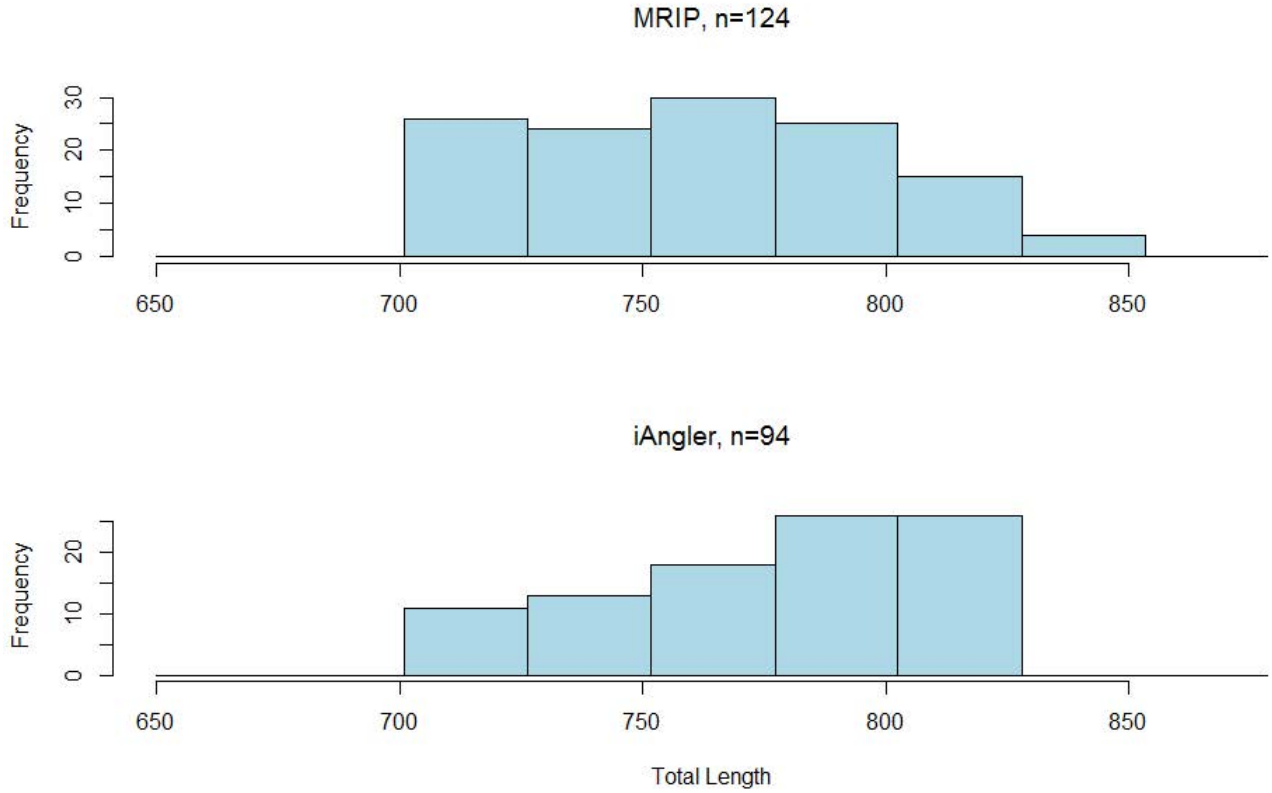


Figure 4-8. Length frequency distributions of Common Snook from the MRIP harvest (top) and iAngler harvest (bottom) datasets for Florida from years 2012-2016.

In the iAngler data set from 2012-2016 there were 394 Spotted Seatrout reported harvested ranging from 381 to 711 with a mean size of 452.8 mm TL. From 2012-2016 there were 10,732 Spotted Seatrout sampled for the MRIP survey ranging from 381 to 781 with a mean size of 440.0 mm TL. The length frequency distributions (Figure 4-9) were significantly different (^{2} =107.9, df=9, p<0.0001).

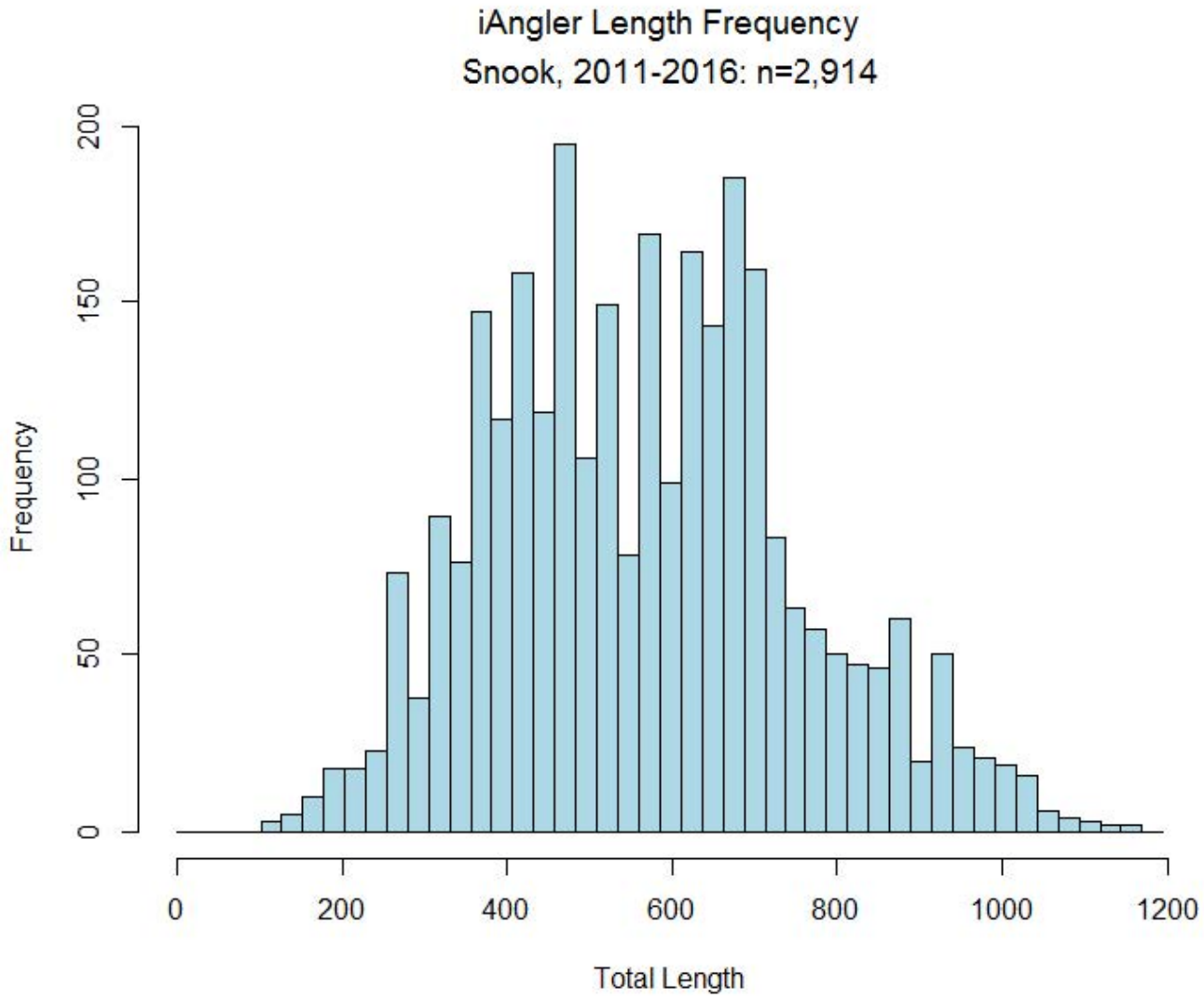


Figure 4-9. Length frequency distribution of released Common Snook from the iAngler app data for Florida from years 2012-2016.

The iAngler data set contained 2,676 Spotted Seatrout that were released from 2012-2016 that ranged from 101 to 1143 mm and a mean of 558.1 TL (Figure 4-10).

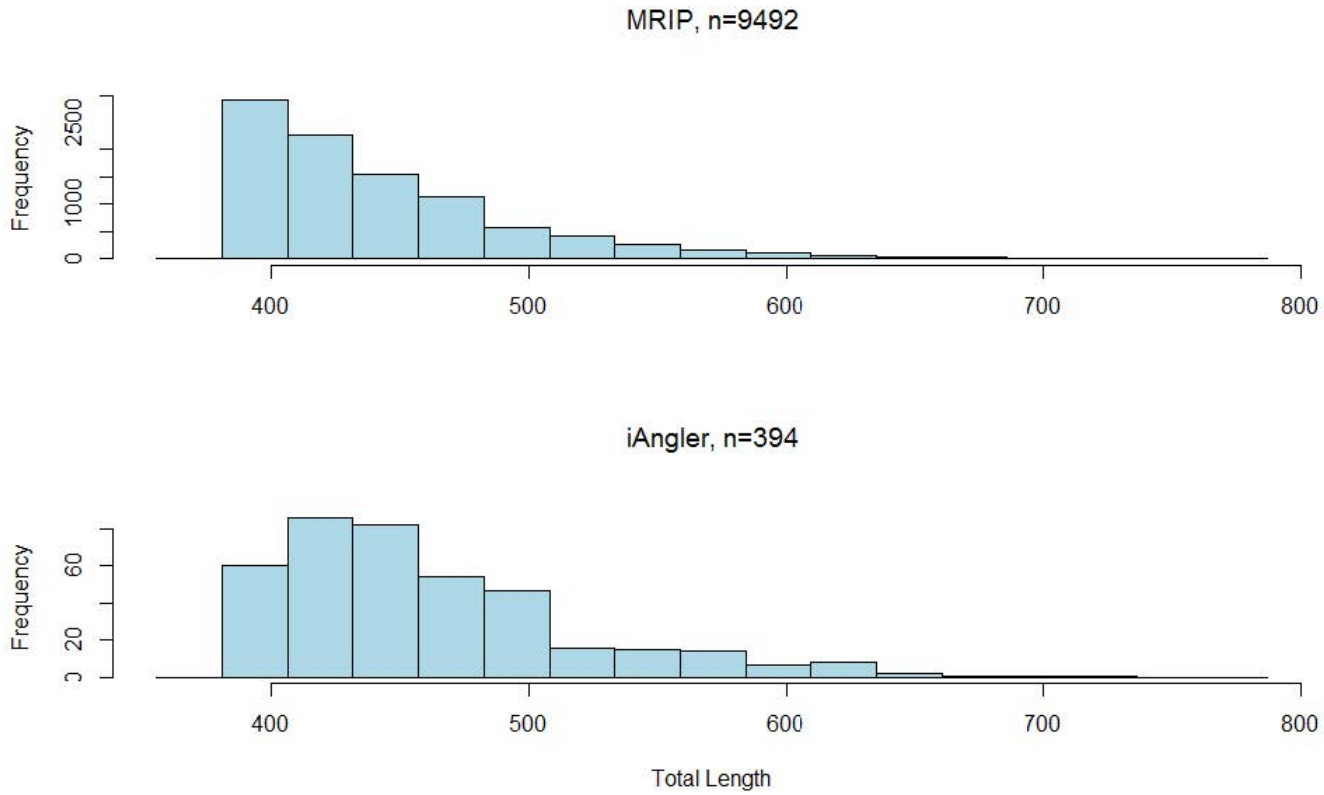


Figure 4-10. Length frequency distributions of Spotted Seatrout from the MRIP harvest (top) and iAngler harvest (bottom) datasets for Florida from years 2012-2016.

In the iAngler data set from 2012-2016 there were 173 Red Drum reported harvested ranging from 457 to 711 with a mean size of 590.7 mm TL. From 2012-2016 there were 3,726 Red Drum sampled for the MRIP survey ranging from 458 to 771 with a mean size of 554.1 mm TL. The length frequency distributions (Figure 4-11) were significantly different (^{2}=477.5, df=9, p<0.0001).

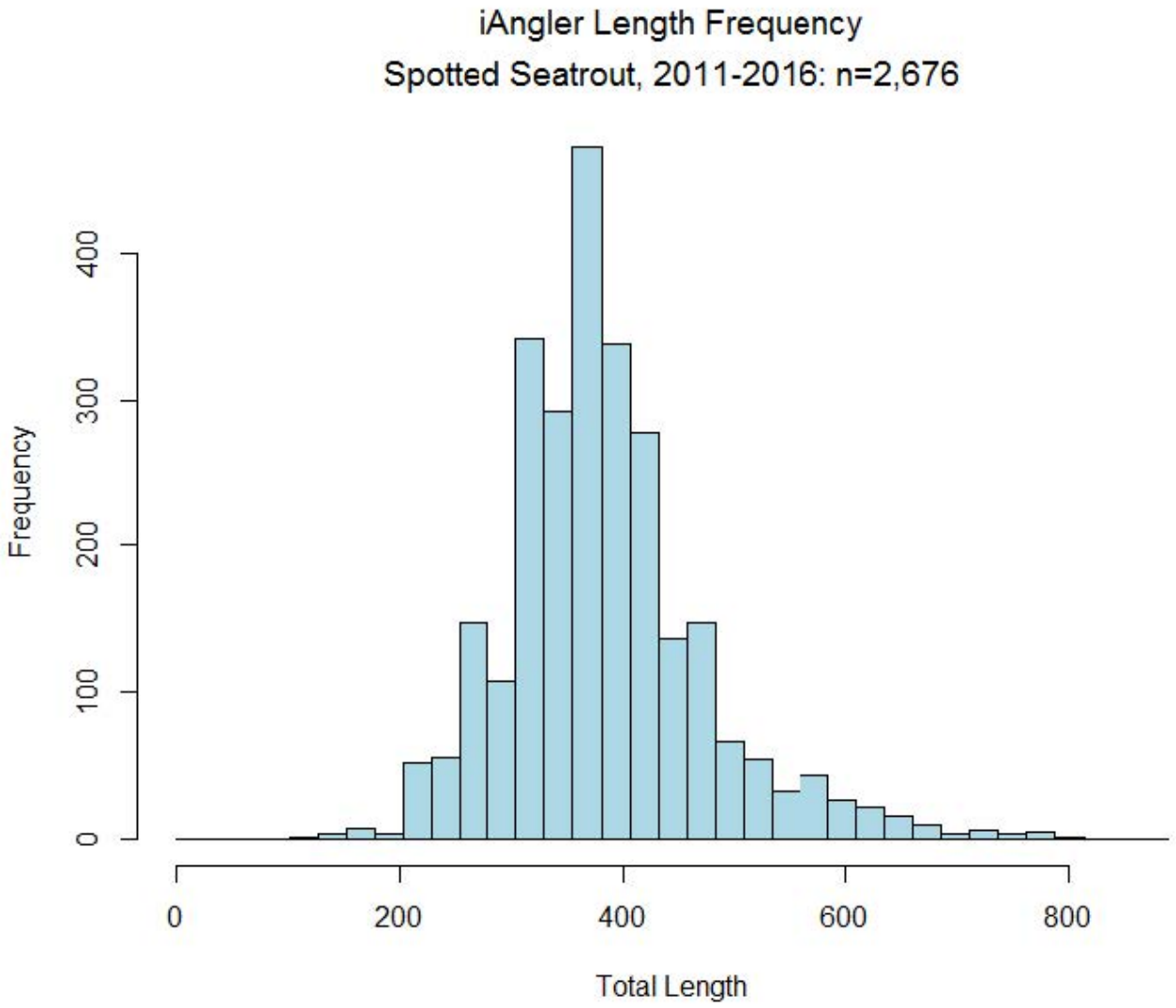


Figure 4-11. Length frequency distribution of released Spotted Seatrout from the iAngler app data for Florida from years 2012-2016.

The iAngler data set contained 1,069 Red Drum that were released from 2012-2016 that ranged from 152 to 1524 mm and a mean of 552.9 TL (Figure 4-12).

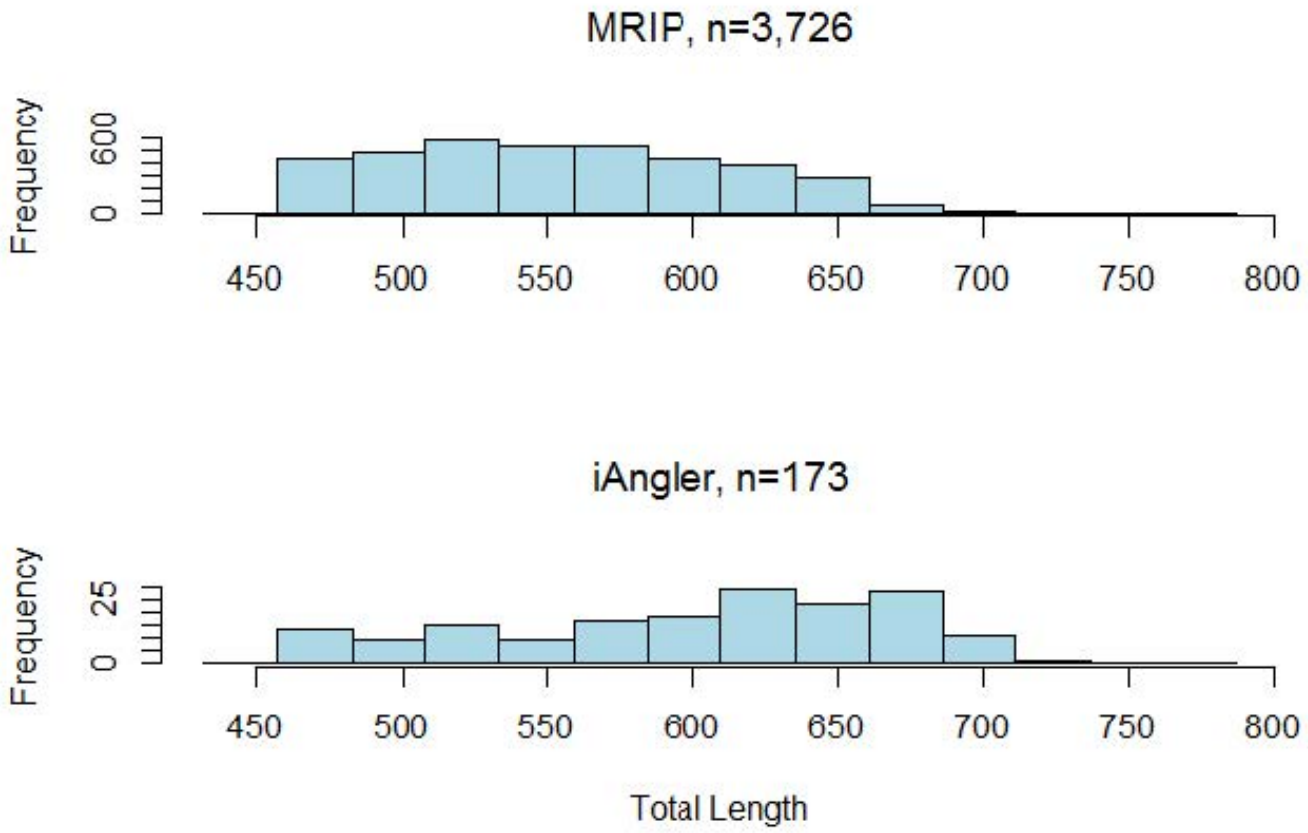


Figure 4-12. Length frequency distributions of Red Drum from the MRIP harvest (top) and iAngler harvest (bottom) datasets for Florida from years 2012-2016.

5. Discussion/Conclusions/Recommendations

The high degree of similarity between catch rate data from the iAngler smartphone app and the MRIP survey suggests an electronic, self-reporting framework can provide information that is usable for the assessment of recreational fisheries. Thus, for fish species where iAngler has adequate sample size (e.g., Common Snook, Spotted Seatrout, Red Drum), the data could be useful for fishery-dependent uses in stock assessment. Although the spatial bias of iAngler makes it inappropriate for usage on a statewide level, this study used only the first two years of the app, when knowledge of the app was spread exclusively by “word-of-mouth” (Brett Fitzgerald, personal communication). The fact that the iAngler and MRIP catch/trip values were similar when compared at an appropriate spatial resolution (i.e. the county clusters) shows the ability of an electronic, self-reporting program to provide representative catch rate data.

The iAngler smartphone app is analogous to paper-based angler diaries, which have been useful in recreational fisheries. Long-term angler diary programs have provided valuable information for monitoring stock status over time (Kerr 1996; Sztramko et al. 1991) . In some cases, when the program runs long enough, it can be used to assess the fishery before and after a major management action such as a change in minimum length limit (MacLennan 1996) . In such cases, an angler diary presents an opportunity for a “natural experiment,” where managers can assess the effect regulations have on fishing behavior and stock status. Ebbers

(1987) showed that angler-supplied information regarding length-frequency distributions, mortality rates, and population estimates was similar to the equivalent data obtained by fishery-independent surveys. Also, because diaries allow anglers to report data right after a trip is taken, they are not as vulnerable to a recall bias as are traditional mail surveys. In fact, diaries were used to reduce the recall bias on the mail-based Illinois Sport Fishing Survey (Tarrant et al. 1993) . The simple nature of a smartphone-based "angler diary" app could conceivably replace the mail surveys and paper-based diaries if administered and monitored by a state fisheries agency. Diaries also have the advantage of addressing the public access bias, which occurs when a large number of trips in a fishery are taken from private access points. To address the public access bias in the Blue Crab (*Callinectes sapidus*) fishery in Maryland and Virginia, Ashford et al. (2010) used a telephone survey to adjust the catch rates obtained from a traditional creel survey, which missed a sizeable amount of effort coming from private sites. However, an electronic, smartphone-based reporting system would represent a simpler and cheaper method to correct this problem. Further, studies that have implemented the use of smartphone- and digital tablet-based reporting programs have noted that most participants prefer them to paper-based logbooks (Baker and Oeschger 2009; Stunz et al. 2014) . Thus, if such electronic self-reporting "angler diaries" were to be employed and controlled in the same way traditional diaries are, they could prove to be an even better method for collecting information from recreational anglers.

Our study is the first to rigorously analyze opt-in, self-reported recreational fisheries data from electronic data collection (e.g., a smartphone app) with a focus on the private angling modes. Stunz *et al.* (2014) used a smartphone/tablet app called "iSnapper" to record data from headboat and private charter boat (collectively, the "for-hire" sector) trips with a focus on the Red Snapper fishery. However, their study involved choosing sixteen captains to become involved with the program and was relatively controlled, whereas our work with iAngler has been on a dataset consisting of true opt-in participants. While their study had the added benefit of a pre- and post-use survey to gauge captains' interest in the app, it did not include an analysis of whether or not the data provided were reliable or useful for assessment (i.e. how it compared to current data collection programs). Stunz *et al.* (2014) highlighted the difference between for-hire vessel captains and the private recreational angling population, calling for a study on that specific mode, and our analysis has begun filling that gap. This study has shown that when a proper sample size of trips exists, an electronic self-reporting platform like the iAngler app could provide a valid measure of catch per unit effort. For example, as the program runs for more years, this catch rate data could be used as a time series to assess relative abundance. Additionally, because the iAngler allows for more comprehensive information on discarded fish (length, weight, hooking location, higher spatial resolution), it has the potential to augment stock assessments in a way that the MRIP survey is not capable of doing. Overall, I found the iAngler smartphone app can provide valuable recreational fisheries data for certain species, especially popular inshore species in urbanized regions of the state of Florida.

One issue with the iAngler data set was the lack of spatial coverage throughout the entire state of Florida. In general, some counties had hundreds (or even a thousand) trips, whereas some had fewer than five. This raises the question of whether this data is useful on a statewide level, as metrics such as catch rate can vary spatially (Smallwood et al. 2006) . Specifically, many of the trips are concentrated in the urbanized regions, such as the southeast coast (our Atlantic county cluster) and—to a lesser extent—southwest Florida. Such information may still be useful, since Florida has already implemented "management zones" for Spotted Seatrout and

Red Drum in the form of variable bag limits throughout the state (eRegulations 2015) . Thus, the app's usefulness could increase if small-scale, regional management plans become more popular. However, to be useful on a larger spatial scale, the app would have to be expanded in its scope and usage. Overall, this spatial bias is not surprising, given the fact that the iAngler app has not been part of any major marketing campaign, meaning any diffusion up to this point has been due to "word-of-mouth" (Brett Fitzgerald, personal communication). If the Snook and Gamefish Foundation were to implement a marketing campaign, it might lead to a more balanced spatial distribution of effort. Any self-reporting program like this could also benefit from a partnership with the state fisheries agency, since strong administrative backing has the potential to increase the success of angler logbook programs (Cooke et al. 2000) .

Another shortcoming of the iAngler data set up to 2013 was the bias in species represented in the catch records. The iAngler app does not have much data on offshore species that are recreationally important to Florida, such as those from the snapper-grouper complex. Also, in the iAngler dataset, Common Snook, Spotted Seatrout, and Red Drum represented a majority of all the saltwater fishing trip catches in the entire state of Florida. This is also not surprising given the historical trajectory of the program. The iAngler smartphone app arose out of the Angler Action Program, which was a logbook program created in 2010 specifically for Common Snook recreational fisheries data (Brett Fitzgerald, personal communication). Because Spotted Seatrout and Red Drum are inshore species like Common Snook, it makes sense for them to be the next species that users of the app begin to report. Another important result from our study is that, judging by both iAngler and the MRIP, the composition of the various species caught can vary quite noticeably in different parts of Florida. Because Florida is so large, it is possible these results reflect changing ranges and relative abundances of fish (e.g. Common Snook are rarely seen in North Florida). However, if it is a function of different types of anglers fishing in different regions of the state, then that could be explored by iAngler should the app someday include the ability to approximate angler typologies (e.g. by collecting demographic information).

There were similarities in the catch/trip data for the three inshore species studied (Common Snook, Spotted Seatrout, and Red Drum). Previous investigations have suggested a bias in self-reported data for measures such as catch rates (Didden 2012) , but in this case the catch/trip data were very similar between collection methods. The most consistently similar distributions of catch/trip between iAngler and the MRIP were for the single-angler subset of the private boat mode and the shore mode. While the comparisons for the full private boat mode were skewed to the right, they still suggested the iAngler data to be similar to the catch/trip values provided by the MRIP survey. The skew of the data could mean that iAngler users are not including their zero-catch trips as much as the rest of their trips, which would otherwise pull down the mean catch/trip estimates to be closer to those of the MRIP survey. If this is the case, such a problem could be corrected by encouraging anglers to report these trips, as they are also important for assessment. Another possibility is that the users of the iAngler app do not have as many zero-catch trips as the entire angling population, which would indicate a bias in the participants of the program. In general, these results are promising, especially for Common Snook, as the results of its 2013 stock assessment update called for supplementing the data from the private boat and shore modes (Muller and Taylor 2013) . The three county clusters chosen all had agreement between iAngler and the MRIP for these three species, with the exception of the shore mode in the Tampa cluster and Spotted Seatrout in the Atlantic cluster, which lacked sufficient trips for making the comparisons. This could be a result of under-representation by iAngler, or a lack of available shore/beach fishing grounds in the three

counties included in the cluster.

One possible point of contention that I address here is the issue of weighting the catch values for the catch/trip comparisons. The MRIP data includes sampling weights for each recorded interview, but they were not included in our analysis mainly because only relative values were of interest for the comparisons themselves. Weighting would not add to the utility of the results, because they would be applied equally to both MRIP and iAngler, depending on the time and location of the fishing trip. The comparisons were made with raw data from both datasets, under the assumption that the weighting would not change the results of our fitting and simulation process.

A potential limitation of this study is the assumption that comparing the iAngler data to similar data obtained by the MRIP is analogous to comparing it to the "expected value," i.e., implying the MRIP collects a true representation of the fisheries in question. While the design of NOAA's access-point surveying program is now said to be unbiased (NOAA 2013) , not all of these corrections were in place for the entirety of time covered in our analysis. For example, for 2012 (the first half of our data), interviewers were instructed to sample when activity was anticipated to be the highest and as long as they saw fit, and it was not until 2013 that consistent and randomly selected time intervals were implemented (John Foster, personal communication). Because of the constant monitoring and correction, the MRIP undergoes on an annual basis, it is paramount to know exactly how these surveys are being conducted. Each year, NOAA releases implementation updates for the design and execution of the MRIP, so that is a good way of assessing the progress and potential problems of the program should our type of comparative study be repeated in the future.

There are many avenues for future research on this subject, especially if the iAngler app is further revised to collect other important fisheries data. First, we recommend a continuation of our analysis, as two years is not long enough to capture long-term trends in the fisheries. An avenue that can be revisited in the future is a comparison of the lengths of individual fish between iAngler and the MRIP survey. Because of the short time period used (2012-2013)—and the fact that anglers are not required to report lengths of fish into the app—there were not enough length records to perform a reliable comparison. However, providing size structure information for stock assessments would be useful, especially for developing an ecosystem-based approach to fisheries management (Shin et al. 2005) . Outside the scope of our study was a more in-depth look at the validity of iAngler's data on discarded fish. Unlike the MRIP survey, iAngler contains the lengths and weights of some of the discarded fish. A study that validates the accuracy of this discard information is of the highest priority, as the lengths of discarded Common Snook have already been incorporated into its most recent stock assessment (Muller and Taylor 2013) . The importance of understanding discards cannot be emphasized enough, as the success of the commonly applied minimum size limit regulation is hinged upon the fate of undersized discards (Coggins et al. 2007) .

Throughout the analysis, I found a few important issues that could be addressed by the iAngler app if it were to be expanded in the future. Many studies emphasize the impact that variable reporting rates can have on conclusions about effort/participation drawn from angler-diary programs (Absher and Collins 1987; Connelly and Brown 1995; Connelly et al. 2000; Harris and Bergersen 1985; Lowry 1978; Tarrant et al. 1993) . One app feature that might allow us to determine a crude individual angler reporting rate for the users of the iAngler app would be an "I

fished" button. This would be an easy, one-click measure that an angler might be more consistent about using than remembering and/or having the time to fill out the information from an entire fishing trip. That way, the number of fully submitted trips could be combined with the "I fished" button to obtain a rough reporting rate for each angler. Finally, if demographic information was required—or at least solicited on a volunteer basis—much more could be learned about the users of iAngler. In addition to making a general comparison to the general angling public, this might allow research avenues to explore why, for example, there is such a lack of data pertaining to offshore reef fish.

In conclusion, I have shown the utility for the iAngler smartphone app's data with regard to various management scenarios, and its potential for supplementing data already collected by the MRIP. Because the app is also equipped to submit other metrics such as lengths and weights of released fish, GPS coordinates of catch, and condition of released fish, it has the potential to provide novel information that the MRIP is not designed to collect—even if such data are not currently robust enough for analysis. Gutowsky et al. (2013) summarize the current uses of smartphone and digital tablets for fisheries science, suggesting that growing technology and usage of smartphones will make such programs more attractive and useful as time goes on. Thus, with consistent backing and revision, the utility of electronic, self-reporting programs for recreational fisheries management has the potential to grow, making them a valuable tool for managers and users.

Assessment of potential angler avidity bias correction

Discussion

The presence of avidity in electronic, self-reporting data collection programs can bias the mean catch rates for an angling population. However, we developed and tested a simple method to mitigate it. The use of geometric means versus arithmetic means illustrated the effect that extreme values of catch/trip can have on accurate estimation of the true central tendency of the data. Meanwhile, adjusting for avidity by using the inverse of reported trips showed that anglers who report many trips have different average catch rates that bias the population level values. Further, this bias needs to be measured, as the effect is not always consistent across species.

We believe our simulation and mean calculation are well justified. From our simulation, we chose to apply the zero-adjusted, avidity-adjusted geometric mean over the avidity-adjusted negative binomial mean because it appeared to approximate the mean better when there are highly dispersed catch/trip records. This dispersion appears to be the case in many instances with data that come from a self-reporting app like iAngler (Jiorle et al.). However, the avidity-adjusted negative binomial mean calculation might be better for fisheries that exhibit low, consistent catch rates among its angling population. Our choice to use a geometric over an arithmetic mean is based on the assumption that angler ability (i.e. catch rates) are log-normally distributed and thus skewed, and in such cases, the geometric mean is the more appropriate choice (Smothers et al. 1999) . For example, in our simulation, when our log-normally distributed angler expected catch rates were treated with a Poisson distribution to obtain reported catch/trip values, the resulting distribution appeared to be negative-binomially distributed. This is the general shape of reported catch/trip values in both iAngler and NOAA's MRIP intercept survey (Jiorle et al.), suggesting our assumptions agree with empirical data. Following Habib (2012) , we calculated our weighted geometric mean by accounting for zero-

catch trips separately. Our choice to use the inverse of reporting rates as the avidity weighting is supported by correlations of response in sampling programs and catch rates in fisheries literature (Carline 1972) .

The simulation-evaluation showed a strong relationship between variability in angler expected catch rates and the impact that the addition of avidity weighting had on mean catch rates. For example, the difference in percent deviation between the zero-adjusted geometric mean and zero-adjusted, avidity-adjusted geometric mean grew at higher standard deviations. This would suggest that the addition of avidity weighting had a larger impact when there existed a small group of anglers who caught a lot of fish and were biasing the unadjusted estimates. A similar relationship was seen between the unadjusted negative binomial fitted mean and the avidity-adjusted negative binomial mean. Also, as variability increased, so too did the accuracy of the zero-adjusted, avidity-adjusted geometric mean. However, the ability to accurately estimate the variance did not improve. Given the underlying log-normal structure that we worked with, it is likely that the low variability (=0.2) in angler expected catch rates created a distribution that was too close to a normal distribution, leading to an overestimation of the variance by the geometric mean. As the variability was increased, the data then become too dispersed for the log-normal structure, leading to underestimates of variance.

In the three species observed from the iAngler dataset (Common Snook, Spotted Seatrout, and Red Drum), adjusting for zero-catch trips, log-normal distribution of angler ability (i.e. skewed data), and angler avidity resulted in changes in mean population catch rates in most county clusters and years observed. While each species had spatial regions and years where the avidity weighting had a relatively larger effect (>20% change), Red Drum catch rates appeared to be the most robust to the weighting (3 instances of a <10% change). This would imply that, out of the three species' data in the iAngler dataset, Red Drum was the one least impacted by the avidity bias. Most importantly, these results show that the avidity bias is not constant—and sometimes not even noticeable—across species or spatial components of a fishery, even within a reporting platform assumed to exhibit such a bias (Didden 2012) .

Although this study focused on electronic, self-reporting programs (e.g. iAngler), this same method could be applied to other data collection programs such as angler diaries or logbooks. Nonresponse, which is similar to avidity, has been shown to plague mail surveys/angler diaries, often leading to highly inflated levels of total effort (Absher and Collins 1987; Connelly and Brown 1995; Harris and Bergersen 1985; Lowry 1978) . If those who fill out and return angler diaries are predominantly more avid anglers, then their numbers of reported trips could be used as a measure of avidity; from here, the zero-adjusted, avidity-adjusted geometric mean could determine whether or not these avid anglers are inflating the mean catch/trip of the angling population through differential reporting. While a properly stratified creel survey (e.g. NOAA's MRIP dockside survey) should not suffer from this avidity bias when calculating mean catch rates, the increased sampling of high-frequency users (i.e. general avidity) can affect economic analyses and estimates of total participation (Thomson 1991) . This effect is likely not a problem for estimating total harvest, as the increased sampling of avid anglers represents their larger contribution to the total catch.

The importance of the avidity bias ultimately depends on how the catch rates are used in a management framework. If they are meant to track relative abundance over time, the magnitude of the mean (i.e. number of fish caught) will not be as important, granted the amount

of avidity is not changing over time. However, with regards to electronic reporting platforms such as iAngler, some novice anglers use the app to help them keep track of successes and failures in their fishing practices (Brett Fitzgerald, personal communication). If this practice becomes more popular, it could become a scenario where avidity is changing, and that could confound the catch rates as an index of abundance. If the catch rates are being used to dictate management goals, then there is a danger when using unadjusted mean catch rates. For example, if an agency's goal for a successful sport-fishery is considered achieved when the mean catch rate reaches three fish/trip, then success would be declared prematurely if differential reporting of avid anglers inflates the catch rate artificially. Managers will need to be specific about how they plan to use data from these electronic, self-reporting platforms because that may determine the proper statistical treatment of the data.

Understanding the representativeness of contributors to an opt-in, self-reporting program is difficult because such programs have no defined panel, or sampling frame (Didden 2012) . In other words, the number and composition of participants is always changing, and there is no easy way of knowing the extent to which they are contributing to the dataset. One possible way to work around this uncertainty would be by obtaining demographic information from everyone who signs up for the program. That way, scientists could make inferences about the users based on attributes such as county of residence, age, and socioeconomic status. It would also be beneficial to know what percentage of a given user's total fishing trips taken is reported to the app. In our study, the assumption that more reported trips implies more trips taken is not assessed. However, it is possible, for example, that an angler reports all eight of his or her trips and would thus incorrectly be considered more avid (and weighted inappropriately) compared to an angler who reports five out of his or her twenty total trips taken in that time period. It is this possibility that makes the "avidity" discussed here different from the avidity discussed in Thomson (1991) , which is based more directly on the frequency of usage. Such unknowns have the potential to compromise the utility of this analysis for treatment of catch rate data.

There are two adjustments that can be made to the actual treatment of the iAngler data in this study. For example, the assessment of the data was done by assigning a weighting factor for a user and considering each trip, whereas our simulation was done by having each angler's expected catch rate contribute to an overall log-normal distribution of angler catch rates. Thus, a possible extension of this work could be to apply fully this hierarchical Bayesian framework of the simulation to the treatment of the data, where mean angler expected catch rates are assumed to come from a log-normal distribution with a hypermean and hypervariance. The observed catches for a given angler would be assumed to be Poisson-distributed, with the Poisson mean coming from the expected catch rate of the hyperdistribution. This is another way to address the avidity (as opposed to just the weighting) because each angler's behavior will only be considered once for the overall estimation of a population's mean catch/trip. Also, since the catch rate distributions in the iAngler dataset appeared to be negative-binomially distributed, another adjustment to the model could be replacing the log-normal structure of angler catch rates with a gamma distribution, since it is the mixing of the gamma and Poisson distributions that ultimately produces a negative binomial structure.

We have shown the utility of a geometric mean for calculating mean catch/trip, with an avidity weighting based on individual-angler reporting rates by applying it to an opt-in, self-reporting smartphone app for recreational fisheries data. As these programs become more popular for collection of fisheries data, it will be critical to assess to what extent the users of the apps are

biasing the estimates of mean catch rates. In the future, it would be beneficial to combine a study on angler avidity with the demographics of an app's users. This way, scientists and managers could have a more complete understanding of how closely the app's clientele represents the angling population, and how this representation might change over time as the app grows or shrinks. This will ensure that such data is being used in the most reliable way possible as managers try to incorporate it into recreational fisheries management.

Phase 2 evaluation

Discussion

In general, the results of this analysis are very similar to those reported in phase 1 which only included data from 2012-2013. The high degree of similarity between catch rate data from the iAngler smartphone app and the MRIP survey suggests an electronic, self-reporting framework can provide information that is usable for the assessment of recreational fisheries. However, this is only apparent for fish species where iAngler has adequate sample size (i.e., Common Snook, Spotted Seatrout, Red Drum). Although the spatial bias of iAngler makes it inappropriate for usage on a statewide level, possible that continued implementation and advertisement could progress the utility already demonstrated by these inshore fishes in these county clusters. The fact that the iAngler and MRIP catch/trip values were similar when compared at an appropriate spatial resolution (i.e. the county clusters) shows the ability of an electronic, self-reporting program to provide representative catch rate data. However, consistent advertisement of the self-reporting app should be conveyed to the public to ensure its user base does not decline, but rather increase over time.

The simple nature of a smartphone-based "angler diary" app could conceivably replace the mail surveys and paper-based diaries if administered and monitored by a state fisheries agency. Diaries also have the advantage of addressing the public access bias, which occurs when a large number of trips in a fishery are taken from private access points. To address the public access bias in the Blue Crab (*Callinectes sapidus*) in Maryland and Virginia, Ashford et al. (2010) used a telephone survey to adjust the catch rates obtained from a traditional creel survey, which missed a sizeable amount of effort coming from private sites. However, an electronic, smartphone-based reporting system would represent a simpler and cheaper method to correct this problem. Further, studies that have implemented the use of smartphone- and digital tablet-based reporting programs have noted that most participants prefer them to paper-based logbooks (Baker and Oeschger 2009; Stunz et al. 2014) . Thus, if such electronic self-reporting "angler diaries" were to be employed and controlled in the same way traditional diaries are, they could prove to be an even better method for collecting information from recreational anglers.

This study is the first to rigorously analyze opt-in, self-reported recreational fisheries data from electronic data collection (e.g., a smartphone app) with a focus on the private angling modes. Stunz *et al.* (2014) used a smartphone/tablet app called "iSnapper" to record data from headboat and private charter boat (collectively, the "for-hire" sector) trips with a focus on the Red Snapper fishery. However, their study involved choosing sixteen captains to become involved with the program and was relatively controlled, whereas our work with iAngler has been on a dataset consisting of true opt-in participants. While their study had the added benefit of a pre- and post-use survey to gauge captains' interest in the app, it did not include an analysis of

whether or not the data provided were reliable or useful for assessment (i.e. how it compared to current data collection programs). Stunz *et al.* (2014) highlighted the difference between for-hire vessel captains and the private recreational angling population, calling for a study on that specific mode, and our analysis, has since filled that gap. This study has shown that when a proper sample size of trips exists, an electronic self-reporting platform like the iAngler app could provide a valid measure of catch per unit effort. For example, as the program runs for more years, this catch rate data could be used as a time series to assess relative abundance. Additionally, because the iAngler allows for more comprehensive information on discarded fish (length, weight, hooking location, higher spatial resolution), it has the potential to augment stock assessments in a way that the MRIP survey is not capable of doing. Overall, we found the iAngler smartphone app can provide valuable recreational fisheries data for certain species, especially popular inshore species in urbanized regions of the state of Florida.

The largest issue found with the iAngler data set was the lack of spatial coverage throughout the entire state of Florida. In general, some counties had hundreds (or even thousands [Palm Beach county]) trips, whereas some had fewer than five. This raises the question of whether this data is useful on a statewide level, as metrics such as catch rate can vary spatially (Smallwood et al. 2006) . Specifically, many of the trips are concentrated in the urbanized regions, such as the southeast coast (our Atlantic county cluster) and—to a lesser extent—southwest Florida. Such information may still be useful, since Florida has already implemented “management zones” for Spotted Seatrout and Red Drum in the form of variable bag limits throughout the state (eRegulations 2015) . Thus, the app’s usefulness could increase if small-scale, regional management plans become more popular. However, to be useful on a larger spatial scale, the app would have to be expanded in its scope and usage. Overall, this spatial bias is not surprising, given the fact that the iAngler app has not been part of any major marketing campaign, meaning any diffusion up to this point has been due to “word-of-mouth.” If the Snook and Gamefish Foundation were to implement a marketing campaign, it might lead to a more balanced spatial distribution of effort. Any self-reporting program like this could also benefit from a partnership with the state fisheries agency, since strong administrative backing has the potential to increase the success of angler logbook programs (Cooke et al. 2000) .

Another shortcoming of the iAngler data was the bias in species represented in the catch records. The iAngler app does not have much data on offshore species (grouper, snapper, etc.) that are recreationally important to Florida. Also, in the iAngler dataset, Common Snook, Spotted Seatrout, and Red Drum represented a majority of all the saltwater fishing trip catches in the entire state of Florida. This is likely due to the historical intent of the program. The iAngler smartphone app arose out of the Angler Action Program, which was a logbook program created in 2010 specifically for Common Snook recreational fisheries data. Because Spotted Seatrout and Red Drum are inshore species like Common Snook, it makes sense for them to be the next species that users of the app begin to report.

As found in Ryan Jiorle’s thesis, there were similarities in the catch/trip data for the three inshore species studied (Common Snook, Spotted Seatrout, and Red Drum). Other investigations have suggested a bias in self-reported data for measures such as catch rates (Didden 2012) , but in this case the catch/trip data were very similar between collection methods. The most consistently similar distributions of catch/trip between iAngler and the MRIP were for the single-angler subset of the private boat mode. While the comparisons for the full private boat and shore mode (to a lesser degree) were skewed, it still suggested the iAngler data to be similar to

the catch/trip values provided by the MRIP survey. It's likely that the skew of the data is due to iAngler users not including their zero-catch trips as much as the rest of their trips, which would otherwise pull down the mean catch/trip estimates to be closer to those of the MRIP survey. This problem could be alleviated by encouraging anglers to report these trips, as they are equally important for correct assessment of the fisheries. Another possibility is that the users of the iAngler app do not have as many zero-catch trips as the entire angling population, which would indicate a bias in the sampled participants of the program. In general, these results are promising, especially for Common Snook, Spotted Seatrout, and Red Drum. The three county clusters chosen all had agreement between iAngler and the MRIP for these three species, with the exception of the shore mode in the Tampa cluster, which lacked sufficient trips for making the comparisons. This could be a result of under-representation by iAngler, or a lack of available shore/beach fishing grounds in the three counties included in the cluster.

A potential limitation of this study is the assumption that comparing the iAngler data to similar data obtained by the MRIP is analogous to comparing it to the "expected value," i.e., implying the MRIP collects a true representation of the fisheries in question. While the design of NOAA's access-point surveying program is now said to be unbiased (NOAA 2013) , not all of these corrections were in place for the entirety of time covered in our analysis.

A useful utility of the iAngler app data is that it allows the inclusion of release data whereas the MRIP only documents harvested individuals at access sites. In this report we compared the harvest data of the three most common species (Common Snook, Spotted Seatrout, and Red Drum). All length frequency distributions were statistically different. The closest statistically was Common Snook. However, this is likely a function of the reduced harvest slot window, limiting the possibilities of harvested sizes unlike the other two species. Spotted Seatrout appeared to be identical, however the difference statistically here is likely a result of the reduced sample size. The number of Spotted Seatrout reported in the MRIP data were 20 fold that of the iAngler app for Spotted Seatrout. This was also apparent for Redfish. The distribution appeared incomplete unlike the MRIP length frequency. This is unfortunate because the iAngler app contained many release records (over 6,000 just for these three species) that could be used to define the size structure for not only harvestable, but incoming year-classes as well. Providing size structure information for stock assessments would be useful, especially for developing an ecosystem-based approach to fisheries management (Shin et al. 2005) .

In conclusion, this report shows only the utility for the iAngler smartphone app's data with regard to various management scenarios, and its potential for supplementing data already collected by the MRIP. Because the app is also equipped to submit other metrics such as lengths and weights of released fish, GPS coordinates of catch, and condition of released fish, it has the potential to provide novel information that the MRIP is not designed to collect—even if such data are not currently robust enough for analysis. Gutowsky et al. (2013) summarize the current uses of smartphone and digital tablets for fisheries science, suggesting that growing technology and usage of smartphones will make such programs more attractive and useful as time goes on. Thus, with consistent backing and revision, the utility of electronic, self-reporting programs for recreational fisheries management has the potential to grow, making them a valuable tool for managers and users.

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7. Comments

Appendix A - Response to Reviewer Comments

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“Unless there is more ubiquitous adoption of e-logs such as iAngler it is unlikely that they will provide the necessary spatial and temporal resolution to augment the MRIP data.” (p6) This is a common theme, and given reporting rates, it doesn’t seem plausible.

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"The analysis indicated that if such a program [iAngler] could be scaled up in participation rate and geographic coverage, data from such a program would potentially be similar to MRIP (such a broad scale comparison is not possible since an app with such coverage does not exist)." (p6)

A broad scale comparison is not possible at this current time and will not be possible unless data collected across multiple apps are combined. This would require data standardization across apps and a central body to address quality assurance/quality checks and data storage.

"Provided sufficient demographic information can be collected the data provided from an app can be readily subsampled to match the demographics of the data it is supplementing. As identified, the ability to subset is completely dependent on the nature of the data collected. Sufficient demographic data would need to be collected to align any data from an app to the categories in the MRIP effort survey or at least to the level used in the MRIP intercept survey." (p7) Nonprobability data are often weighed to conform to population control totals (quasi-randomization, super-population models) and subsequently treated as a probability sample and used for inference. This seems like a more useful application than subsampling nonprobability data to "align any data from an app".

The intent of this statement was to imply that data from the app could be filtered to align with the reference data set (i.e., MRIP).

On several occasions, the report references rotating panels when referring to the pool of participants that report via an app. This is not consistent with the traditional concept of a rotating panel, in which panelists are randomly selected and moved in and out of the panel at regular, pre-determined intervals.

The term rotating panel is used incorrectly since the panels that use apps are not randomly selected but are self-selected. The use of rotating was used to imply a continuous turnover rate. The reality is after analysis of reporting and use rates that the majority of individuals only use the app once.

"In general, app user retention is low and the same is true for fishing apps. Generally, there is only 5% retention after 5 months. The iAngler app has a 10% retention rate after 1 year. Most users report only a single trip and a very small percentage of the users repot a high volume of trips (Figure 1-1). It is reasonable to quantify the panel that participates in the iAngler app as highly variable and rapidly rotating." (p9) This is the second recent example we've seen of an app with extremely low reporting rates, which suggests that anglers are not especially interested in app reporting.

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the high turnover rate results in low sample sizes.

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The inspection of the participation rates would suggest that app reporting is a novelty that is utilized only once by the majority of participants.

"…simulation results suggest that the low number of records for a number of species in the MRIP is likely to result in biased and imprecise estimates of total catch as the spatial coverage of the data is refined these biases are likely to be exacerbated." (p14) I believe the simulation only showed the impact of sample size on precision – the figure showing "changes in potential bias" present a simulated distribution of errors that appear to be unskewed with a mean of zero.

Yes, on average the results should be unbiased but there is a potential for the results to be skewed at any given time. This variability adds to the overall variance in reported catch and adds to the uncertainty in assessments. The reality is that a long time series of catch is needed to overcome this effect.

The report suggests that app data could supplement MRIP data. Given the low reporting and retention rates, as well as the limited geographic scope, would it be more economical to increase the quantity of data by increasing MRIP sample sizes?

Turnover in app use is rapid and retention and recruitment at a broad geographic scale will require a monetary investment. Currently, it is unknown what the investment needs to be. A cost benefit analysis, if possible, would indicate if investment in MRIP, particularly in areas where uncertainty in catch rate estimates were high, would be more beneficial. Given the highly localized nature of the iAngler data, app use through 'word-of-mouth' is localized and scope is limited.

One assumption in the use of the self-reported data is consistent participation. However it is likely that regulations will impact the extent of volunteers.

Consistent participation is not a requirement of data use. High volume of a representative sample of the angling population and broad spatial coverage (or local coverage if the question is local) is what is needed. Therefore, representativeness is crucial.

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event.

It remains to be seen how much the results would contribute to stock assessments. Generally assessments are done on a spatial scale of stock which is beyond the bounds of the iAngler data collection. The information would perhaps be best used in addressing smaller scale management issues.

Currently, app data does seem to be suited to local management scale issues. Absent any information the app data is the ‘best’ available data (i.e., Gulf coast snook discard length frequency). A careful assessment of how uncertainty of recreational catch and sample size of catch and discards needs to be done to determine the sample sizes necessary to improve stock assessments.

In Figure 3-1, as well as Appendix A, the predicted binomial values do not seem fit particularly well in many cases. It would be useful to present the residuals to examine fit.

The residuals would be a useful diagnostic. In some instances, the negative binomial distribution is influenced by reported high catch rates. Given the sample sizes this is potentially misleading for the posterior modal estimates but is captured in the uncertainty estimates for the binomial distribution parameters. The relative difference plots capture this uncertainty.

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Assumption that number of trips and avidity are independent may be flawed. Good fishermen are good because they fish more than others. Consequently, the sampling bias in the simulation may be under-estimated as depending on the bias catch rates of the fishermen with higher avidity. Additionally, the subset of fishermen who fish alone in a boat are likely very avid fishermen. Therefore adjusting the mean for avidity within this subset of high avidity anglers may be somewhat biased.

Yes this is true. The analysis presented was to indicate that if avidity is known then it can be corrected for. The reality is that we do not know the relationship between avidity and catch rate nor do we understand the relationship between avidity and app use. There are MRIP data to assess the relationship between stated avidity and catch rate and this analysis is currently being done. However, no data currently exist to validate the other assumptions. To use app data effectively these assumptions need to be assessed.

One issue not addressed in the report is data access and privacy rights. If the anglers voluntarily produce the data for a private entity which is then transmitted to scientists, there would have to be some increased infrastructure to handle the volume required to cover more species and area.

Not sure if that is something private industry would do for low cost.

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"A well designed study and a good discussion of potential roles for angler apps in data collection. Early participation drop off by subscribers would appear to be a problem that requires attention before angler apps can be considered as a viable way approach to addressing data gaps in current data collection programs."

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Assessing and refining the collection of app-based angler information in relation to stock assessment.

UF project PJ 00120399
14114_NA10NMF434001

Final Report

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Background

One of the recommendations made in the National Research Council's 2006 review of recreational survey methodology was to explore the potential for using panel survey methodology to obtain fisheries information (NRC, 2006)[1]. Currently, numerous examples exist of informal volunteer panel based electronic angler reporting systems that allow recreational anglers to record catch and fishing trip information. These panels take the form of web-based electronic logbooks that make use of smart phone as well as other forms of mobile technology targeting similar types of information. There can be distinct differences in how panel participants are recruited, and panels maintained. Individual angler logs may vary by length of the recall period, the resolution and quality of catch and effort information obtained and angler incentives to report trip information. The motivation for the creation of a web-based angler survey or log may be out of concern for a particular stock or just a desire to provide a way for anglers/members a means to more accurately track their fishing trips. Whatever the rationale, there are some minimum data needs that must be addressed if the logs are to provide meaningful data for stock assessment purposes. How the data can be used will depend on how well they represent fishing activity and behavior (i.e., panel recruitment and maintenance and identification of potential sources of reporting bias among panel participants). Statistical considerations concerned with panel recruitment and maintenance were discussed recently at an MRIP funded workshop on "Opt-In" angler panels (Didden, 2012)[2]. Currently there are no minimum standards for how panels are constructed (i.e., recruited), the types of data collected or for the units reported. There may be an expectation among well-meaning panel participants and organizers that their data be used, and a tendency to presume foul play when they are not used as expected to inform stock assessments. Ironically, one of the cautions included in the NRC review was that stock assessment biologists were made aware of the data limitations (NRC, 2006). That caution could certainly be extended to participant anglers in electronic logbook programs and organizations that may have unrealistic expectations for how their data may be used. The defense of any decision to include or exclude data from this increasingly popular source is greatly facilitated through a well-designed set of criteria that outlines minimum requirements for data types and quality as well as for the selection process used to recruit panel members. By setting criteria or standards and making those standards available to angling groups, who wish to avail of electronic reporting, decisions to include or exclude logbook data in the stock assessment

[1] National Research Council (2006). Review of Recreational Fisheries Survey Methods. National Academy of Sciences, Washington, D.C. 187pp.

[2] Didden, J. (2012). Summary of Feb 2, 2012 Workshop on Opt-In Angler Panels. MRIP Report 10pp.

process can be defended at data workshops. Guidance to angler groups and organizations wishing to establish electronic reporting systems or improve existing reporting systems, needs to take the form of a set of recommended practices that includes recommendations for minimum data elements and standards. By providing a template that ranks usability of data provided in e-logs in terms of data needs (including adaptability to future data needs), data quality, ability to account for potential sources of bias, and meet minimum standards for consideration as valid data sources, angler expectations for data use are clearly defined, and the potential of angler e-logs to augment state and federal data collection programs can be explored. The process may allow for integration of an increasingly visible potential source of data under the MRIP umbrella.

Project Description

University of Florida will partner with Florida Fish and Wildlife Conservation Commission (FWC) to evaluate angler e-log programs. Initially this evaluation will be done on data from the iAngler application developed by the Snook and Gamefish Foundation (SGF) but may be extended to the International Game Fish Association (IGFA) application as well as Greg Stunz's iSnapper application at Texas A&M. Application data and panels will be compared to information collected by MRIP. The evaluation of e-log data will be run in two phases. Phase 1, in consultation with FWC and SGF, will evaluate the utility of e-log data to help inform stock assessment and its potential as a fishery dependent data source. The expected outcomes of phase 1 are outlined below. Phase 2 will reevaluate the utility and scope of e-log data once recommendations from phase 1 are implemented.

Description of Goods and Services

Phase 1

1.1 Description of stock assessment needs and evaluation of the potential for angler e-logs to provide information that is usable in stock assessments. The initial description will include at least two angler based electronic reporting/logging systems in addition to the iAngler application developed by the Snook and Gamefish Foundation

1.2 Description of minimum data elements and standards for inclusion of angler e-log data in stock assessments.

1.3 Development of protocols for ranking or evaluating angler e-Logs based on data requirements.

1.4 Evaluation of the potential for certification standards as determined by compliance with minimum data standards.

1.5 Evaluation of the iAngler log devised by the Snook and Gamefish Foundation in its current form for use as a potential source of data for stock assessments. The evaluation will include:

1.5.1 Evaluation of the panel in terms of selection bias and volume of information obtained.

1.5.2 Description and critique of the survey instrument and information components.

1.5.3 Description and evaluation of data elements in terms of formatting, minimum data requirements, data quality and participant behavior (reporting patterns).

1.5.4 Outline of improvements necessary for inclusion of iAngler data in stock assessment process.
1.5.5 Description of practical improvements to the iAngler system that will address sources of bias in terms of data usability.
1.5.6 Set expectations for the inclusion of iAngler data at the assessment level based on criteria for:

a. scientific defensibility – must be able to identify and/or account for bias.
b. compatibility with existing data.
c. stock assessment needs.

1.6 Assessment of recommended improvements to the iAngler system. Recommended improvements will form the basis for a set of recommended practices and minimum data requirements to be made available to entities interested in providing data for stock assessment purposes.

Phase 2

2.1 Re-evaluation of e-log data following recommendation from 1.6
2.2 Re-evaluation (year 2) of e-log data following recommendation from 1.6 and recommendation from

Goods and Services reported on in this final report.

This summary report combines information in previous reports for phases 1 and 2 with the addition of a simulation clarifying the potential impacts of under sampling recreational participants in terms of its impact on the potential bias and precision of catch estimates as well as a final recommendations section.

List of abbreviations

AAP	The Angler Action Program, which refers to the Snook and Gamefish Foundation's initiative to collect anglers' self-reported recreational fisheries data. Under this program are apps such as iAngler, Chesapeake Catch, and iAngler Tournament
MCMC	Markov chain Monte Carlo, a family of sampling methods; in this project, refers to a specific type of simulation
MRFSS	Marine Recreational Fishery Statistics Survey, the National Oceanic and Atmospheric Administration's original program used to collect recreational fisheries data from fishers

MRIP	Marine Recreational Information Program, which is the revised version of MRFSS, and the program currently used to collect recreational fisheries information
NOAA	The National Oceanic and Atmospheric Administration, the federal agency under the Department of Commerce, who has the responsibility (among others) of sustainably managing fisheries that operate in federal waters
NRC	The National Research Council, which was responsible for conducting the critique of the Marine Recreational Fishery Statistics Survey
SDT	Smartphones and Digital Tablets, which refers to the family of electronic devices with wireless Internet connectivity capabilities

Executive summary

Fisheries professionals need to collect data on and manage recreational fisheries more effectively, so different organizations and agencies have begun utilizing electronic, self-reporting platforms to supplement current sampling programs. We assess the utility of the iAngler smartphone "app"—one such sampling program—for recreational fisheries stock assessment by characterizing the dataset and comparing specific metrics to those of NOAA's Marine Recreational Information Program (MRIP). Note that access to data from other apps was not possible for the projects. Metrics compared were the spatial distribution of trips by county, frequency of catch for the ten most commonly reported species, and species-specific catch rates. We conducted "catch frequency" and catch rate comparisons for different spatial designations in Florida and catch rate comparisons for different fishing modes. Data from iAngler exhibits a strong spatial bias toward southeast Florida and a bias toward three common inshore species: Common Snook (*Centropomus undecimalis*), Spotted Seatrout (*Cynoscion nebulosus*), and Red Drum (*Sciaenops ocellatus*). However, iAngler catch rates for these three species were similar to those of the MRIP. Because a majority of trips reported to iAngler came from a relatively small number of anglers, we used a simulation to develop a proper weighting for angler avidity. Using a geometric mean that accounted for zero-catch fishing trips and angler avidity, we recalculated catch rates for Common Snook, Spotted Seatrout, and Red Drum and found avidity to have a variable yet noticeable impact on catch rates. This study shows the potential for electronic, self-reporting programs to provide reliable recreational fisheries data, as long as spatial coverage is sufficient, and avidity is accounted for.

1 Objectives Summary

Phase 1

1.1 Description of stock assessment needs and evaluation of the potential for angler e-logs to provide information that is usable in stock assessments. The initial description will include at least two angler based electronic reporting/logging systems in addition to the iAngler application developed by the Snook and Gamefish Foundation

There are three main needs for conventional stock assessments in relation to the qualification recreational fisheries that can potentially be met by angler e-logs 1) The quantification of catch rates with greater accuracy so that the estimation of total harvest (retained, live and dead discards) can be estimated with percent standard errors (PSE) within an acceptable range (generally <30%); 2) The quantification of size frequencies for all catch components (retained, live and dead discards). 3) Improving the understanding of the spatial distribution of fishing effort. Currently the MRIP program does not provide sufficient spatial or temporal coverage to accurately estimate catch at the state resolution for species that are infrequently encountered resulting in PSE >>30%. In addition, currently the MRIP program does not quantify the size distribution or depth of discards. For a number of species (e.g., Red Snapper), mortalities from discards can represent a large proportion of the allowable catch. Given the size and depth dependency in discard mortality rates, the ability to more accurately quantify this component of the catch is necessary. In addition, MRIP quantifies the spatial distribution of effort at a coarse resolution such as state or federal waters and at the county of intercept. Such information is insufficient to quantify the potential effect of depth on discard mortality rates.

From the analysis presented in this document (sections 3 and 4) it is apparent that e-logs have the potential to provide this information but because that are still in their infancy and lack the spatial coverage to augment the MRIP data except in areas where participation is high. Unfortunately, areas of high participation, at least for the iAngler app, are currently too localized to be considered an accurate reflection of the angling community even though the catch rates and length frequencies are comparable to MRIP. Unless there is more ubiquitous adoption of e-logs such as iAngler it is unlikely that they will provide the necessary spatial and temporal resolution to augment the MRIP data for the purpose to stock assessment at more localized (eg., regional or state) levels.

The data availability and geographic scope of the iAngler data are limited and the initial intent of the iAngler app was not to collect information that could be used in stock assessment. Our intent with the study was to present an apples to apples comparison between the available data in iAngler and the current best available data which is the MRIP to demonstrate that where comparisons were possible the data were similar. The analysis indicated that if such a program could be scaled up in participation rate and geographic coverage, data from such a program would potentially be similar to MRIP (such a broad scale comparison is not possible since an app with such coverage does not exist). These results were positive and suggest that even with all the concerns of potential biases that could be introduced by a rotating panel of participants, the data told the same story. There are two critical points that should be made here. 1) The ability to subset and alter the app data at the level of the individual gives any analysis a high degree of flexibility in defining the sampling probabilities and the potential to reduce biases that result from avidity etc. This only becomes a problem if the participant pool is reduced to a limited

number of individuals. 2) MRIP was designed to answer questions at the national level and given the potential hit and miss nature of the sampling from the MRIP program at finer spatial scales, app data, provided it is available in an area may provide a better depiction of the catch and composition information. We have also done some length-frequency comparison that also show a similar pattern in the data from iAngler and MRIP which suggest a potential to use apps to collect more detailed discard information (this is not currently done with the iAngler app). The potential for apps like iAngler to provide supplementary information exists: the two data sources match but data such as the size distribution of discards is currently not collected. With no further modification to the type of data collected in the iAngler app it would be possible to use the data to supplement MRIP catch rates and length frequency of retained catch information but only at the limited spatial scale over which iAngler data are collected. Further modification of the app would be required to collect data on the location and size structure of discards and a much broader geographic scope of use would be needed before data could be used for most stock assessments.

1.2 Description of minimum data elements and standards for inclusion of angler e-log data in stock assessments.

Venturelli et al. (2016) provide a list of potential data elements to be included at a minimum for any e-log entry. Fishing trips should be georeferenced with the intended target species acknowledged. The length of time fishing should be recorded. Catch data should include at a minimum, the species, number and fate (e.g., retained, released). Additional information for each fish regardless of fate such as length and weight can provide valuable information for assessments. Information on angler demographics and behavior can also be essential for defining the sampling frame and evaluation of data for potential biases.

From the analysis performed in this report a number of recommendations can be made with respect to the minimum data requirements for the inclusion of e-log data. Currently very little demographic information is collected by e-logs. This is in part due to privacy issues and not wanting to overburden users with lengthy registration. This lack of demographic information makes it challenging to directly compare the composition of anglers using e- logs to those included in the MRIP intercept survey or phone/mail survey. While there is no guarantee that demographic data is a logical comparison to make to validate effort and catch information it would be an additional check and allow for comparison with intercept or license data. The minimum requirements for this data would likely be age, sex, race. A number of app developers have indicated that such data can be mined from social media sources. For e-log data to be useful for the estimation of total harvest in conjunction with the MRIP program catch rate data collected from an e-log must be compatible with MRIP data streams. This requires that catch by trip by location (kept, releases alive, released dead) by species can be attributed to an individual angler so that catch rate can be calculated. One of the challenges integrating e-log data with MRIP to estimate total catch is attributing e-log catch to MRIP locations. For e-log data to be useful in improving estimates of discard mortality for live discards requires at a minimum that in addition to catch information, length and ideally depth of capture be reported.

Provided sufficient demographic information can be collected the data provided from an app can be readily subsampled to match the demographics of the data it is supplementing. As identified, the ability to subset is completely dependent on the nature of the data collected. Sufficient demographic data would need to be collected to align any data from an app to the categories in the MRIP effort survey or at least to the level used in the MRIP intercept survey. Unlike angler license databases, the effort and intercept surveys are not dependent on the license database. App data on user demographics is a critical development that will be needed for app data to be useful in stock assessment. Should sufficient data be available then apple to apple comparisons would be made for data validation though it would be necessary to perform appropriate QAQC on app reported data. This is potentially the greatest cost associated with the use of app data. While adjustments to application design is straight forward and cost effective, database alignment and validation between applications and MRIP may require modifications to both data collection methods.

1.3 Development of protocols for ranking or evaluating angler e-Logs based on data requirements.

The following list of angler apps is listed in Venturelli et al. (2016) Fangstdatabanken, Fangstjournalen, FishBrain, Great Lakes Fish Finder, iAngler, iFish Forever, IGFA, iSnapper, Mijn VISmaat, Snapper Check. All of these apps record the minimum data listed above and more producing data that is on par with traditional creel programs at a greater spatial and temporal resolution. All of these apps are adequate in regards to the information collected. The analysis that follow in this report clearly indicated that the information collected using the iAngler app is similar to that collected in the MRIP program suggesting little difference between the data sources when and where comparison were made. Some general recommendations can be put forward in terms of developing a ranking/evaluation scheme:

- Periodically data from e-logs should be compared to other programs such as traditional logbook or creel programs. If no significant differences are found between the distributions it would seem reasonable to use the e-log data for application at the spatial extent of the data.
- Data should not be used if sample sizes are insufficient to define the statistical distribution of the data. In the analyses presented in this report direct comparisons between the statistical distribution of catch rate data were made between e-log and MRIP. A formal power analysis should be done to determine the minimum sample size when comparisons are made.
- An understanding between angler behavior as it relates to app use is essential for understanding reporting bias and to ultimately use e-log data to estimate effort. Very little work had been done to understand: the relationship between app users and the general angling population (demographics, angling avidity, angling skill), the relationship between angling avidity and reporting avidity, as well as the nature of reported trips relative to other trips.
- Data validation and alignment will be an ongoing cost of any app program but would not be cost prohibitive given the potential data gaps that could be covered by app data (e.g., greater sampling of species specific catch rates at finer spatial scales and the sampling of

discard size and locations.). The cost (i.e., incentives) of maintaining a rotating panel of sufficient size and geographic scope is currently unknown given the lack of demographic information associated with app data. Maintenance of what would likely need to be a large pool of users over a broad geographic range would likely require an expansive advertising campaign and incentives. Such programs could be maintained at a state level provided there was data harmonization between applications.

1.4 Evaluation of the potential for certification standards as determined by compliance with minimum data standards.

Given the specialized nature of many e-logs and the nature of free market enterprise it is unlikely that a single app or set of apps will have sufficient coverage to meet the requirements for all but highly localized assessments. This reality requires the development of a centralized information system to which app developers can upload data collected from users. As outlined in Venturelli et al (2016) for data collected from apps to be of use in assessment there is a need to (i) identify a minimum data set that the majority of app developers are willing to share for scientific or management purposes; (ii) adopt formal, internationally recognized, and general standards for metadata and data collection that can be applied to any angler app; (iii) identify those apps that meet some or all of these standards; and (iv) conduct research to evaluate standards. This will require the establishment of a standards council at national and international levels. Minimum data requirements have been identified above and every app would need to be certified by the council. The harsh reality is that research will need to be funded continually determine the reliability of the data provided.

1.5 Evaluation of the iAngler log devised by the Snook and Gamefish Foundation in its current form for use as a potential source of data for stock assessments. The evaluation will include:

1.5.1 Evaluation of the panel in terms of selection bias and volume of information obtained.

In general app user retention is low and the same is true for fishing apps. Generally, there is only 5% retention after 5 months. The iAngler app has a 10% retention rate after 1 year. Most users report only a single trip and a very small percentage of the users report a high volume of trips (Figure 1-1). It is reasonable to quantify the panel that participates in the iAngler app as highly variable and rapidly rotating. How some of this bias can be addressed is dealt with in section 3. No demographic data is available for the users except location.

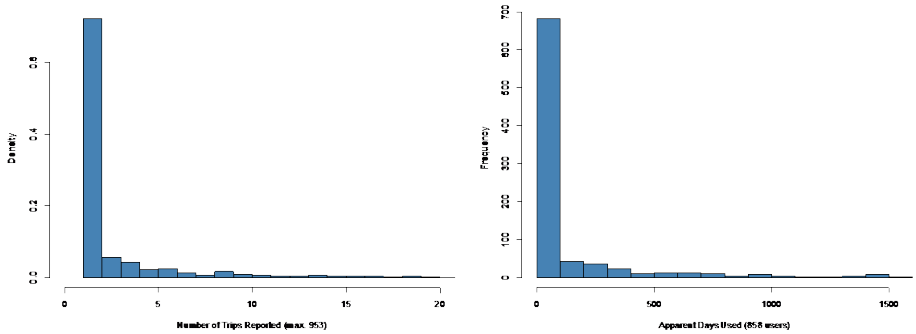


Figure 1-1 Left Panel – Number of trips reported by users of the iAngler app. Right Panel - Apparent number of days users used the iAngler app

1.5.2 Description and critique of the survey instrument and information components.

See section 3

1.5.3 Description and evaluation of data elements in terms of formatting, minimum data requirements, data quality and participant behavior (reporting patterns).

See section 3

1.5.4 Outline of improvements necessary for inclusion of iAngler data in stock assessment process.

See section 3

1.5.5 Description of practical improvements to the iAngler system that will address sources of bias in terms of data usability.

See section 3

1.5.6 Set expectations for the inclusion of iAngler data at the assessment level based on criteria for:

a. scientific defensibility – must be able to identify and/or account for bias.
b. compatibility with existing data.
c. stock assessment needs.

1.6 Assessment of recommended improvements to the iAngler system. Recommended improvements will form the basis for a set of recommended practices and minimum data requirements to be made available to entities interested in providing data for stock assessment purposes.

See section 3

Summary

The high degree of similarity between the catch rate data from the iAngler smartphone app and the MRIP survey suggests an electronic, self-reporting framework can provide information that is usable for the assessment of recreational fisheries. Thus, for fish species where iAngler has adequate sample size (e.g., common snook, spotted seatrout, red drum), the data should be useful for fishery-dependent uses in stock assessment. Although the spatial bias of iAngler makes it inappropriate for usage on a statewide level, this study used only the first two years of the app, when knowledge of the app was spread exclusively by "word-of-mouth" (Brett Fitzgerald, personal communication). The fact that the iAngler and MRIP catch/trip values were similar when compared at an appropriate spatial resolution (i.e. the county clusters) shows the ability of an electronic, self-reporting program to provide representative catch rate data. While it was clear that the avidity bias was present for some of these species in certain spatial regions, the application of a relatively elegant weighting factor can adjust for these biases provided they are understood.

A smartphone app used for collecting recreational fisheries data can be thought of as an angler diary, which has been useful for recreational fisheries managers. For example, paper-based diaries have been used to track relative abundance over time (Kerr 1996; Sztramko et al. 1991), compare a fishery before and after a change in regulation (MacLennan 1996), provide biological data (Ebbers 1987), and correct for the recall bias (Tarrant et al. 1993). Now that there is evidence of the reliability of a smartphone app framework, programs like iAngler can be used for most, if not all, of these issues—at a much smaller cost and in a form anglers appear to prefer (Baker and Oeschger 2009; Stunz et al. 2014). This type of program could even be applied to situations often addressed with a telephone survey, such as the elimination of the public access bias, which arises in creel surveys when many trips are taken from private access points (Ashford et al. 2010). Electronic, self-reporting platforms have the potential to become a valuable data collection method for many different types of questions in fisheries management.

In certain management scenarios, a fisheries manager may want to know individual catch rates, and a smartphone app such as iAngler may be reliable if the data is properly treated for angler avidity. For example, if an agency desires a certain percentage of the angling population to have a certain catch rate, this information cannot be obtained from a population-level mean CPUE. Here, it is likely best to weight each angler's contributions to the overall dataset by using the inverse of his or her avidity as the weight. Further, as Thomson (1991) showed, this type of bias can even exist in carefully implemented creel surveys. Thus, the weighting developed in

this work has applications not only to electronic, self-reporting programs, but other types of surveys as well.

One of the main strengths an app like iAngler has is the ability to provide comprehensive data on individual fish (e.g. lengths of fish, both retained and discarded), but unfortunately, such information was not submitted in high enough sample sizes in the first two years to be useful. Having information on the size structure of fish can help provide size-based indicators of the fishery's health (Shin et al. 2005). While the MRIP survey collects the lengths of retained catch, many fisheries regulated by a minimum size limit have high discard rates. In this event, a program like the iAngler app has the potential to be the main contributor of length data, as it provides the opportunity for anglers to record lengths of released fish. The importance of understanding discarding cannot be emphasized enough, as the success of the commonly applied minimum size limit regulation is hinged upon the fate of undersized discards (Coggins et al. 2007). Future studies should attempt to perform length comparisons between the MRIP survey and the iAngler dataset. For released fish, a possible avenue of research could be to compare iAngler's length distribution of discards to that of a fisheries independent survey.

Some other possibilities for future research include repeating these same analyses with a longer time series of data from the app as well as developing an understanding of the demographics and behavior of the app's users. The question of whether or not electronic, self-reporting data collection programs can provide a relative index of abundance for stock assessment would be better supported with data that comes from more than two years, as was the case with this study. By understanding the different types of anglers that contribute to the program, the data from an app like iAngler could be more appropriately utilized. For instance, changes in individual catch rates could not be safely attributed to a change in stock status if it is not known whether avidity has changed. Also, a survey could be distributed to the users of the app to determine what percentage of each angler's total number of trips were reported through the app. Many studies emphasize the impact that variable reporting rates can have on measures of effort/participation (Absher and Collins 1987; Connelly and Brown 1995; Connelly et al. 2000; Harris and Bergersen 1985; Lowry 1978; Tarrant et al. 1993).

This research has shown that electronic, self-reporting smartphone apps can provide data for recreational fisheries management that is comparable to the programs already in place. Although the spatial coverage and overall usage is insufficient for iAngler to stand alone as a primary data source, its most useful attribute will be its ability to provide novel types of data (e.g. discard data, lengths, increased spatial resolution) that will supplement recreational fisheries management.

2 Detailing the impact of under sampling of recreational catch estimation

Accurate and precise estimation of the composition and magnitude of harvest and discards from the recreational fishing sector, in particular the private recreational fishing sector, is a deficiency in many quantitative stock assessments. Most assessments rely on information from the national MRIP survey to quantify harvest and discard removals. However, the MRIP and its predecessor MRFSS were intended to quantify recreational fisheries at the national level and as a result can lead to inaccurate and imprecise estimates at the spatial scale considered for many species due to sparse sampling at finer spatial scales.

Within this section we develop a simple simulation model to demonstrate how the precision and bias of catch estimates from stratified random sampling programs such as MRIP changes as a function of the proportion of the angling population sampled. Our intent is to demonstrate that sparse sampling has the potential to severely bias catch estimates to the point of them being potentially misleading in terms of dynamic changes in the fishery. We will further demonstrate that small increases in sampling coverage can result in large improvements in estimates and that there is a potential for electronic forms of catch reporting to provide the necessary coverage to achieve the desired level of accuracy and precision for quantitative assessments.

Model Structure

To simulate data collection from a coastal fishery, 3 population centers were established along the coastline with 10 potential access points. Population density around each center was modeled as a normal distribution and distributions were combined to determine the coast wide population density. Access points were distributed in relation to modeled population density so that areas with higher population density contained more access points. A single target species distribution was modeled as a normal distribution along the coastline.

The recreational angling population was modeled by assigning each individual to a location along the coast in proportion to the simulated population density. This was necessary so that the travel cost to each access point could be calculated for each angler. Each angler was then assigned a skill level from a lognormal distribution which determined their individual expected catchability. Individual were then assigned a total number of trip taken within a season using a negative binomial distribution. Trips were assumed independent of skill level. Expected catch rate was then calculated for each angler/access point combination by averaging the target species population density over 10 spatial areas around each access point. The value of an access point was then calculated for each angler as the difference between expected catch rate and scaled travel distance. For each angler/trip combination, an access point was selected as a weighted random draw and the exact spatial location near the access point selected for fishing was assumed in proportion to the expected local catch rates with some random variation added. This process resulted in a potential sampling frame of trips as the associated catch to be potentially sampled by an MRIP type program.

To determine the weights assigned to each access point for the stratified random sampling program, expected effort at each ramp was determined assuming the value associated with the average angler. The number of samples taken was then distributed at each ramp based on the expected effort levels. The number of trips sampled varied between 1-20% of the trips taken.

Average expected catch rate and the associated standard error was calculated assuming stratified random sampling and expanded to total catch assuming the total number of trips taken was assessed accurately. Estimated total catch from sampling was then compared to the actual total catch for the simulated population. To map out the potential bias a precision of estimate of 2000 simulations were run.

Assessment of accuracy and bias

Simulation indicate that bias and precision both improve as the proportion of the total number of trips sampled increases (Figure 1-1). Standard error declined rapidly with little change in the estimate after 10% of the trips sampled. Gains in bias were less rapid but simulations suggest there are little gains beyond sampling 20% of the population. There is the potential for very large positive and negative bias in estimated catch a low proportion sampled.

These simulation results suggest that the low number of records for a number of species in the MRIP is likely to result in biased and imprecise estimates of total catch as the spatial coverage of the data is refined these biases are likely to be exacerbated. With large fluctuation in the estimated catch resulting from the sampling process and not the fishery. However, large improvement can be gained with increasing the number of trips sampled, provided these samples are representative of the potential sampling frame of trips. These results suggest that validated records from electronic reporting platform such as phone apps can increase the proportion of trips sampled and have the potential to improve the estimates of recreational catch utilized in stock assessment.

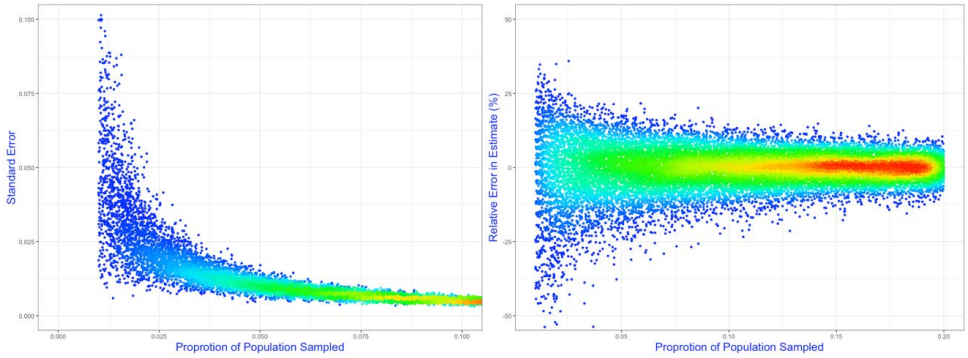


Figure 2-1 Left Panel - changes in the distribution of estimated standard error as a function of the proportion of the total number of trips sampled. Right Panel - changes in the potential bias of total catch estimated as a function of the proportion of the total number of trips sampled. Color represents the density of the distribution with blue indicating low density grading to red as high.

3.1 Phase 1 evaluation of iAngler

Background

Recreational fishing has high economic importance in the United States, with over 33 million participants nationwide, taking approximately 455 million fishing trips in 2011 (US Department of the Interior et al. 2011). This—combined with the fact that recreational fisheries can cause overfishing (Coleman et al. 2000; Post et al. 2002)—means there is a need to evaluate the recreational fishing sector during the stock assessment process. In the Gulf of Mexico, recreational landings have often exceeded commercial landings for high-profile stocks such as Red Snapper *Lutjanus campechanus* (Coleman et al. 2000) and Gag *Mycteroperca microlepis* (NOAA 2014). Other stocks such as Common Snook *Centropomus undecimalis* and Red Drum *Sciaenops ocellatus* no longer have a commercial sector, so stock assessments require data from the recreational fisheries. In order to ensure long-term sustainability of such stocks, scientists and managers need a process for gathering reliable information from recreational anglers.

Sampling recreational anglers is a challenging process that depends on the willingness of anglers to participate in data collection and the quality of data provided. A creel survey is one of the most commonly utilized methods, where interviewers are hired to collect catch and trip information from anglers. If surveys are not properly designed (e.g., stratified or random sampling), biases will occur (NRC 2006). Further, obtaining precise estimates is difficult given the broad spatial and temporal extent of recreational fishing.

Self-reported angler catches can be obtained through a variety of mechanisms. Angler diaries are a common reporting tool, where anglers record their own trip and catch information and submit it to managers. While these are less expensive to employ than creel surveys, they often suffer from poor participation rates (Cooke et al. 2000). Angler diaries also depend on the ability of anglers to accurately identify species and record information. Some organizations and agencies are attempting to take advantage of burgeoning mobile electronic technologies to address the challenges of sampling recreational anglers. Software has been designed for smartphones and digital tablets (SDTs) that allow anglers to self-report data from all aspects of their fishing trips, effectively taking the form of an electronic angler diary. One example of this is the iSnapper program piloted by a Stunz et al. (2014), which recruited for-hire boat captains to volunteer their catch information for Gulf of Mexico Red Snapper fishing trips through a smartphone/tablet app. The Snook & Gamefish Foundation has developed the Angler Action Program (AAP), which is used primarily in Florida and the Chesapeake Bay area. The original smartphone app under the AAP is known as iAngler, which began in 2012.

There is concern among most fisheries scientists that the data provided by self-reporting platforms cannot provide accurate recreational fisheries data (Didden 2012), although electronic programs specifically had not yet been tested for data reliability. The chief concern arises out of the fact that these programs do not randomly select their participants, so the data provided could be coming from a nonrepresentative portion of the angling population. If this is the case, there is a chance that such a program could produce biased estimates of metrics like catch per unit effort

(CPUE) and participation (Didden 2012). It has also been shown that, for traditional paper-based angler diaries, there is a bias created by the disproportionately higher diary usage by the more avid anglers in a fishery (Absher and Collins 1987; Connelly and Brown 1995; Connelly et al. 2000; Harris and Bergersen 1985; Lowry 1978; Tarrant et al. 1993). Thus, in order for fishery managers to be able to trust that smartphone app datasets are useful for recreational fisheries assessment, it must be shown that metrics such as angler catch rate are similar to what is seen in randomly sampled surveys, such as the Marine Recreational Information Program (MRIP) intercept survey performed by the National Oceanic and Atmospheric Administration (NOAA). These programs must also be tested for the avidity bias among its participants, and if it should be present, corrected for such a bias.

The goal of this study was to determine the utility of an electronic, self-reporting smartphone app for the purposes of recreational fisheries assessment and management. I chose the iAngler smartphone app as an example of one of these programs because of its multiple years of implementation. The two main goals of this project were 1) to determine the validity of its catch information by comparing it to the MRIP survey; and 2) to develop a method for correcting for an avidity bias. In order to assess the reliability of its catch information, I first found appropriate species and spatial resolutions for comparison and then determined whether or not the catch/trip data provided were similar to those of the MRIP survey. For the avidity bias correction, I used a simulation model to determine the best possible weighting factor and then applied it to certain stocks' catch/trip estimates in the iAngler dataset. The results of this research show the ability of electronic, self-reporting programs to contribute to the management of recreational fisheries.

The economic importance of recreational fishing in the United States engenders the need to adequately assess stocks and manage for sustainability. The conclusion that recreational fisheries have the potential to cause overfishing (Coleman et al. 2004; Post et al. 2002) means that, by law, this sector must be included in a fisheries management plan under the Magnuson-Stevens Act if the fishery exists in federal waters (generally, beyond three miles from shore). In the Gulf of Mexico, recreational landings have often exceeded commercial landings for high-profile stocks such as Red Snapper *Lutjanus campechanus* (Coleman et al. 2004) and Gag *Mycteroperca microlepis* (NOAA 2014). Other stocks such as Common Snook *Centropomus undecimalis* and Red Drum *Sciaenops ocellatus* no longer have a commercial sector, so stock assessments require data from the recreational fisheries. In order to ensure long-term sustainability of such stocks, scientists and managers need a process for gathering reliable information from recreational anglers.

Sampling and assessing the marine recreational sector is challenging. Recreational fisheries are diverse and dispersed, and monitoring on this scale becomes costly (Pereira and Hansen 2003). In addition to collecting data on the biological aspects of the stock in question, recreational fisheries scientists must also understand the vastly different attributes of the anglers themselves. For example, anglers that are highly specialized (i.e., skill, commitment) have a higher willingness-to-pay when it comes to fishing as an activity (Oh et al. 2005). More and less

specialized anglers also differ in the types of fishing (e.g., high catch rates of small fish versus exclusively large fish) they prefer (Chipman and Helfrich 1988). This information, although potentially critical, can be difficult to accurately collect.

Even when programs are implemented to sample recreational anglers, potential biases exist. Malvestuto *et al.* (1978) provided an overview of creel surveys (specifically, roving creel surveys) and developed methods for obtaining catch and effort estimates from incomplete trips. However, biases in creel survey data still exist due to limited spatial coverage of surveys (NRC 2006), as well as heterogeneous probabilities of contacting various angler types. For example, Thomson (1991) discussed how the increased sampling of more avid anglers has the potential to bias total participation estimates and economic analyses. Another potential problem exists when a fishery features users that have private access to the resource because interviewers have no way of intercepting them at a public access point (Ashford et al. 2010).

Angler logbooks, or diaries, are an alternate data source to traditional creel surveys and allow anglers to record their own fisheries data to later submit to managers. While this format theoretically eliminates the public access bias, it can still suffer from other potential problems. For instance, like intercept surveys, logbooks could have biases arising from an angler's prestige bias, or the tendency to inflate the number and/or sizes of catches. Some new sources of biases can arise with this type of program, such as nonresponse bias, poor identification of species, and inaccurate measurement. However, with proper support from an administrative body, angler diaries can provide valuable fisheries data at a much lower cost (Cooke et al. 2000).

Since 1979, the National Oceanic and Atmospheric Administration (NOAA) has been employing an access-point intercept survey combined with a telephone survey to estimate catch and effort of marine recreational fisheries. Originally known as the Marine Recreational Fishery Statistics Survey (MRFSS), it began an effectively continuous revision process in 2006 following a critique by the National Research Council; now it is known as the Marine Recreational Information Program (MRIP). The system uses telephone surveys of coastal residents for estimation of recreational fishing effort and a stratified, multi-stage cluster sample for the intercept surveys to estimate catch per unit effort (NRC 2006). Although the survey design is now believed to be largely unbiased, the fundamental challenges of sampling recreational anglers continues to provide challenges, even for such a carefully constructed process.

Recent attention has been given to developing methods of real-time data collection for fast, adaptive forms of fisheries management. This idea has become more palpable as smartphones and digital tablets have become more powerful and versatile. Because they can have built-in GPS, photography, and temperature-measuring capabilities (among many others), they have become attractive tools for data collection (Gutowsky et al. 2013). Despite concerns of durability and convenience, it is becoming more common for smartphones and digital tablets to be waterproof, physically resistant, and have solar charging and "cloud," or back-up software capabilities (Gutowsky et al. 2013). A few fisheries data collection programs of this nature have already been piloted for the recreational sector. Baker and Oeschger (2009) implemented a text-

message-based program to collect trip and catch information from for-hire captains (charter and headboats), using a compact syntax called RECTEXT. Stunz *et al.* (2014) had for-hire captains use an iPhone/iPad application (or "app") called "iSnapper" in lieu of physical papers for their mandatory reporting of Red Snapper trips. In both studies, feedback was solicited from the users of the programs, and mainly positive reviews were received, even from those who were not initially familiar with text messaging or smartphone technology. One program that has been in usage since 2012 is the Snook and Gamefish Foundation's iAngler app, yet it has not been characterized or analyzed. One main advantage these electronic self-reporting apps have over traditional sampling programs such as the MRIP is the ability to collect comprehensive information on discarded fish and improved spatial information. Given the existence of programs like these and the ever-increasing prevalence and capabilities of smartphones, electronic, self-reporting fisheries data collection programs are expected to increase in popularity in the future.

There is a need to evaluate the validity of angler-reported catches from smartphone apps with respect to traditional creel survey data. In this study, I conducted a comparative study between iAngler—a smartphone app for angler-reported trip and catch information—and NOAA's MRIP survey, with a focus on its access-point intercept survey. The objective of this study was two-fold: 1) to summarize the basic characteristics of the iAngler data set with respect to its extent of usage and participants; and 2) to make direct comparisons between iAngler and MRIP for spatial distribution of effort, most commonly caught species, and mean catch-per-trip of selected species. By determining whether or not the dataset provided by iAngler is of a similar quality to that of MRIP, I can suggest the appropriate contexts for using this self-reported data for future recreational fisheries management. This general methodology can also be used for the purposes of assessing the data quality of other opt-in, self-reporting fisheries sampling programs, which will likely become more common in the future.

Methods

MRIP

The MRIP data used in this study come from NOAA's online, publicly accessible database (http://www.st.nmfs.noaa.gov/recreational-fisheries/access-data/data-downloads/index), which contains the raw data collected in the access-point angler intercept surveys. The access-point intercept survey is hereafter referred to as the "MRIP survey," as I did not include data from the MRIP telephone survey for our analysis. Each interview is given a unique "ID code" and covers one interview, which could represent one or multiple anglers in a trip. Catch is divided into three categories and identified by species: 1) "claim" refers to all of the fish that were caught, retained, and available for the interviewer to inspect for lengths and weights; 2) "harvest" refers to all unavailable, retained catch (i.e., those filleted or used as bait and any catch that was discarded dead); and 3) "release" refers to all fish discarded alive. Spatial data include

the state and county of the trip as well as how far from shore (generally, greater or less than 3 miles, but 10 miles for the gulf coast of Florida). The mode of the fishing trip is recorded (e.g., private/rental boat, shore/beach, man-made structure, charter boat).

I specifically worked with data from 2012-2013 in the state of Florida (the first two years of the iAngler app's operation), and in some cases, worked with data by county. The species were chosen based on those that had sufficient data in iAngler (for comparisons), and those were Common Snook *Centropomous undecimalis*, Spotted Seatrout *Cynoscion nebulosus*, and Red Drum *Sciaenops ocellatus*. I then compared the data by mode (private boat mode, single-angler private boat trips, shore trips, and charter boat trips) and spatial designation (both statewide and smaller scale, "county clusters"). The "single-angler private boat" mode refers to a specific subset of the full private boat mode, and it contains trips with only a single angler in the fishing party. For trips with multiple anglers in the boat, it is difficult to allocate the retained catches between the anglers (Meaghan Bryan, personal communication). Thus, the single-angler mode was considered separately because it has the potential to provide data on an individual-angler catch rate. The county clusters were chosen based on representation in the iAngler data set and are as follows: Atlantic (Brevard, Indian River, St. Lucie, Martin, Palm Beach, and Broward counties); Ft. Myers (Charlotte, Lee, Sarasota, and Collier counties); and Tampa (Hillsborough, Pinellas, and Manatee counties).

For the purposes of counting trips, the number of trips was considered the number of "ID codes" that met the desired criteria. Whenever catch is mentioned, this refers to the total catch of all fish of a given species—for the MRIP survey, the value for total catch=claim+harvest+release. In the MRIP survey, if a trip has no catch for the given species, the interviewer can still note the primary and secondary species targeted, if applicable. In this event, I considered only the primary species sought for the purposes of calculating species-specific catch rates.

iAngler

One opt-in, electronic, self-reporting fisheries data collection program that has not been piloted or critically assessed is the Snook and Gamefish Foundation's iAngler smartphone app, which exists under its Angler Action Program (AAP). Originally implemented in 2010 as a program for collecting physical logbook data on Common Snook and uploading to a computer at home, the AAP was expanded in 2012 to smartphones, included all freshwater and marine species, and became known as iAngler (Brett Fitzgerald, personal communication). Through this app, users can submit relevant information regarding a recreational fishing trip, such as time fished, number of fish caught/released, length, weight, GPS location of fishing spots, and even a photograph of the fish. What makes it different than the programs referenced in Baker and Oeschger (2009) and Stunz et al. (2014) is the ability to collect information from all fishing modes and not just for-hire captains. However, because iAngler has not been critically assessed,

its validity is in question, even though its discard information for Common Snook has already been included in state stock assessments (Muller and Taylor 2013).

All of the iAngler data were retrieved with the permission of the Snook and Gamefish Foundation. The iAngler data differs from MRIP in that, users of the iAngler smartphone app choose to participate by their own decision, and they report all of the data through the app's interface. These data are then automatically collected and stored in the Angler Action Program database.

The number of trips in the iAngler database was considered as the number of unique "Trip IDs." Because iAngler only distinguishes between fish kept versus fish released, catch here implies total catch, which is represented by the sum of iAngler's "Quantity Caught" and "Quantity Released."

The data consisted of MRIP surveys and iAngler submissions (self-reported fishing trips, saltwater only) for the entire state of Florida from 2012 through 2013. Between these two databases, I made comparisons of number of reported trips by county, most commonly caught species, number of fish caught per trip, catch and lengths of fish caught. The number of trips will also be referred to as "effort," and the number of fish caught in a trip will be referred to as "catch/trip" or simply catch rate. Because the MRIP data are divided into catch, trip, and size (of each fish) data, I used Microsoft Access to merge relevant information pertaining to catch, location and duration of trips, and lengths of the fish caught. Likewise, I used a similar method in Access for bringing iAngler's spatial information and lengths for individual fish into the main catch dataset.

General Data Comparison

I created effort distribution maps showing each county's percent of total effort for the state of Florida for both the iAngler and MRIP datasets and compared these relative proportions using a chi-square goodness of fit test. Because MRIP surveys are weighted according to expected fishing effort, the MRIP theoretically provides an unbiased spatial distribution of effort throughout the state. Thus, any differences in spatial fishing effort distribution between iAngler and the MRIP likely indicated a bias in spatial coverage of iAngler data.

I tabulated the total number of each dataset's unique trip/intercept-survey identifier. In iAngler, there would be separate entries not only for separate species in a given trip, but also if the angler fished at different locations within that trip. For the purpose of determining the number of trips per county, I pooled the species and fishing-spot identifiers and considered them one trip. I also extracted the number of iAngler users contributing to each county to calculate a mean "submissions-per-user." In iAngler, a county that had a large number of reported trips would not be considered well-represented if they all came from a small number of anglers.

I evaluated the percentage of trips where the most common species were caught (includes kept and released fish) in each of the two datasets. This was estimated as the total number of trips and counting the top ten most commonly caught species. These percentages represented

trips where a given species was caught, and thus, the sum of these values across species would exceed 100% because it is common to catch multiple species per trip. To avoid confusion with the composition of catch, this metric will be referred to as "catch frequency."

Species-Specific Comparisons

The specific subsets for species, fishing mode, and spatial location were obtained by filtering according to state, county (when necessary), and then by species and fishing mode. All of the combinations of species (Common Snook, Spotted Seatrout, and Red Drum), mode (private boat; single-angler private boat; shore; and charter), and spatial designation (statewide, Atlantic cluster, Ft. Myers cluster, and Tampa cluster) were considered, for a total of 48 comparisons of mean catch/trip between iAngler and MRIP reported trips.

To compare the catch/trip estimates between the iAngler app and MRIP survey, I compared the mean and dispersion of each data set's catch records. A distribution of catch/trip was created by plotting the catches for a given scenario; because each catch value came from the trip level, this represented a frequency distribution of catch/trip for a species, mode, and spatial combination for the years 2012-2013. Because of the distributions' shapes, I fitted the data using a negative binomial distribution, with the mean (μ) and size (n, i.e. dispersion) parameterization (Figure 3-1; a complete list of catch/trip plots is shown in Appendix A). That is, I used the negative binomial distribution parameters to predict the behavior of the catch/trip values (Equation 3-1).

$$Predicted\ catch\ /trip = \frac{(x+n-1)!}{(n-1)!\,x!}\left(\frac{n}{n+\mu}\right)^{n}\left(1-\frac{n}{n+\mu}\right)^{x} \qquad (3\text{-}1)$$

Here, x indicates a reported catch/trip value for that given scenario (species, mode, spatial designation). I only compared data sources if both the iAngler and MRIP subsets of data had at least 30 records of catch. Each distribution was fitted using a Markov-chain Monte Carlo simulation (100,000 runs, 5,000-run burn-in period) with a Metropolis-Hastings algorithm. This created estimates for the mean and dispersion parameters of the negative binomial distribution. Using these parameters, I drew 10,000 random samples from the parameters' posterior distributions to create simulated catch/trip distributions for each species-mode-spatial combination. Then, by subtracting the MRIP distribution from the corresponding iAngler distribution, I obtained a "difference distribution" and observed the degree of overlap between them. I presented the 80% and 20% quantiles as well as the median for this resulting distribution. The 80% is included because in a likelihood ratio test framework, the 80% quantile would give an indication of the 95% confidence interval (Anderson 2007). Thus, if the 80% quantiles of a difference distribution included zero, the corresponding iAngler and MRIP catch/trip distributions were considered "similar."

I also compared length distributions of fish caught with each database using the same species, fishing mode, and spatial designation combinations as in the catch/trip analysis. Catches were divided into similar length bins (for a given iAngler-MRIP pair) and compared using a chi-

square goodness of fit test. Comparisons were not made if ≥20% of the length bins had expected frequencies less than 5. In general, there are fewer length records than the total number of fish caught. In MRIP, only fish that are retained and whole are available for length measurements, leaving out discarded fish and those already filleted. In iAngler, due to the voluntary nature of the app, not every fish that is caught and kept is measured for length. However, this information is still important because, if the length distributions of caught fish in iAngler can be shown to be similar to those of MRIP, then a length distribution of discarded fish from iAngler might be reliable—a metric not provided by the MRIP survey.

Results

General Data Comparisons

One important feature of the iAngler data is that submissions are highly variable throughout the state of Florida. From 2012-2013, the distribution of trips by county was significantly different from that of MRIP (X^2=7,609, df=34, p<0.0001), with a strong bias toward counties along the south-central Atlantic coast (Figure 2-2). The number of reported saltwater angling trips ranged from 0 (Clay, Jefferson, and Nassau counties) to 1,115 (Palm Beach), with a total of 3,572 trips (Table 3-1). For the MRIP, the number of access-point interviews by county ranged from 40 (Walton county) to 7,686 (Pinellas county), with a mean of 1,837 and a median of 1,192 interviews. Of the counties that reported trips to iAngler, the mean number of trips was 90, while the median was 16. For those same counties, the number of different users of the app ranged from 1 (Baker, Dixie, Escambia, Flagler, Franklin, Putnam, St. Johns, Wakulla, and Walton counties) to 65 (Brevard), with a mean of 14 and a median of 6. The iAngler dataset is characterized by high spatial variability, which could make it problematic if used for state-level assessment purposes.

The statewide values for catch frequency in the iAngler dataset showed a high percentage of Common Snook (*Centropomus undecimalis*), Spotted Seatrout (*Cynoscion nebulosus*), and Red Drum (*Sciaenops ocellatus*) when compared to the MRIP dataset. This is a trend throughout the data, as the iAngler app was initially created to supplement the state stock assessments with data on Common Snook and later expanded to include other species. Common Snook were caught on more than one-third of the trips reported to the iAngler app, which is more than ten times the percentage of MRIP trips reporting Common Snook catches (Table 3-2). Out of the top ten most commonly reported species from each data set, seven species were shared between the two, with only Common Snook, Yellowtail Snapper (*Ocyurus chrysurus*), and Tarpon (*Megalops atlanticus*) being unique to iAngler and Pinfish (*Lagodon rhomboides*), Hardhead Catfish (*Ariopsis felis*), and Blue Runner (*Caranx crysos*) being unique to MRIP. When the data from each sampling program were re-normalized to include only trips that reported catches of the seven shared species, there was still a significant difference between the percentages of each species in the catch (X^2=372.070, df=6, p<0.0001). The presence of seven shared species

suggests there is some degree of overlap between the trips being reported by iAngler and the trips being interviewed by the MRIP survey.

The catch frequencies for the county clusters were similar to that of the statewide scale, but with a few differences in species. In the Atlantic county cluster (southeast Florida), there were five species shared in the top ten list of most commonly caught species (Table 3-3), and when they were re-normalized and compared, their relative proportions were also significantly different (X^2=177.69, df=4, p<0.0001). This is the only case where Red Drum was not the third most reported catch in the iAngler dataset (Crevalle Jack). In the Ft. Myers county cluster, there were six species shared among the top ten species (Table 3-4), and their re-normalized relative proportions were significantly different (X^2=75.778, df=5, p<0.0001). This was the only instance where Common Snook were among the top ten most reported catches for the MRIP dataset. Finally, in the Tampa county cluster, there were 7 species shared in the top ten (Table 3-5), and their re-normalized relative proportions were significantly different (X^2=76.309, df=6, p<0.0001). This cluster had the highest proportion of Common Snook, Spotted Seatrout, and Red Drum when they are considered together. For all three county clusters, as well as at the state level, four species that were consistently shared in the top ten list of most commonly reported catches were Spotted Seatrout, Crevalle Jack (*Caranx hippos*), Gray (Mangrove) Snapper (*Lutjanus griseus*), and Ladyfish (*Elops saurus*). The differing catch frequencies in the iAngler and MRIP datasets suggests that, while there is some degree of overlap in the trips reported through each program, the relative proportions of trips targeting the various species are different. However, this does not negate the value of making comparisons on a species-by-species basis.

Because iAngler showed a strong bias toward Common Snook, Spotted Seatrout, and Red Drum—popular inshore species in Florida—these three fish were used for further comparisons with the MRIP data. Red Snapper (*Lutjanus campechanus*), Red Grouper (*Epinephelus morio*), and Gag Grouper (*Mycteroperca microlepis*) were three other species also used to assess the status of iAngler with regards to important offshore stocks.

Species-Specific Comparisons

Angler catch/trip data for all private boat mode trips showed similar means in all cases between iAngler and the MRIP (Appendix B). There were enough trips (n>30) to make catch/trip comparisons for all of the inshore species-mode combinations for all spatial designations, as well as the three offshore species at the state level (Figure 3-3). This fishing mode is the most comprehensive in the iAngler dataset. No other fishing mode had enough data from both iAngler and the MRIP to perform catch/trip comparisons for the offshore species, and so they are not further discussed. For the inshore species, all comparisons of catch/trip between iAngler and the MRIP for the private boat mode resulted in similar distributions (Figure 3-4). In all scenarios, the 20% quantiles lay to the right of zero; because I subtracted the simulated MRIP catch/trip values from the iAngler catch/trip values, this suggests the iAngler values were consistently larger across species and spatial designations. This could be due to a smaller

proportion of zero-catch trips in iAngler as opposed to that of the MRIP data. Still, Common Snook in the Atlantic county cluster, and Red Drum in the Ft. Myers and Tampa clusters were the only instances where the 20% quantile did not include zero, so there was ultimately a high degree of similarity between the two data sets' catch/trip estimates. This tendency toward zero for the 20% quantiles was seen even in some of the cases where the 80% quantiles were skewed farther to the right, which suggests the central tendency of these difference distributions was near zero regardless of the degree of overdispersion seen in the catch/trip data. Overall, the iAngler dataset provides very similar catch/trip data to the MRIP for these three inshore species.

I also evaluated the private boat mode for trips that only consisted of one angler in the party, and the catch/trip values were also similar for the three species in question. However, as mentioned before, no offshore species had enough records to fit with parameters and make a comparison. All of the inshore species had sufficient data at the various spatial designations (Figure 3-5). It appears iAngler captures proportionately more of these single-angler private boat trips than does MRIP, as evidenced by the fact that the discrepancy between the numbers of records between these two programs is generally smaller than with the whole private boat mode. The 80% quantiles of the difference distributions for this mode suggest that all corresponding catch/trip distributions are similar (Figure 3-6). Overall, the catch/trip comparisons for this mode provided a higher degree of agreement than for the entire private boat mode. The intervals are not consistently skewed toward the right, and for 8 of the 12 comparisons, the median value was zero. In light of the spatial bias on the statewide scale, it is important that the data are similar on the level of the county clusters—especially for the counties near Tampa, which have the highest effort according to the MRIP survey. The overall similarity across species and spatial designations shows that iAngler can provide catch/trip data that are comparable to that of the MRIP survey for single-angler trips taken on a private boat.

Despite having some gaps in the data for both iAngler and the MRIP survey, the shore mode catch/trip values were similar when comparisons were possible. Comparisons were not possible for any of the species in the Tampa cluster or Spotted Seatrout in the Atlantic cluster, but sufficient data existed for the other spatial designations (Figure 3-7). For the rest of the scenarios, all comparisons suggest the iAngler and MRIP catch/trip data to be similar (Figure 3-8). In 7 out of the 8 comparisons, the median catch/trip value was zero. Also, when compared to the private boat mode, the 80% quantiles for the shore mode comparisons are tighter. Taken together, these two points indicate the iAngler and MRIP data have not only similar central tendencies, but similar dispersions as well. The shore mode of iAngler has considerably fewer trips in the Tampa cluster, but actually exceeds the total number of MRIP trips for nearly all cases in the other two clusters (especially Common Snook). In these events, the mean catch rate data for iAngler are very similar to those of the MRIP survey.

Species-specific data for the charter boat mode was extremely deficient in the iAngler dataset and so are not included in the analysis. Likewise, iAngler's length data for retained catch were insufficient for the chi-square goodness-of-fit test. Thus, the length data for retained catch

for iAngler are at least insufficient to test, even for the popular inshore species—if not altogether different.

Discussion

The high degree of similarity between catch rate data from the iAngler smartphone app and the MRIP survey suggests an electronic, self-reporting framework can provide information that is usable for the assessment of recreational fisheries. Thus, for fish species where iAngler has adequate sample size (e.g., Common Snook, Spotted Seatrout, Red Drum), the data could be useful for fishery-dependent uses in stock assessment. Although the spatial bias of iAngler makes it inappropriate for usage on a statewide level, this study used only the first two years of the app, when knowledge of the app was spread exclusively by "word-of-mouth" (Brett Fitzgerald, personal communication). The fact that the iAngler and MRIP catch/trip values were similar when compared at an appropriate spatial resolution (i.e. the county clusters) shows the ability of an electronic, self-reporting program to provide representative catch rate data.

The iAngler smartphone app is analogous to paper-based angler diaries, which have been useful in recreational fisheries. Long-term angler diary programs have provided valuable information for monitoring stock status over time (Kerr 1996; Sztramko et al. 1991). In some cases, when the program runs long enough, it can be used to assess the fishery before and after a major management action such as a change in minimum length limit (MacLennan 1996). In such cases, an angler diary presents an opportunity for a "natural experiment," where managers can assess the effect regulations have on fishing behavior and stock status. Ebbers (1987) showed that angler-supplied information regarding length-frequency distributions, mortality rates, and population estimates was similar to the equivalent data obtained by fishery-independent surveys. Also, because diaries allow anglers to report data right after a trip is taken, they are not as vulnerable to a recall bias as are traditional mail surveys. In fact, diaries were used to reduce the recall bias on the mail-based Illinois Sport Fishing Survey (Tarrant et al. 1993). The simple nature of a smartphone-based "angler diary" app could conceivably replace the mail surveys and paper-based diaries if administered and monitored by a state fisheries agency. Diaries also have the advantage of addressing the public access bias, which occurs when a large number of trips in a fishery are taken from private access points. To address the public access bias in the Blue Crab (*Callinectes sapidus*) fishery in Maryland and Virginia, Ashford et al. (2010) used a telephone survey to adjust the catch rates obtained from a traditional creel survey, which missed a sizeable amount of effort coming from private sites. However, an electronic, smartphone-based reporting system would represent a simpler and cheaper method to correct this problem. Further, studies that have implemented the use of smartphone- and digital tablet-based reporting programs have noted that most participants prefer them to paper-based logbooks (Baker and Oeschger 2009; Stunz et al. 2014). Thus, if such electronic self-reporting "angler diaries" were to be employed and controlled in the same way traditional diaries are, they could prove to be an even better method for collecting information from recreational anglers.

Our study is the first to rigorously analyze opt-in, self-reported recreational fisheries data from electronic data collection (e.g., a smartphone app) with a focus on the private angling

modes. Stunz *et al*. (2014) used a smartphone/tablet app called "iSnapper" to record data from headboat and private charter boat (collectively, the "for-hire" sector) trips with a focus on the Red Snapper fishery. However, their study involved choosing sixteen captains to become involved with the program and was relatively controlled, whereas our work with iAngler has been on a dataset consisting of true opt-in participants. While their study had the added benefit of a pre- and post-use survey to gauge captains' interest in the app, it did not include an analysis of whether or not the data provided were reliable or useful for assessment (i.e. how it compared to current data collection programs). Stunz *et al.* (2014) highlighted the difference between for-hire vessel captains and the private recreational angling population, calling for a study on that specific mode, and our analysis has begun filling that gap. This study has shown that when a proper sample size of trips exists, an electronic self-reporting platform like the iAngler app could provide a valid measure of catch per unit effort. For example, as the program runs for more years, this catch rate data could be used as a time series to assess relative abundance. Additionally, because the iAngler allows for more comprehensive information on discarded fish (length, weight, hooking location, higher spatial resolution), it has the potential to augment stock assessments in a way that the MRIP survey is not capable of doing. Overall, I found the iAngler smartphone app can provide valuable recreational fisheries data for certain species, especially popular inshore species in urbanized regions of the state of Florida.

One issue with the iAngler data set was the lack of spatial coverage throughout the entire state of Florida. In general, some counties had hundreds (or even a thousand) trips, whereas some had fewer than five. This raises the question of whether this data is useful on a statewide level, as metrics such as catch rate can vary spatially (Smallwood et al. 2006). Specifically, many of the trips are concentrated in the urbanized regions, such as the southeast coast (our Atlantic county cluster) and—to a lesser extent—southwest Florida. Such information may still be useful, since Florida has already implemented "management zones" for Spotted Seatrout and Red Drum in the form of variable bag limits throughout the state (eRegulations 2015). Thus, the app's usefulness could increase if small-scale, regional management plans become more popular. However, to be useful on a larger spatial scale, the app would have to be expanded in its scope and usage. Overall, this spatial bias is not surprising, given the fact that the iAngler app has not been part of any major marketing campaign, meaning any diffusion up to this point has been due to "word-of-mouth" (Brett Fitzgerald, personal communication). If the Snook and Gamefish Foundation were to implement a marketing campaign, it might lead to a more balanced spatial distribution of effort. Any self-reporting program like this could also benefit from a partnership with the state fisheries agency, since strong administrative backing has the potential to increase the success of angler logbook programs (Cooke et al. 2000).

Another shortcoming of the iAngler data set up to 2013 was the bias in species represented in the catch records. The iAngler app does not have much data on offshore species that are recreationally important to Florida, such as those from the snapper-grouper complex. Also, in the iAngler dataset, Common Snook, Spotted Seatrout, and Red Drum represented a majority of all the saltwater fishing trip catches in the entire state of Florida. This is also not

surprising given the historical trajectory of the program. The iAngler smartphone app arose out of the Angler Action Program, which was a logbook program created in 2010 specifically for Common Snook recreational fisheries data (Brett Fitzgerald, personal communication). Because Spotted Seatrout and Red Drum are inshore species like Common Snook, it makes sense for them to be the next species that users of the app begin to report. Another important result from our study is that, judging by both iAngler and the MRIP, the composition of the various species caught can vary quite noticeably in different parts of Florida. Because Florida is so large, it is possible these results reflect changing ranges and relative abundances of fish (e.g. Common Snook are rarely seen in North Florida). However, if it is a function of different types of anglers fishing in different regions of the state, then that could be explored by iAngler should the app someday include the ability to approximate angler typologies (e.g. by collecting demographic information).

There were similarities in the catch/trip data for the three inshore species studied (Common Snook, Spotted Seatrout, and Red Drum). Previous investigations have suggested a bias in self-reported data for measures such as catch rates (Didden 2012), but in this case the catch/trip data were very similar between collection methods. The most consistently similar distributions of catch/trip between iAngler and the MRIP were for the single-angler subset of the private boat mode and the shore mode. While the comparisons for the full private boat mode were skewed to the right, they still suggested the iAngler data to be similar to the catch/trip values provided by the MRIP survey. The skew of the data could mean that iAngler users are not including their zero-catch trips as much as the rest of their trips, which would otherwise pull down the mean catch/trip estimates to be closer to those of the MRIP survey. If this is the case, such a problem could be corrected by encouraging anglers to report these trips, as they are also important for assessment. Another possibility is that the users of the iAngler app do not have as many zero-catch trips as the entire angling population, which would indicate a bias in the participants of the program. In general, these results are promising, especially for Common Snook, as the results of its 2013 stock assessment update called for supplementing the data from the private boat and shore modes (Muller and Taylor 2013). The three county clusters chosen all had agreement between iAngler and the MRIP for these three species, with the exception of the shore mode in the Tampa cluster and Spotted Seatrout in the Atlantic cluster, which lacked sufficient trips for making the comparisons. This could be a result of under-representation by iAngler, or a lack of available shore/beach fishing grounds in the three counties included in the cluster.

One possible point of contention that I address here is the issue of weighting the catch values for the catch/trip comparisons. The MRIP data includes sampling weights for each recorded interview, but they were not included in our analysis mainly because only relative values were of interest for the comparisons themselves. Weighting would not add to the utility of the results, because they would be applied equally to both MRIP and iAngler, depending on the time and location of the fishing trip. The comparisons were made with raw data from both

datasets, under the assumption that the weighting would not change the results of our fitting and simulation process.

A potential limitation of this study is the assumption that comparing the iAngler data to similar data obtained by the MRIP is analogous to comparing it to the "expected value," i.e., implying the MRIP collects a true representation of the fisheries in question. While the design of NOAA's access-point surveying program is now said to be unbiased (NOAA 2013), not all of these corrections were in place for the entirety of time covered in our analysis. For example, for 2012 (the first half of our data), interviewers were instructed to sample when activity was anticipated to be the highest and as long as they saw fit, and it was not until 2013 that consistent and randomly selected time intervals were implemented (John Foster, personal communication). Because of the constant monitoring and correction, the MRIP undergoes on an annual basis, it is paramount to know exactly how these surveys are being conducted. Each year, NOAA releases implementation updates for the design and execution of the MRIP, so that is a good way of assessing the progress and potential problems of the program should our type of comparative study be repeated in the future.

There are many avenues for future research on this subject, especially if the iAngler app is further revised to collect other important fisheries data. First, we recommend a continuation of our analysis, as two years is not long enough to capture long-term trends in the fisheries. An avenue that can be revisited in the future is a comparison of the lengths of individual fish between iAngler and the MRIP survey. Because of the short time period used (2012-2013)—and the fact that anglers are not required to report lengths of fish into the app—there were not enough length records to perform a reliable comparison. However, providing size structure information for stock assessments would be useful, especially for developing an ecosystem-based approach to fisheries management (Shin et al. 2005). Outside the scope of our study was a more in-depth look at the validity of iAngler's data on discarded fish. Unlike the MRIP survey, iAngler contains the lengths and weights of some of the discarded fish. A study that validates the accuracy of this discard information is of the highest priority, as the lengths of discarded Common Snook have already been incorporated into its most recent stock assessment (Muller and Taylor 2013). The importance of understanding discards cannot be emphasized enough, as the success of the commonly applied minimum size limit regulation is hinged upon the fate of undersized discards (Coggins et al. 2007).

Throughout the analysis, I found a few important issues that could be addressed by the iAngler app if it were to be expanded in the future. Many studies emphasize the impact that variable reporting rates can have on conclusions about effort/participation drawn from angler-diary programs (Absher and Collins 1987; Connelly and Brown 1995; Connelly et al. 2000; Harris and Bergersen 1985; Lowry 1978; Tarrant et al. 1993). One app feature that might allow us to determine a crude individual angler reporting rate for the users of the iAngler app would be an "I fished" button. This would be an easy, one-click measure that an angler might be more consistent about using than remembering and/or having the time to fill out the information from an entire fishing trip. That way, the number of fully submitted trips could be combined with the

"I fished" button to obtain a rough reporting rate for each angler. Finally, if demographic information was required—or at least solicited on a volunteer basis—much more could be learned about the users of iAngler. In addition to making a general comparison to the general angling public, this might allow research avenues to explore why, for example, there is such a lack of data pertaining to offshore reef fish.

In conclusion, I have shown the utility for the iAngler smartphone app's data with regard to various management scenarios, and its potential for supplementing data already collected by the MRIP. Because the app is also equipped to submit other metrics such as lengths and weights of released fish, GPS coordinates of catch, and condition of released fish, it has the potential to provide novel information that the MRIP is not designed to collect—even if such data are not currently robust enough for analysis. Gutowsky et al. (2013) summarize the current uses of smartphone and digital tablets for fisheries science, suggesting that growing technology and usage of smartphones will make such programs more attractive and useful as time goes on. Thus, with consistent backing and revision, the utility of electronic, self-reporting programs for recreational fisheries management has the potential to grow, making them a valuable tool for managers and users.

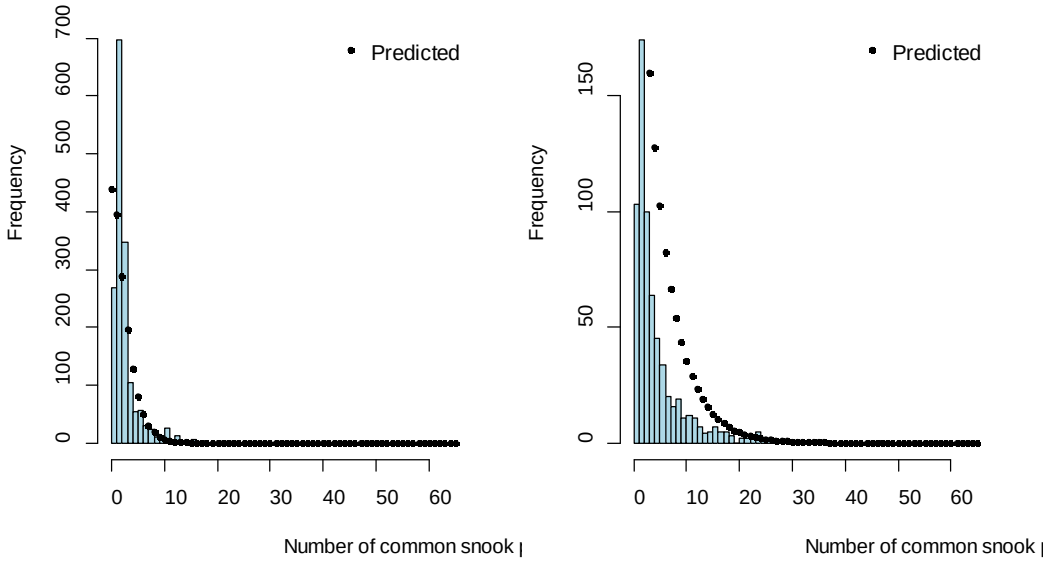


Figure 3-1. Sample plots showing the frequency distributions of number of common snook caught per trip in the private boat mode of the MRIP (left) and iAngler (right) datasets in the Atlantic county cluster, years 2012-2013. Black dots are the predicted values obtained from the fitted negative binomial distribution.

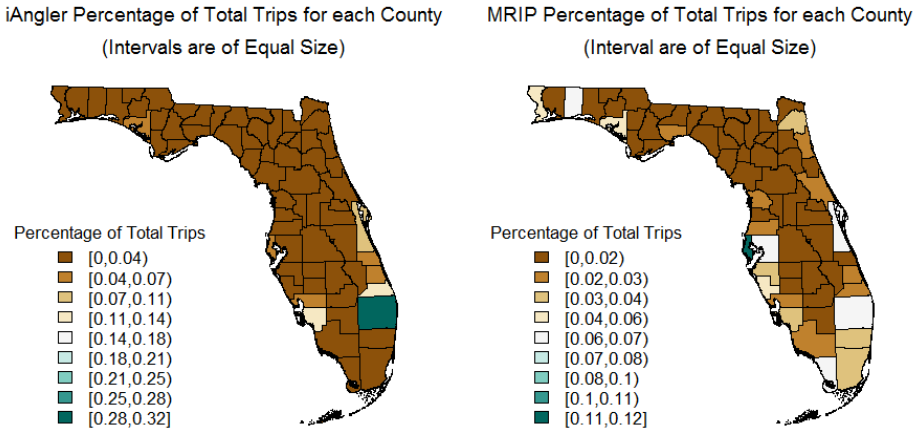


Figure 3-2. Maps comparing the distribution of trips by county between iAngler (left) and MRIP (right)

State	666/ 1930	633/ 9846	546/ 7093	71/ 1198	35/ 1427	44/ 1632
Atlantic	434/ 409	321/ 1143	259/ 883	25/ 35	7/ 62	5/ 53
Ft. Myers	91/ 684	115/ 1356	122/ 1244	0/ 9	2/ 367	4/ 219
Tampa	107/ 703	113/ 3082	105/ 1953	0/ 33	5/ 576	7/ 679
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor

MRIP poor

Both poor

Both sufficient

Figure 3-3. Summary of data quality in relation to comparing the catch/trip distributions for all private boat mode trips. Each cell contains the number of trips for iAngler (top) and MRIP (bottom), where n=30 is the minimum number of samples required to fit to a negative binomial distribution. Each color indicates which, if either, dataset had enough records.

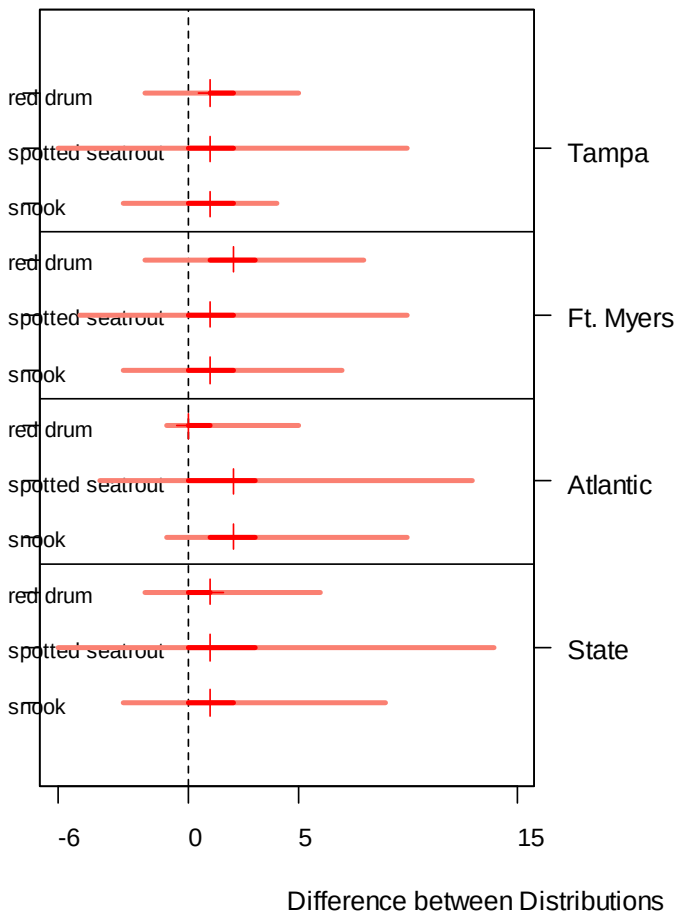


Figure 3-4. Difference between iAngler and MRIP simulated catch/trip distributions for the private boat mode. Crosses represent the median, dark red bars represent the 20% quantiles, and the light red bars represent the 80% quantiles.

State	333/ 280	325/ 1280	287/ 1108	2/ 32	1/ 59	4/ 100
Atlantic	204/ 61	165/ 144	136/ 94	0/ 0	0/ 6	0/ 2
Ft. Myers	37/ 82	68/ 163	58/ 177	0/ 2	0/ 17	1/ 18
Tampa	82/ 111	79/ 422	78/ 341	0/ 0	1/ 24	1/ 48
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor

MRIP poor

Both poor

Both sufficient

Figure 3-5. Summary of data quality in relation to comparing the catch/trip distributions for single-angler private boat mode trips only. Each cell contains the sample size for iAngler (top) and MRIP (bottom), where n=30 is the minimum number of samples required to fit to a negative binomial distribution. Each color indicates which, if either, dataset had enough records.

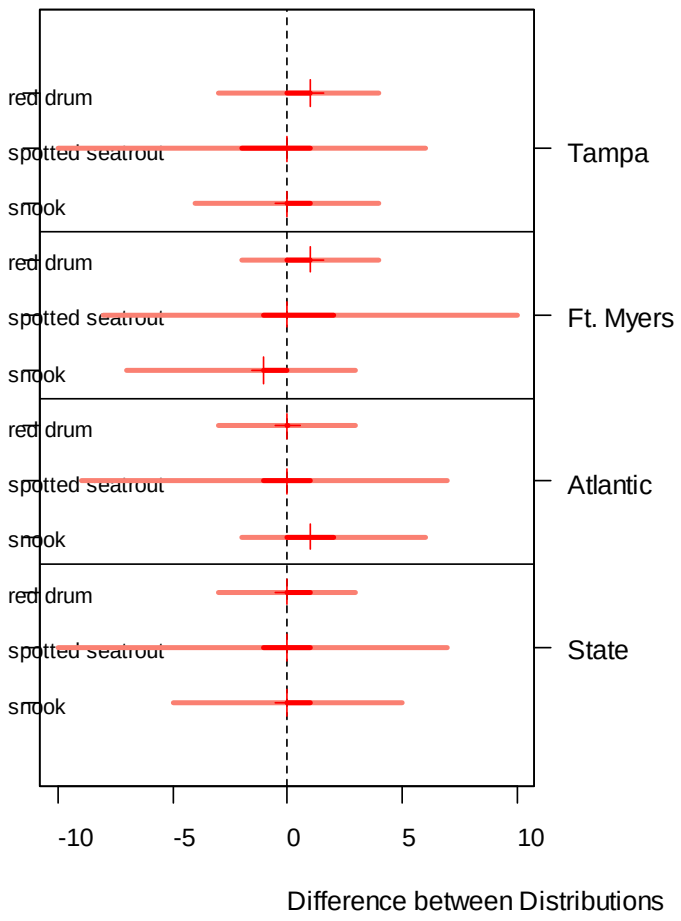


Figure 3-6. Difference between iAngler and MRIP simulated catch/trip distributions for the single-angler private boat mode trips only. Crosses represent the median, dark red bars represent the 20% quantiles, and the light red bars represent the 80% quantiles.

State	921/ 361	362/ 559	246/ 558			
Atlantic	573/ 22	123/ 29	59/ 112			
Ft. Myers	326/ 81	217/ 58	105/ 69			
Tampa	14/ 48	13/ 243	10/ 88			
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor

MRIP poor

Both poor

Both sufficient

Figure 3-7. Summary of data quality in relation to comparing the catch/trip distributions for shore mode trips. Each cell contains the sample size for iAngler (top) and MRIP (bottom), where n=30 is the minimum number of samples required to fit to a negative binomial distribution. Each color indicates which, if either, dataset had enough records. Red snapper, red grouper, and gag are not considered because they are not inshore species, where shore trips occur.

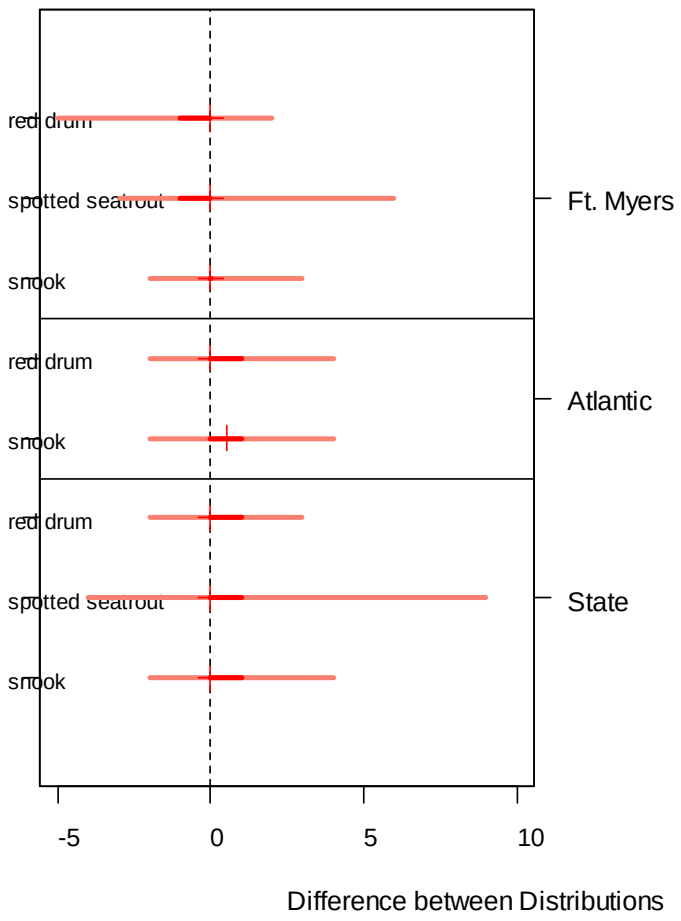


Figure 3-8. Difference between iAngler and MRIP simulated catch/trip distributions for the shore mode. Crosses represent the median, dark red bars represent the 20% quantiles, and the light red bars represent the 80% quantiles.

Table 3-1. A summary of number of saltwater angling trips per county and users reporting these trips. MRIP does not distinguish its reports by user, so there is not column for number of users or trips/user.

	iAngler				MRIP	
County	No.Trips	Proportion	No.Users	Trips/User	Trips	Proportion
Bay	127	0.035	20	6.350	3019	0.047
Brevard	316	0.088	65	4.862	3926	0.061
Broward	31	0.009	17	1.824	1725	0.027
Charlotte	170	0.047	16	10.625	1077	0.017
Citrus	22	0.006	9	2.444	1192	0.019
Clay	0	0.000	0	0.000	50	0.001
Collier	43	0.012	17	2.529	1376	0.021
Dixie	27	0.008	1	27.000	285	0.004
Duval	11	0.003	8	1.375	2265	0.035
Escambia	1	0.000	1	1.000	3392	0.053
Flagler	2	0.001	1	2.000	371	0.006
Franklin	4	0.001	1	4.000	443	0.007
Gulf	20	0.006	6	3.333	414	0.006
Hernando	3	0.001	3	1.000	804	0.013
Hillsborough	99	0.028	31	3.194	3679	0.057
Indian River	124	0.035	16	7.750	828	0.013
Lee	381	0.106	39	9.769	2160	0.034
Levy	10	0.003	2	5.000	777	0.012
Manatee	29	0.008	10	2.900	2555	0.040
Martin	398	0.111	52	7.654	1475	0.023
Miami-Dade	21	0.006	14	1.500	2213	0.034
Monroe	100	0.028	34	2.941	4263	0.066
Nassau	0	0.000	0	0.000	471	0.007

Okaloosa	10	0.003	6	1.667	3875	0.060
Palm Beach	1115	0.311	50	22.300	3896	0.061
Pasco	10	0.003	6	1.667	1130	0.018
Pinellas	177	0.049	55	3.218	7686	0.120
Santa Rosa	4	0.001	2	2.000	604	0.009
Sarasota	101	0.028	21	4.810	3061	0.048
St. Johns	3	0.001	1	3.000	894	0.014
St. Lucie	125	0.035	33	3.788	1169	0.018
Taylor	6	0.002	3	2.000	674	0.010
Volusia	73	0.020	24	3.042	1548	0.024
Wakulla	1	0.000	1	1.000	952	0.015
Walton	1	0.000	1	1.000	40	0.001

Table 3-2. Comparing the percentage and number of trips where each species was caught on the state level

iAngler (3,573 total trips)			MRIP (64,289 total trips)		
Species	Percentage of trips caught	Number of trips caught	Species	Percentage of trips caught	Number of trips caught
Common Snook	38%	1372	Spotted Seatrout	14%	9029
Spotted Seatrout	25%	891	Pinfish	9%	5976
Red Drum	18%	628	Gray Snapper	7%	4647
Crevalle Jack	10%	342	Ladyfish	7%	4428
Gray Snapper	6%	218	Red Drum	7%	4239
Ladyfish	6%	217	Crevalle Jack	6%	3737
Spanish Mackerel	3%	121	Hardhead Catfish	5%	3415
Yellowtail Snapper	3%	120	Spanish Mackerel	5%	3136

Tarpon	2%	87	Red Snapper	5%	3012
Red Snapper	2%	72	Blue Runner	4%	2693

Table 3-3. Comparing the percentage and number of trips where each species was caught for the Atlantic county cluster

iAngler (2,107 total trips)			MRIP (13,019 total trips)		
Species	Percentage of trips caught	Number of trips caught	Species	Percentage of trips caught	Number of trips caught
Common Snook	44%	929	Crevalle Jack	10%	1318
Spotted Seatrout	20%	430	Spotted Seatrout	7%	931
Crevalle Jack	11%	226	Little Tunny	7%	894
Red Drum	9%	199	Blue Runner	7%	858
Gray Snapper	6%	116	Gray Snapper	6%	760
Yellowtail Snapper	5%	101	Hardhead Catfish	5%	670
Tarpon	2%	44	Ladyfish	5%	591
Mutton Snapper	4%	80	Dolphin (Mahi)	4%	483
Ladyfish	4%	77	Bluefish	3%	436
Blue Runner	2%	52	Pinfish	3%	428

Table 2-4. Comparing the percentage and number of trips where each species was caught for the Ft. Myers county cluster

iAngler (694 total trips)	MRIP (6,298 total trips)

Species	Percentage of trips caught	Number of trips caught	Species	Percentage of trips caught	Number of trips caught
Common Snook	37%	258	Spotted Seatrout	22%	1387
Spotted Seatrout	33%	230	Gray Snapper	15%	921
Red Drum	26%	183	Red Drum	12%	749
Ladyfish	13%	89	Ladyfish	11%	716
Crevalle Jack	11%	74	Pinfish	11%	685
Spanish Mackerel	7%	51	Common Snook	9%	537
Gray Snapper	4%	29	Hardhead Catfish	8%	523
Tarpon	3%	21	Sheepshead	8%	477
Gulf Flounder	3%	18	Red Grouper	7%	447
Florida Pompano	2%	17	Crevalle Jack	7%	430

Table 3-5. Comparing the percentage and number of trips where each species was caught for the Tampa county cluster

iAngler (304 total trips)			MRIP (13,920 total trips)		
Species	Percentage of trips caught	Number of trips caught	Species	Percentage of trips caught	Number of trips caught
Common Snook	44%	133	Spotted Seatrout	21%	2958
Spotted Seatrout	43%	132	Pinfish	19%	2603
Red Drum	37%	111	Ladyfish	10%	1451
Gray Snapper	9%	26	Red Grouper	9%	1319

Spanish Mackerel	7%	22	Spanish Mackerel	9%	1253
Crevalle Jack	7%	21	White Grunt	8%	1146
Ladyfish	6%	18	Red Drum	8%	1124
Gulf Flounder	6%	18	Gag	7%	957
Gag	4%	11	Gray Snapper	7%	909
Tarpon	3%	8	Crevalle Jack	6%	899

3.2 Assessment of potential angler avidity bias correction

Introduction

Florida contains the largest recreational fisheries in the USA, and in some cases, recreational catches have surpassed the landings of Florida's commercial fisheries (Coleman et al. 2004). One of the recommendations made in the National Research Council's 2006 review of recreational survey methodology was to explore the potential for using panel survey methodology (i.e. survey with specific pool of potential recipients) to obtain fisheries information to help meet the data demands required for adequate assessment of the population impacted (NRC 2006). These panel programs are intended to inform data deficiencies in current sampling methods such as access-point angler-intercept surveys (e.g. National Oceanic and Atmospheric Administration's [NOAA] MRIP dockside survey) and telephone surveys (e.g. NOAA's MRIP phone survey). These panels can take the form of mail-in surveys, angler diaries/logbooks, and more recently, electronic self-reporting angler logbooks in the form of smartphone and digital tablet (SDT) "apps." Statistical considerations concerned with panel recruitment and maintenance were discussed recently at an MRIP-funded workshop on "Opt-In" angler panels (Didden 2012). Currently there are no minimum standards for how panels/survey participants are constructed (i.e., recruited), the types of data collected, or the units reported.

One reason SDTs have become platforms for fisheries reporting is because of their growing reliability and technical capabilities (Gutowsky et al. 2013). Another advantage is that they have the potential to provide real-time data to fisheries managers. One such example was an SMS text-message-based program that was piloted to allow for-hire captains in North Carolina to send shorthand reports of their catch information to an online database (Baker and Oeschger 2009). Another program is an iPhone/iPad "app" called "iSnapper" that for-hire captains in the Gulf of Mexico can use instead of traditional logbooks to report their trip and catch information (Stunz et al. 2014). Both of these studies note generally positive reviews from the users of the pilot studies, even those who were not initially familiar with the platform that was used. One program that is available to all recreational anglers is the Snook and Gamefish Foundation's "iAngler" smartphone app. Originally developed as the Angler Action Program for the Common Snook *Centropomus undecimalis* fishery, it has since been expanded to include all species and areas, both freshwater and saltwater. The iAngler app is one such platform under the Angler Action Program, which features other specialized apps, such as Chesapeake Catch (for recreational fishing trips in the Chesapeake Bay area).

Each type of sampling scheme has its own set of strengths and weaknesses, and the challenge for fisheries professionals is to identify these weaknesses and correct for them. Some common biases in recreational fisheries sampling programs are prestige bias, public access bias for intercept surveys (Ashford et al. 2010), recall bias, nonresponse bias, and avidity bias. The nonresponse bias occurs when participants in a program exhibit different fishing behavior from those who choose not to participate in the program. For example, when comparing a 12-month mail survey with a phone follow-up for the nonrespondents and a quarterly phone survey,

Connelly et al. (2000) found that estimates of mean number of days fished were higher among respondents than nonrespondents—leading to an inflated estimate of fishing effort. Tarrant et al. (1993) used a phone survey to contact nonrespondents of mail surveys and angler diaries and found that initial respondents reported fishing nearly twice as many days as those who did not respond. In fact, the nonresponse of less avid anglers generally leads to estimates of total participation that are too high (Absher and Collins 1987; Connelly and Brown 1995; Connelly et al. 2000; Harris and Bergersen 1985; Lowry 1978). Managers who want to perform economic analyses might then overestimate the value a fishery has if effort is artificially inflated. Likewise, if fisheries scientists combine total effort with CPUE estimates derived from creel surveys, the inflated estimates of total effort could lead to biased estimates for total catch for the fishery.

Using multiple studies to validate each other is the most common way to address these biases. For example, phone surveys are an effective way to correct for nonresponse and public access bias (Ashford et al. 2010; Connelly et al. 2000; Tarrant et al. 1993). Angler diaries can be used to address the recall bias inherent in mail surveys (Connelly and Brown 1995). Thus, while every method has a vulnerability to certain biases, each can often be used to fill the gaps of another tool. Because electronic, self-reporting platforms, such as those on apps and tablets, are analogous to angler diaries, they are likely prone to suffer from similar biases. However, it also means they could serve as a validation tool if distributed appropriately.

Despite the growing popularity of using smartphones and digital tablets as tools for fisheries data collection (Gutowsky et al. 2013), it remains unclear to what extent these biases are present in self-reporting, electronic sampling platforms. While it is generally assumed these same biases exist as in other self-reporting programs such as angler diaries (Didden 2012), a smartphone app has potentially important differences from its paper counterpart. The real-time capability of a smartphone- or digital tablet-based logbook theoretically reduces or eliminates the effect of the recall bias, assuming anglers report in real-time. An unanswered question is then whether or not a nonrespondent or avidity bias is present. It is possible that the decreased time investment of an electronic reporting system would make all users more likely to use the platform, especially since there is nothing to be physically mailed out or further reported after the data is entered.

The propensity of anglers to self-report data can vary within an angling population, and this can bias catch rate estimates if those reporting more frequently have different catch rates than those reporting less. For example, anglers submitting information through a mail-based survey exhibited a mean CPUE twice as high as the estimate obtained from a creel survey (Carline 1972). However, angler avidity does not bias catch rate data in a stratified random creel survey because the probability of being sampled is naturally tied to one's contribution to the overall angling population. The relative number of trips reported by each user in a program such as iAngler does, in fact, have the potential to bias catch rates.

In this paper, we look to explore the effect of angler avidity in the iAngler smartphone app data for two reasons. First, this dataset has not been piloted or critically assessed in relation

to the characteristics of its users, so any assumptions of avidity bias for such a program do not yet have scientific backing. Second, citizen science recreational fisheries sampling programs such as this require evaluation of potential biases in angler catch rates, and avidity may be the most likely bias. Our objectives are to 1) determine if the iAngler dataset contains avid reporters; 2) use a simulation-evaluation framework to determine the proper treatment of self-reported data for calculating mean catch rates; and 3) see how much the avidity bias impacts mean catch rates estimates in the iAngler dataset.

Methods

Data

We received data from the Angler Action Program's iAngler database, courtesy of the Snook and Gamefish Foundation. This consisted of recreational fishing trips from 2012-2013, and we focused this analysis on three clusters of adjacent counties in the state of Florida because the iAngler dataset has a spatial bias in effort on the statewide level (Jiorle et al). These clusters are indicated as follows: the "Atlantic" cluster (Brevard, Indian River, St. Lucie, Martin, Palm Beach, and Broward counties); "Ft. Myers" cluster (Charlotte, Lee, Sarasota, and Collier counties); and "Tampa" cluster (Hillsborough, Pinellas, and Manatee counties). By tabulating the number of records associated with each user, we determined the number of reported trips per angler as well as an angler-specific mean catch rate ("catch/trip" or catch rate) for each species. The number of trips per angler indicates how dispersed the data are among the users, and if these users with an above-average reporting rate have different mean catch rates, then an avidity bias will be present. Whether or not the avid reporters have a higher, lower, or similar catch rate to the rest of the users will determine the presence and extent of the bias itself.

Simulation-Evaluation

We developed a simulation to compare methodologies aimed at estimating overall angler-CPUE, recognizing that both zero-catch trips and angler avidity will introduce bias. To generate trip-level data, we first assumed that angler avidity was proportional to an individual angler's mean expected catch rate. Angler mean expected catch rate over the angling population of 100 anglers was assumed to follow a log-normal distribution with a population mean and standard deviation (Figure 3-9). Bootstrap sampling of the angler population with replacement in proportion to their avidity generated 1,000 trip records. For an individual trip record from an individual angler, reported catch rate was randomly drawn from a Poisson distribution with a mean equal to the individual angler's expected catch rate. This process resulted in a distribution of reported catch rates that can be described by a negative binomial distribution (Figure 3-10).

Working under the assumption that average angler catch rate is likely to follow a log-normal distribution and reported catch rates are over-dispersed relative to this distribution, five

models were evaluated to determine the most appropriate method for recovering the overall population mean expected catch rate. When calculating the adjusted mean catch/trip, we used a geometric mean (as opposed to the arithmetic mean) that more accurately reflects the central tendency when the distribution is skewed (Smothers et al. 1999). Also, because real-world fisheries data has many zero-catch trips, it is necessary to treat the positive-catch and zero-catch trips separately, as the logarithm function cannot be applied to zero. Habib (2012) derives geometric mean calculations for data that includes zeros:

$$g = \frac{n_+ g_+ + n_0 g_0}{n} = \frac{n_+}{n} g_+ \tag{3-2}$$

where g is the weighted average geometric mean, n is the total number of samples, g_+ and g_0 are the geometric means of the positive and zero values, respectively (note $g_0=0$), and n_+ and n_0 are the numbers of positive- and zero-catch trips, respectively. This method more explicitly accounts for the presence of zero-catch trips when calculating mean catch rates.

We assumed that the reporting rate (i.e. number of trips reported) of a given angler was a measure of the angler's avidity, and weighted the geometric mean using avidity as a "penalty." Thus, in our simulation, anglers who reported more trips had their average catch rate weighted less than a less avid angler to correct for potential avidity bias. First, we accounted for the avidity related to non-zero-catch trips with

$$W_+ = \frac{1}{v} \tag{3-3}$$

where $W+$ is the weight for a given non-zero-catch trip and v is the associated avidity (equivalent to that angler's reporting rate, or number of trips reported). To create the overall weighting factor W, which accounts for all trips, we used

$$W = \frac{W_+}{\sum_{i=1}^{k} \frac{1}{v_i}} \tag{3-4}$$

where v_i is the avidity associated with all trips, and k is the number of reported trips. Thus our equation for calculating avidity-adjusted geometric mean G for the angling population's catch/trip was

$$G = \frac{n_+}{n} e^{\sum_{j=1}^{k} W \log r_j} \tag{3-5}$$

where r_j is the reported catch/rate for a given report. This geometric mean calculation that accounts for zero-catch trips and avidity was compared against a geometric mean accounting for zeros but not angler avidity and a geometric mean from only positive records. Two negative binomial models were also fit to the data, one accounting for angler avidity and the other with no weighting. This simulation was conducted for three levels of variability within individual-angler expected catch rates. Because angler ability was distributed log-normally, this variability was determined by the distribution's standard deviation, which we assigned σ=0.2, 0.5, and 0.8. Overall, the method that came closest to match the true mean (i.e. reduced the avidity we introduced) was considered the best for treating real data that may suffer from this type of bias.

Application to iAngler Data

Using the zero-adjusted, avidity-adjusted geometric mean from the simulation-evaluation, we calculated adjusted catch/trip estimates for three inshore species—Common Snook *Centropomus undecimalis*, Spotted Seatrout *Cynoscion nebulosus*, and Red Drum *Sciaenops ocellatus*—that had sufficient records in the iAngler dataset. While this process is similar to the process used in simulation described above, one difference is that we had no need to derive our reporting from the angler's mean catch rate since the number of trips per user is given by the dataset. We considered the subset of the private boat fishing mode trips that only consisted of a single angler to avoid complications regarding the allocation of fish among multiple members of a fishing party. These geometric means, adjusted for zero-catch trips and angler avidity, were compared to geometric mean catch/trip estimates that only accounted for zero-catch trips (a "raw" geometric mean). We also calculated raw arithmetic means as well as avidity-adjusted arithmetic means. The comparison of an arithmetic versus geometric mean allowed us to determine whether expected angler catch rates were log-normally distributed. The comparison of raw to avidity-adjusted means allowed us to determine whether or not angler avidity was biasing the data set.

Results

Summary of iAngler Data

For all saltwater trips in the state of Florida from 2012-2013, there were 402 users of the app, who reported a total of 3,573 trips, but just 56 of the users reported 77.5% of all the trips. The mean number of reports for each user was 8.89 trips, yet the median was only 2 trips. For Common Snook trips that fell under the private boat, single-angler designation, there were 69 users who reported 330 total trips, and 12 of the users accounted for 66.1% of those trips. Likewise, for Spotted Seatrout trips that fell under the private boat, single-angler designation, there were 60 users who reported 323 trips, yet 7 of the users reported 72.1% of the trips. Finally, for Red Drum trips that fell under the private boat, single-angler designation, there were 59 users who reported 283 trips, and 8 of those users reported 72.1% of the trips. All of these data suggest there are a small number of avid anglers using the iAngler app that account for a majority of the trips. As a result, there is a need to investigate to what extent this fact might be impacting the mean catch rate for these three species.

Simulation-Evaluation

The simulation-evaluation determined that the zero-adjusted, avidity-adjusted geometric mean has the most potential to approximate a true mean catch rate when avidity is present. In the low variability case (σ=0.2), all of the estimation methods fall primarily within 20% of the true mean, with the exception of the unadjusted (non-zero-catch trips only) geometric mean (Figure 3-3). In fact, for the avidity-adjusted negative binomial mean, the first and third quartiles contain zero, where 0% deviation indicates the true mean was fully recovered. The regions of 1.5 times the interquartile ranges for the zero-adjusted geometric mean and the unadjusted negative binomial mean include the 0% deviation. Overall, at this low amount of variability in angler ability, the negative binomial fitting process appears to approximate the true mean better than the geometric mean processes.

In the moderate variability case (σ=0.5), the zero-adjusted, avidity-adjusted geometric mean best approximated the true mean catch/trip, although the zero-adjusted geometric mean and avidity-adjusted negative binomial mean also performed well (Figure 3-4). Once again, the unadjusted geometric mean provided the poorest approximation for the true mean catch rate. This suggests that, at low and moderate variability in expected angler catch rates, the number of zero-catch trips has a large impact on the estimated mean. Meanwhile, adjusting for avidity does not lead to as large of a change.

In the high variability case (σ=0.8), the zero-adjusted, avidity-adjusted geometric mean was the best approximation for the true mean catch/trip, with 1.5 times the interquartile range including the 0% deviation (Figure 3-5). The avidity-adjusted negative binomial mean was a reasonable approximation, but the other three techniques featured deviations of 100% or more. In this instance, the addition of adjustments for zero-catch trips did not have as much of an effect as the other two cases, while adjusting for avidity led to a more noticeable drop in percent deviation. This is likely a result of avidity being a more powerful effect with more variable (i.e. higher) catch rates that are being reported by the avid anglers.

The standard deviations from the zero-adjusted, avidity-adjusted geometric means flip from a positive deviation in the low variability scenario (σ=0.2) to negative deviations in the moderate (σ=0.5) and high (σ=0.8) variability scenarios (Figure 3-6). In other words, as the expected catch rates of anglers become more dispersed, this particular geometric mean technique predicts proportionately less variation in reported catch/trip values—going from overestimating the variance to underestimating it.

Application to the iAngler Dataset

Overall, the effect of zero-catch trips and avidity in the iAngler dataset influenced mean catch rate estimates for all three species considered. In all situations, the raw geometric mean

provided a lower value than the raw arithmetic mean. In nearly all regions and years, the addition of the zero-adjusted, avidity-adjusted geometric mean (as compared to a raw geometric mean) resulted in smaller catch/trip estimates, suggesting that the avid anglers in the dataset had higher catch rates than the rest of the users. For example, in the Common Snook data, all scenarios except Ft. Myers in 2012 and Tampa in 2013 had lower mean catch rates after avidity weighting was introduced (Table 3-6). Likewise, for Spotted Seatrout, the avidity weighting led to smaller mean catch rates in five of six cases; in the event where the weighted catch rate was higher (Tampa 2013), this suggests the avid anglers had lower catch rates than the rest of the app's users (Table 3-7). For Red Drum, the avidity weighting decreased the mean catch rate in four cases, increased it in one case, and had roughly no difference for one case (Table 3-8). The fact that Red Drum was affected differently (to a lesser extent) than Common Snook and Spotted Seatrout shows that the impact of avidity is not necessarily constant across species in the iAngler dataset.

Discussion

The presence of avidity in electronic, self-reporting data collection programs can bias the mean catch rates for an angling population. However, we developed and tested a simple method to mitigate it. The use of geometric means versus arithmetic means illustrated the effect that extreme values of catch/trip can have on accurate estimation of the true central tendency of the data. Meanwhile, adjusting for avidity by using the inverse of reported trips showed that anglers who report many trips have different average catch rates that bias the population level values. Further, this bias needs to be measured, as the effect is not always consistent across species.

We believe our simulation and mean calculation are well justified. From our simulation, we chose to apply the zero-adjusted, avidity-adjusted geometric mean over the avidity-adjusted negative binomial mean because it appeared to approximate the mean better when there are highly dispersed catch/trip records. This dispersion appears to be the case in many instances with data that come from a self-reporting app like iAngler (Jiorle et al.). However, the avidity-adjusted negative binomial mean calculation might be better for fisheries that exhibit low, consistent catch rates among its angling population. Our choice to use a geometric over an arithmetic mean is based on the assumption that angler ability (i.e. catch rates) are log-normally distributed and thus skewed, and in such cases, the geometric mean is the more appropriate choice (Smothers et al. 1999). For example, in our simulation, when our log-normally distributed angler expected catch rates were treated with a Poisson distribution to obtain reported catch/trip values, the resulting distribution appeared to be negative-binomially distributed. This is the general shape of reported catch/trip values in both iAngler and NOAA's MRIP intercept survey (Jiorle et al.), suggesting our assumptions agree with empirical data. Following Habib (2012), we calculated our weighted geometric mean by accounting for zero-catch trips separately. Our choice to use the inverse of reporting rates as the avidity weighting is supported

by correlations of response in sampling programs and catch rates in fisheries literature (Carline 1972).

The simulation-evaluation showed a strong relationship between variability in angler expected catch rates and the impact that the addition of avidity weighting had on mean catch rates. For example, the difference in percent deviation between the zero-adjusted geometric mean and zero-adjusted, avidity-adjusted geometric mean grew at higher standard deviations. This would suggest that the addition of avidity weighting had a larger impact when there existed a small group of anglers who caught a lot of fish and were biasing the unadjusted estimates. A similar relationship was seen between the unadjusted negative binomial fitted mean and the avidity-adjusted negative binomial mean. Also, as variability increased, so too did the accuracy of the zero-adjusted, avidity-adjusted geometric mean. However, the ability to accurately estimate the variance did not improve. Given the underlying log-normal structure that we worked with, it is likely that the low variability (σ=0.2) in angler expected catch rates created a distribution that was too close to a normal distribution, leading to an overestimation of the variance by the geometric mean. As the variability was increased, the data then become too dispersed for the log-normal structure, leading to underestimates of variance.

In the three species observed from the iAngler dataset (Common Snook, Spotted Seatrout, and Red Drum), adjusting for zero-catch trips, log-normal distribution of angler ability (i.e. skewed data), and angler avidity resulted in changes in mean population catch rates in most county clusters and years observed. While each species had spatial regions and years where the avidity weighting had a relatively larger effect (>20% change), Red Drum catch rates appeared to be the most robust to the weighting (3 instances of a <10% change). This would imply that, out of the three species' data in the iAngler dataset, Red Drum was the one least impacted by the avidity bias. Most importantly, these results show that the avidity bias is not constant—and sometimes not even noticeable—across species or spatial components of a fishery, even within a reporting platform assumed to exhibit such a bias (Didden 2012).

Although this study focused on electronic, self-reporting programs (e.g. iAngler), this same method could be applied to other data collection programs such as angler diaries or logbooks. Nonresponse, which is similar to avidity, has been shown to plague mail surveys/angler diaries, often leading to highly inflated levels of total effort (Absher and Collins 1987; Connelly and Brown 1995; Harris and Bergersen 1985; Lowry 1978). If those who fill out and return angler diaries are predominantly more avid anglers, then their numbers of reported trips could be used as a measure of avidity; from here, the zero-adjusted, avidity-adjusted geometric mean could determine whether or not these avid anglers are inflating the mean catch/trip of the angling population through differential reporting. While a properly stratified creel survey (e.g. NOAA's MRIP dockside survey) should not suffer from this avidity bias when calculating mean catch rates, the increased sampling of high-frequency users (i.e. general avidity) can affect economic analyses and estimates of total participation (Thomson 1991). This effect is likely not a problem for estimating total harvest, as the increased sampling of avid anglers represents their larger contribution to the total catch.

The importance of the avidity bias ultimately depends on how the catch rates are used in a management framework. If they are meant to track relative abundance over time, the magnitude of the mean (i.e. number of fish caught) will not be as important, granted the amount of avidity is not changing over time. However, with regards to electronic reporting platforms such as iAngler, some novice anglers use the app to help them keep track of successes and failures in their fishing practices (Brett Fitzgerald, personal communication). If this practice becomes more popular, it could become a scenario where avidity is changing, and that could confound the catch rates as an index of abundance. If the catch rates are being used to dictate management goals, then there is a danger when using unadjusted mean catch rates. For example, if an agency's goal for a successful sport-fishery is considered achieved when the mean catch rate reaches three fish/trip, then success would be declared prematurely if differential reporting of avid anglers inflates the catch rate artificially. Managers will need to be specific about how they plan to use data from these electronic, self-reporting platforms because that may determine the proper statistical treatment of the data.

Understanding the representativeness of contributors to an opt-in, self-reporting program is difficult because such programs have no defined panel, or sampling frame (Didden 2012). In other words, the number and composition of participants is always changing, and there is no easy way of knowing the extent to which they are contributing to the dataset. One possible way to work around this uncertainty would be by obtaining demographic information from everyone who signs up for the program. That way, scientists could make inferences about the users based on attributes such as county of residence, age, and socioeconomic status. It would also be beneficial to know what percentage of a given user's total fishing trips taken is reported to the app. In our study, the assumption that more reported trips implies more trips taken is not assessed. However, it is possible, for example, that an angler reports all eight of his or her trips and would thus incorrectly be considered more avid (and weighted inappropriately) compared to an angler who reports five out of his or her twenty total trips taken in that time period. It is this possibility that makes the "avidity" discussed here different from the avidity discussed in Thomson (1991), which is based more directly on the frequency of usage. Such unknowns have the potential to compromise the utility of this analysis for treatment of catch rate data.

There are two adjustments that can be made to the actual treatment of the iAngler data in this study. For example, the assessment of the data was done by assigning a weighting factor for a user and considering each trip, whereas our simulation was done by having each angler's expected catch rate contribute to an overall log-normal distribution of angler catch rates. Thus, a possible extension of this work could be to apply fully this hierarchical Bayesian framework of the simulation to the treatment of the data, where mean angler expected catch rates are assumed to come from a log-normal distribution with a hypermean and hypervariance. The observed catches for a given angler would be assumed to be Poisson-distributed, with the Poisson mean coming from the expected catch rate of the hyperdistribution. This is another way to address the avidity (as opposed to just the weighting) because each angler's behavior will only be considered once for the overall estimation of a population's mean catch/trip. Also, since the catch rate

distributions in the iAngler dataset appeared to be negative-binomially distributed, another adjustment to the model could be replacing the log-normal structure of angler catch rates with a gamma distribution, since it is the mixing of the gamma and Poisson distributions that ultimately produces a negative binomial structure.

We have shown the utility of a geometric mean for calculating mean catch/trip, with an avidity weighting based on individual-angler reporting rates by applying it to an opt-in, self-reporting smartphone app for recreational fisheries data. As these programs become more popular for collection of fisheries data, it will be critical to assess to what extent the users of the apps are biasing the estimates of mean catch rates. In the future, it would be beneficial to combine a study on angler avidity with the demographics of an app's users. This way, scientists and managers could have a more complete understanding of how closely the app's clientele represents the angling population, and how this representation might change over time as the app grows or shrinks. This will ensure that such data is being used in the most reliable way possible as managers try to incorporate it into recreational fisheries management.

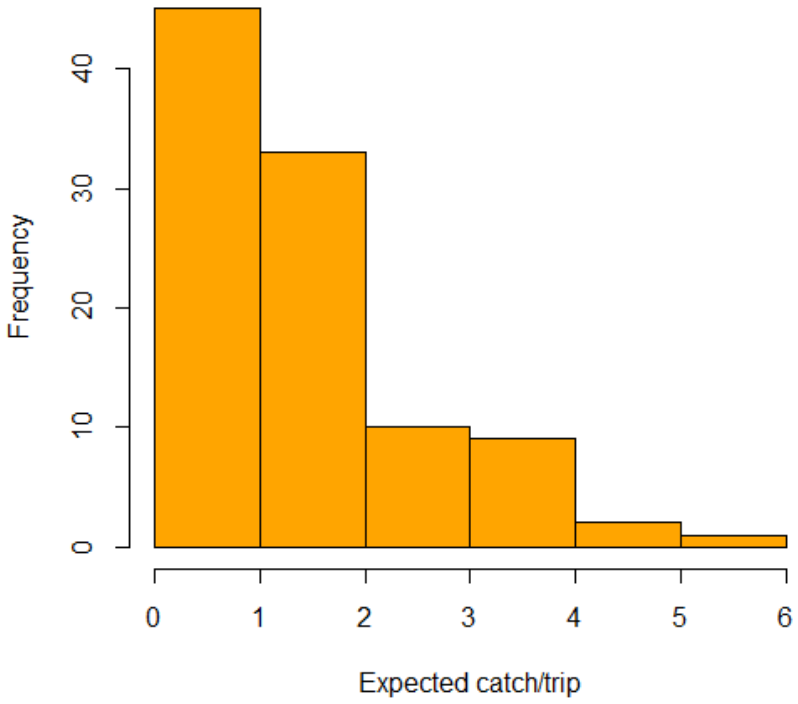


Figure 3-9. Simulated individual-angler expected mean catch rate, log-normally distributed

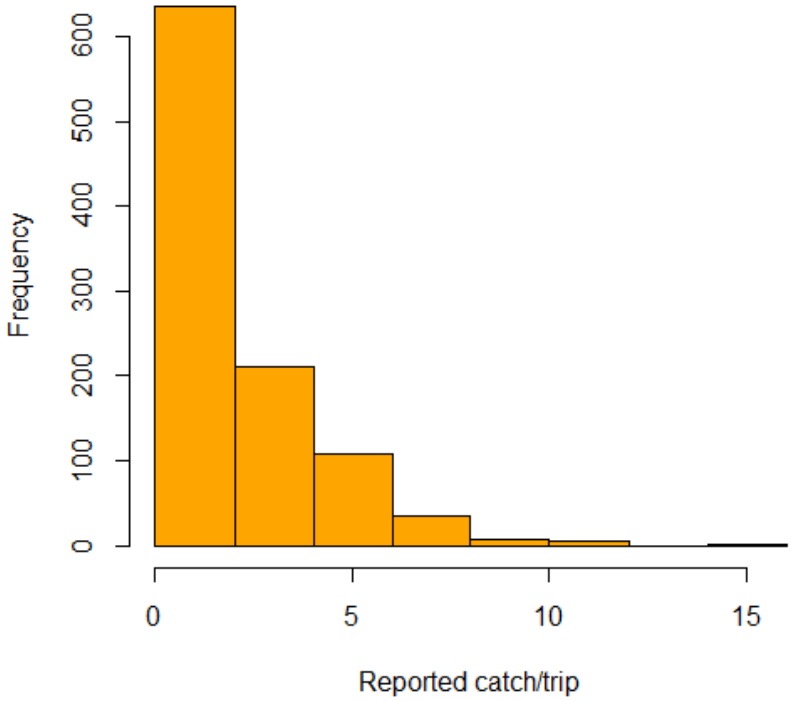


Figure 3-10. Simulated reported catch/trip obtained by sampling from a Poisson distribution, where the trips are drawn according to each angler's avidity. An angler's avidity is based on log-normally distributed expected catch rates (see Figure 3-9).

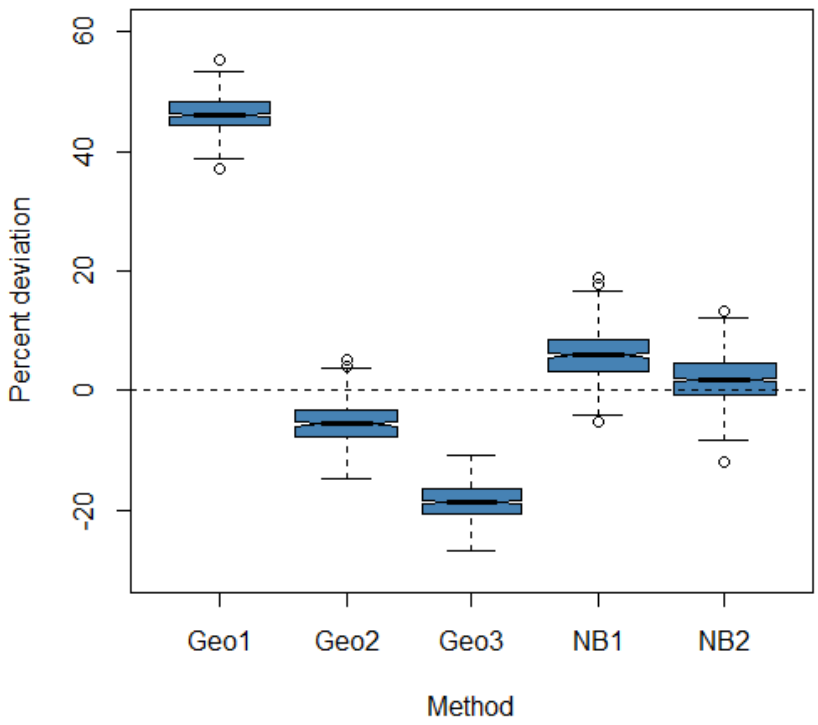


Figure 3-11. Boxplot showing the percent deviation from the true mean for five catch rate calculations (σ=0.2). The estimation methods used are: Geo1=unadjusted geometric mean; Geo2=geometric mean adjusted for zero-catch trips; Geo3=geometric mean adjusted for zero-catch trips and avidity; NB1=unadjusted negative binomial mean parameter; and NB2=negative binomial mean parameter adjusted for avidity.

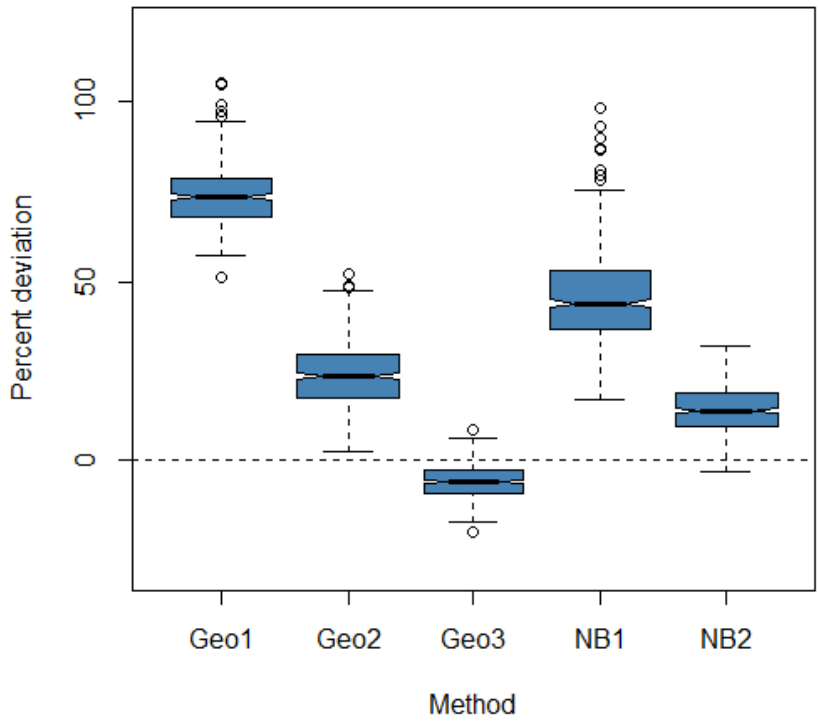


Figure 3-12. Boxplot showing the percent deviation from the true mean for five catch rate calculations (σ=0.5). The estimation methods used are: Geo1=unadjusted geometric mean; Geo2=geometric mean adjusted for zero-catch trips; Geo3=geometric mean adjusted for zero-catch trips and avidity; NB1=unadjusted negative binomial mean parameter; and NB2=negative binomial mean parameter adjusted for avidity.

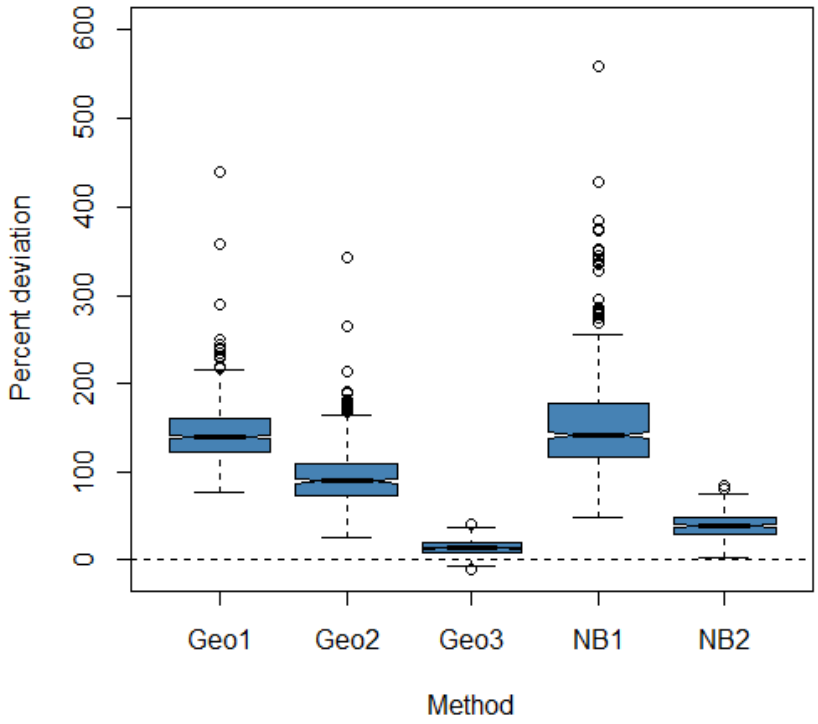


Figure 3-13. Boxplot showing the percent deviation from the true mean for five catch rate calculations (σ=0.8). The estimation methods used are: Geo1=unadjusted geometric mean; Geo2=geometric mean adjusted for zero-catch trips; Geo3=geometric mean adjusted for zero-catch trips and avidity; NB1=unadjusted negative binomial mean parameter; and NB2=negative binomial mean parameter adjusted for avidity.

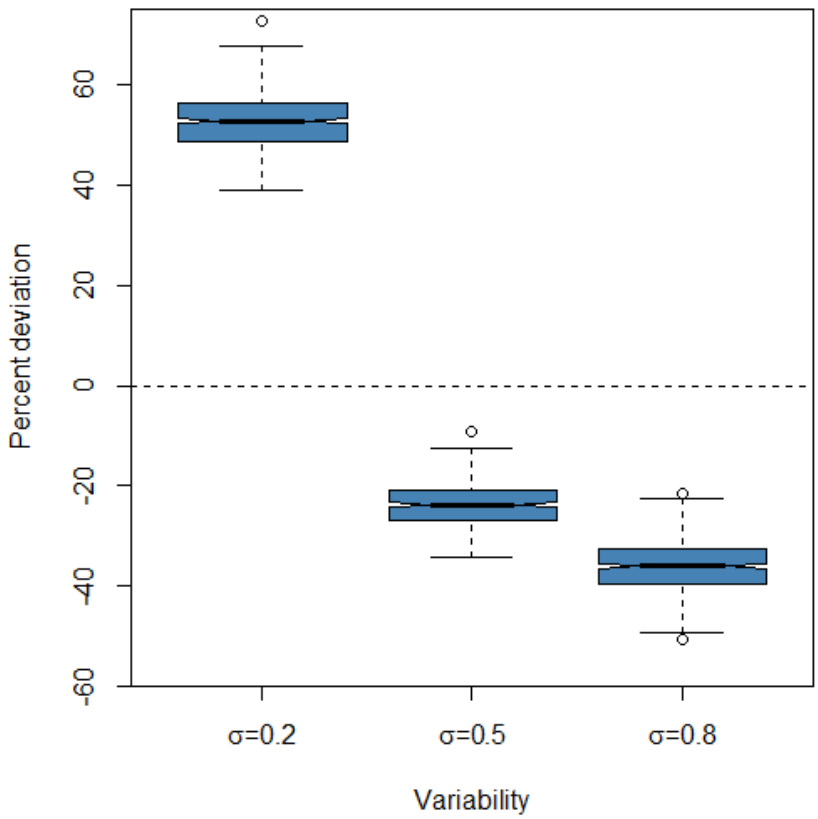


Figure 3-14. Percent deviation in the standard deviation estimates for the zero-adjusted, avidity-adjusted geometric mean calculations, under the three levels of variability. Recall, σ=0.2 indicates low variability in expected catch rates, and σ=0.8 indicates high variability.

Table 3-6. Mean catch/trip (in fish-per-trip) estimates for Common Snook using four different calculations. "Raw" refers to an unweighted (zero-adjusted for geometric means) mean, while "avidity-adjusted" refers to avidity weighting (and zero-adjusted for geometric means).

	Raw				Avidity-adjusted			
	Arithmetic mean	Arithmetic variance	Geometric mean	Geometric variance	Arithmetic mean	Arithmetic variance	Geometric mean	Geometric variance
Atlantic 2012	3.1	14	2.2	1.2	2.8	11	1.6	1.6
Atlantic 2013	2.7	11	1.9	1.4	2.0	7.3	1.5	1.5
Ft. Myers 2012	1.6	1.2	1.4	1.3	2.0	1.5	1.7	1.3
Ft. Myers 2013	2.5	7.6	2.0	0.67	2.9	9.0	1.6	1.2
Tampa 2012	2.3	4.7	1.8	1.4	1.8	3.6	1.4	1.4
Tampa 2013	1.6	1.4	1.4	1.0	2.1	1.4	1.6	1.0

Table 3-7. Mean catch/trip (in fish-per-trip) estimates for spotted seatrout using four different calculations. "Raw" refers to an unweighted (zero-adjusted for geometric means) mean, while "avidity-adjusted" refers to avidity weighting (and zero-adjusted for geometric means).

	Raw				Avidity-adjusted			
	Arithmetic mean	Arithmetic variance	Geometric mean	Geometric variance	Arithmetic mean	Arithmetic variance	Geometric mean	Geometric variance
Atlantic 2012	4.3	35	2.8	1.8	6.0	130	2.5	2.9
Atlantic 2013	2.9	6.7	2.4	1.1	2.6	3.4	1.9	1.1
Ft. Myers 2012	4.8	39	2.9	2.4	2.9	15	1.8	2.2
Ft. Myers 2013	4.0	17	3.0	1.6	3.9	9.2	2.7	1.3
Tampa 2012	4.1	35	2.5	1.8	3.9	37	2.0	1.9
Tampa 2013	3.6	10	2.6	1.8	6.0	11	4.4	1.5

Table 3-8. Mean catch/trip (in fish-per-trip) estimates for red drum using four different calculations. "Raw" refers to an unweighted (zero-adjusted for geometric means) mean, while "avidity-adjusted" refers to avidity weighting (and zero-adjusted for geometric means).

	Raw				Avidity-adjusted			
	Arithmetic mean	Arithmetic variance	Geometric mean	Geometric variance	Arithmetic mean	Arithmetic variance	Geometric mean	Geometric variance
Atlantic 2012	1.0	3.8	0.79	0.35	1.0	1.6	0.62	0.67
Atlantic 2013	1.1	1.3	0.94	0.52	1.4	2.3	0.88	0.83
Ft. Myers 2012	2.8	5.7	2.1	1.7	3.1	8.5	2.2	1.9
Ft. Myers 2013	2.1	3.3	1.7	1.3	2.2	2.8	1.6	1.2
Tampa 2012	2.1	8.2	1.5	1.0	1.7	4.5	1.2	1.2
Tampa 2013	1.9	3.0	1.5	0.92	2.2	1.6	1.5	0.89

APPENDIX A

REPORTED CATCH/TRIP DISTRIBUTIONS FOR ALL SPECIES, MODES, AND SPATIAL DESIGNATIONS

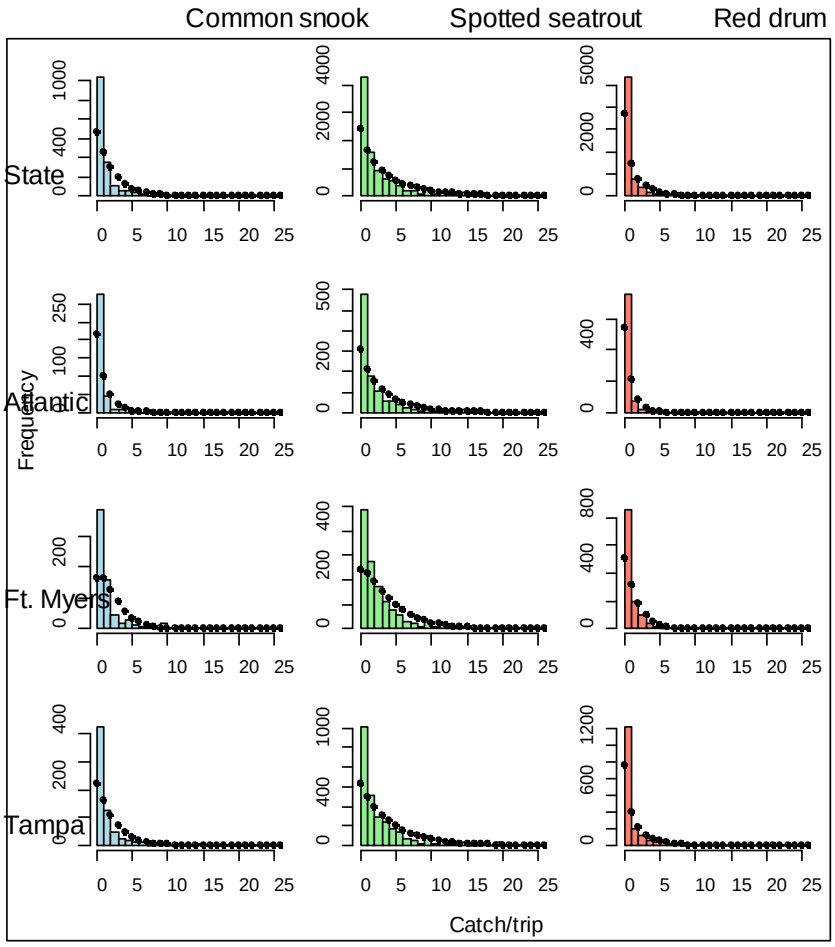


Figure A-1. All catch/trip plots and predicted values for the MRIP private boat mode. Predicted values are shown by a "•"; if no dots are presented, it corresponds to a scenario where there were not enough reported trips to accurately fit the distribution.

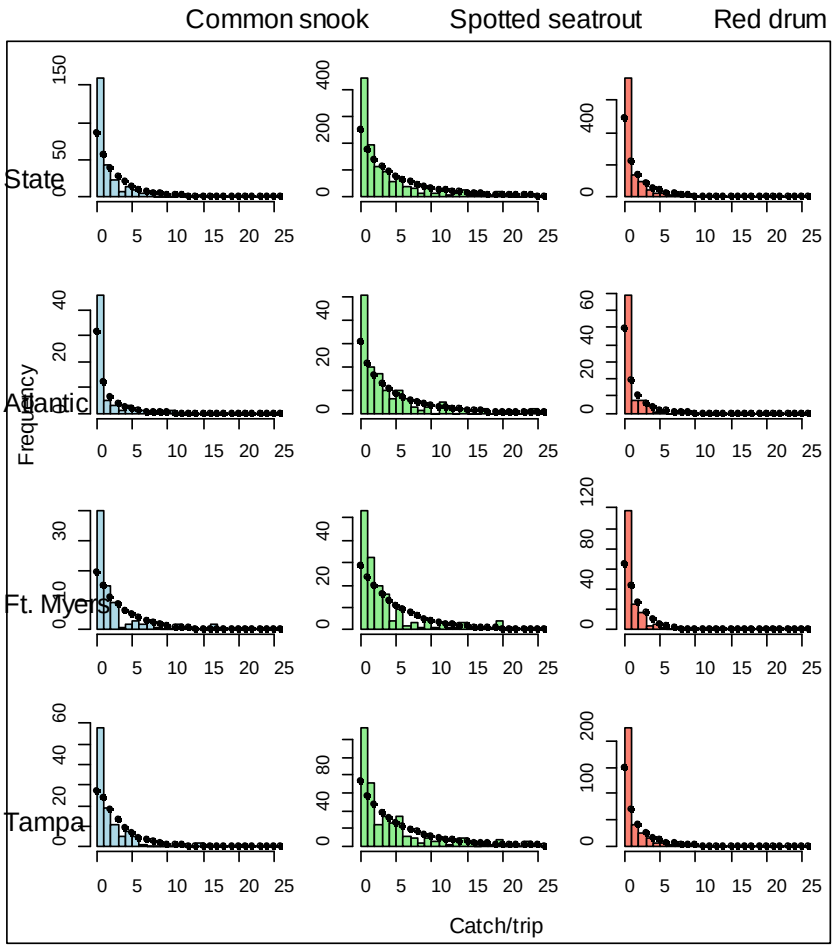


Figure A-2. All catch/trip plots and predicted values for the MRIP single-angler private boat mode. Predicted values are shown by a "•"; if no dots are presented, it corresponds to a scenario where there were not enough reported trips to accurately fit the distribution.

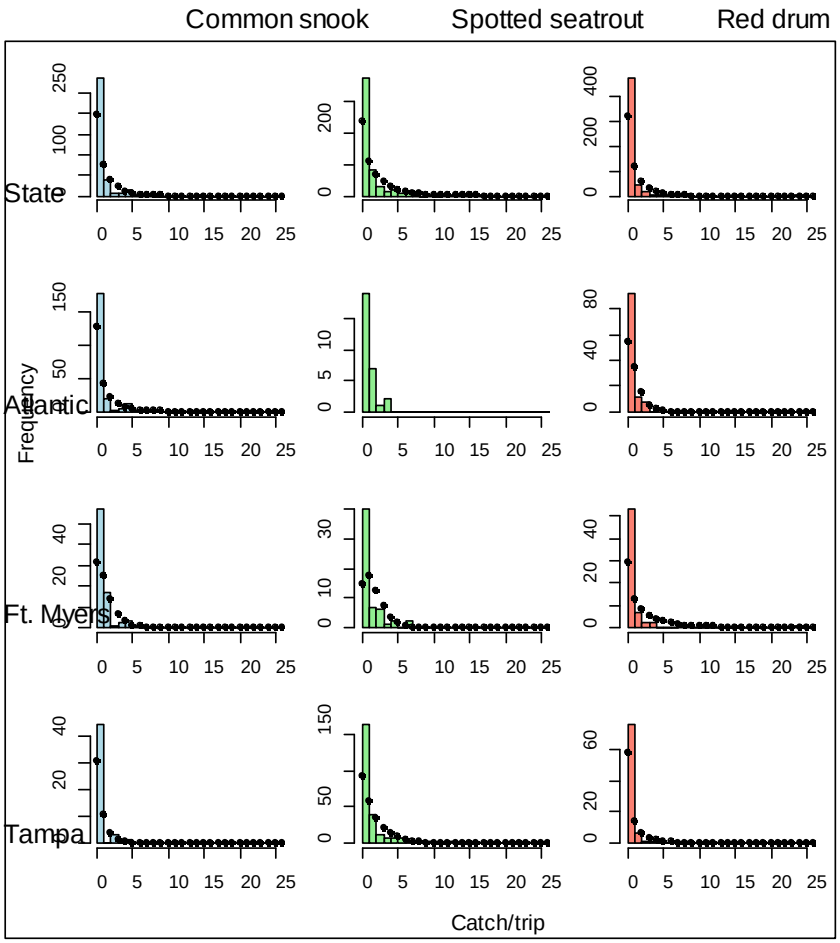


Figure A-3. All catch/trip plots and predicted values for the MRIP shore mode. Predicted values are shown by a "•"; if no dots are presented, it corresponds to a scenario where there were not enough reported trips to accurately fit the distribution.

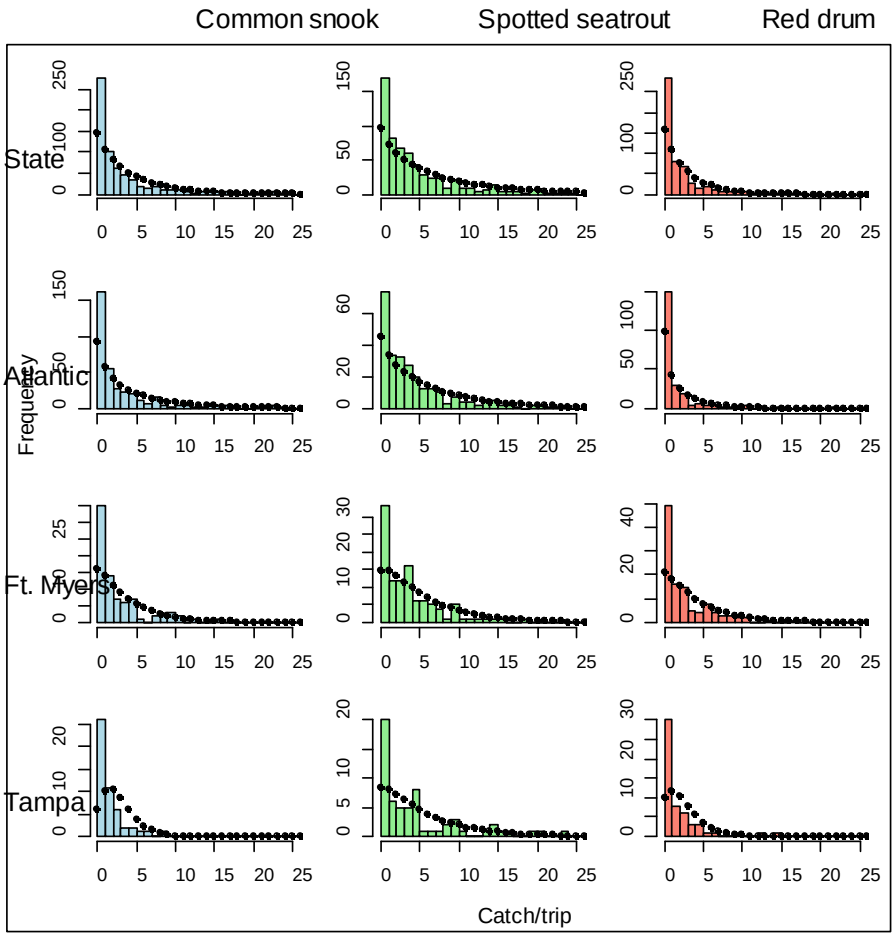


Figure A-4. All catch/trip plots and predicted values for the iAngler private boat mode. Predicted values are shown by a "•"; if no dots are presented, it corresponds to a scenario where there were not enough reported trips to accurately fit the distribution.

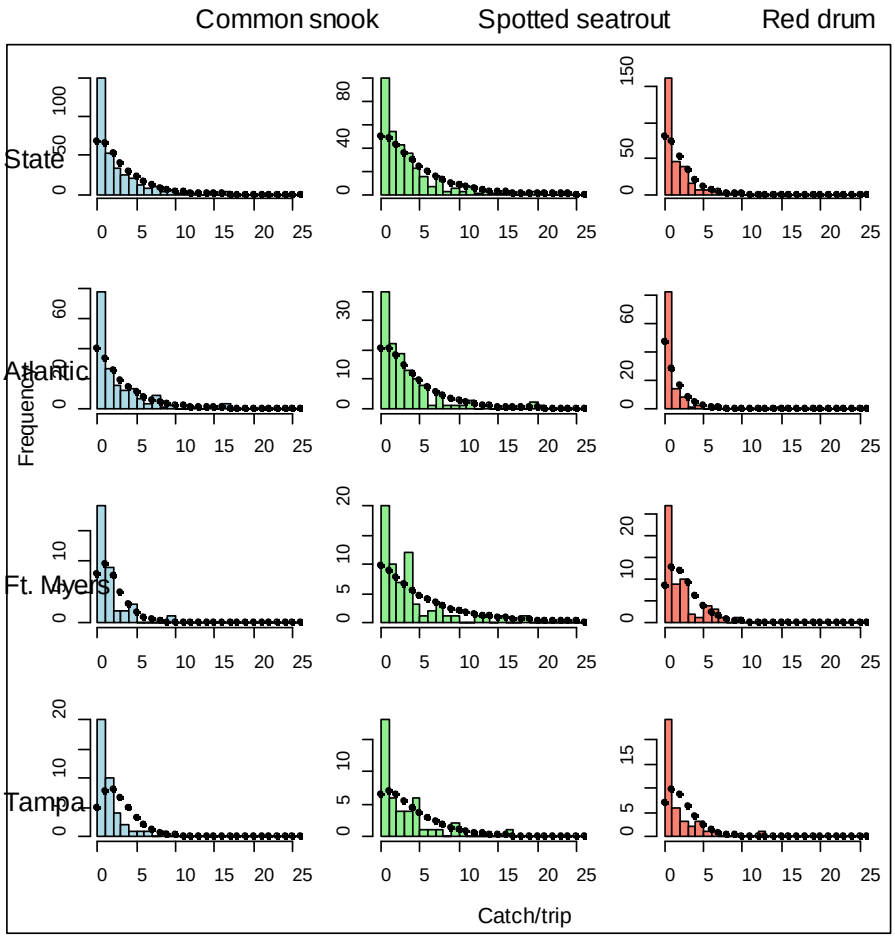


Figure A-5. All catch/trip plots and predicted values for the iAngler single-angler private boat mode. Predicted values are shown by a "•"; if no dots are presented, it corresponds to a scenario where there were not enough reported trips to accurately fit the distribution.

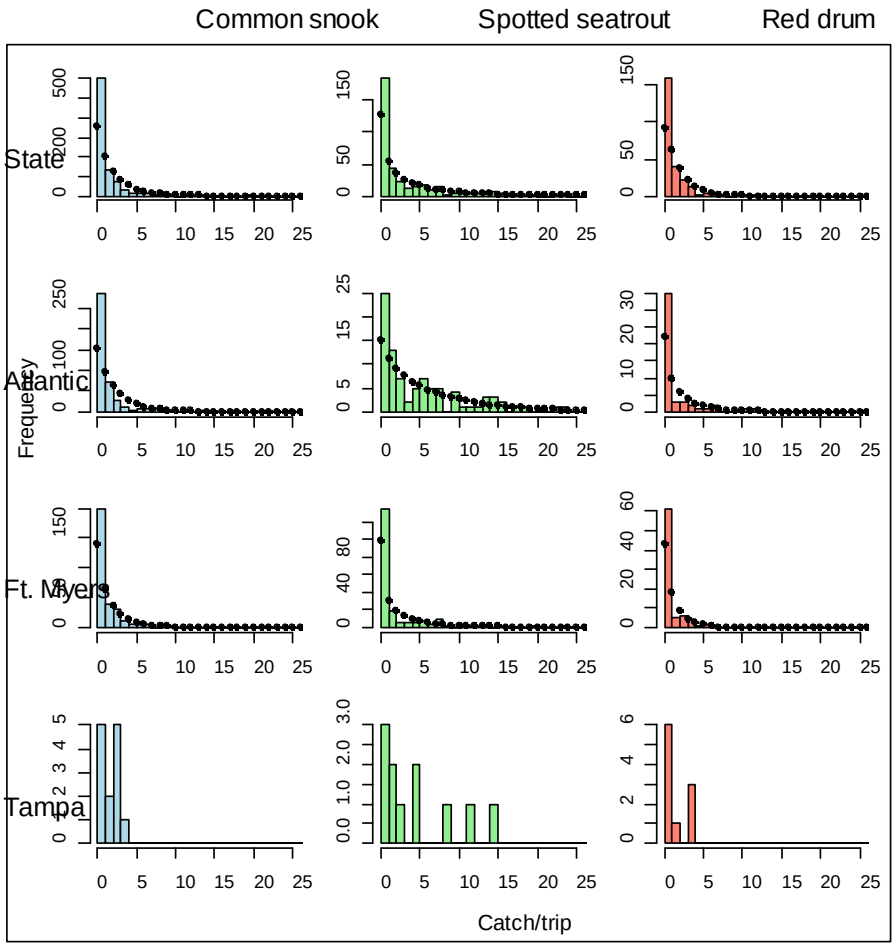


Figure A-6. All catch/trip plots and predicted values for the iAngler shore mode. Predicted values are shown by a "•"; if no dots are presented, it corresponds to a scenario where there were not enough reported trips to accurately fit the distribution.

APPENDIX B

MAXIMUM LIKELIHOOD PARAMETER ESTIMATES FOR THE NEGATIVE BINOMIAL DISTRIBUTION FITS USED IN IANGLER-MRIP CATCH/TRIP COMPARISONS

Table B-1. Maximum likelihood estimates for negative binomial parameters used to simulate private boat mode catch/trip distributions. "Pt." refers to the point estimate, and "Range" refers to the 95% quantile. N/A indicates there were not enough reported trips to fit with a negative binomial, and an extremely large value for the range of the dispersion parameter indicates the data were closer to a Poisson than negative binomial distribution.

		Mean μ				Dispersion n			
		MRIP		iAngler		MRIP		iAngler	
	Species	Pt.	Range	Pt.	Range	Pt.	Range	Pt.	Range
State	Common snook	1.78	[1.69, 1.88]	4.06	[3.73, 4.45]	1.11	[1.00, 1.24]	0.88	[0.77, 1.00]
	Spotted seatrout	3.73	[3.64, 3.82]	6.95	[6.38, 7.62]	0.81	[0.79, 0.84]	0.83	[0.74, 0.93]
	Red drum	1.22	[1.17, 1.26]	2.61	[2.37, 2.91]	0.57	[0.54, 0.61]	0.91	[0.77, 1.08]
Atlantic	Common snook	0.92	[0.80, 1.06]	4.24	[3.78, 4.78]	0.92	[0.67, 1.31]	0.73	[0.62, 0.86]
	Spotted seatrout	2.93	[2.73, 3.15]	6.18	[5.47, 7.02]	0.90	[0.81, 1.01]	0.85	[0.72, 1.01]
	Red drum	0.64	[0.58, 0.72]	1.85	[1.55, 2.23]	0.96	[0.73, 1.31]	0.58	[0.45, 0.75]
Ft. Myers	Common snook	2.15	[2.00, 2.33]	3.60	[2.91, 4.52]	1.81	[1.51, 2.18]	1.14	[0.78, 1.66]
	Spotted seatrout	3.69	[3.49, 3.90]	5.25	[4.40, 6.34]	1.26	[1.14, 1.38]	1.23	[0.90, 1.66]
	Red drum	1.35	[1.26, 1.44]	3.92	[3.26, 4.75]	1.22	[1.04, 1.45]	1.15	[1.15, 1.57]
Tampa	Common snook	2.00	[1.83, 2.18]	2.76	[2.39, 3.18]	1.14	[0.96, 1.36]	4.35	[2.45, 12.84]
	Spotted seatrout	3.92	[3.77, 4.08]	5.42	[4.53, 6.58]	0.99	[0.93, 1.05]	1.19	[0.86, 1.61]
	Red drum	1.35	[1.26, 1.45]	2.58	[2.18, 3.06]	0.58	[0.52, 0.65]	2.31	[1.43, 4.18]

Table B-2. Maximum likelihood estimates for negative binomial parameters used to simulate single-angler private boat mode catch/trip distributions. "Pt." refers to the point estimate, and "Range" refers to the 95% quantile. N/A indicates there were not

enough reported trips to fit with a negative binomial, and an extremely large value for the range of the dispersion parameter indicates the data were closer to a Poisson than negative binomial distribution.

		Mean μ				Dispersion n			
		MRIP		iAngler		MRIP		iAngler	
	Species	Pt.	Range	Pt.	Range	Pt.	Range	Pt.	Range
State	Common snook	2.48	[2.15, 2.88]	2.90	[2.60, 3.23]	0.89	[0.70, 1.12]	1.43	[1.13, 1.81]
	Spotted seatrout	5.26	[4.93, 5.63]	4.32	[3.88, 4.82]	0.80	[0.73, 0.87]	1.27	[1.05, 1.53]
	Red drum	1.68	[1.55, 1.84]	1.83	[1.63, 2.07]	0.63	[0.55, 0.72]	1.83	[1.32, 2.68]
Atlantic	Common snook	1.26	[0.85, 1.97]	2.96	[2.56, 3.44]	0.55	[0.28, 1.06]	1.14	[0.85, 1.52]
	Spotted seatrout	4.70	[3.88, 5.80]	3.90	[3.37, 4.56]	0.80	[0.60, 1.04]	1.34	[1.00, 1.78]
	Red drum	1.14	[0.83, 1.60]	1.24	[1.00, 1.53]	0.60	[0.34, 1.10]	1.19	[0.73, 2.17]
Ft. Myers	Common snook	3.32	[2.61, 4.32]	1.95	[1.52, 2.41]	0.99	[0.66, 1.43]	3.32	[10^9, 10^{107}]
	Spotted seatrout	4.75	[4.03, 5.68]	5.47	[4.29, 7.11]	1.00	[0.77, 1.27]	1.07	[0.72, 1.53]
	Red drum	1.62	[1.35, 1.95]	2.55	[2.06, 3.14]	1.14	[0.78, 1.69]	3.42	[1.70, 15.25]
Tampa	Common snook	2.55	[2.10, 3.14]	2.83	[2.38, 3.35]	1.31	[0.89, 1.96]	3.70	[2.01, 10.56]
	Spotted seatrout	5.40	[4.86, 6.04]	4.04	[3.29, 5.01]	0.90	[0.77, 1.05]	1.49	[0.97, 2.28]
	Red drum	1.69	[1.45, 1.98]	2.33	[1.93, 2.81]	0.66	[0.51, 0.84]	3.27	[1.69, 10.82]

Table B-3. Maximum likelihood estimates for negative binomial parameters used to simulate shore mode catch/trip distributions. "Pt." refers to the point estimate, and "Range" refers to the 95% quantile. N/A indicates there were not enough reported trips to fit with a negative binomial, and an extremely large value for the range of the dispersion parameter indicates the data were closer to a Poisson than negative binomial distribution.

		Mean μ				Dispersion n			
		MRIP		iAngler		MRIP		iAngler	
	Species	Pt.	Range	Pt.	Range	Pt.	Range	Pt.	Range
State	Common snook	1.03	[0.87, 1.22]	1.80	[1.66, 1.97]	0.64	[0.48, 0.87]	0.84	[0.69, 0.92]
	Spotted seatrout	1.94	[1.72, 2.20]	3.70	[3.20, 4.36]	0.62	[0.52, 0.73]	0.49	[0.41, 0.59]
	Red drum	0.89	[0.78, 1.02]	1.50	[1.26, 1.70]	0.64	[0.50, 0.81]	1.20	[0.92, 1.97]
Atlantic	Common snook	1.07	[0.85, 1.36]	2.01	[1.82, 2.23]	0.47	[0.33, 0.66]	0.90	[0.76, 1.07]
	Spotted seatrout	N/A	N/A	6.07	[4.99, 7.51]	N/A	N/A	0.84	[0.63, 1.11]
	Red drum	0.82	[0.66, 1.00]	1.68	[1.16, 2.53]	2.92	[8.37, 10^{135}]	0.61	[0.33, 1.12]
Ft. Myers	Common snook	1.15	[0.93, 1.41]	1.40	[1.20, 1.65]	2.58	[1.74, 10^{86}]	0.68	[0.52, 0.90]
	Spotted seatrout	1.57	[1.26, 1.92]	2.35	[1.86, 3.01]	4.91	[3.60, 10^{94}]	0.35	[0.27, 0.46]
	Red drum	2.03	[1.44, 2.98]	0.94	[0.70, 1.27]	0.56	[0.35, 0.87]	0.75	[0.42, 1.53]
Tampa	Common snook	0.58	[0.37, 0.90]	N/A	N/A	0.89	[0.36, 10^{29}]	N/A	N/A
	Spotted seatrout	1.63	[1.39, 1.92]	N/A	N/A	0.98	[0.72, 1.35]	N/A	N/A
	Red drum	0.77	[0.51, 1.23]	N/A	N/A	0.36	[0.19, 0.66]	N/A	N/A

4 Phase 2 evaluation

See phase 1 for methods

2.1 Re-evaluation of e-log data following recommendation from 1.6. Phase 2 compares iAngler with MRPI using an additional 3 years of data for a total for 5 years (2012-2016) to determine if the two data collection methods are comparable. In addition, Phase two present a comparison between iAngler and MRIP length frequencies for species where sufficient data was available. For relevant figures and table a side by side comparison of results from 2012-13 and 2012-16 are presented.

Results

General Data Comparisons

One important feature of the iAngler data is that submissions are highly variable throughout the state of Florida. From 2012-2016, the distribution of trips by county was significantly different from that of MRIP (X^2=7,719, df=34, p<0.0001), with a strong bias toward counties along the south-central Atlantic coast (Figure 4-1). The number of reported saltwater angling trips ranged from 0 (Clay, Jefferson, and Nassau counties) to 2,030 (Palm Beach), with a total of 6,111 trips (Table 4-1). For the MRIP, the number of access-point interviews by county ranged from 63 (Clay county) to 15,365 (Pinellas county), with a mean of 3,716 and a median of 2,843 interviews. Of the counties that reported trips to iAngler, the mean number of trips was 116, while the median was 12. For those same counties, the number of different users of the app ranged from 1 (Baker, Dixie, Escambia, Flagler, Franklin, Putnam, St. Johns, Wakulla, and Walton counties) to 76 (Brevard), with a mean of 16 and a median of 7. The iAngler dataset is characterized by high spatial variability, which could make it problematic if used for state-level assessment purposes.

The statewide values for catch frequency in the iAngler dataset showed a high percentage of Common Snook (*Centropomus undecimalis*), Spotted Seatrout (*Cynoscion nebulosus*), and Red Drum (*Sciaenops ocellatus*) when compared to the MRIP dataset. This is a trend throughout the data, as the iAngler app was initially created to supplement the state stock assessments with data on Common Snook and later expanded to include other species. Common Snook were caught on nearly one-third (31%) of the trips reported to the iAngler app, which is more than ten times the percentage of MRIP trips reporting Common Snook catches (Table 4-2). Out of the top ten most commonly reported species from each data set, six species were shared between the two, with Common Snook, Yellowtail Snapper (*Ocyurus chrysurus*), Red Snapper (*Lutjanus campechanus*), and Tarpon (*Megalops atlanticus*) being unique to iAngler and Pinfish (*Lagodon rhomboides*), Hardhead Catfish (*Ariopsis felis*), White Grunt (*Haemulon plumierii*), and Blue Runner (*Caranx crysos*) being unique to MRIP. When the data from each sampling program were re-normalized to include only trips that reported catches of the six shared species, there was still a significant difference between the percentages of each species in the catch (X^2=347.1, df=5, p<0.0001). However, the presence of six shared species suggests there is some degree of

overlap between the trips being reported by iAngler and the trips being interviewed by the MRIP survey.

The catch frequencies for the county clusters were similar to that of the statewide scale, but with a few differences in species. In the Atlantic county cluster (southeast Florida), there were five species shared in the top ten list of most commonly caught species (Table 4-3), and when they were re-normalized and compared, their relative proportions were also significantly different (X^2=171.69, df=4, p<0.0001). In the Ft. Myers county cluster, there were six species shared among the top ten species (Table 4-4), and their re-normalized relative proportions were significantly different (X^2=77.79, df=5, p<0.0001). This was the only instance where Common Snook were among the top ten most reported catches for the MRIP dataset. Finally, in the Tampa county cluster, there were 7 species shared in the top ten (Table 4-5), and their re-normalized relative proportions were significantly different (X^2=71.34, df=6, p<0.0001). This cluster had the highest proportion of Common Snook, Spotted Seatrout, and Red Drum when they are considered together. For all three county clusters, as well as at the state level, four species that were consistently shared in the top ten list of most commonly reported catches were Spotted Seatrout, Crevalle Jack (*Caranx hippos*), Gray (Mangrove) Snapper (*Lutjanus griseus*), and Ladyfish (*Elops saurus*). The differing catch frequencies in the iAngler and MRIP datasets suggests that, while there is some degree of overlap in the trips reported through each program, the relative proportions of trips targeting the various species are different. However, this does not negate the value of making comparisons on a species-by-species basis.

Because iAngler showed a strong bias toward Common Snook, Spotted Seatrout, and Red Drum, popular inshore species in Florida, these three fish were used for further comparisons with the MRIP data. Red Snapper (*Lutjanus campechanus*), Red Grouper (*Epinephelus morio*), and Gag Grouper (*Mycteroperca microlepis*) were three other species also used to assess the status of iAngler with regards to important offshore stocks.

Species-Specific Comparisons

Catch per Trip

Angler catch/trip data for all private boat mode trips showed similar means in all cases between iAngler and the MRIP. There were enough trips (n>30) to make catch/trip comparisons for all of the inshore species-mode combinations for all spatial designations, as well as the three offshore species at the state level (Figure 4-2). This fishing mode is the most comprehensive in the iAngler dataset. No other fishing mode had enough data from both iAngler and the MRIP to perform catch/trip comparisons for the offshore species, and so they are not further discussed. For the inshore species, all comparisons of catch/trip between iAngler and the MRIP for the private boat mode resulted in similar distributions (Figure 4-3). In all scenarios, the 20% quantiles lay to the right of zero; because we subtracted the simulated MRIP catch/trip values from the iAngler catch/trip values, this suggests the iAngler values were consistently larger across species and spatial designations. This could be due to a smaller proportion of zero-catch trips in iAngler as opposed to that of the MRIP data. Still, Common Snook in the Tampa county cluster and Red Drum in the Atlantic cluster were the only instances where the 20% quantile did not include zero, so there was ultimately a high degree of similarity between the two data sets' catch/trip estimates. This tendency toward zero for the 20% quantiles was seen even in some of

the cases where the 80% quantiles were skewed farther to the right, which suggests the central tendency of these difference distributions was near zero regardless of the degree of overdispersion seen in the catch/trip data. Overall, the iAngler dataset provides very similar catch/trip data to the MRIP for these three inshore species.

Private boat mode was evaluated for trips that only consisted of one angler in the party, and the catch/trip values were also similar for the three species in question. However, as mentioned before, no offshore species had enough records to fit with parameters and make a comparison. All of the inshore species had sufficient data at the various spatial designations (Figure 4-4). It appears iAngler captures proportionately more of these single-angler private boat trips than does MRIP, as evidenced by the fact that the discrepancy between the numbers of records between these two programs is generally smaller than with the whole private boat mode. The 80% quantiles of the difference distributions for this mode suggest that all corresponding catch/trip distributions are similar (Figure 4-5). Overall, the catch/trip comparisons for this mode provided a higher degree of agreement than for the entire private boat mode. The intervals are not consistently skewed toward the right, and for 9 of the 12 comparisons, the median value was zero. In light of the spatial bias on the statewide scale, it is important that the data are similar on the level of the county clusters—especially for the counties near Tampa, which have the highest effort according to the MRIP survey. The overall similarity across species and spatial designations shows that iAngler can provide catch/trip data that are comparable to that of the MRIP survey for single-angler trips taken on a private boat.

Despite having some gaps in the data for both iAngler and the MRIP survey, the shore mode catch/trip values were similar when comparisons were possible. Comparisons were not possible for any of the species in the Tampa cluster, but sufficient data existed for the other spatial designations (Figure 4-6). For the rest of the scenarios, all comparisons suggest the iAngler and MRIP catch/trip data to be similar (Figure 4-7). In 4 out of the 9 comparisons, the median catch/trip value was zero. Also, when compared to the private boat mode, the 80% quantiles for the shore mode comparisons are tighter. Taken together, these two points indicate the iAngler and MRIP data have not only similar central tendencies, but similar dispersions as well. The shore mode of iAngler has considerably fewer trips in the Tampa cluster, but actually exceeds the total number of MRIP trips for nearly all cases in the other two clusters (especially Common Snook). In these events, the mean catch rate data for iAngler are very similar to those of the MRIP survey.

Species-specific data for the charter boat mode was extremely deficient in the iAngler dataset and so are not included in the analysis. Likewise, iAngler's length data for retained catch were insufficient for the chi-square goodness-of-fit test. Thus, the length data for retained catch for iAngler are at least insufficient to test, even for the popular inshore species, if not altogether different.

Length Data

In the iAngler data set from 2012-2016 there were 103 Common Snook reported harvested ranging from 711 to 819 with a mean size of 776.1 mm (Total Length; TL). From 2012-2016 there were 132 Common Snook sampled for the MRIP survey ranging from 711 to 834 with a

mean size of 763.4 mm TL. The length frequency distributions (Figure 4-7) were significantly different (X^2=45.79, df=4, p<0.0001). The iAngler data set contained 2,914 Common Snook that were released from 2012-2016 that ranged from 71 to 963 mm and a mean of 462.5 TL (Figure 4-8).

In the iAngler data set from 2012-2016 there were 394 Spotted Seatrout reported harvested ranging from 381 to 711 with a mean size of 452.8 mm TL. From 2012-2016 there were 10,732 Spotted Seatrout sampled for the MRIP survey ranging from 381 to 781 with a mean size of 440.0 mm TL. The length frequency distributions (Figure 3-9) were significantly different (X^2=107.9, df=9, p<0.0001). The iAngler data set contained 2,676 Spotted Seatrout that were released from 2012-2016 that ranged from 101 to 1143 mm and a mean of 558.1 TL (Figure 4-10).

In the iAngler data set from 2012-2016 there were 173 Red Drum reported harvested ranging from 457 to 711 with a mean size of 590.7 mm TL. From 2012-2016 there were 3,726 Red Drum sampled for the MRIP survey ranging from 458 to 771 with a mean size of 554.1 mm TL. The length frequency distributions (Figure 4-11) were significantly different (X^2=477.5, df=9, p<0.0001). The iAngler data set contained 1,069 Red Drum that were released from 2012-2016 that ranged from 152 to 1524 mm and a mean of 552.9 TL (Figure 4-12).

Discussion

In general, the results of this analysis are very similar to those reported in phase 1 which only included data from 2012-2013. The high degree of similarity between catch rate data from the iAngler smartphone app and the MRIP survey suggests an electronic, self-reporting framework can provide information that is usable for the assessment of recreational fisheries. However, this is only apparent for fish species where iAngler has adequate sample size (i.e., Common Snook, Spotted Seatrout, Red Drum). Although the spatial bias of iAngler makes it inappropriate for usage on a statewide level, possible that continued implementation and advertisement could progress the utility already demonstrated by these inshore fishes in these county clusters. The fact that the iAngler and MRIP catch/trip values were similar when compared at an appropriate spatial resolution (i.e. the county clusters) shows the ability of an electronic, self-reporting program to provide representative catch rate data. However, consistent advertisement of the self-reporting app should be conveyed to the public to ensure its user base does not decline, but rather increase over time.

The simple nature of a smartphone-based “angler diary” app could conceivably replace the mail surveys and paper-based diaries if administered and monitored by a state fisheries agency. Diaries also have the advantage of addressing the public access bias, which occurs when a large number of trips in a fishery are taken from private access points. To address the public access bias in the Blue Crab (*Callinectes sapidus*) in Maryland and Virginia, Ashford et al. (2010) used a telephone survey to adjust the catch rates obtained from a traditional creel survey, which missed a sizeable amount of effort coming from private sites. However, an electronic, smartphone-based reporting system would represent a simpler and cheaper method to correct this problem. Further, studies that have implemented the use of smartphone- and digital tablet-based reporting programs have noted that most participants prefer them to paper-based logbooks

(Baker and Oeschger 2009; Stunz et al. 2014). Thus, if such electronic self-reporting "angler diaries" were to be employed and controlled in the same way traditional diaries are, they could prove to be an even better method for collecting information from recreational anglers.

This study is the first to rigorously analyze opt-in, self-reported recreational fisheries data from electronic data collection (e.g., a smartphone app) with a focus on the private angling modes. Stunz *et al.* (2014) used a smartphone/tablet app called "iSnapper" to record data from headboat and private charter boat (collectively, the "for-hire" sector) trips with a focus on the Red Snapper fishery. However, their study involved choosing sixteen captains to become involved with the program and was relatively controlled, whereas our work with iAngler has been on a dataset consisting of true opt-in participants. While their study had the added benefit of a pre- and post-use survey to gauge captains' interest in the app, it did not include an analysis of whether or not the data provided were reliable or useful for assessment (i.e. how it compared to current data collection programs). Stunz *et al.* (2014) highlighted the difference between for-hire vessel captains and the private recreational angling population, calling for a study on that specific mode, and our analysis, has since filled that gap. This study has shown that when a proper sample size of trips exists, an electronic self-reporting platform like the iAngler app could provide a valid measure of catch per unit effort. For example, as the program runs for more years, this catch rate data could be used as a time series to assess relative abundance. Additionally, because the iAngler allows for more comprehensive information on discarded fish (length, weight, hooking location, higher spatial resolution), it has the potential to augment stock assessments in a way that the MRIP survey is not capable of doing. Overall, we found the iAngler smartphone app can provide valuable recreational fisheries data for certain species, especially popular inshore species in urbanized regions of the state of Florida.

The largest issue found with the iAngler data set was the lack of spatial coverage throughout the entire state of Florida. In general, some counties had hundreds (or even thousands [Palm Beach county]) trips, whereas some had fewer than five. This raises the question of whether this data is useful on a statewide level, as metrics such as catch rate can vary spatially (Smallwood et al. 2006). Specifically, many of the trips are concentrated in the urbanized regions, such as the southeast coast (our Atlantic county cluster) and—to a lesser extent—southwest Florida. Such information may still be useful, since Florida has already implemented "management zones" for Spotted Seatrout and Red Drum in the form of variable bag limits throughout the state (eRegulations 2015). Thus, the app's usefulness could increase if small-scale, regional management plans become more popular. However, to be useful on a larger spatial scale, the app would have to be expanded in its scope and usage. Overall, this spatial bias is not surprising, given the fact that the iAngler app has not been part of any major marketing campaign, meaning any diffusion up to this point has been due to "word-of-mouth." If the Snook and Gamefish Foundation were to implement a marketing campaign, it might lead to a more balanced spatial distribution of effort. Any self-reporting program like this could also benefit from a partnership with the state fisheries agency, since strong administrative backing has the potential to increase the success of angler logbook programs (Cooke et al. 2000).

Another shortcoming of the iAngler data was the bias in species represented in the catch records. The iAngler app does not have much data on offshore species (grouper, snapper, etc.) that are recreationally important to Florida. Also, in the iAngler dataset, Common Snook, Spotted

Seatrout, and Red Drum represented a majority of all the saltwater fishing trip catches in the entire state of Florida. This is likely due to the historical intent of the program. The iAngler smartphone app arose out of the Angler Action Program, which was a logbook program created in 2010 specifically for Common Snook recreational fisheries data. Because Spotted Seatrout and Red Drum are inshore species like Common Snook, it makes sense for them to be the next species that users of the app begin to report.

As found in Ryan Jiorle's thesis, there were similarities in the catch/trip data for the three inshore species studied (Common Snook, Spotted Seatrout, and Red Drum). Other investigations have suggested a bias in self-reported data for measures such as catch rates (Didden 2012), but in this case the catch/trip data were very similar between collection methods. The most consistently similar distributions of catch/trip between iAngler and the MRIP were for the single-angler subset of the private boat mode. While the comparisons for the full private boat and shore mode (to a lesser degree) were skewed, it still suggested the iAngler data to be similar to the catch/trip values provided by the MRIP survey. It's likely that the skew of the data is due to iAngler users not including their zero-catch trips as much as the rest of their trips, which would otherwise pull down the mean catch/trip estimates to be closer to those of the MRIP survey. This problem could be alleviated by encouraging anglers to report these trips, as they are equally important for correct assessment of the fisheries. Another possibility is that the users of the iAngler app do not have as many zero-catch trips as the entire angling population, which would indicate a bias in the sampled participants of the program. In general, these results are promising, especially for Common Snook, Spotted Seatrout, and Red Drum. The three county clusters chosen all had agreement between iAngler and the MRIP for these three species, with the exception of the shore mode in the Tampa cluster, which lacked sufficient trips for making the comparisons. This could be a result of under-representation by iAngler, or a lack of available shore/beach fishing grounds in the three counties included in the cluster.

A potential limitation of this study is the assumption that comparing the iAngler data to similar data obtained by the MRIP is analogous to comparing it to the "expected value," i.e., implying the MRIP collects a true representation of the fisheries in question. While the design of NOAA's access-point surveying program is now said to be unbiased (NOAA 2013), not all of these corrections were in place for the entirety of time covered in our analysis.

A useful utility of the iAngler app data is that it allows the inclusion of release data whereas the MRIP only documents harvested individuals at access sites. In this report we compared the harvest data of the three most common species (Common Snook, Spotted Seatrout, and Red Drum). All length frequency distributions were statistically different. The closest statistically was Common Snook. However, this is likely a function of the reduced harvest slot window, limiting the possibilities of harvested sizes unlike the other two species. Spotted Seatrout appeared to be identical, however the difference statistically here is likely a result of the reduced sample size. The number of Spotted Seatrout reported in the MRIP data were 20 fold that of the iAngler app for Spotted Seatrout. This was also apparent for Redfish. The distribution appeared incomplete unlike the MRIP length frequency. This is unfortunate because the iAngler app contained many release records (over 6,000 just for these three species) that could be used to define the size structure for not only harvestable, but incoming year-classes as well. Providing

size structure information for stock assessments would be useful, especially for developing an ecosystem-based approach to fisheries management (Shin et al. 2005).

In conclusion, this report shows only the utility for the iAngler smartphone app's data with regard to various management scenarios, and its potential for supplementing data already collected by the MRIP. Because the app is also equipped to submit other metrics such as lengths and weights of released fish, GPS coordinates of catch, and condition of released fish, it has the potential to provide novel information that the MRIP is not designed to collect—even if such data are not currently robust enough for analysis. Gutowsky et al. (2013) summarize the current uses of smartphone and digital tablets for fisheries science, suggesting that growing technology and usage of smartphones will make such programs more attractive and useful as time goes on. Thus, with consistent backing and revision, the utility of electronic, self-reporting programs for recreational fisheries management has the potential to grow, making them a valuable tool for managers and users

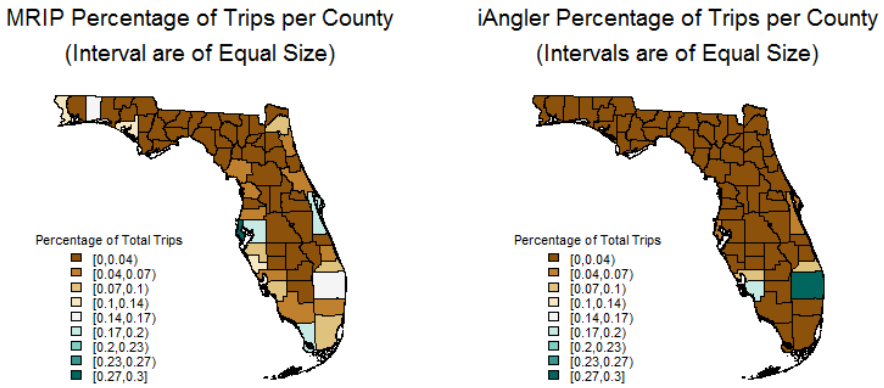


Figure 4-1. Maps comparing the distribution of trips by county between iAngler (left) and MRIP (right).

2012-2013

State	666/ 1930	633/ 9846	546/ 7093	71/ 1198	35/ 1427	44/ 1632
Atlantic	434/ 409	321/ 1143	259/ 883	25/ 35	7/ 62	5/ 53
Ft. Myers	91/	115/	122/	0/	2/	4/

iAngler poor
MRIP poor
Both poor

	684	1356	1244	9	367	219
Tampa	107/ 703	113/ 3082	105/ 1953	0/ 33	5/ 576	7/ 679
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

Both sufficient

2012-2016

State	864/ 5362	807/ 18932	672/ 15289	88/ 2764	39/ 3300	47/ 3293
Atlantic	532/ 246	399/ 2035	318/ 1638	26/ 210	9/ 101	5/ 103
Ft. Myers	136/ 1557	138/ 2625	158/ 2316	0/ 28	2/ 839	5/ 501
Tampa	136/ 2359	150/ 5970	114/ 4247	0/ 72	6/ 1523	9/ 1407
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor

MRIP poor

Both poor

Both sufficient

Figure 4-2. Summary of data quality in relation to comparing the catch/trip distributions for all private boat mode trips. Each cell contains the number of trips for iAngler (top) and MRIP (bottom), where n=30 is the minimum number of samples required to fit to a negative binomial distribution. Each color indicates which, if either, dataset had enough records.

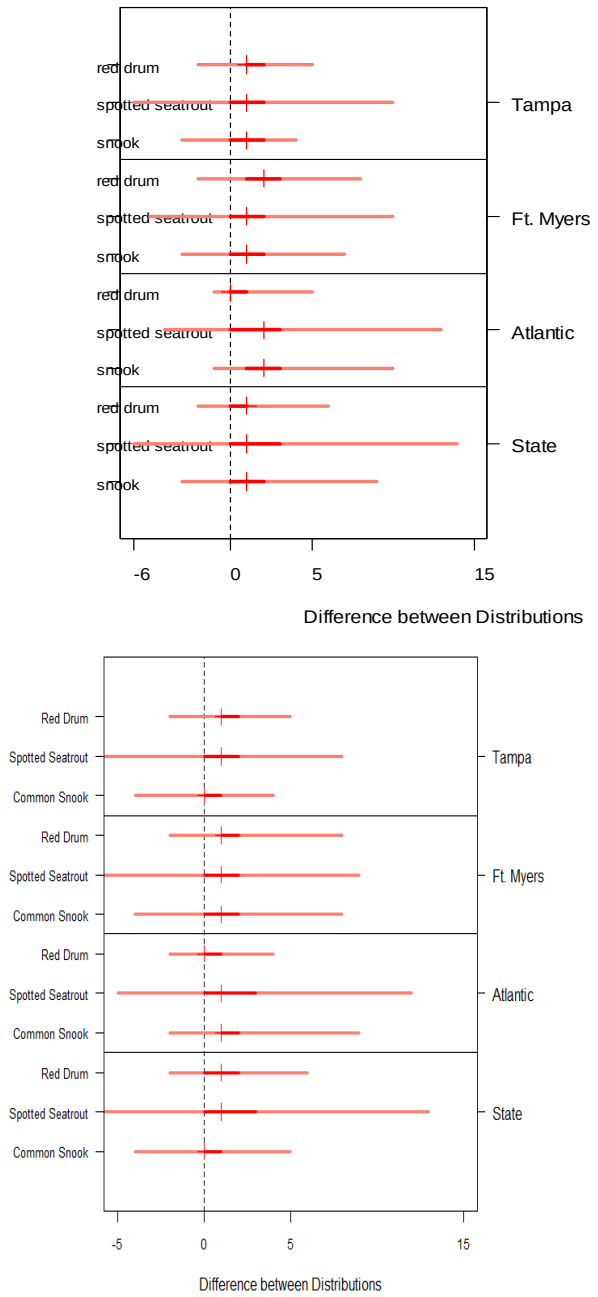


Figure 4-3. Difference between iAngler and MRIP simulated catch/trip distributions for the private boat mode. Crosses represent the median, dark red bars represent the 20% quantiles, and the light red bars represent the 80% quantiles. 2012-2013 top, 2012-2016 bottom.

2012-2013

State	333/ 280	325/ 1280	287/ 1108	2/ 32	1/ 59	4/ 100
Atlantic	204/ 61	165/ 144	136/ 94	0/ 0	0/ 6	0/ 2
Ft. Myers	37/ 82	68/ 163	58/ 177	0/ 2	0/ 17	1/ 18
Tampa	82/ 111	79/ 422	78/ 341	0/ 0	1/ 24	1/ 48
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor
MRIP poor
Both poor
Both sufficient

2012-2016

State	455/ 862	392/ 2550	348/ 2470	4/ 70	2/ 131	5/ 222
Atlantic	265/ 170	209/ 264	177/ 219	0/ 0	0/ 6	0/ 2
Ft. Myers	63/ 216	80/ 343	71/ 357	0/ 3	0/ 17	1/ 18
Tampa	102/ 382	89/ 859	81/ 748	0/ 0	1/ 24	2/ 48
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor
MRIP poor
Both poor
Both sufficient

Figure 4-4. Summary of data quality in relation to comparing the catch/trip distributions for single-angler private boat mode trips only. Each cell contains the sample size for iAngler (top) and MRIP (bottom), where n=30 is the minimum number of samples required to fit to a negative binomial distribution. Each color indicates which, if either, dataset had enough records.

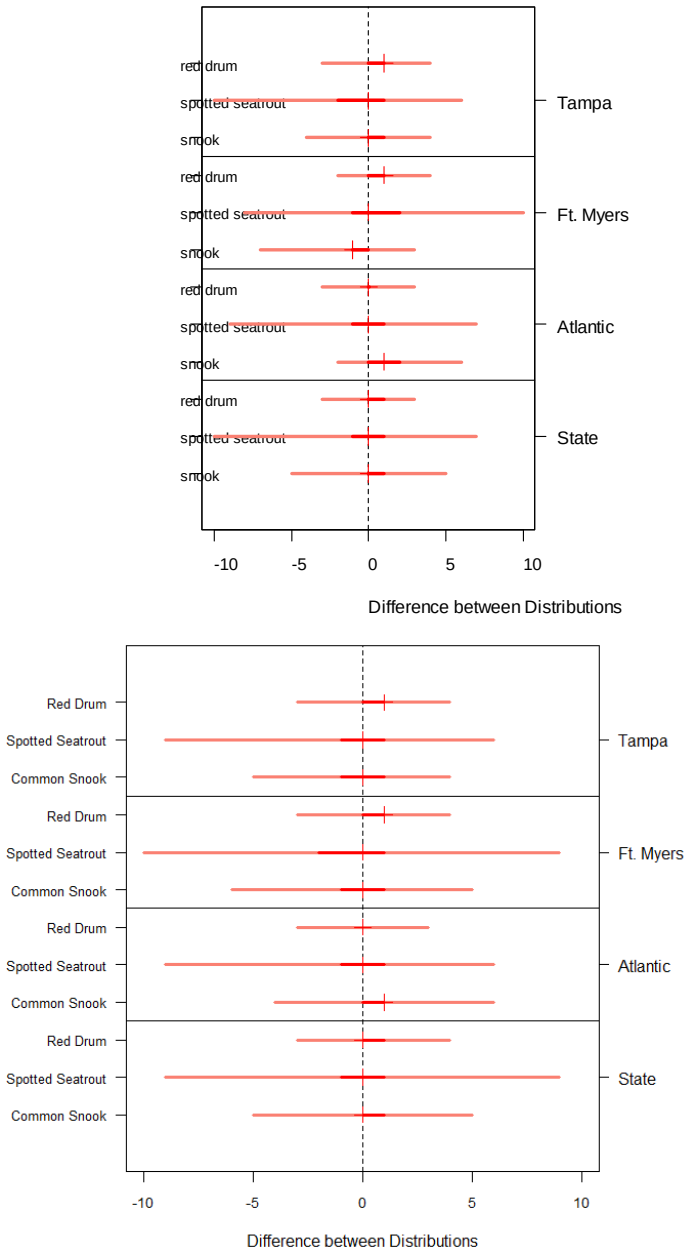


Figure 4-15. Difference between iAngler and MRIP simulated catch/trip distributions for the single-angler private boat mode trips only. Crosses represent the median, dark red bars represent the 20% quantiles, and the light red bars represent the 80% quantiles. 2012-2013 top, 2012-2016 bottom.

2012-2013

State	921/ 361	362/ 559	246/ 558			
Atlantic	573/ 22	123/ 29	59/ 112			
Ft. Myers	326/ 81	217/ 58	105/ 69			
Tampa	14/ 48	13/ 243	10/ 88			
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

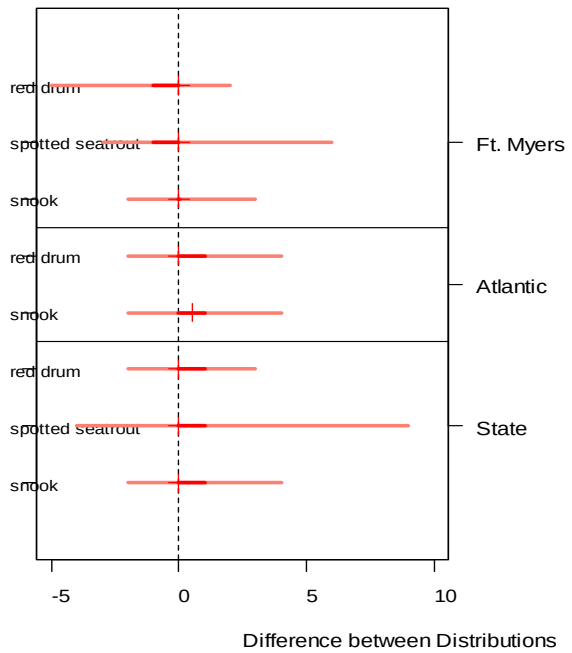
iAngler poor
MRIP poor
Both poor
Both sufficient

2012-2016

State	1680/ 830	665/ 866	348/ 1025			
Atlantic	769/ 570	134/ 45	81/ 246			
Ft. Myers	865/ 151	503/ 88	178/ 97			
Tampa	28/ 93	14/ 292	10/ 134			
	Common Snook	Spotted Seatrout	Red Drum	Red Snapper	Red Grouper	Gag

iAngler poor
MRIP poor
Both poor
Both sufficient

Figure 4-16. Summary of data quality in relation to comparing the catch/trip distributions for shore mode trips. Each cell contains the sample size for iAngler (top) and MRIP (bottom), where n=30 is the minimum number of samples required to fit to a negative binomial distribution. Each color indicates which, if either, dataset had enough records. Red snapper, red grouper, and gag are not considered because they are not inshore species, where shore trips occur.



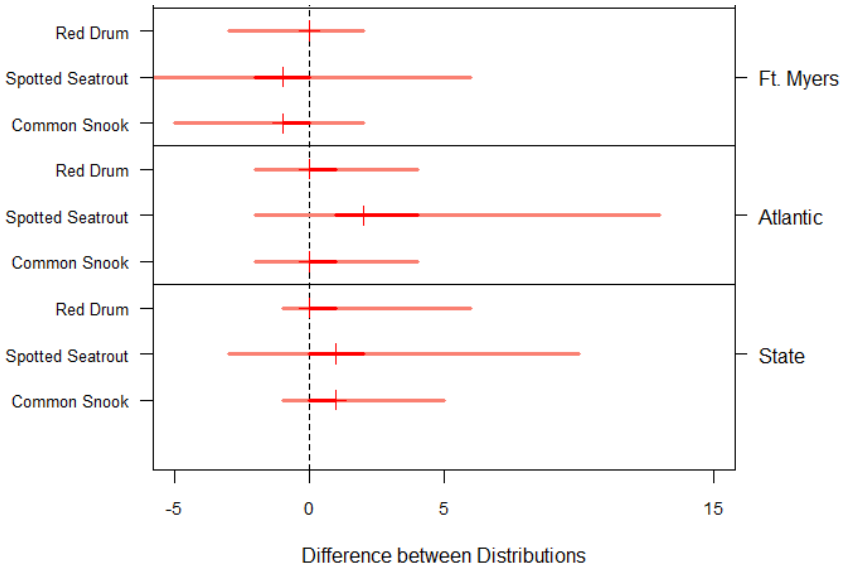


Figure 4-17. Difference between iAngler and MRIP simulated catch/trip distributions for the shore mode. Crosses represent the median, dark red bars represent the 20% quantiles, and the light red bars represent the 80% quantiles. 2012-2013 top, 2012-2016 bottom.

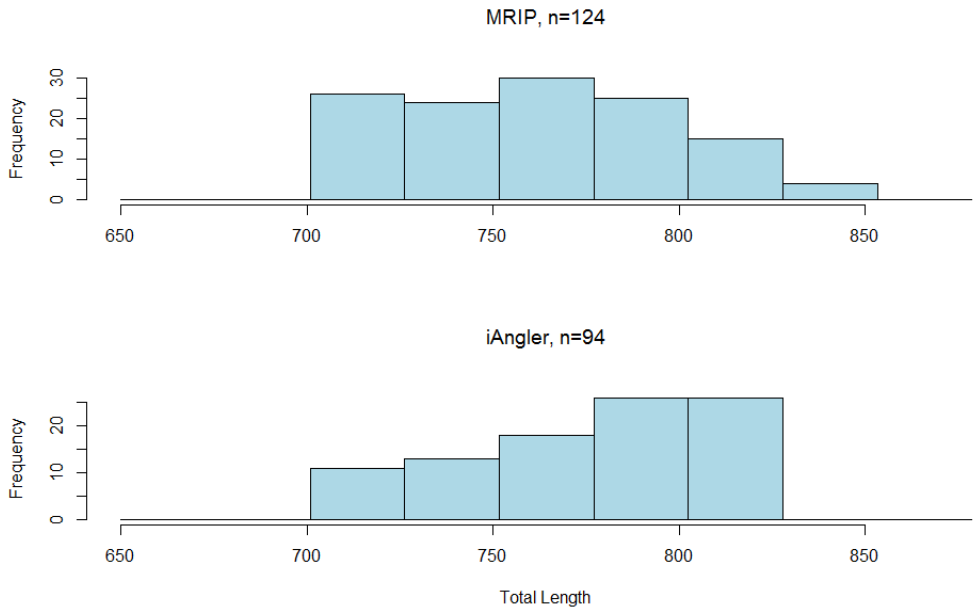


Figure 4-8. Length frequency distributions of Common Snook from the MRIP harvest (top) and iAngler harvest (bottom) datasets for Florida from years 2012-2016.

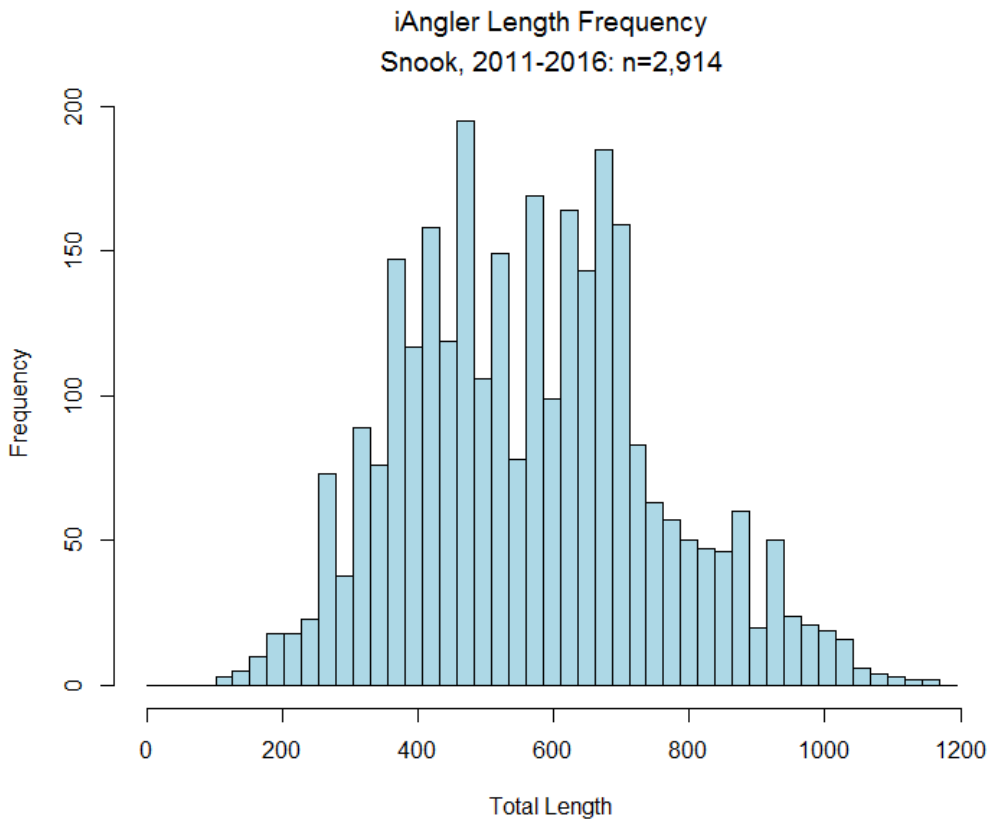


Figure 4-9. Length frequency distribution of released Common Snook from the iAngler app data for Florida from years 2012-2016.

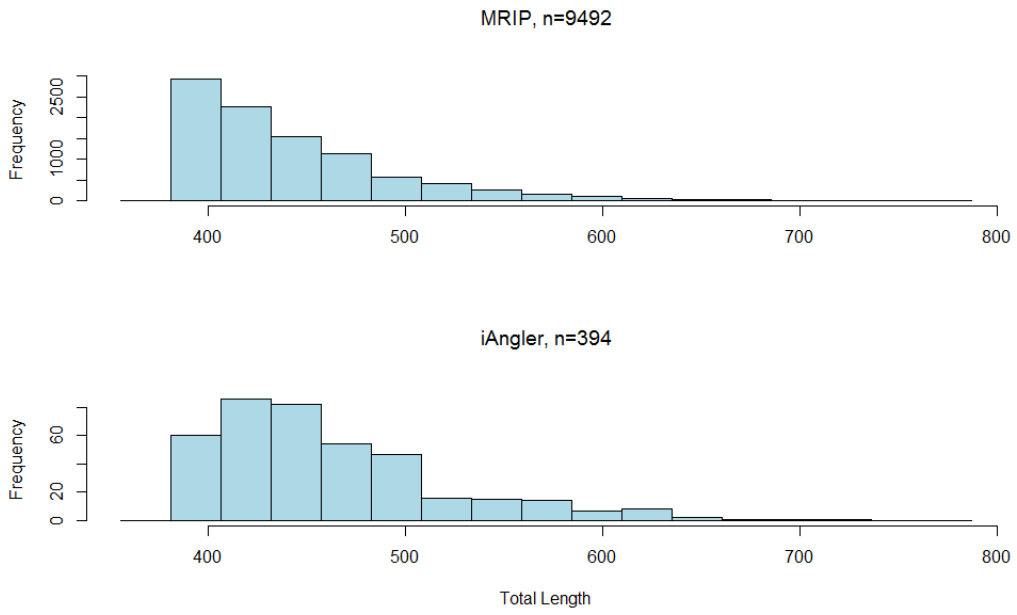


Figure 4-10. Length frequency distributions of Spotted Seatrout from the MRIP harvest (top) and iAngler harvest (bottom) datasets for Florida from years 2012-2016.

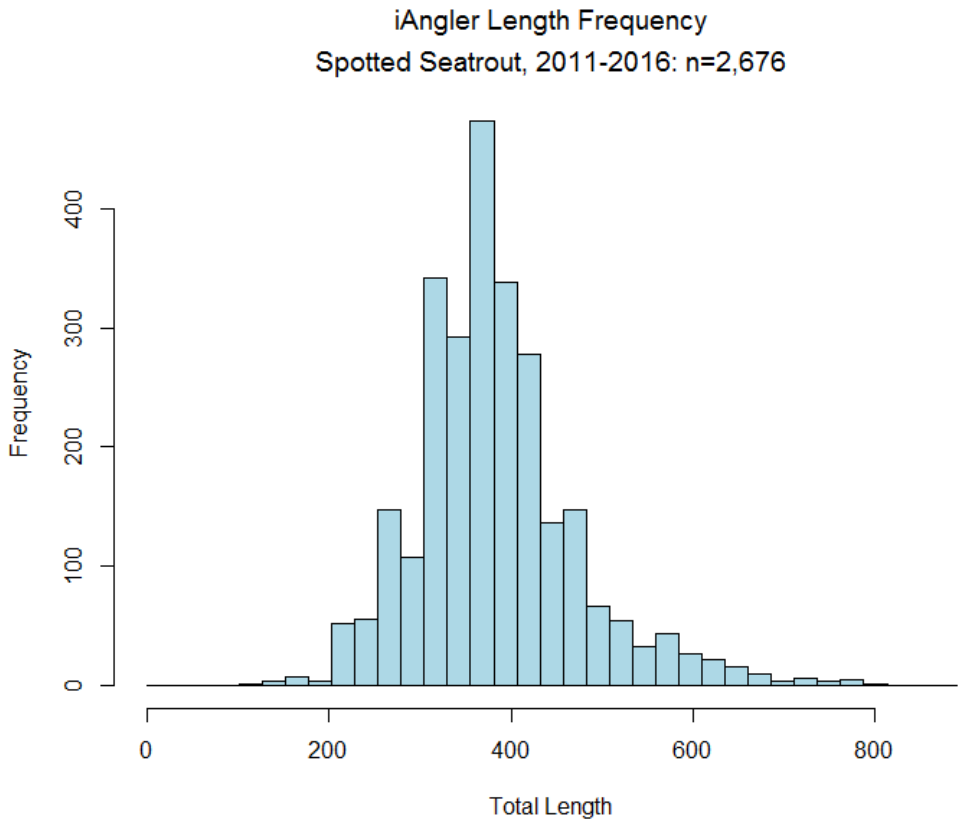


Figure 4-11. Length frequency distribution of released Spotted Seatout from the iAngler app data for Florida from years 2012-2016.

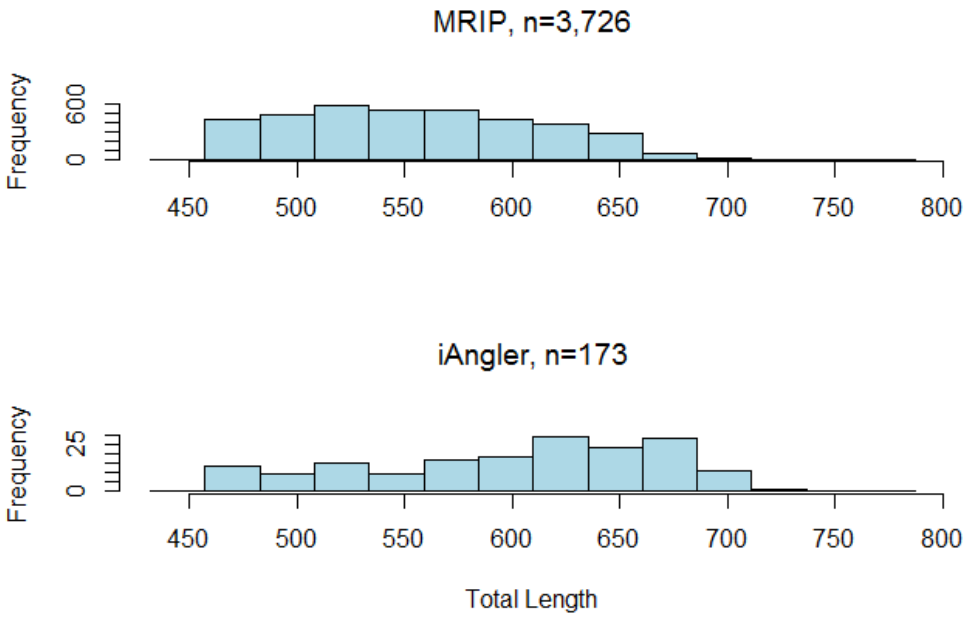


Figure 4-12. Length frequency distributions of Red Drum from the MRIP harvest (top) and iAngler harvest (bottom) datasets for Florida from years 2012-2016

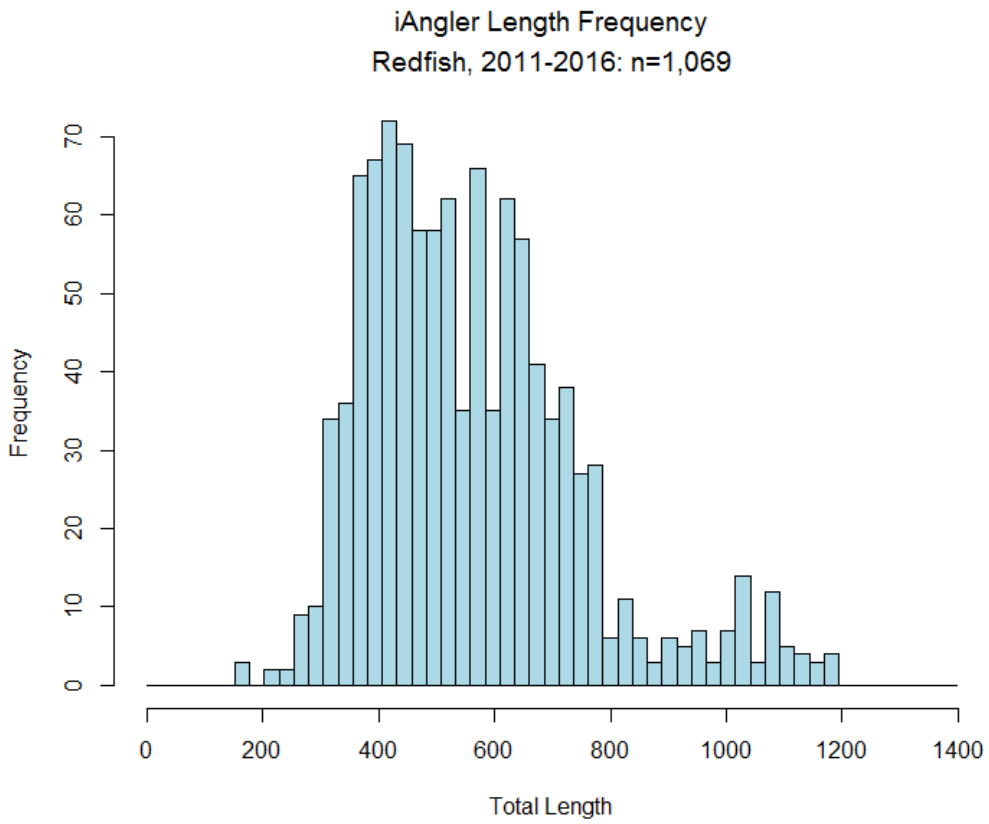


Figure 4-13. Length frequency distribution of released Red Drum from the iAngler app data for Florida from years 2011-2016.

Table 4-9. A summary of the number of saltwater angling trips per county in Florida for the iAngler and MRIP data.

	iAngler		MRIP	
County	Trips	Proportion	Trips	Proportion
Bay	185	0.030	5324	0.041
Brevard	415	0.068	8759	0.067
Broward	102	0.017	3279	0.025
Charlotte	507	0.083	2397	0.018
Citrus	36	0.006	3000	0.023
Clay	0	0.000	63	0.000
Collier	99	0.016	2601	0.020
Dixie	44	0.007	457	0.004
Duval	20	0.003	4938	0.038
Escambia	4	0.001	5645	0.043
Flagler	4	0.001	512	0.004
Franklin	10	0.002	1069	0.008
Gulf	38	0.006	959	0.007
Hernando	7	0.001	1578	0.012
Hillsborough	140	0.023	9695	0.075
Indian River	208	0.034	1692	0.013
Lee	1345	0.220	4094	0.031
Levy	10	0.002	1718	0.013
Manatee	46	0.008	4895	0.038
Martin	486	0.080	3583	0.028
Miami-Dade	115	0.019	4455	0.034
Monroe	140	0.023	10339	0.079
Nassau	3	0.000	1042	0.008
Okaloosa	16	0.003	7024	0.054
Palm Beach	2030	0.332	8006	0.062
Pasco	10	0.002	2927	0.023
Pinellas	244	0.040	15678	0.121
Santa Rosa	7	0.001	1770	0.014
Sarasota	195	0.032	2356	0.018
St. Johns	9	0.001	1110	0.009
St. Lucie	190	0.031	6132	0.047
Taylor	22	0.004	1225	0.009
Volusia	93	0.015	3346	0.026
Wakulla	2	0.000	1528	0.012
Walton	1	0.000	164	0.001

Table 4-2. Comparing the percentage and number of trips where each species was caught on the state level

iAngler (6,111 total trips)			MRIP (130,063 total trips)		
Species	Percentage of trips caught	Number of trips caught	Species	Percentage of trips caught	Number of trips caught
Common Snook	31%	1915	Spotted Seatrout	13%	17437
Spotted Seatrout	21%	1294	Gray Snapper	9%	11957
Red Drum	13%	815	Pinfish	8%	10287
Crevalle Jack	11%	690	Red Drum	7%	9187
Ladyfish	9%	520	Ladyfish	7%	8475
Gray Snapper	6%	373	Hardhead Catfish	6%	7919
Yellowtail Snapper	4%	240	Crevalle Jack	6%	7849
Spanish Mackerel	4%	217	Red Grouper	5%	5940
Tarpon	2%	140	Spanish Mackerel	4%	5731
Red Snapper	2%	93	White Grunt	4%	5658

Table 4-3. Comparing the percentage and number of trips where each species was caught for the Atlantic county cluster

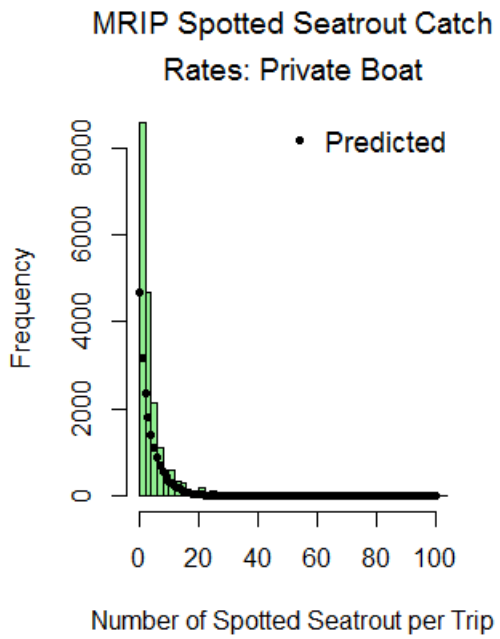
iAngler (2,676 total trips)			MRIP (26,314 total trips)		
Species	Proportion of trips caught	Number of trips caught	Species	Proportion of trips caught	Number of trips caught
Common Snook	0.46	1214	Crevalle Jack	0.08	2201
Spotted Seatrout	0.38	984	Spotted Seatrout	0.06	1690
Crevalle Jack	0.15	401	Little Tunny	0.05	1233
Red Drum	0.13	334	Blue Runner	0.05	1201
Gray Snapper	0.07	186	Gray Snapper	0.04	1080
Yellowtail Snapper	0.06	159	Hardhead Catfish	0.04	989
Tarpon	0.05	132	Ladyfish	0.03	908
Mutton Snapper	0.05	123	Dolphin (Mahi)	0.03	865
Ladyfish	0.05	121	Bluefish	0.03	762
Blue Runner	0.03	86	Pinfish	0.03	678

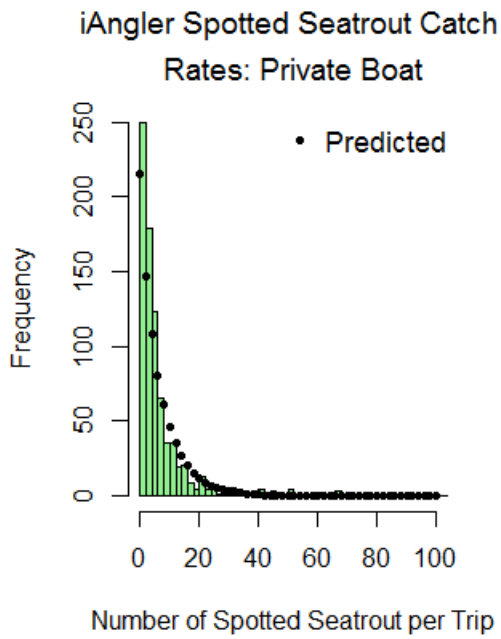
Table 4-4. Comparing the percentage and number of trips where each species was caught for the Ft. Myers county cluster

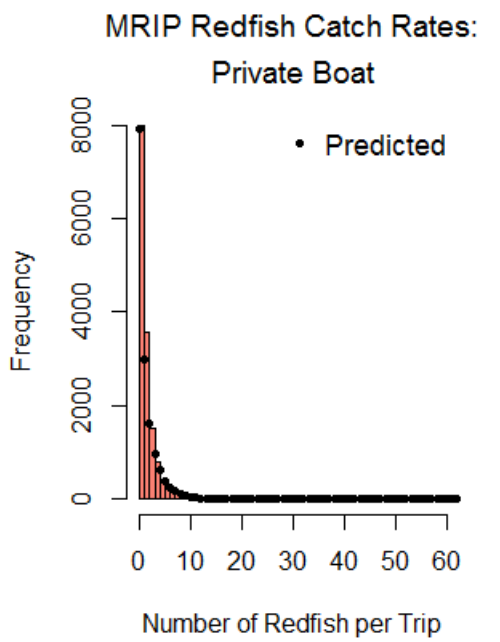
iAngler (1,386 total trips)			MRIP (14,797 total trips)		
Species	Proportion of trips caught	Number of trips caught	Species	Proportion of trips caught	Number of trips caught
Common Snook	0.32	445	Spotted Seatrout	0.20	2893
Spotted Seatrout	0.31	432	Gray Snapper	0.12	1711
Red Drum	0.26	365	Red Drum	0.12	1703
Ladyfish	0.09	123	Ladyfish	0.11	1565
Crevalle Jack	0.09	119	Pinfish	0.08	1121
Spanish Mackerel	0.07	98	Common Snook	0.05	777
Gray Snapper	0.04	56	Hardhead Catfish	0.05	768
Tarpon	0.02	25	Sheepshead	0.05	705
Gulf Flounder	0.02	22	Red Grouper	0.05	677
Florida Pompano	0.02	22	Crevalle Jack	0.04	609

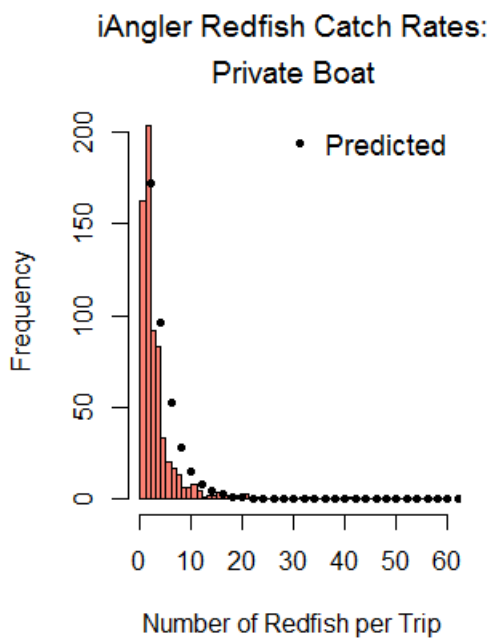
Table 4-5. Comparing the percentage and number of trips where each species was caught for the Tampa county cluster

iAngler (698 total trips)			MRIP (21,349 total trips)		
Species	Proportion of trips caught	Number of trips caught	Species	Proportion of trips caught	Number of trips caught
Common Snook	0.35	242	Spotted Seatrout	0.32	6788
Spotted Seatrout	0.33	232	Pinfish	0.23	5004
Red Drum	0.29	199	Ladyfish	0.13	2877
Gray Snapper	0.06	45	Red Grouper	0.10	2090
Crevalle Jack	0.06	41	Spanish Mackerel	0.09	1890
Spanish Mackerel	0.06	40	White Grunt	0.09	1888
Ladyfish	0.05	36	Red Drum	0.08	1760
Gulf Flounder	0.05	34	Gag	0.08	1734
Gag	0.03	18	Gray Snapper	0.08	1654
Tarpon	0.02	14	Crevalle Jack	0.08	1634


MRIP Spotted Seatrout Catch Rates: Private Boat
Predicted
Frequency
0
2000
4000
6000
8000
0
20
40
60
80
100
Number of Spotted Seatrout per Trip


iAngler Spotted Seatrout Catch Rates: Private Boat
Predicted
Frequency
0
50
100
150
200
250
0
20
40
60
80
100
Number of Spotted Seatrout per Trip


MRIP Redfish Catch Rates: Private Boat
Predicted
Frequency
0
2000
4000
6000
8000
0
10
20
30
40
50
60
Number of Redfish per Trip


iAngler Redfish Catch Rates: Private Boat
Predicted
Frequency
0
50
100
150
200
0
10
20
30
40
50
60
Number of Redfish per Trip

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