Implementation of the *iSnapper* smartphone application to collect data across all recreational sectors in the Gulf of Mexico

FY 2014 Final Report
for

MARINE RECREATIONAL INFORMATION PROGRAM

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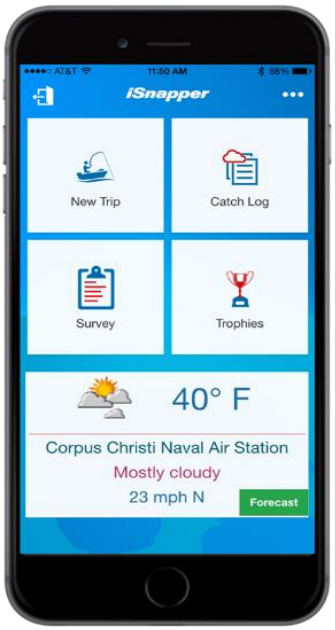

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I. Abstract

One of the most difficult aspects in fisheries management is the ability to collect timely catch data from the private fishing sector to estimate total recreational harvest. The lack of timely and robust data from recreational anglers (i.e., private anglers and for-hire charters) creates management challenges and controversy, as managers seek to optimize fisheries harvest. We created *iSnapper*, a smart device application ("app") designed for private recreational anglers, to log their catch and effort information during the 2015 federal Red Snapper season (June 1st – 10th). During the 10-day season a total of 163 trips were logged using the app, and these anglers harvested a total of 1,519 Red Snapper. Additional data collected included trip length, general fishing location, fishing depth, number of anglers, and number of fish released. Self-reported data was validated by comparing trips submitted using *iSnapper* to dockside creel interviews (259), with a total of 11% of trips validated. Using a capture-recapture design along with these validated trips, we developed an estimator that showed in 2015 private recreational anglers in Texas reported 4.1% of their trips, had a harvest error rate of +5.1%, and harvested a total of 58,251 Red Snapper (± 25,344 SE) weighing an estimated 277,752 lbs. This is comparable to Texas Parks and Wildlife harvest estimates of 32,062 Red Snapper (± 4,409 SE) weighing an estimated 153,525 lbs. Also included in the app was a socioeconomic survey, with 95 unique respondents reporting their average distance traveled was 89 miles, spent approximately $200 for bait and tackle, consumed 82 gallons of fuel, and 61% had a yearly household income over $100,000. This study shows that smart device apps are a very effective method for collecting private recreational fisheries data, and when coupled with strong validation strategies these data can be used by fisheries managers to estimate total harvest of recreationally important fisheries and also examine important questions such as discard mortality, depth fished, and a variety of socioeconomic parameters.

II. Executive Summary

Red Snapper is one of the most highly targeted species in the northern Gulf of Mexico. This fishery has been classified as overfished since the late 1980's, and this designation has led to drastic reductions in both season and bag limits. Uncertain and unpredictable recreational catch rates along with a federal court ruling required managers to build in large harvest buffers to prevent overfishing, and these measures have created even shorter seasons with only 10 days in 2015. Ironically, this situation has also created a much narrower window for fisheries managers to collect catch data further compounding the harvest estimate issues.

A major challenge to improving recreational season length and alleviating some of this controversy is the lack of timely catch data. Supplementing the Marine Recreational Information Program (MRIP) with an electronic data collection system would provide more timely and robust information, thereby allowing managers to refine catch estimates and reduce buffers that could lead to optimizing the harvest and allow for longer recreational seasons. Thus, we created *iSnapper*, a smart device application designed for private anglers to log their catch and effort data. Mobile applications provide a unique opportunity to provide better data that will work in combination with current MRIP survey protocols to provide a supplementary means of rapid in-season (and out of season) catch information that would otherwise be unavailable. In addition to catch statistics, this type of reporting mechanism generates additional data that are typically difficult to collect such as fish discard rates, fishing depth, effort estimates, and socioeconomic parameters that will help optimize the fishery's full potential from both a harvest and an economic perspective. The concept of electronically collected and self-reported data certainly has many challenges; however, this pilot showed *iSnapper* has the ability to overcome many of these obstacles while generating real-time, validated, and reliable private recreational catch data for fisheries managers – something needed by all groups involved to improve access to the Red Snapper fishery.

A key component to this study was the validation of catch data submitted by anglers, with creel interviews conducted to verify accuracy of user-entered information. These data were compared to trips submitted via *iSnapper* using the vessel registration number as the key linking parameter. A majority of the data analyzed within this report occurred during the federal Red Snapper season (June 1 – 10), because there was an increased number of creel surveys and fishing activity during this time allowing for the best probability of intercepting an *iSnapper* user

for validation. From the validated trips we calculated a reporting and harvest error rate and developed an estimator (specifically for this project) to calculate the total number of Red Snapper harvested, and the total number of private recreational angler trips in Texas during 2015.

iSnapper was introduced to anglers via extensive outreach and advertising campaign employing TV, radio, print, and social media. A total of 163 trips were submitted using *iSnapper* by Texas private recreational anglers harvesting a total of 2,012 fish during the federal season. Red Snapper was the most dominate species captured (1,519; 75.5%), with all trips reporting at least one Red Snapper harvested. A variety of other species were also caught, with King Mackerel and Dolphinfish as the other most commonly harvested species. The mean reported discard rate for Red Snapper was 56.1%, with the highest rate of 74.3% occurring at depths between 21 – 30 m.

A total of 969 private recreational Red Snapper anglers were encountered during surveys at Texas boat ramps. The creels from these anglers represented 259 fishing trips and harvested a total of 2,268 Red Snapper. To validate the self-reported data, these trips were compared with those submitted using *iSnapper*. The sampling was done using a mark and recapture approach, with *iSnapper* users being recaptured during the creel survey. Of the *iSnapper* trips, a total of 18 were validated during the dockside interviews, generating an 11% validation rate. From these validated trips we calculated an overall reporting rate of 4.1% as well as an error rate of +5.1%. Using the reporting rate and error estimates from the federal season, along with creel data provided by TPWD for the entire year, the estimated total number of Red Snapper harvested by Texas private recreational anglers was 58,251 fish (± 25,344 SE) weighing an estimated 277,752 lbs by 23,358 angler trips (± 6,660 SE) in 2015. Although not the focus of this study, we had an additional 13 charter for-hire trips submitted using *iSnapper* throughout summer 2015, which was surprising given the popularity of previous versions of *iSnapper* piloted with the for-hire Federal Reef Fish permit holders. Different than private recreational anglers, charter captains had a longer federal Red Snapper season (40 days; June 1 – July 14) and during this time reported harvesting a total of 76 Red Snapper, 25 Dolphinfish, 6 King Mackerel, 1 Warsaw Grouper, and 1 Yellowedge Grouper (seven total trips). Six additional trips were submitted in August from state waters with a harvest of 128 Red Snapper, and no other species were reported.

In addition to catch and effort data, the app also collected socioeconomic information from participants. The survey was a separate feature built into the app that allowed anglers to fill

out and submit the survey, but was not linked to particular fishing trips. A total of 100 surveys were completed with 95 unique respondents. Approximately 98% of the respondents were male, with 93% residing in Texas. The average distance traveled per trip was 89.3 miles (± 7.3 SE) with a mean expenditure in bait and tackle for the trip was $197.40 (± $34.22 SE), and boats consumed on average 82.4 gallons of fuel (± 12.0 SE). These results demonstrate the utility for smart devices to collect these types of socioeconomic data that are essential to valuating the fishery.

Overall, this project demonstrated that smart device applications can be successfully designed to collect catch and effort data from the private recreational fishing sector to greatly enhance and supplement current data collection approaches. An advantage of this approach is the timeliness of the data collection provided, particularly in circumstances of shorted seasons where traditional MRIP approaches may not be as feasible. We were able to streamline data collection by gathering all the pertinent information in only a few screens making the data entry quick and easy, allowing anglers to report catch information for multiple species, as well as discard mortality, depth fished, and a variety of socioeconomic components of the fishery. The program was also voluntary, and that may have contributed to a lower than our desired reporting rate. Although mandatory reporting certainly does not guarantee 100% compliance, comparisons should be made across states where reporting is mandatory to determine how this influences the accuracy of the estimates. However, even without mandatory reporting, we found that smart device app technology has great potential to collect valuable catch and effort data quickly and efficiently from the private sector and can be used to make catch estimates. While this pilot was specifically targeting Red Snapper anglers, *iSnapper* has the potential to improve management for a variety of fisheries. By combining these smart device technologies with traditional fish survey methods, managers have improved tools to gather more information to make better informed decisions.

III. Purpose

A. Description of the problem

One of the major challenges to fisheries management is the ability to collect timely catch data from the recreational fishing sector. Recently, management measures have led to an increasing need for more timely and accurate estimates of recreational catch and effort data for assessing stocks (Griffiths et al. 2010). The problem is further compounded with shortened seasons and the need for rapid in-season measurements of catch. The lack of timely and robust data from this sector has created problems when fisheries managers calculate the annual harvest quota well after the season has ended and this has led to major conflicts among users for species such as Red Snapper (*Lutjanus campechanus*). This species is highly sought after by both commercial and recreational fishers and its management is one of the most controversial in the United States. For example, the inability to rapidly gauge recreational catch has resulted in the sector exceeding the allocation for the past 21 of 24 years. A recent 2014 federal court ruling resulted in federal managers implementing a 20% buffer to prevent the overages. Compounding the problem, anglers are also catching larger snapper each year; thus, reaching the quota faster than in previous years. All of these factors have led to very short federal fishing seasons (10 days in 2015, 9 days in 2014), despite anglers seeing a resurgence of Red Snapper. These shortened seasons hinder the ability of traditional approaches to collect accurate data from recreational anglers, because they were not designed to collect data in this manner. The Marine Recreational Information Program (MRIP) has modified their sampling protocols to increase the amount of data collected from anglers during these short windows. However, there is still a need for rapid in-season and near real-time data collection. Here we developed a novel data collection tool for the private recreational sector using smartphone/tablet applications ("apps") and web-based data entry portals.

In the past decade there has been a dramatic increase in the number of people using mobile phones. With this emerging technology, a new avenue of data collection was developed using apps as the platform for data collection. The concept was initially tested in the fisheries field by having recreational anglers submit text messages of their catch and effort data (Baker and Oeschger 2009). However, the 160 character maximum severely limited what could be included in the message, making it difficult to report an entire day of fishing. Currently, nearly two-thirds of Americans own a smartphone (Pew Research Center 2015), so the next logical step

is to move from a text message data collection system to creating a specialized app that can be created and then downloaded onto the phones. More recently, smart devices have redefined the technological market allowing users to do a multitude of operations including accessing the internet using cellular data; thus, there is a high potential to use smart devices to collect more informative fisheries catch data.

Collecting data via smart device technology incorporates another recent trend using citizen scientists (individuals that are amateurs or nonprofessionals) to collect a substantial amount of data for relatively little cost. The data submitted by these citizen scientists are considered "self-reported," because these individuals are reporting without any direct validation from state or federal managers. The benefit in collecting and using self-reported data is that these citizen scientists provide managers with data that would otherwise be unavailable and they feel a sense of empowerment by being able to contribute to the conservation and management of their natural resources (Cohn 2008). Scientists are also recognizing the potential of self-reported data from smart device apps that have been created merely for entertainment purposes. One such app, *iFish*, is essentially a catch log for freshwater anglers throughout the United States and Canada. Catch and effort data is submitted by the user and this information can be used by fisheries managers to better understand local hotspots or how fishing pressures change depending on season (Papenfuss et al. 2015). We proposed and tested the potential to use this technology in the private recreational Red Snapper sector.

The Red Snapper fishery in the Gulf of Mexico is an ideal testbed to examine the feasibly of a voluntary smart device data collection app for private recreational anglers. Due to the limited federal Red Snapper season, fishery managers must rely on collecting as much data as possible from this sector while the brief season is open. Creating an app not only provides fisheries managers with near real-time data, but it can also collect a multitude of other important information (e.g. socioeconomic data, release mortality, etc.). A lack of timely data hinders the management of this fishery because data generated from directed creel surveys takes months before it is transcribed, edited, reviewed, and available for management advice. During this time, data submitted using an app could be analyzed and the total harvest could be estimated in a much more rapid fashion, allowing for in-season monitoring of the recreational harvest, which could potentially increase the season length, and reduce the 20% management buffer.

While an app provides the ability to collect more robust and timely harvest data, validating the quality is of paramount importance. The most critical and informative validation measure is to visually inspect the entire catch when it is landed dockside to confirm that submitted catch reports are consistent. This validation allows managers to calculate the reporting rate as well as error estimates based on anglers who may have, for example, misidentified certain species of fish or have inaccurately reported their total harvest. These estimates can then be extrapolated to all of the trips that were interviewed at the boat ramps to calculate more accurate total harvest estimates.

Given the potential of smart device apps to improve the management for many fisheries, our aim of this study was to supplement the current MRIP data collection program by developing and testing new technologies to enhance recreational fisheries data collection. In 2011, Harte Research Institute for Gulf of Mexico Studies (HRI) released *iSnapper* for use in the charter for-hire industry and had overwhelming success with the project with major buy-in and support from participants (Stunz et al. 2016, in prep). Due to this success, the original concept was redesigned to create an app that could be used in the private recreational sector as well as for charter captains.

B. Objectives of the project

The specific objectives of this study were to:

1) Develop and implement *iSnapper* as a data collection app (for Apple, Android, and Windows platforms including a web portal) for private recreational anglers in the Gulf of Mexico;
2) Compare *iSnapper* data from panels of private anglers to TPWD creel survey data to validate the applicability of electronic data collection;
3) Collect and assess socioeconomic data from reef fish fishery participants using *iSnapper;*
4) Provide *iSnapper* as a data collection tool for NOAA-approved programs targeting Red Snapper in the Gulf of Mexico.

IV. Approach

iSnapper development

Despite creating a very successful prior version of *iSnapper* (v1.0), it was necessary to re-design the platform to create a submission process easy and aesthetically pleasing for private recreational anglers that were not as incentivized as for-hire captains to enter catch data. Thus, working with Elemental Methods, LLC we recreated *iSnapper* (v2.0) on Apple's iOS®, as well as two new platforms, Android® and Windows®. Both smartphone and tablet versions were created for each platform to give individuals different and the most comprehensive entry options.

Application Architecture

The *iSnapper* v2.0 app was created and built upon *iSnapper* v1.0 and used to collect catch and effort data from private recreational angler boat owners, as well as charter boat operators, throughout the Gulf of Mexico. This version was specifically adapted to be most suitable to private recreational anglers; however, most of the features and data collection options were available to continue to gather these data in the for-hire sector. Anglers were asked to enter their catch data by "adding" the species captured from the provided list of all the commonly caught species in the Gulf of Mexico (Figure 1) that included easy to select images. Once a species was selected, they provided the number harvested and released individuals. The average depth fished and general fishing area were also required fields and indicated by clicking on an image of the Gulf of Mexico. Effort data was gathered by providing the number of anglers on the vessel, and fishing times were also collected. Several new features were also implemented to build a multi-functional app in a very user friendly environment to promote use by private anglers. Some of these features include current weather and tide information based on location, the ability to submit pictures of unidentified fish directly to researchers, and each trip can be shared on the individual's social media networks (Facebook® and Twitter®).

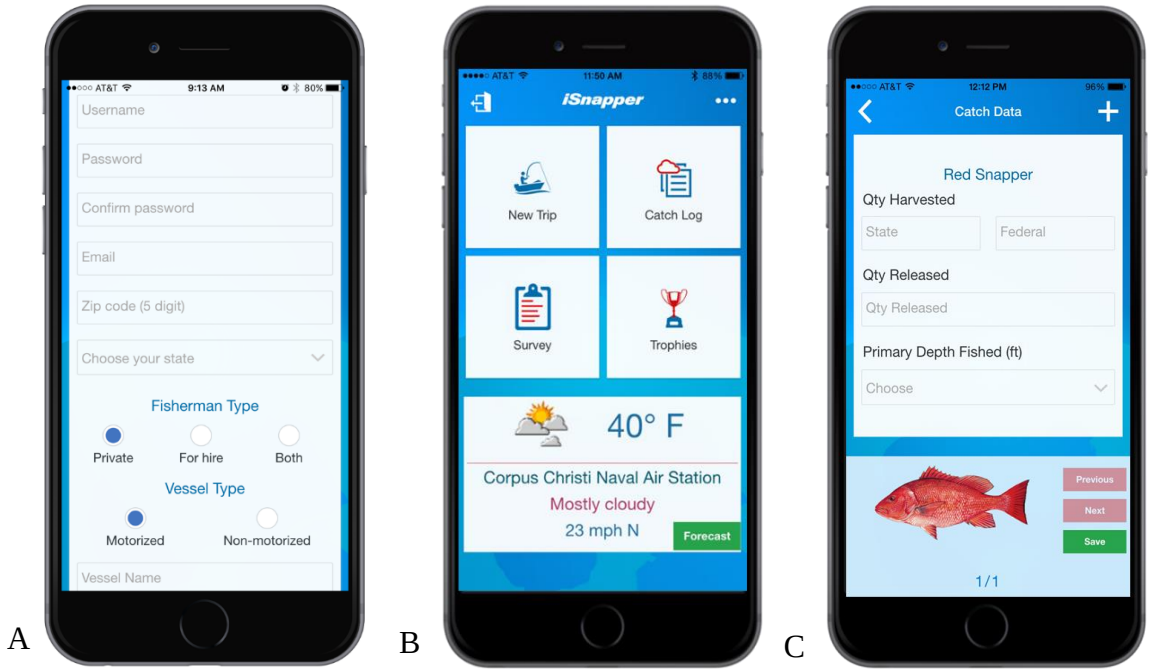


Figure 1. Screenshots of the registration screen (A), home screen (B), and the species catch screen (C).

Web Portal

Anglers were not limited to only using smart devices to submit their trips. We also created an online *iSnapper* webportal (https://isnapperonline.org, Figure 2) that anglers could use if they did not have a smart device, or potentially encountered problems submitting their catch using the app. This option provided anglers with the opportunity to register or login using the same username they created when registering on the *iSnapper* app and enter their catch information online. Additionally, the webportal allowed anglers to login and view their catch data and saved photos from previous trips. The webportal was also designed to store all user and trip information for administrator access and data download as needed throughout the season.

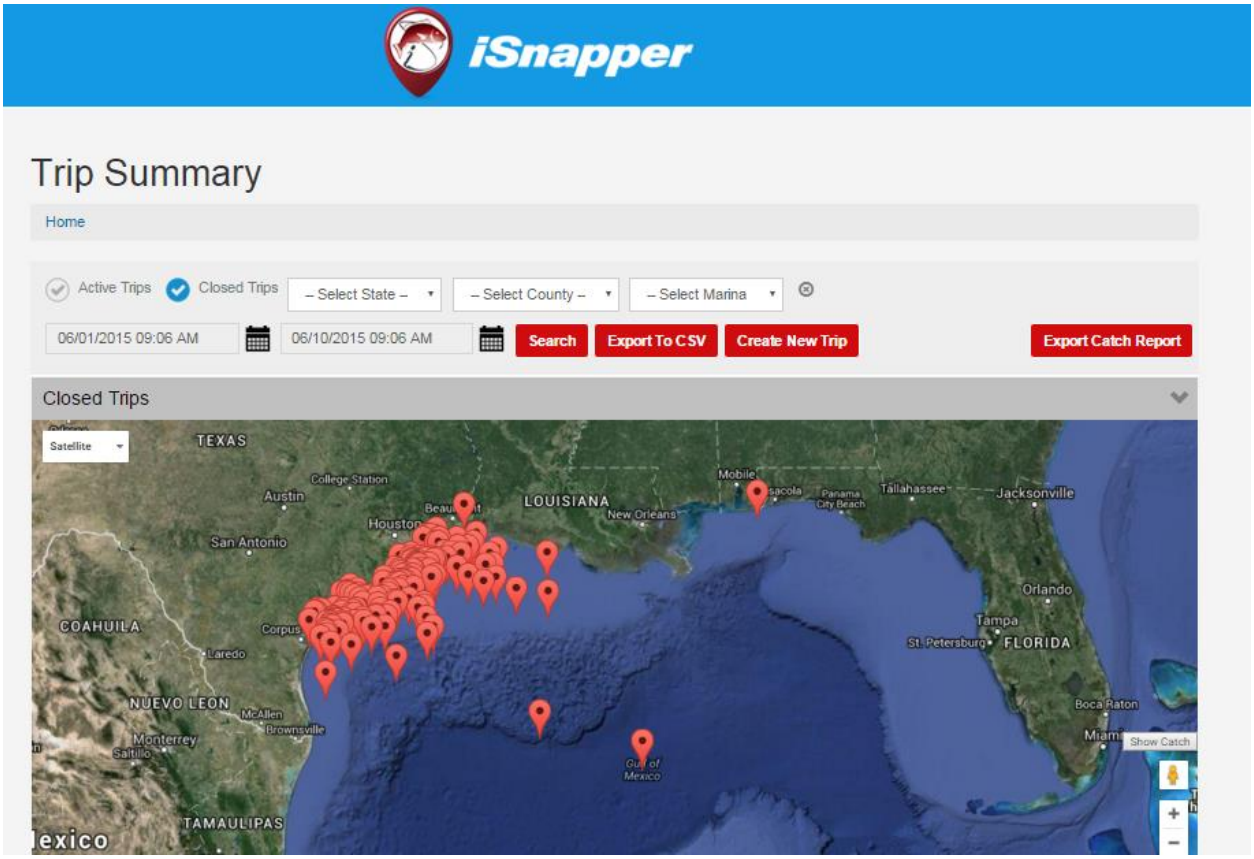


Figure 2. Image of the webportal with all trips from the federal season displayed.

Panelist Selection

A crucial portion of this study involved the validation of self-reported data. Originally, we planned on selecting a defined list of panelists from known Red Snapper anglers that represented a variety of angling frequency types using a stratified systematic random sampling design and then target these panelists at boat ramps during the Red Snapper season. However, this plan represented some insurmountable obstacles given this was the first pilot of this type. For example, we quickly discovered that a robust database of individual Red Snapper anglers that we could draw from did not exist, these anglers could not be assigned to ports of origin, and there was no information regarding their angling frequency. Thus, this initial plan was reconsidered and a new approach, and in hindsight a much better method, was developed after extensive consultations with MRIP statisticians (Lynne Stokes, Ph.D.) wherein we created a more inclusive design that involved collecting data from all *iSnapper* users, which was used as the initial "panel." Now future studies have the ability to draw from this created panel of users

that was built from known Red Snapper anglers. Briefly, the overall design was based on the well-established mark and recapture theory (Laplace 1786), where *iSnapper* registered users were considered "marked," and then "recaptured" during boat ramp creel surveys after completing a fishing trip. The initial identification of anglers was randomized by sending out postcards, media outreach, and distributing informational wallet cards to as many anglers as possible without prior knowledge of their willingness to participate in the study or with what frequency they fish for Red Snapper.

Outreach

In collaboration with media and outreach partners at TPWD, we sent two postcard flyers that provided information about *iSnapper,* to as wide of an audience as we could identify. This included the 610 known Texas Red Snapper anglers that had been identified in their long-term data set along with mailings to charter captains and other participants in the *iSnapper v1.0* pilot. The private anglers were encountered by TPWD creel surveys who had captured at least one Red Snapper on their trip during the last five years. A second mailing was also sent near the season opening to alert anglers that *iSnapper* was available for download and use. To further increase the number of *iSnapper* users, we also advertised in several state and local magazines, radio, and television news and public service segments. We also created of an informative webpage (www.iSnapper.org) separate from the data collection portal, and these information sites were pushed extensively through social media avenues (e.g., Facebook® and Twitter®) by both HRI and TPWD and created an account on two of the most popular saltwater fishing forums to inform anglers about the app. In addition, TPWD produced flyers, wallet cards, and laminated signs that were distributed to bait shops and anglers several weeks prior to the opening of the federal Red Snapper season. Before the start of the season coordinators of groups such as the Coastal Conservation Association Texas, Saltwater Enhancement Association, and Texas Sea Grant volunteered to educate their members and contact them about the app and encouraged them to submit their catch using *iSnapper*.

Validation

Validation was performed at boat ramps by both TPWD surveyors and HRI staff by creeling as many boats as possible to intercept private recreational anglers using *iSnapper* after a

fishing trip. During the private recreational federal Red Snapper season (June 1 – June 10) 7 additional TPWD creel surveys were conducted with the intent to "recapture" as many *iSnapper* users as possible. Additionally, to augment creeling effort HRI staff conducted 5 surveys at high use marinas and boat ramps during the federal Red Snapper recreational season, and TPWD increased the number of random creel surveys throughout the 'high use' season (May 15 – November 20, 2015) from 764 in 2014 to 832 in 2015. Despite these targeted creels at high use sites, the anglers were still randomly intercepted, because interviewers did not know if any *iSnapper* trips had been started or submitted prior to the creel survey. During the interviews, one angler (typically the captain or designee) from the boat was asked how many Red Snapper were harvested, the number of anglers on the boat, depth fished, and if they had reported their catch using *iSnapper*. The accuracy of data submitted with *iSnapper* were validated by cross-referencing the creel surveys using vessel registration numbers to determine if their reported catch was the same as what was recorded dock-side. Certainly, by maximizing the numbers of validations that could be performed, the most accurate catch estimates could be determined. Anglers that were encountered not using the app were also surveyed, and they were informed about *iSnapper*, the value of using it, and were highly encouraged to download and use it for the duration of the federal and state Red Snapper seasons.

Catch Estimation

The traditional method for estimating recreational catch for most species and locations uses two complementary surveys of anglers, one to measure "effort" (number of fishing trips) done by phone or mail, and one to measure mean catch per trip, done face-to-face with dockside interviews. Use of electronic reporting allows effort estimates to be reported by the anglers on the day when the fishing actually took place, reducing problems with inaccurate estimates due to recall bias. However, using this data requires a validation process to monitor how accurate the reporting is. Anglers were encouraged to submit their trip data prior to arriving back in case they were intercepted by TPWD or HRI at the dock to prevent any bias and ensure independence in the self-reported data and validation process. With both the self-reported data and the validation, the population and sample data can be broken down into four categories (Figure 3) to calculate the number of trips and Red Snapper harvested. All of the categories, aside from the 'not reported or creeled', are used in a new estimator developed specifically for this project to

calculate the reporting and error rates to estimate the total Red Snapper harvest for private recreational anglers using self-reported data in 2015. The new estimator had to be developed since this type of data has yet to be included in catch and effort estimates. To calculate the total harvest or total number of anglers, the following equation was used:

$$\hat{t}_{y2} = t_{y^*} + \frac{n_1}{\hat{n}_1}\left(\hat{t}_y - \hat{t}_{y^*}\right) = t_{y^*} + n_1\hat{\bar{\delta}}$$

where $\hat{\bar{\delta}}$ is an estimator of $\bar{\delta} = (t_y - t_{y^*})/n_1$ which is the total population underreport averaged over the units in the reporting domain (i.e. the *iSnapper* reports). In the formula, t_{y^*} is the reported removals of Red Snapper (or reported number of anglers) based on the *iSnapper* app. n_1 is the number of vessel trips which reported their Red Snapper catch using *iSnapper*. $\hat{t}_y$ and $\hat{t}_{y^*}$ are the estimated Red Snapper catch (or number of anglers) of the whole population and the reporting domain, estimated from the validation sample only. The equation above is the best estimator ($\hat{t}_{y2}$) for these data, and while details on the derivation can be found in Liu et al. (*In prep;* Appendix 1).

		Sample Validated	
		Yes	No
Reported	Yes	Reported and validated	Reported, not creeled
	No	Not reported, creeled	Not reported or creeled

Figure 3. Illustration of the population and sample data.

Registration

Anglers were able to download *iSnapper* at the App store (iOS) and Google Play (Android). Once downloaded, the first step in the data submission process involved anglers registering to set-up their *iSnapper* account (Figure 1A). At registration, participants provided their vessel registration numbers, giving a unique identifier critical for validation. Also, contact information was collected to allow administrators to contact anglers to resolve any observed errors. Once registered, the angler was able to immediately enter and submit their catch information from fishing trips. The process to submit a trip involved 3 simple steps (Figure 3). All of these steps could be done in less than five minutes, and typically within two minutes depending on the number of different species caught during the trip. Steps:

(1) Open the app and provide the date, time, marina/boat ramp the boat was launching from, and the number of anglers;

(2) Fill in the catch data by selecting the species caught and entering number of fish harvested and released; and

(3) End the trip by selecting a general fishing location on a map and the primary depth fished for the trip and submitting.

There were several features that made the process easy, streamlined, and as user friendly as possible. For example, the date and time was automatically populated for the current time both when starting a new trip and closing a trip, but could be adjusted if the angler forgot to create a trip before leaving the dock. Additionally, when anglers harvested Red Snapper the app divided the catch into two categories: fish harvested in state waters and fish harvested in federal waters. Additionally, Red Snapper anglers were required to report the primary fishing depth on the catch screen. All species commonly captured throughout the Gulf of Mexico were included in the app, allowing anglers to submit their entire catch not only Red Snapper. Once the trip was finalized and submitted anglers could not edit nor delete their entry in the app or on the webportal. The only way to change trip information was to email HRI and have one of the researchers log in and adjust the trip. This was very important because to calculate an accurate error estimate, we compared the number of fish reported to the number of fish counted during dockside interviews. If anglers were capable of changing their catch information after submission, calculating the error rate would not be valid because anglers would have the ability to change the number of fish

submitted on *iSnapper* if they were interviewed at the boat ramps by TPWD or HRI staff. Finally, all required app updates were "pushed" the user's phone as needed.

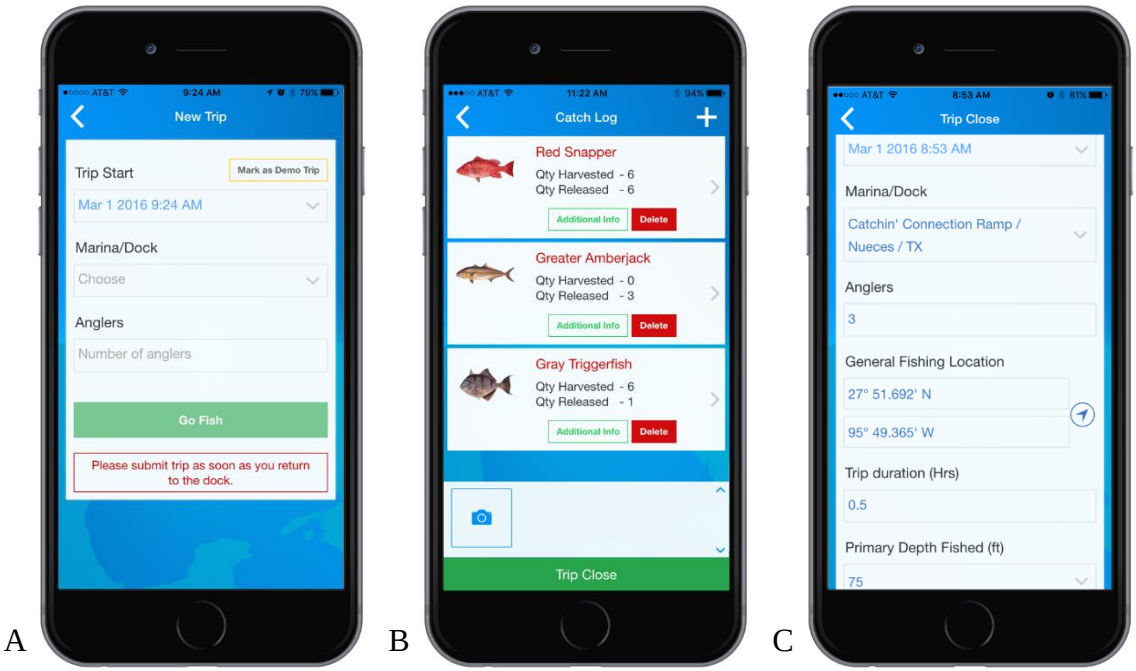


Figure 4. Screenshots of the new trip screen (A), catch log (B), and trip close screen (C).

Socioeconomics Survey

While the previous three steps were required of all trips, there were other optional features that anglers could choose to enter. One of the features that proved to be very beneficial is the availability to collect additional socioeconomic information. The socioeconomic survey was a separate optional feature in the app and available on the home screen. Questions in the survey were similar to those used in the previous version of *iSnapper*; however, after receiving feedback from NOAA, we included additional questions to get more refined information regarding the cost of trips and distances traveled (Table 1). Even with these additions, the survey was brief and took less than five minutes.

Table 1. Socioeconomic questions included in *iSnapper*.

How many people in total, including yourself, live in your household? Please include those people who fish and who don't fish.

How many people in your household, including children and adults, have been recreational saltwater fishing in the last 12 months anywhere in the Gulf of Mexico region including inshore and offshore?
How many days did you spend saltwater fishing in the last 12 months?
How many of these days were spent offshore?
If this fishing trip is part of a longer trip in which you will spend at least one night away from your permanent residence, how many days will this trip last?
What is your primary and secondary (if applicable) zip code? (Enter zip codes separated by comma Ex: 12345,12346)
Gender
What is the total distance traveled by boat during this trip? (Miles)
Do you keep your boat at a marina or trailered?
What is the estimated bait and tackle expenses for this trip?
What is the horsepower of your boat?
What is the estimated fuel consumption used for this trip? (Gallons)
Which of the following best describes your household's annual income, before taxes? (US$)

For-Hire provision

Given the successful *iSnapper* pilot study in the for-hire sector and groundswell of interest by others, many groups routinely inquired as to the availability of its use. Thus, we redesigned *iSnapper* to include fields specifically for the for-hire captains so they could continue to submit trips, and the registration process enabled us to distinguish between private and for-hire trips. If a user selected the for-hire option during registration, state and/or federal permit numbers were required to complete the process. For-hire reporting followed the same format as with private anglers, and these trips were also validated at boat ramps, but for the majority of the analyses were not included due to the small number of for-hire trips reported.

V. Findings

Development and implementation of iSnapper as a data collection app:

The adaptation of *iSnapper* from a mobile application targeting for-hire captains to one that could be universally used by all recreational anglers was very successful. Since the release on May 15, 2015 the app was downloaded on 945 different devices through the end of 2015. The majority of the users (71%, 672 downloads) were operating a device with iOS (Apple®) platform, the remainder were Android-based users. A total of 393 individuals registered to use the app, with 199 users providing valid vessel registration numbers. During the initial development stages, the Windows® platform was an appealing operating systems, and we had anticipated high number of users. However, options for app development and the subsequent phase out of this platform by most developers lead to little interest, and we delayed implementing this platform to focus on the other two more popular formats. Moreover, with only 3% of all cell phone users listing Windows® as their phone type (Pew Research Center 2015), and that number rapidly declining, we do not recommend development of this platform for future data collection.

During the 10 day Federal Red Snapper season (June 1 – 10, 2015) there were 171 trips submitted using the app or the online web portal, with 163 trips from Texas private recreational anglers (Table 2). Red Snapper was the most dominant species captured, with all trips reporting a harvest of at least one Red Snapper. Other species commonly captured were King Mackerel (*Scomberomorus cavalla*), Cobia (*Rachycentron canadum*), and Dolphinfish (*Coryphaena hippurus*) (Table 3). A total of 2,012 fish were harvested during the federal season, with 75.5% of the harvested fish being Red Snapper. The next most prominent species harvested were Dolphinfish, King Mackerel, Vermilion Snapper (*Rhomboplites aurorubens*), and Blackfin Tuna (*Thunnus atlanticus*). Most trips (private and for-hire) using *iSnapper* were located within the continental shelf, generally within 100 nm offshore Texas (Figure 4A). Most vessels harvested 7 Red Snapper from their selected fishing locations, while some harvested 25 – 56 Red Snapper in these general areas throughout the season (Figure 4B). Despite a federal bag limit of 2 Red Snapper per angler, anglers were able to keep a maximum of 4 fish if 2 were from state waters. To calculate the estimated Red Snapper harvest the average length of fish recorded by TPWD was converted using the TPWD length/weight conversion chart (http://txmarspecies.tamug.edu/length-weight.cfm) and multiplying the weight by the total number of fish harvested. An additional 22 trips were started by Texas anglers during the federal season, but not completed. Despite including a feature to alert anglers if they had a trip open

longer than 24 hours, as well as reaching out to these anglers via email on multiple occasions, these trips were never submitted.

Although it was an abbreviated 10-day season, the weather conditions were optimal for offshore fishing. Light winds and small seas enabled most vessels to get out to fish federal waters (> 9 nautical miles), especially for some of the smaller (< 25') boats. The National Weather Service issues small craft advisories starting at wind speeds greater than 12.9 m/s. Average wind speeds throughout the federal season were never greater than 4.6 m/s and average wave height did not exceed 0.7 m (Table 2). With the conditions being relatively similar throughout the season, we were able to use the creel and app data to determine what days of the week corresponded with increased angler activity during the limited season. A majority (60%) of anglers fishing for Red Snapper went out on one of three days during the season: opening day (Monday), or the following Friday and Saturday (Figure 5). Not surprisingly, the day with the highest fishing pressure (Saturday) corresponded to the highest estimated daily harvest of 5,314 lbs.

Table 2. Number of self-reported trips using *iSnapper* from private recreational anglers in Texas during the federal Red Snapper season (June 1st - June 10th). Trips refers to the number of users that submitted fish captured during the season. Anglers includes all individuals on the boat that were targeting Red Snapper for at least a portion of their trip. Total released is the number of Red Snapper captured in either state or federal waters but discarded either due to size or bag limits. Harvested state is the number of Red Snapper harvested from state waters. Harvested federal is the number of Red Snapper harvested from federal waters. Daily harvest is the combined number of Red Snapper harvested from both state and federal waters. The asterisk (*) indicates what would be considered the weekend for a typical Red Snapper angler (Friday – Sunday).

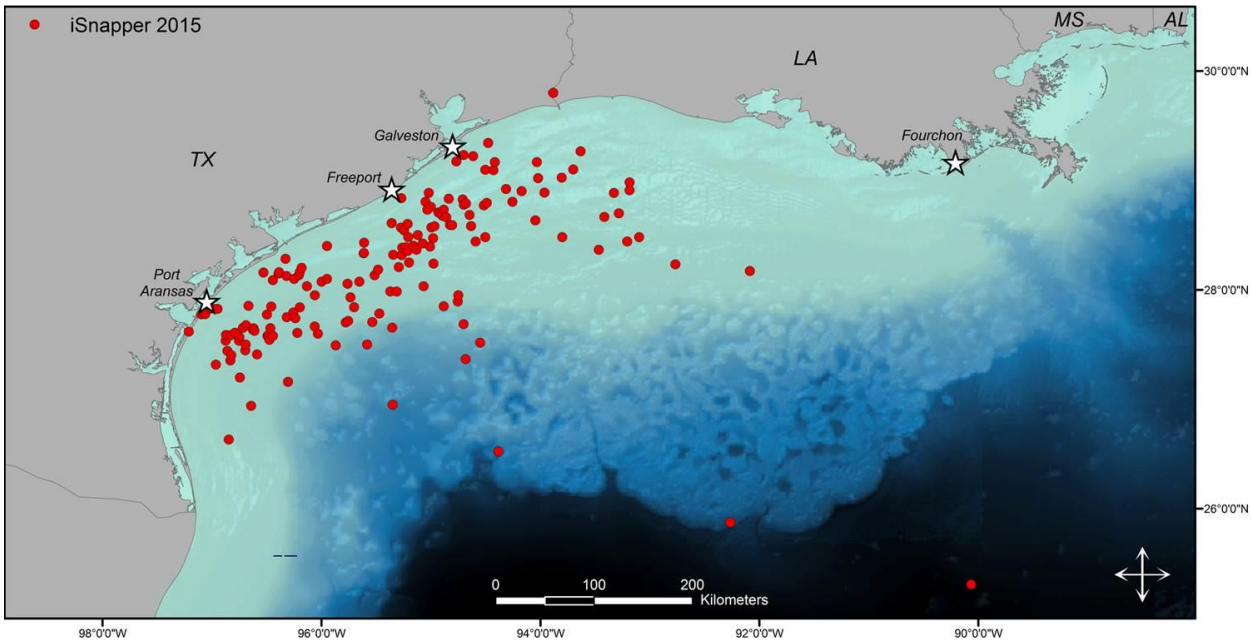
Day	Trips	Anglers	Total Released	Harvested State	Harvested Federal	Daily Harvest	Average Wind speed (m/s) +/- SE	Average Wave height (m)
6/1 (Mon)	23	84	191	22	178	200	2.4 +/- 0.11	0.4 +/- 0.02
6/2 (Tue)	22	80	272	40	155	195	1.9 +/- 0.18	0.3 +/- 0.01
6/3 (Wed)	17	55	300	11	97	108	3.6 +/- 0.19	0.3 +/- 0.01
6/4 (Thu)	11	37	230	17	74	91	4.6 +/- 0.16	0.7 +/- 0.02
6/5 (Fri)*	23	105	259	24	206	230	4.2 +/- 0.21	0.4 +/- 0.02
6/6 (Sat)*	27	124	309	62	227	289	2.7 +/- 0.25	0.4 +/- 0.01
6/7 (Sun)*	19	89	148	25	174	199	4.0 +/- 0.25	0.4 +/- 0.01
6/8 (Mon)	10	40	115	12	79	91	4.1 +/- 0.28	0.5 +/- 0.02
6/9 (Tue)	7	30	96	10	60	70	3.2 +/- 0.17	0.4 +/- 0.02
6/10 (Wed)	4	19	20	8	38	46	4.2 +/- 0.22	0.5 +/- 0.02
Total	163	663	1940	231	1288	1519	3.5 +/- 0.08	0.4 +/- 0.006

Table 3. Summary of the species captured and released as reported using *iSnapper* by private recreational anglers during the Red Snapper federal season (June 1 – June 10). Number captured includes the combined number of fish harvested and released. An asterisk (*) next to a species name indicates the species is considered a bait fish. A horizontal dash (-) in the discard rate column indicates all fish captured were harvested. Number of anglers is not mutually exclusive by species, since several species are typically caught during one trip.

Species	Number Captured	Percent of Total Capture	Number Harvested	Discard Rate	Number Released	Number of Anglers
Red Snapper	3459	82.0%	1519	56.1%	1940	663
King Mackerel	139	2.4%	85	38.8%	54	148
Dolphinfish	119	1.0%	98	17.6%	21	99
Blue Runner*	57	0.7%	42	26.3%	15	21
Cobia	50	0.9%	30	40.0%	20	115
Gulf Menhaden*	50	< 0.1%	50	-	0	2
Blackfin Tuna	48	0.5%	37	22.9%	11	20
Greater Amberjack	42	1.7%	4	90.5%	38	57
Vermilion Snapper	42	0.1%	40	4.8%	2	34
Great Barracuda	39	1.5%	5	87.2%	34	18
Atlantic Sharpnose Shark	23	0.8%	5	78.3%	18	14
Gray Triggerfish	18	0.6%	4	77.8%	14	30
Golden Tilefish	15	< 0.1%	15	-	0	18
Atlantic Spadefish	14	0.2%	10	28.6%	4	10
Lane Snapper	10	< 0.1%	9	10.0%	1	17
Crevalle Jack	9	0.3%	2	77.8%	7	14
Almaco Jack	7	0.1%	5	28.6%	2	8
Tripletail	7	< 0.1%	6	14.3%	1	16
Rainbow Runner	6	0.1%	4	33.3%	2	9
Rock Hind	6	< 0.1%	6	-	0	9
Bermuda Chub	5	0.1%	2	60.0%	3	7
Gray Snapper	5	< 0.1%	4	20.0%	1	17
Little Tunny	5	< 0.1%	5	-	0	10
Remora	5	0.1%	2	60.0%	3	11
Bonito	4	0.1%	2	50.0%	2	10
Blacktip Shark	3	< 0.1%	2	33.3%	1	8
Sand Seatrout	3	< 0.1%	3	-	0	6
Scamp	3	< 0.1%	2	33.3%	1	10
Spanish Mackerel	3	< 0.1%	3	-	0	6
Atlantic Bonito	2	< 0.1%	1	50.0%	1	7
Dog Snapper	2	< 0.1%	2	-	0	4
Lesser Amberjack	2	0.1%	0	100.0%	2	4
Spotted Seatrout	2	< 0.1%	1	50.0%	1	2

Species	Number Captured	Percent of Total Capture	Number Harvested	Discard Rate	Number Released	Number of Anglers
Wahoo	2	< 0.1%	1	50.0%	1	11
Yellowfin Tuna	2	< 0.1%	2	-	0	4
Blue Marlin	1	< 0.1%	0	100.0%	1	4
Bull Shark	1	< 0.1%	0	100.0%	1	5
Cubera Snapper	1	< 0.1%	1	-	0	4
Gag Grouper	1	< 0.1%	0	100.0%	1	6
Great Hammerhead Shark	1	< 0.1%	0	100.0%	1	3
Horse-eye Jack	1	< 0.1%	1	-	0	3
Others	1	< 0.1%	0	100.0%	1	5
Sailfish	1	< 0.1%	0	100.0%	1	5
Sandbar Shark	1	< 0.1%	0	100.0%	1	6
Scalloped Hammerhead	1	< 0.1%	0	100.0%	1	4
Warsaw Grouper	1	< 0.1%	1	-	0	4
Yellowedge grouper	1	< 0.1%	1	-	0	4
Total	4220	100%	2012	52.3%	2208	1492

A



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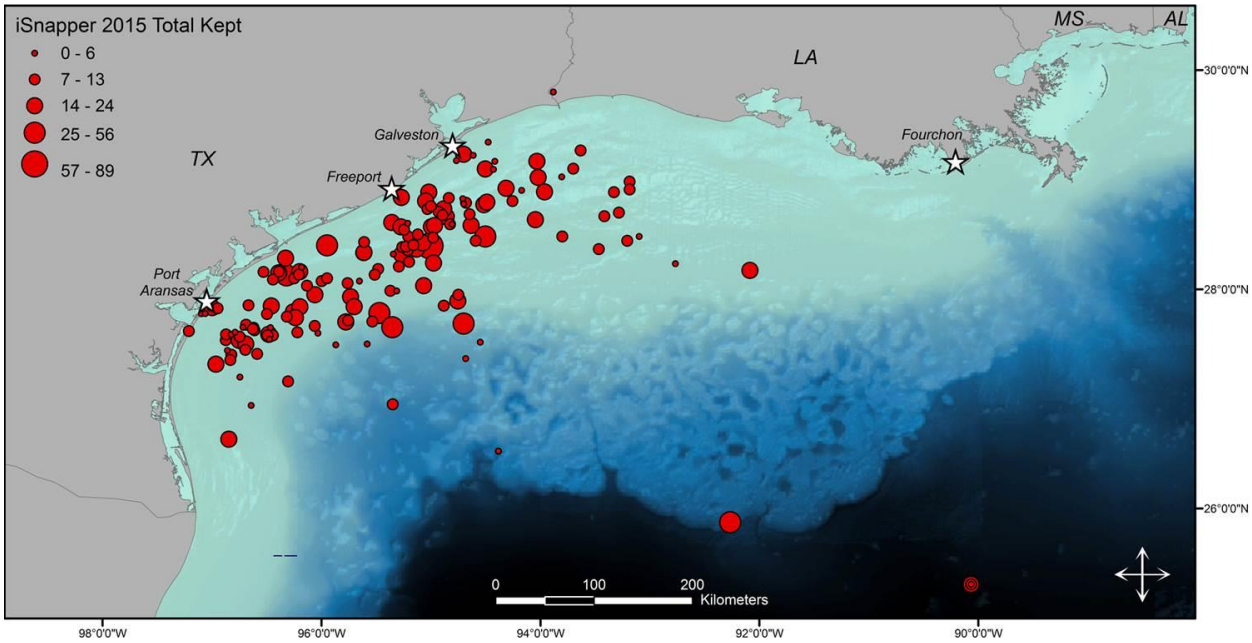

Figure 5. Approximate fishing locations (A) and total harvest by location (B) for *iSnapper* users during the 2015 Red Snapper season (June 1 – June 10). Locations on or outside of the continental shelf are likely errant entries, with the site on the shelf edge being the default location when the map loads on the app.

The majority of Red Snapper were caught at depths of 40 m or less (52.4%), with the most common reported depth of capture between 31 – 40 m (1,042 caught, 31.6%, Table 4). The overall estimated discard rate for Red Snapper was 56.1%, with the highest rate of 74.3% occurring at depths between 21 – 30 m. A total of eight trips did not report their fishing depth, which accounts for the 100 Red Snapper released at unknown depths. The depth range where most fish were retained occurred between 71 – 80 m, although there were relatively few (n = 68) Red Snapper captured at these depths.

Table 4. Depth of capture for Red Snapper during the federal season (June 1 - 10) as reported using *iSnapper* by private recreational anglers in Texas. The discard rate by depth was calculated by dividing the number released by the total number captured. The overall discard rate was calculated by dividing the total number released by the total number captured. Unknown depth refers to trips where a depth of 0 ft was reported in the app.

Depth (m)	Number Released	Number Harvested	Discard Rate
1 - 10	10	8	55.6%
11 - 20	48	91	34.5%
21 - 30	399	138	74.3%
31 - 40	611	431	58.6%
41 - 50	596	600	49.8%
51 - 60	0	0	0.0%
61 - 70	112	82	57.7%
71 - 80	15	53	22.1%
81 - 90	0	0	0.0%
91+	49	67	42.2%
Unknown	100	49	67.1%
Total	1940	1519	56.1%

Validation of self-reported data:

During the 10 day federal season a total of 1,018 private recreational Red Snapper anglers were encountered at Texas boat ramps. Not all of these anglers were “unique” individuals, with some anglers going out on multiple days. These anglers represented 259 trips and harvested 2,268 Red Snapper (Table 5). Of the 163 trips submitted using *iSnapper*, 18 were interviewed at the boat ramp, generating an 11% trip validation rate and an overall reporting rate of 4.1% (see Appendix 1 for additional details on calculations). Two trips reported a higher number of fish harvested than

were recorded during the creel survey and one trip reported fewer fish harvested, for a total reporting error of +5.1%. Most of the trips encountered at boat ramps occurred on June 5 and June 6 (Friday and Saturday; Figure 5). Close to half (45.2%) of the total Red Snapper harvest was recorded during these two days. While the app was created with the capability of capturing the trip start and end times, initially it did not capture the date and time when the trip was actually submitted. Unfortunately, it is difficult to know if anglers submitted trips prior to being interviewed. Following the federal season, we did update the app to begin collecting submission date and time, but there were not enough trips validated after the correction to calculate an adjusted error rate. However, we feel the error rate is fairly accurate as not every trip had 100% reporting accuracy (Table 5), as one would expect if they submitted their data after being interviewed.

Table 5. Creel survey summary of private recreational anglers intercepted during the federal Red Snapper season (June 1 - June 10) by TPWD and HRI scientists. The harvest reported by all *iSnapper* users is included for ease of comparison between the app and creel surveys. Validated trips were anglers that submitted a trip using the app and were also interviewed at their landing location. Reporting accuracy rate for validated trips was calculated by dividing the app harvest by the creel reported harvest and multiplying by 100.

Day	Boat Trips	Anglers	Creel Harvest	*iSnapper* Harvest	Validated Trips	Reporting Accuracy Rate
6/1/2015 (Mon)	33	107	278	200	2	100%
6/2/2015 (Tue)	13	42	113	195	2	100%
6/3/2015 (Wed)	22	87	206	108	0	-
6/4/2015 (Thu)	24	80	210	91	2	63%
6/5/2015 (Fri)	63	246	581	230	5	96%
6/6/2015 (Sat)	78	307	643	289	6	84%
6/7/2015 (Sun)	11	45	108	199	0	-
6/8/2015 (Mon)	7	33	65	91	1	100%
6/9/2015 (Tue)	5	13	38	70	0	-
6/10/2015 (Wed)	3	9	26	46	0	-
Total	259	969	2268	1519	18	94.9%

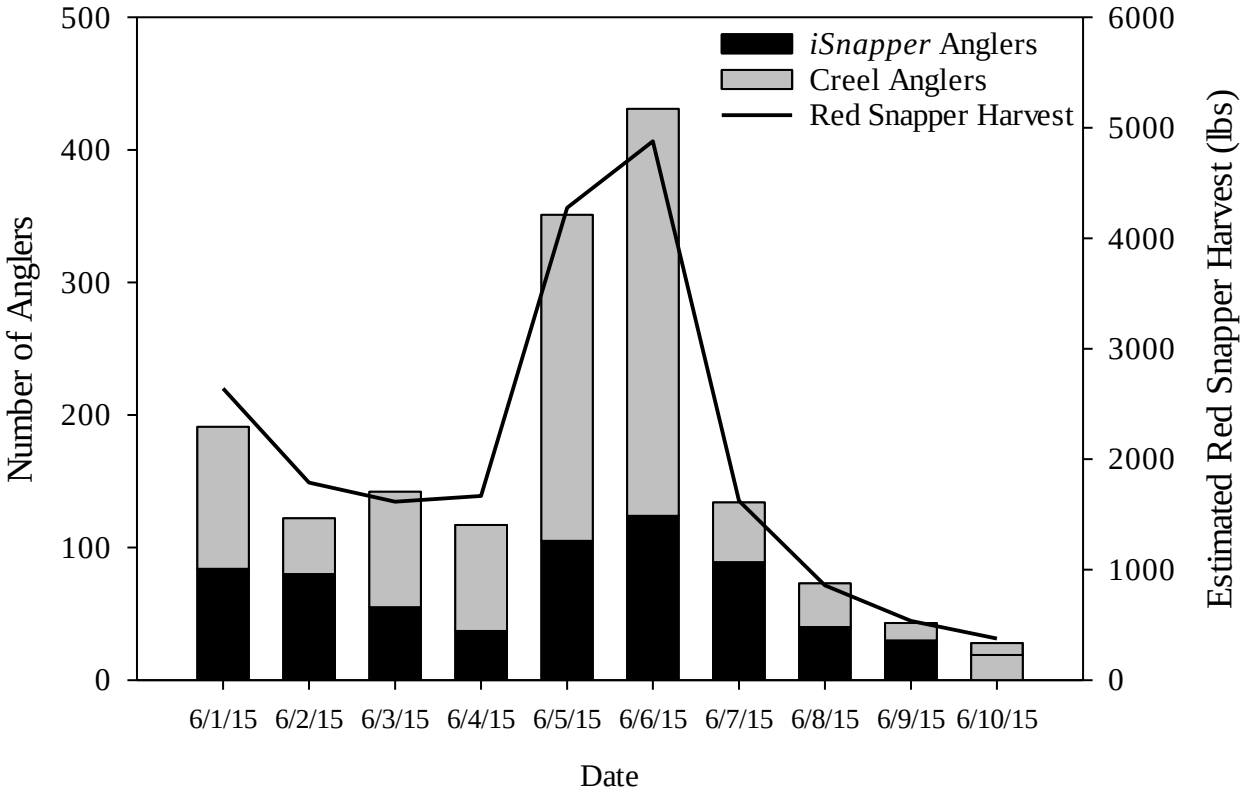

Figure 6. Total number of Red Snapper anglers reporting using *iSnapper* (black bar) or intercepted at boat ramps (gray bar) fishing for Red Snapper during the federal season. Estimated Red Snapper harvest was calculated by taking the average length of fish recorded by TPWD, converting the length to an estimated weight using the TPWD length/weight conversion chart (http://txmarspecies.tamug.edu/length-weight.cfm) and by multiplying that weight with the total number of fish harvested.

After the federal season, anglers were encouraged to continue using *iSnapper* to report their state catch. The TPWD also continued their increased creel surveys to encounter Red Snapper anglers and validate additional trips. From June 11th until the last reported creel with Red Snapper on November 4th an additional 165 boats were interviewed with 1,734 Red Snapper harvested. Only 38 trips harvesting a total of 433 Red Snapper were reported using *iSnapper*, with one boat validated during this time and it was a charter for-hire vessel. The number of Red Snapper harvested was accurate (20), although with the app they reported one less angler than what was recorded by TPWD.

iSnapper total Red Snapper harvest estimate:

Texas is unique in that the harvest of Red Snapper occurs all year in state waters. Using the reporting rate and error estimates from the federal season, along with creel data provided by TPWD for the entire year, the estimated total number of Red Snapper captured by Texas private recreational anglers was 58,251 fish (SE = ±25,344; see Appendix 1 for SE calculations). Using the reporting rates we calculated the total number of Red Snapper angler trips was 23,358 (SE = ± 6,660). To provide a landings estimate for private recreational anglers, the average size of fish captured from both federal and state waters was calculated and then the weight was estimated using a length/weight conversion website provided by TPWD (http://txmarspecies.tamug.edu/length-weight.cfm). In Federal waters the Red Snapper mean length harvested was 22.1 inches and the mean estimated weight harvested was 5.63 lbs. In State waters the mean size of 20.2 inches, which is approximately 4.25 lbs. Using the harvest estimates and average weights, the estimated landings of Red Snapper for Texas private anglers in 2015 was 277,752 lbs (Table 6).

Table 6. Total Red Snapper harvest estimates for 2015 using data from *iSnapper* and TPWD data. Angler-trips is the estimated total number of anglers fishing, which includes anglers fishing for multiple days.

Method	Number Harvested	Weight (lbs)	Angler-Trips
iSnapper	58,251 (± 25,344 SE)	277,752	23,358
TPWD	32,062 (± 4,409 SE)	153,525	11,154

Socioeconomic data:

Following the launch of *iSnapper* on May 11th, a total of 100 socioeconomic surveys were completed by 95 unique respondents. Most of these entries occurred after the opening of the federal season, with the most single day entries occurring on June 4th (Figure 6). A total of 98% of respondents were men and 93% of respondents were Texas residents (Figure 7). On average, participants went saltwater fishing 35 days over the past 12 months, with 14 days of those spent offshore. Most (70%) participants also trailered their boats. In terms of household income of Red Snapper anglers, approximately 25% had an annual household income of over $200,000 and approximately 61% had incomes over $100,000 (Figure 8). The average distance these anglers traveled per trip was 89.3 miles (± 7.09 SE), using an estimated 82 gallons of fuel (± 12.0 SE). The average cost of bait and tackle for the trip was $197 (± 34.22 SE).

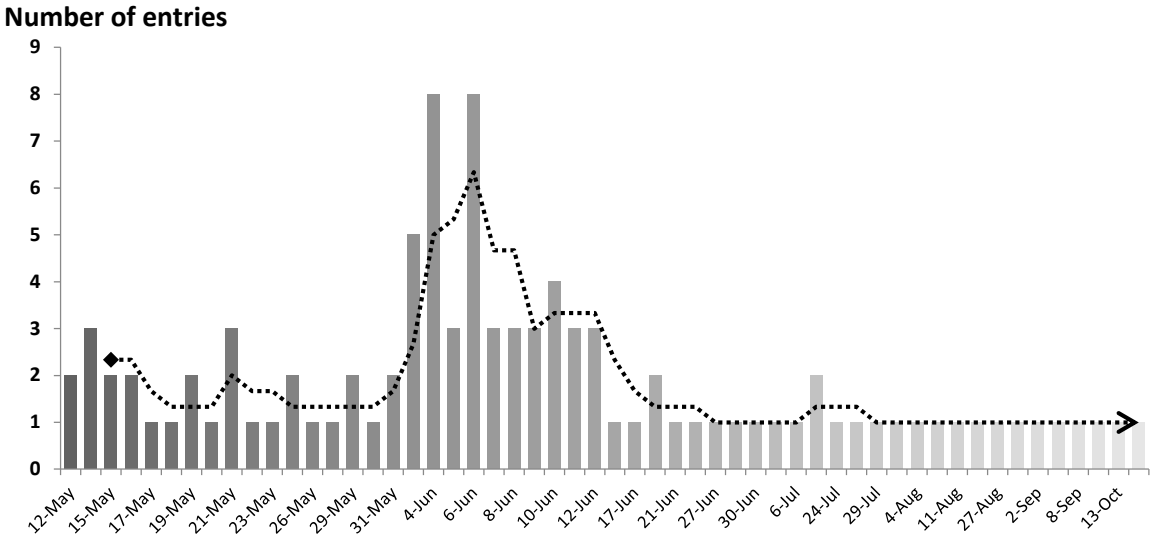

Figure 7. Number of socioeconomic surveys submitted each day following the release of *iSnapper*. The dotted line indicates the two day lag average, where the number of entries from the previous two days were averaged.

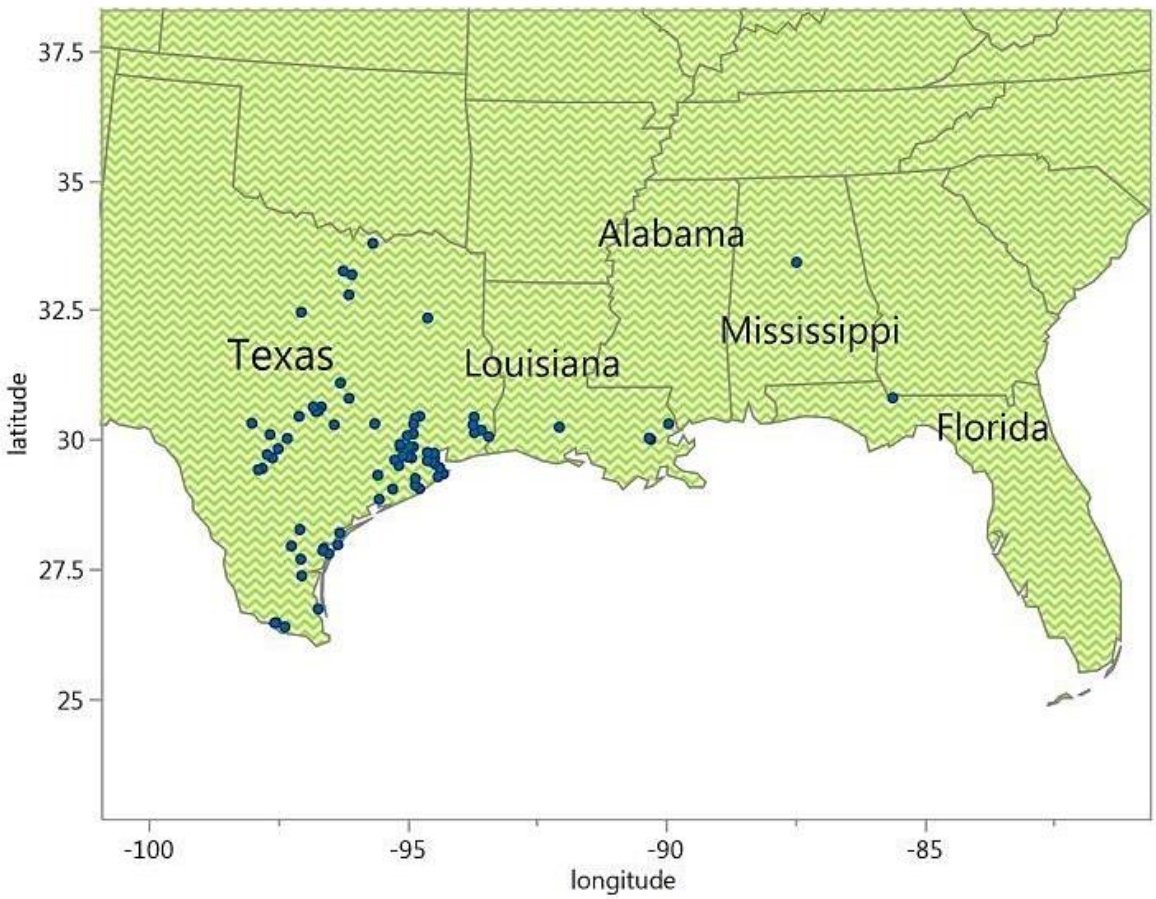

Figure 8. The primary residence locations based on zip code for anglers submitting a socioeconomic survey using *iSnapper*.

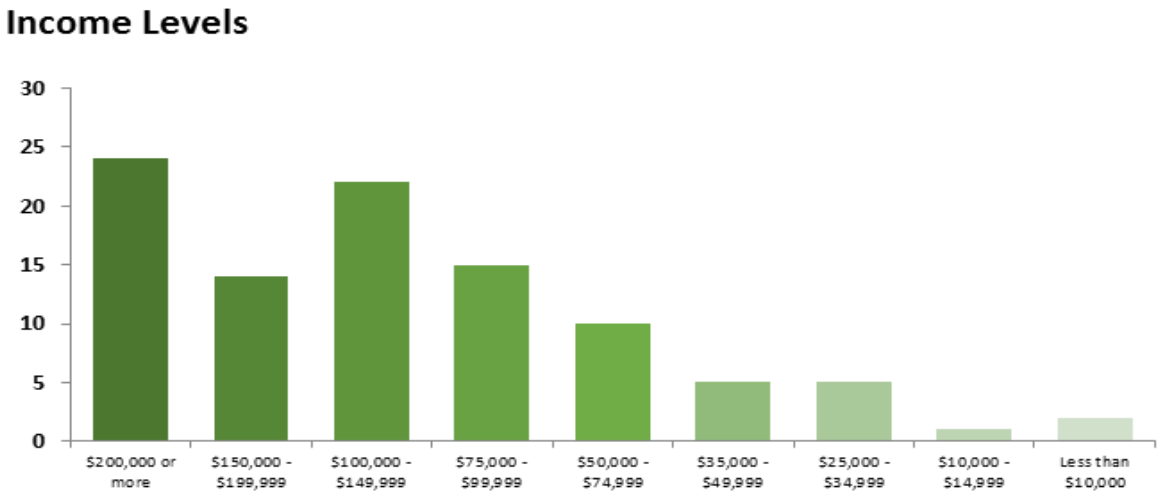

Figure 9. The average annual household income for respondents using *iSnapper*.

iSnapper in the for-hire fishery and use in Exempted Fishing Permits:

During development of the initial proposal, there were several Exempted Fishing Permits under consideration in the for-hire sector. *iSnapper* was proposed as an ideal data collection tool for these programs; however, none of these materialized to test the viability in these programs. Nevertheless, it still represented a valuable tool for data collection in the for-hire sectors, and *iSnapper v1.0* was very successful and popular. In 2015 the for-hire captains had a 44 day season where they could harvest Red Snapper in federally managed waters from June 1st until July 15th. Curiously, there were few trips reported from this sector using this pilot - *iSnapper v2.0*, and this low reporting did not allow for catch estimates to be performed for this sector. Six for-hire captains submitted seven trips during their season and harvested a total of 76 Red Snapper, 25 Dolphinfish, 6 King Mackerel, 1 Warsaw Grouper, and 1 Yellowedge Grouper. Six additional state water trips were submitted by one user who harvested a total of 128 Red Snapper and did not report any other species captured or harvested. In terms of discards, these captains reported no Red Snapper released during the 44 day season in federal waters. Whereas when fishing in state waters, a total of 45 were released. Despite having so few trips reported, two of the for-hire trips were validated with creel surveys. Including these data with the validations from the private recreational data decreased the overall error rate from 5.1% to 4.1%. Nevertheless, these did not represent enough sample size to make valid harvest estimates for this sector.

VI. Discussion

This project demonstrates that smart device apps can successfully and efficiently be used as a data collection tool for private recreational anglers. The near-real time data collected can greatly aid in the timeliness of the data generated, which is especially important in the Red Snapper federal fishery which was only open for 10 days in 2015. This real-time data collection allows for fishery managers to make more accurate estimates of the total harvest as well as better determine the fishing effort. Collecting fisheries-dependent data is certainly key for effective fisheries management, and this process is typically characterized as being labor intensive, expensive, and often has relatively long time delays to produce final products. These inherent characteristics do not always mesh with certain management measures that create very short seasons, or afford the ability for managers to assess catch in relation to annual catch targets during the season, but often occur well-beyond the “projected” season closure. This makes adaptive management difficult and prone to

risk if these targets are exceeded before the catch can be calculated, and it also contributes to inefficiencies in management. These issues could not be more apparent than in private recreational fisheries. Many of these problems have the potential to be allayed by supplementing (or even validating) traditional fishery dependent surveys with data from smart device application technology and data collection. For example, these devices capture portions of the fishery that are likely missed by traditional creel surveys (e.g., private dock and marinas) and collected a host of data that traditional surveys do not. These devices also allow for collection of spatial/locational fishing effort, refined effort estimates, discard rates, depth fished, socioeconomic data and a host of other parameters. Much of these data are collected in a seamless user friendly fashion that is often automated. Overall, this study clearly demonstrates the high potential of using electronic reporting apps to aid in the private recreational fishing data collection and provide traditional and new forms of data in a very efficient and timely manner.

The need for more robust, accurate, and timely data from the private recreational sector is making the use of smart devices as data reporting tools more of a reality. These devices allow anglers to self-report their catch and effort data without having to rely on being intercepted and interviewed by state agencies. It also enables anglers that have private docks to report their catch, which previously was not possible and often had to be estimated, since there is not a point of encounter such as at boat ramps. With high private angler reporting rates, managers will be able to more precisely estimate total harvest that likely would benefit the access to the fishery. Knowing how many private anglers need to report each year can be estimated, but greatly depends on what the desired or acceptable standard error rate is, which would need to be set by State and Federal managers. With high precision in the total harvest, the ability for these apps to collect near real-time data can be used to make in-season adjustments to season length based on the current harvest. This is particularly important for a species such as Red Snapper that has such a short season, where traditionally the harvest could not be estimated during the season, because it took months of data entry and analysis that were processed only after it fishing had ended. While the user-submitted data is immediately available through the web portal, harvest estimates can only be calculated once the creel data has been entered and trips have been validated. A reasonable time frame to calculate a final harvest for the federal Red Snapper season is three weeks following the close of the season; however, “preliminary” estimates could be made sooner. The three-week time frame is due to the time it takes for TPWD to process creel data for validation. This amount of time allows for the

creel data to be entered, trips validated, and then estimating the harvest, which is generally much faster than traditional methods.

With the prevalence of smart phones and the relative low cost of creating an app (Stunz et al., in prep), this type of data collection has a large potential to greatly benefit managers. If designed properly, the apps can provide catch and effort data as well as supplementary information such as depth of capture and release condition at relatively low cost once developed. Depending on what questions fisheries managers seek to understand, the app can be created with additional features and options to address specific concerns about a fishery in a particular region or focus area. For example, in *iSnapper* we provided a section where anglers could describe the release method and condition of fish that were released. With these data, the post-release mortality could be calculated for species in the Gulf that experience significant barotrauma (Lutjanids, Serranids), which could then be incorporated in overall fishing mortality estimates or estimates of depth fished. As a practical example, it has been shown that Red Snapper survival is highest when fish are caught in shallower waters (< 30 m) during the cooler months and are released using either rapid recompression (descender devices) or venting tools (Drumhiller et al. 2014, Curtis et al. 2015). Currently, there are no estimates of what methods private recreational anglers commonly use to release Red Snapper. Since all of those key parameters are collected in *iSnapper* it would be possible to gauge if anglers are releasing fish that have been vented, are descending them using various devices, or are simply discarding them without any barotrauma treatment. This information would help estimate survival rates based on our current knowledge of the likelihood fish survive based on the depth and season captured, which ultimately would provide information for more accurate discard mortality calculations. In addition, since the app is publically available the potential to collect an expansive data set with relatively little effort would be invaluable to management agencies to better address barotrauma issues and how they impact fisheries. This is just one example of how ancillary data collected by these techniques go beyond traditional catch and effort estimates.

A key component of ensuring self-reported data are valid and of practical use in fisheries management is a strong validation process. Requiring users to provide their vessel registration numbers allowed scientists to compare trips submitted with the app reported data to dockside creel surveys to measure the accuracy of self-reported data. Partnering with TPWD proved to be an efficient way to validate self-reported data, since creel agents are already routinely interviewing

boats for their coast-wide biological assessments. Ideally to improve estimates and reduce variability, expanding creeling effort to maximize validations, particularly future directed creel survey in areas of high use, would allow for greater harvest estimate accuracy. For example, the number of boat ramps and marinas that have access to the Gulf are relatively limited in Texas. Out of the 258 boat ramps that are sampled by TPWD Coastal Fisheries, from 2011 – 2014 only 31 ramps recorded Red Snapper harvest, and even fewer (13) recorded Red Snapper landings for more than ten trips. Due to the short federal season, it would be feasible to increase the number of creel surveys done at these highly used ramps to increase the validation rate, making the data more reliable. In addition, with this type of 'mark and recapture' method, managers can determine *a priori* the number trips needing to be validated to obtain an ideal, or acceptable, standard error for their harvest estimate. Due to the high expense and time cost of creel surveys, knowing the minimum number of trips that must be validated to reach a certain standard error rate would improve efficiency while allowing accurate catch estimate calculations.

One of the unique aspects of this pilot was the ability to collect data from the entire recreational fishing universe and use that information to make harvest and effort estimates. This type of capture-recapture survey methodology allowed us to have a strong data validation component, while also ensuring a randomized sampling design. From the calculated reporting rate and the error estimates, we were able to estimate the total Red Snapper harvest for 2015, as well as the number of angler trips fishing for this species. Understanding how many private anglers are targeting Red Snapper is critically important, as it has been difficult for TPWD to estimate the total number of Red Snapper anglers due to the high number of Texas residences that have private docks. Certainly, this is assuming similar validation characteristics of private dock anglers as those using public areas. However, there is no indication there are systematic discrepancies here, but this would be an area to improve validation and estimates to calibrate "private" landings.

We calculated that the 2015 landings from *iSnapper* were 277,752 lbs compared to 153,525 lbs estimated by TPWD. Based on our validation studies, these appear to be reasonable estimates of the private recreational harvest for 2015, but they are also characterized by a high degree of error. This estimate is the first independent assessment from the traditional harvest methodology and represents only one data point. Clearly, more data collection would need to be performed to increase the confidence in this estimate. Thus, some caution should be taken when evaluating these data for any type of management advice. While the estimates are somewhat larger here, it was also not

unexpected, given the app likely captures a segment of the fishery not surveyed using the standard state methodology. There are several plausible explanations for this difference. The estimate was characterized by a high standard error rate, and the lower bounds of our estimate fall within TPWD estimates. Also, we collected data from anglers that might not have the opportunity to be interviewed by TPWD, particularly people that have a private dock or arrive back to the boat ramps after 6 pm, when the creel assignments end. Thus, *iSnapper* allows these anglers an opportunity to have their catch included in the state harvest estimates. Finally, the 10-day federal season was characterized by ideal fishing conditions. Ideal weather led to high fishing effort, and our observations showed at certain times the boats arriving at the dock could easily overwhelm a creeling location leading to an underestimate. Overall, greater user buy-in would translate into additional submitted trips decreasing the standard error and ultimately calculating a more accurate harvest and angler estimate, making the data more useful for fisheries managers.

The method of data validation proved to be valuable in more than just estimating the total harvest of Red Snapper from the Texas private recreational fishery. Because this study was a capture-recapture design, it allows for flexibility and prioritization when determining how best to sample the population of private recreational anglers. For example, if managers seek a specific reporting rate, they would be able to calculate the number of trips that need to be validated during creel surveys. Additionally, to minimize the standard error of a harvest estimate, managers could also determine how many anglers need to report their catch for their desired estimate. Another major benefit is that the actual number of private recreational anglers in the fishery does not need to be known beforehand. These characteristics and benefits of a capture-recapture design show the feasibility of collecting statistically sound self-reported data that can and should be used by state and federal managers.

While the reporting rate was acceptable, and we were able to generate confident estimates, we anticipated more trip submissions. This was especially the case given the perceived interest in the fishery and extensive outreach and advertising campaigns undertaken. We would expect the reporting rate to increase through time as anglers become more aware and familiar with the app. Moreover, given the nature of “recreational” fishing, many anglers may not be willing to go the extra effort to enter data on a voluntary basis, given this is an activity to escape from these sort of tasks. Thus, future efforts should seek to maximize awareness in the private recreational community and simplify and streamline data entry as much as possible to ensure an enjoyable experience that

anglers will want to return and enter trips. Even though we had a very high number of downloads, we attribute some of the low reporting due to the app being voluntary. For example, Alabama has had mandatory Red Snapper reporting since 2014. This program has had a higher reporting rate - approximately 25% of Alabama private recreational vessels reported their catch (Alabama Department of Conservation and Natural Resources 2015). Because 2015 was the first season *iSnapper* was used for private recreational data collection, our reporting rate of 4.1% is encouraging. We believe there will be far greater participation in the future since it appears as though a majority of anglers were simply not aware of the app, and most interviewed seemed very willing to report their catch. This problem could be resolved by building on the current momentum from 2015 and continued advertising to inform anglers about the premise behind *iSnapper* and why private recreational data collection is critical. Nevertheless, we were still able to generate viable estimates and confidence intervals around those catches. Clearly, from these examples voluntary or mandatory reporting still does not ensure the majority of anglers report, and future studies should focus on the trade-offs associated with mandatory versus voluntary reporting and how these different collection frames influence the estimates and associated errors.

In general, we discovered that using the app requires a behavioral change by private anglers outside of their normal routine. They have to start a trip using the app prior to leaving the dock and then also submit the trip once they return to port. It will take time for anglers to commit and remember to use *iSnapper* for every trip. Additionally, with the Red Snapper fishery being so contentious, there is often mistrust between the anglers and fisheries managers, which at least in discussion with some contributed to their unwillingness to provide fishery-dependent data. As is the case for any data collection endeavor rather it be in person or electronic, some anglers voiced opposition to any type of information transfer such as refusing creels, data entry, etc. Fortunately, the events were rare, and the capture-recapture statistical methodology is robust enough to account for these non-reports. Nevertheless, these findings point toward a need for additional outreach and education directed towards private recreational anglers and how reporting would benefit them, because generally we found most are unaware but willing to help and take what steps are necessary to provide better catch estimates.

iSnapper provides a convenient mechanism to collect socioeconomic data on the users of the resource. This allows managers to conduct equivalent socioeconomic 'monitoring' similar to standard bio-physical measurements instead of ad-hoc processes that are common whether it be

commercial (Clay et al., 2014) or recreational (Carter, 2015) estimates. Furthermore, the socioeconomic data is connected from the angler at the time of the activity rather than the individual having to recall expenditures and other activity several months later when contacted for a phone, mail, or online survey. While it is not a stratified random sampling of anglers, the convenient sampling can provide valuable data to identify emerging trends that may require additional study as well as coupling it with traditional survey data. Even with our limited sample size (n=95) this pilot study demonstrated that anglers would voluntarily offer information on expenditures, as well as other data, when not prompted in a formal survey. Assessments of economic impacts and effort in recreational fisheries can be enhanced by knowing the distance of trips taken, consumption of fuel, and expenditures on bait and tackle.

Despite redesigning the app to be more marketable to the private recreational fishing sector, *iSnapper* also collected data with similar data fields for the for-hire sector. However, we were very astonished that only six *iSnapper* users were for-hire charter captains, despite extensive outreach to this community, particularly for Texas. We attribute the low numbers to Amendment 40 passing, which separated the for-hire boats from the private recreational boats into two separate sectors. With this change the for-hire boats were strongly encouraged to adopt a reporting system similar to that of the commercial vessels. There is also ongoing pilot programs using vessel monitoring system (VMS). Other states were capturing the for-hire industry using their data collection program (e.g., Snapper Check in AL, and LACreel in LA) in their region. This may have led to confusion within the sector as to what reporting mechanism to use. Nevertheless, the current version of *iSnapper* was designed with a charter for-hire component and is readily available for use if desired.

VII. Conclusions and Recommendations for Improvements

Our data collection pilot study demonstrated that a smart device “apps” are viable fisheries management tools that effectively collect near real-time fisheries-dependent data from the recreational fishing sector. The app can also be customized to collect important and difficult to obtain data (e.g., discard and location information) that may be used to better estimate parameters such as fishing mortality. While this pilot was specifically targeting Red Snapper anglers, *iSnapper* has the potential to be used to help with management of other species, since all commonly caught species in the Gulf of Mexico are included in the app. The use of this new type of technology as a data collection tool has much potential when recreational anglers see the value in providing their

catch data. Due to the short federal Red Snapper season, data collection tools like *iSnapper* in collaboration with federal (i.e., MRIP) and state creel surveys can be used to improve current harvest estimates as well as collection of ancillary fisheries and socio-economic data. In general, we had very positive feedback from anglers, and continuing the momentum created from 2015 would be beneficial to state and federal managers and result in additional data.

After examining the results from this study there are several key items that would improve any future data collection efforts using *iSnapper* and some lessons learned during this pilot. The majority of the issues uncovered related to problems when collecting self-reported data from private anglers; however, many have the ability to be improved:

- Mandatory reporting of all anglers targeting Red Snapper may be a logical next step in obtaining a larger dataset from the app. While mandatory reporting does not guarantee that all anglers will report, there would likely be more trips submitted which would allow for a more robust data set and a reduction in variability in catch estimates; thus, helping with the accuracy of the total landings estimates for the season. Analysis of a voluntary versus mandatory program would be beneficial to assess the cost-benefit of each system. No changes would need to be implemented in the app for mandatory reporting. The only change would be to create an account for enforcement to log into so they can view current trips.
- Another unforeseen issue that occurred during this project was that in some circumstances users did not providing accurate vessel registration numbers. While users were required to provide a valid vessel format (ex. TX1234TX), cross referencing the numbers provided with an actual state registry list was not possible during this pilot. Ideally, the registration would be linked with TPWD Boater's Registration office and users would query the database using their name and address to select their boat during the *iSnapper* registration process. Being able to confirm the vessel registration prior to the angler entering data would be very beneficial as it would improve validation at the marina. In the current study the trips with false registration numbers were excluded from our validated process and contributed to a lower validation rate. With all registered users required to find and select their boat would ensure that every *iSnapper* user encountered at the ramps would become a validated trip.

- One of the most difficult aspects of conducting a voluntary study is user involvement. Despite an extensive outreach campaign by both TPWD and HRI, a majority of anglers interviewed were not aware of the app. When anglers were informed about *iSnapper*, some suggested it was unlikely that they were going to download and report their 2015 catch since the federal season was only 10 days and many only fished one or two days of the entire season. These anglers expressed they did not believe their one day of fishing would have any impact on the data or it would be worth reporting, despite understanding the need for better data. This lack of knowledge and limited season was likely a motivating factor influencing the number of trips submitted.
- Another challenge was having anglers change their behavior to use a smart device app. As with any type of behavioral change it takes time to get people actively participating and anglers typically have their own fishing routines. Introducing an extra step of starting a trip on the app before they leave the dock and then submitting their catch prior to getting back to the dock takes additional effort. Not only do users have to be willing to participate, but they also need to remember to use *iSnapper* when typically their phones are stored throughout the trip and not used until after they are back at the dock. Although the app is user friendly and a trip can be filled out in typically less than five minutes, it is still an extra step anglers are not accustomed to doing and have to make a concerted effort to complete.
- The feedback from anglers while encountered at boat ramps was encouraging. Many of them were hopeful that a new way to collect harvest data could be the answer to providing more accurate and robust data which could lend itself to allowing for an increase in the quota. In addition, all anglers that were asked to provide feedback regarding the app were impressed by the features and ease of use, which is promising when considering the potential for *iSnapper* for the 2016 Red Snapper season.

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APPENDIX I.

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Estimation of Total from a Population of Unknown Size and Application to Estimating Recreational Red Snapper Catch in Texas

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Summary: This research was motivated by the problem of estimating total recreational red snapper landings in Texas. The data available for estimation came both from angler self-reports made using a smartphone app and dockside validation samples, which are conducted as creel surveys. The two data sources can be thought of as capture-recapture experiment, where the parameter of interest is population total instead of population size, the usual parameter of interest in these experiments. We developed several estimators of total, and compared them to one suggested by Pollock et al. (1994) that makes use only of the validation sample data, but not the self-reports. All the proposed estimators allow measurement error in the self-reports and do not make any assumptions about the representativeness of the self-reports. The validation sample must be a probability sample for valid inference, but our estimators can accommodate a complex sample design that includes unequal selection probabilities and clustering. We provide recommendations about conditions under which one of the estimators discussed may be preferred to another. Finally, we present an analysis of the Texas red snapper data using the proposed methods.

Key words: Capture-recapture; Measurement error; Probability sample; Ratio estimator

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1. Introduction

Capture-recapture is a common method used to estimate population size. Laplace first used this technique in 1786 to estimate the population size of France (Stigler, 1986). Much of the development of the method was by ecologists for estimating wildlife population sizes. The method has recently been applied in other areas, such as disease surveillance (Hoque et al., 2005) and census undercount estimation (Mulry and Spencer, 1993).

The method can be described as follows. Suppose we want to estimate the total number of fish, say N, in a lake. A random sample of n_1 fish is caught, marked, and released. A second sample of n_2 fish is captured, and m of them are noted as previously marked. Assuming the proportions of marked fish are the same in the second sample and the population, we can equate the two proportions,

$$\frac{n_1}{N} = \frac{m}{n_2}.$$

This gives the classical estimator, called the Lincoln–Petersen index due to the pioneering work of two ecologists (Le Cren, 1965):

$$\hat{N} = \frac{n_1 n_2}{m}. \tag{1}$$

This estimator is also the maximum likelihood estimator of N under an assumed hypergeometric model for the second sample attributes. Its variance is estimated by

$$\hat{V}(\hat{N}) = \frac{n_1^2 n_2 (n_2 - m)}{m^3}.$$

Consistency of $\hat{N}$ relies on some assumptions implied by the hypergeometric model:

(1) The population is closed, meaning that no units immigrate to or emigrate from the population during the sampling period.

(2) All units have the same (and non-zero) probability of selection into the recapture sample, regardless of either their characteristics or prior capture

(3) There are no matching errors; i.e., units caught in the first sample can be identified if caught again.

In our application, the data are collected as described above, but the goal is different from that of the usual capture recapture methodology. It is to estimate the total t_y of some attribute y over a population, rather than to estimate the population size itself. Pollock et al. (1994) considered this problem, but in his application, y was observable only for the units selected in the second sample. He proposed to estimate t_y by

$$\hat{t}_{yp} = \hat{N}\bar{y} \tag{2}$$

with $\hat{N}$ as in (1) and $\bar{y}$ as the sample average of the y's from the recaptured units. In this paper, we propose alternative estimators of t_y that can be used when information about y is available from both samples.

Our motivation was to produce an estimate of the number of red snapper removed from the Gulf of Mexico in one season by recreational anglers in Texas. The population consists of recreational angling trips in which any red snapper were caught and the parameter of interest is t_y, the number caught on all trips. Self-reports of removals made by the anglers via smartphone app provided newly available information for estimation. The traditional method for estimating recreational catch for most species and locations is the product of estimates from two complementary surveys of anglers, one by phone or mail to measure "effort" (number of trips) and one face-to-face at dockside to measure mean catch per trip. Improvements to the designs of these surveys have been underway for about a decade, since a review by the National Research Council (2006) identified potential sources of error in the estimation system. The methodology proposed in this paper was developed for estimating removals for one species in one place, but our method could be useful for any fishery management program that allows anglers to self-report their catch using real-time reporting

methods. Such reporting programs are becoming more common for estimating recreational angler removals as the technologies (smartphone and tablet apps) become more available.

If angler compliance and accuracy were perfect, then using self-reports would save time and money, and would improve the quality of information about removals. But neither is perfect, and to determine how imperfect, a monitoring process is required. Most states experimenting with using angler self-reports collect a validation sample at dockside, using a probability sample design over a frame of ocean access points crossed with work shifts, such as 4 or 6-hour time blocks. Then all trips ending at the sampled access point and shift enter the sample, and their catch is observed.

The data from these two sources (angler-initiated reports and dockside samples) can be viewed as coming from a capture-recapture experiment, where the reported vessel trips are the capture sample, and the validation sample of trips is the recapture sample. The goal is to estimate the total (number of fish removed) over a population (of vessel trips) of unknown size. The capture sample is not randomly selected, but the recapture sample is, which is sufficient for valid estimation. One difference from Pollock's scenario is that the validation sample is selected according to a complex design, so that generalizations of expressions (1) and (2) are needed. A second difference is that more information about y is available, since the self-reports contain a reported value for all $n_1 - m$ reported but unvalidated trips, besides the n_2 of the validation sample. However, the reported values cannot be assumed accurate, due to intentional or inadvertent measurement error. We propose estimators that make use of the additional data without assuming it is without error, and that can accommodate a complex design.

In Section 2, we introduce three new estimators of total and discuss their properties. In Section 3, we analytically compare these estimators with each other and with $\hat{t}_{yp}$ under various assumptions about the accuracy and representativeness of the self-reports. Section

4 contains results from simulation studies, including those designed to mimic some of the features of our application. We apply the estimation method to the Texas data in Section 5. Discussion follows in Section 6.

2. Estimators of Population Totals using Capture-Recapture Methods

Let N denote population size, y_i a value associated with the ith of the N units, and d_1 the set of n_1 self-reporting units. d_1 is not assumed to be representative of the population nor is it a probability sample, but rather is regarded as a domain. Each unit in d_1 reports a value for y, but the ith unit's report is denoted by y_i^* to distinguish it from the truth, y_i. No assumptions are made about the relationship between y and y^*. A validation sample s_2 is selected according to a probability design, and the value of y_i is obtained for each sampled unit. A subset of s_2 will match self-reported trips; these units will have both y and y^* available. The goal is to estimate $t_y = \sum_{i=1}^{N} y_i$ using the data from d_1 and s_2.

The population and sample data can be visualized as shown in Figure 1. The first row represents the reporting domain d_1 and includes the trips with y^* available, while the second row contains trips without y^*. The first column contains trips in the validation sample, for which y is available; the second column contains the trips without observable y. The upper left cell represents the m matched units with observable y and y^*; the upper right cell represents the $n_1 - m$ reported (y^* known) but unvalidated trips; the lower left cell represents the $n_2 - m$ validated (y known), but unreported vessel trips. The lower right cell represents the rest of the population for which no data can be observed.

[Figure 1 about here.]

Pollock's estimator (2) can be generalized for a complex design to

$$\hat{t}_{yp} = \frac{n_1}{\hat{p}_1}\hat{\bar{y}} = n_1 \frac{\hat{t}_y}{\hat{n}_1}, \tag{3}$$

where $\hat{p}_1 = \frac{\sum_{i \in S_2} w_i r_i}{\sum_{i \in S_2} w_i} = \frac{\hat{n}_1}{\hat{N}}$; $\hat{\bar{y}} = \frac{\sum_{i \in S_2} w_i y_i}{\sum_{i \in S_2} w_i} = \frac{\hat{t}_y}{\hat{N}}$; the $r_i's$ are indicators of reporting ($r_i = 1$ if

the ith unit is included in d_1 and is 0 otherwise); and the $w_i's$ are the sampling weights for the units in s_2. Then $\hat{t}_{yp}$ can be regarded as a ratio estimator with auxiliary variable r_i and ratio

$$B_p = t_y/n_1.$$

We propose a new ratio estimator that is an extension of $\hat{t}_{yp}$. Its auxiliary variable is $r_i y_i^*$, with calibrating ratio

$$B_c = t_y / \sum_{i=1}^{N} r_i y_i^* = t_y / t_{y^*}, \tag{4}$$

where $t_{y*} = \sum_{i \in d_1} y_i^* = \sum_{i=1}^{N} r_i y_i^*$ denotes the total reported catch. This yields the estimator

$$\hat{t}_{yc} = t_{y*} \frac{\sum_{i \in s_2} w_i y_i}{\sum_{i \in s_2} w_i r_i y_i^*} = t_{y^*} \frac{\hat{t}_y}{\hat{t}_{y^*}}. \tag{5}$$

This estimator can be thought of as the reported removals inflated by the estimated proportion of removals reported $\left(\frac{\sum_{i \in S_2} w_i r_i y_i}{\sum_{i \in S_2} w_i y_i}\right)$, and adjusted for reporting errors by a multiplicative correction factor $\left(\frac{\sum_{i \in S_2} w_i r_i y_i}{\sum_{i \in S_2} w_i r_i y_i^*}\right)$. $\hat{t}_{yc}$ can be thought of as a generalization of the capture recapture estimator, where totals of y and y^* replace counts of units in the two data collection periods.

The accuracy of y_i^* influences which of $\hat{t}_{yp}$ and $\hat{t}_{yc}$ is best. If $y^* = y$, $\hat{t}_{yc}$ might be expected to outperform $\hat{t}_{yp}$ since it uses more information. As y_i^* becomes less accurate, $\hat{t}_{yc}$ would be expected to perform worse, until eventually $\hat{t}_{yp}$ would be preferred. One way to avoid having to make the choice between the estimators is to compute a linear combination of the two estimators, where the weights are selected to minimize its variance. This estimator is a special case of what Olkin (1958) called the multivariate ratio estimator, whose form for combining two estimators is

$$\hat{t}_{MR} = (1 - W)\hat{t}_{yp} + W\hat{t}_{yc}. \tag{6}$$

Olkin (1958) also showed (eqn. (3.1), p. 157) that the optimal weight W when the validation sample is a simple random sample (SRS) can be approximated to order $O(1/n)$ by

$$w_{SRS} = \frac{S_{dp}^2 - S_{dp,dc}}{S_{dp}^2 + S_{dc}^2 - 2S_{dp,dc}}, \tag{7}$$

where S_{dp}^2, S_{dc}^2, and $S_{dp,dc}$ denote the variances and covariance of the residuals from the ratio models.

In our application, these residuals are: $d_{pi} = y_i - B_p r_i$ and $d_{ci} = y_i - B_c r_i y_i^*$, and their variances and covariances can be expressed as shown in the Appendix in (A.2), (A.3), and (A.4). Thus from (7), w_{SRS} simplifies to

$$w_{SRS} = \frac{t_{y^*}}{t_y}\frac{S_{1,yy^*}}{S_{1y^*}^2} = \frac{t_{y^*}}{t_y}\frac{S_{1y}}{S_{1y^*}}R_{1,yy^*}, \tag{8}$$

where R_{1,yy^*}, S_{1,yy^*}, S_{1y} and S_{1y^*} are the correlation, covariance, and standard deviations of y and y^* in the reporting domain d_1. Thus the optimal estimator gives $\hat{t}_{yc}$ the majority of weight ($w_{SRS} > \frac{1}{2}$) when

$$R_{1,yy^*} > \frac{CV_{1y}}{2p_1 CV_{1y^*}},$$

where $p_1 = n_1/N$ is the reporting rate, and CV_{1y} and CV_{1y^*} are the coefficients of variation of y and y^* in the reporting domain.

In practice, w_{SRS} must be estimated in order to use $\hat{t}_{MR}$. We consider two estimators. For the first, we replace the components of (8) with estimators calculated from the observed data, as suggested in Olkin (1958). For our application, one such estimator is

$$\hat{w}_{SRS,1} = \frac{t_{y^*}}{\hat{t}_{yc}}\frac{s_{1,yy^*}}{s_{1y^*}^2}, \tag{9}$$

where $s_{1y^*}^2$ and s_{1,yy^*} are the estimated variance and covariance between y and y^* in the reporting domain, made from the matched sample. (Alternatively, one could use $\hat{t}_{yp}$ or implicitly define an estimator by substituting $\hat{t}_{MR}$ for t_y in (6), or use the observable value of $S_{1y^*}^2$ in the denominator of $\hat{w}_{SRS,1}$. Simulation showed little difference in performance among these possibilities.) We denote the resulting estimator by $\hat{t}_{y1}$. The second estimator we consider is simpler and near optimal when reporting errors are small. Note from (8) that when $y = y^*$, $w_{SRS} = t_{y^*}/t_y$. Thus we estimate w_{SRS} by

$$\hat{w}_{SRS,2} = \frac{t_{y^*}}{\hat{t}_{yc}}. \tag{10}$$

The resulting estimator can be simplified to

$$\hat{t}_{y2} = t_{y^*} + \frac{n_1}{\hat{n}_1}(\hat{t}_y - \hat{t}_{y^*}) = t_{y^*} + n_1\hat{\bar{\delta}}, \tag{11}$$

where $\delta_i = y_i - r_i y_i^*$ and $\bar{\delta} = (t_y - t_{y^*})/n_1$ is the total population underreport averaged over the reporting domain. In contrast to $\hat{t}_{yc}$, this estimator augments the reported removals by an estimate of an additive rather than a multiplicative component.

When the validation sample has a complex design, it can be accounted for in $\hat{t}_{yp}$ and $\hat{t}_{yc}$ as shown in (3) and (5), and these estimators combined as in (6). Olkin (1958) generalized (7) to produce an appropriate expression for W in (6) when the sample has a stratified design. For a general complex design, however, it is useful to note that the optimal value for W is

$$W = \frac{V(\hat{t}_{yp}) - Cov(\hat{t}_{yp}, \hat{t}_{yc})}{V(\hat{t}_{yp}) + V(\hat{t}_{yc}) - 2Cov(\hat{t}_{yp}, \hat{t}_{yc})}, \tag{12}$$

which reduce to Olkin's expressions for SRS and stratified designs when Taylor series variance approximations are used. However modern survey software can provide estimates of the variances and covariance for any design, so that explicit expressions are not needed for each design type. The optimal W will not be well approximated by (7) if the design effects for the two estimators differ greatly, so that the simplified forms shown in $\hat{w}_{SRS,1}$ and $\hat{w}_{SRS,2}$ and the resulting estimators will no longer approximate the optimal estimator.

In the next section, we focus only on SRS designs. We compare the variances of the estimators when the validation sample is a SRS to help us understand their relative performance when features of the data collection operation, such as reporting rate, change. The goal is to understand whether some estimators are better than others for certain applications. In Section 4, we extend the comparison to complex designs via simulation.

3. Comparison of estimators of population total

We compare the approximate variances of the three estimators, $\hat{t}_{yp}$, $\hat{t}_{yc}$, and $\hat{t}_{y2}$, to that of $\hat{t}_{MR}$ under a SRS design for the validation sample. We do not consider $\hat{t}_{y1}$ separately since its large sample behavior is that of $\hat{t}_{MR}$. These variance expressions, displayed in the Appendix in (A.9) - (A.12), show that when the validation sample has an SRS design, their ratios are unaffected by the size of the validation sample n_2, the population size N, or the total itself, t_y. They do depend on the reporting rate ($p_1 = n_1/N$), the correlation and CV's of y and y^* in the reporting domain (R_{1,yy^*}, CV_{1y}, and CV_{1y^*}), the ratio of the mean of y in the reporting domain to its mean in the population ($\bar{y}_1/\bar{y}$), and the same ratio for $y^*(\bar{y}_1^*/\bar{y})$.

Therefore we present comparisons of the variances of the three estimators to that of $\hat{t}_{MR}$ for the following three scenarios: (1) no errors in reporting and reporters are representative of the entire population; (2) errors in reporting, but reporters are representative of the population; and (3) no errors in reporting, but reporters are not representative of the population. We examine the loss of precision for each of the three estimators $\hat{t}_{yp}$, $\hat{t}_{yc}$, and $\hat{t}_{y2}$, as compared to $\hat{t}_{MR}$.

In scenario 1, we assume that $y = y^*$ for all units in the reporting domain (so that $R_{1,yy^*} = 1$, $\bar{y}_1 = \bar{y}_1^*$, and $CV_{1y} = CV_{1y^*}$) and that reporters are representative of the population, which is defined to mean that $\bar{y}_1 = \bar{y}$ and $CV_{1y} = CV_y$. Of course, this will occur on average if reporting is "at random", though this is not necessary. Figure 2 displays the ratio of the large sample variance of $\hat{t}_{MR}$ to that of each of the three estimators as functions of the reporting rate p_1. Comparison of the two panels, (a) and (b), illustrate how the ratios change with CV_y, which are set to 0.32 and 0.55, respectively. When $CV_y = 0$, $\hat{t}_{yp}$ and $\hat{t}_{yc}$ are equivalent. When $CV_y > 0$, $\hat{t}_{yp}$ is more efficient than $\hat{t}_{yc}$ when reporting rate is small, but grows less efficient as it increases. The cross-over point occurs when $p_1 = 1/2$ regardless

of CV_y, but the advantage for $\hat{t}_{yc}$ grows with CV_y. $\hat{t}_{y2}$ is uniformly optimal in this case since $y = y^*$.

[Figure 2 about here.]

Next we examined the performance of the estimators when the self-reports are not accurate ($y \neq y^*$), but the reporters are representative of the population ($\bar{y}_1 = \bar{y}$ and $CV_{1y} = CV_y$). The variance of $\hat{t}_{yp}$ is unaffected by measurement error, since it does not use y^*. We see from (A.11) that errors increase the variance of $\hat{t}_{MR}$ by decreasing R_{1,yy^*}, while (A.10) shows that they affect the performance of $\hat{t}_{yc}$ through both R_{1,yy^*} and CV_{1y^*}. Since CV_{1y^*} can either increase or decrease when $y \neq y^*$, the effect of measurement error on the variance of $\hat{t}_{yc}$ is not clear. Finally, from (A.12), we see that the variance of $\hat{t}_{y2}$ is affected by errors through R_{1,yy^*}, CV_{1y^*}, and also through the ratio $\bar{y}_1^*/\bar{y}$. Thus we compared the estimators under two measurement error models that impact these parameters differently. They are the classical measurement error (CME) model (see, e.g., Carroll et al. 2006, Section 1.2) and the Berkson model (Berkson, 1950).

The CME model specifies that

$$y^* = y + e, \tag{13}$$

where $e \sim (0, \alpha S_y^2)$, with y and e independent, where $S_y^2 = \sum_{i=1}^N (y_i - \bar{y})^2/(N-1)$ is the variance of y in the finite population. When (13) holds, $R_{1,yy^*} = \frac{1}{\sqrt{1+\alpha}}$, $CV_{1y^*} = CV_{1y}\sqrt{1+\alpha}$, and $\bar{y}_1^*/\bar{y} = \bar{y}_1/\bar{y}$. The Berkson model reverses the role of y and y^* and specifies that

$$y = y^* + e, \tag{14}$$

where $e \sim (0, \beta S_{y^*}^2)$, with y^* and e independent. For example, if anglers attenuate their reported catch (because they do not want to report an extremely large or small catch), then the Berkson model would be more appropriate then the CME model. Under (14), the

domain parameters would be $R_{1,yy^*} = \frac{1}{\sqrt{1+\beta}}$ and $\bar{y}_1^*/\bar{y} = \bar{y}_1/\bar{y}$. Berkson error causes CV_{1y^*} to decrease; $CV_{1y^*} = CV_{1y}/\sqrt{1+\beta}$.

Figure 3 shows the variance ratios of $\hat{t}_{MR}$ to $\hat{t}_{yp}$, $\hat{t}_{yc}$, and $\hat{t}_{y2}$ as functions of R_{1,yy^*}, where $CV_y = 0.32$ and reporting rate $p_1 = 0.7$. The two panels show the difference in relative performance of the estimators when the measurement error structure differs; CME is assumed for panel (a) and Berkson error for panel (b). Recall from Figure 2a that $\hat{t}_{yc}$ and $\hat{t}_{y2}$ would be preferred to $\hat{t}_{yp}$ for these settings when $y = y^*$. Figure 3a shows that this advantage is lost when CME afflicts y^*, unless the correlation between y and y^* is substantial (about 0.7 for $\hat{t}_{y2}$ and 0.84 for $\hat{t}_{yc}$), but when y^* has Berkson error, the relative performance returns to its no-error order. This is because Berkson error does increase the variance of $\hat{t}_{yc}$ and $\hat{t}_{y2}$, but not as severely as CME does for the same correlation, while the effect of the two models on the variance of $\hat{t}_{MR}$ is the same. In fact, the large sample variance of $\hat{t}_{y2}$ is identical to that of the optimal estimator in this case, even though errors occur. The point here is that the structure of the measurement error matters for determining which estimator is best, and the preference depends on more than R_{1,yy^*}.

[Figure 3 about here.]

Finally, we again assume that $y = y^*$, but that reporters are not representative. Instead, the mean and variance of y differ for reporters and non-reporters, affecting the estimators' variances through $\bar{y}_1/\bar{y}$ and CV_{1y}. To assess how these parameters change, we must specify a mechanism for determining the reporters. We examined the two extremes: that reporters are those with the largest or smallest catch. Thus, the reporters are assumed to be those in the top (bottom) $100p_1\%$ of y's distribution. The effect of these mechanisms on $\bar{y}_1/\bar{y}$ and CV_{1y} depends on the distribution of y.

We considered two distributions for y, one continuous (normal) and one discrete (zero-truncated Poisson). When y is normal, the distribution of y in the high removal reporting

domain is that of an upper tail truncated normal, with truncation point $A = \bar{y}+S_y\Phi^{-1}(1-p_1)$, where Φ is the standard normal CDF . The low removal reporting domain was defined similarly. Thus the moments of y in the reporting domain are easily calculated (see e.g., Johnson and Kotz (1970), pp. 81-83). When y is zero-truncated Poisson, the y in the reporting domain will also be truncated Poisson, but at a value larger than 0. The moments of the general k-truncated Poisson are also easily calculated (e.g., see Johnson and Kotz (1970)). Because of the discreteness of the distribution, only some values of p_1 are possible for this reporting model. We calculated CV_{1y^*} and $\bar{y}_1^*/\bar{y}$ and the large sample variances of $\hat{t}_{yp}$, $\hat{t}_{yc}$, $\hat{t}_{y1}$, and $\hat{t}_{MR}$ for a range of p_1.

Figure 4 shows the variance ratios as functions of the reporting rate p_1 when the domain contains high-removal reporters. Figure 4a shows the result for y normally distributed with $CV_y = 0.32$ and Figure 4b when y is a zero-truncated Poisson with $\lambda = 1.79$, which yields $CV_y \approx 0.55$. Thus the differences in Figure 2 and Figure 4 illustrates the impact of non-representative reporting only. A comparison shows that high-removal non-representative reporting improves the relative performance of $\hat{t}_{yc}$, especially for small p_1. $\hat{t}_{yp}$ alone declines in performance compared to the best estimator as reporting rate increases.

[Figure 4 about here.]

Web Table 1 shows how much non-representative reporting affects the absolute and not just the relative variance of the estimators under largest and smallest removal reporting for the normal case. For each estimator, the ratio of its variance when reporters are representative to its variance when reporters are not representative (larger for the upper and smaller for the lower half of the table) is displayed. The comparisons are made for two reporting rates: $p_1 = 0.15$ and $p_1 = 0.70$. The table shows that it can be advantageous to the estimators if reporters are those with high removals, and detrimental if reporters are those with low removals. This observation is easy to explain intuitively for $\hat{t}_{yc}$ and $\hat{t}_{y2}$, since they use the

reported y values directly, so when the large values of y are known because they are reported, less uncertainty remains for the unseen domain. It is less obvious why this would also be the case for $\hat{t}_{yp}$, since no reported values of y are used in the estimator. The reason lies in the fact that when reporters ($r_i = 1$) are those with large removals, then the correlation between r_i and y_i in the population increases, reducing the variance of $\hat{t}_{yp}$, since it is a ratio estimator.

The analytical results above are based on relationships among variances valid for large samples. We conducted a simulation study to investigate whether the relationships between the variances of the estimators were maintained, and how inference should be conducted in small samples. The results of these studies are reported in the next section.

4. Simulation studies to examine inference for population totals

Bias in the Lincoln Peterson index and its standard error estimate are known to be substantial when the number of matches between the two capture periods is small. In our application, reporting rate and thus the number of matches was small since reporting was not mandatory. Even if the reporting rate is large, managers may be interested in estimates for poststrata (e.g., for-hire and private anglers), whose validation sample counts and thus number of matches may be small. Since all of the proposed estimators are related to the Lincoln Peterson index, we were interested in determining if bias causes problems for inference in our application. We were also interested in relative performance of the estimators for complex designs. Therefore, we conducted several simulation studies to examine these issues.

Because we can express the estimators $\hat{t}_{yp}$, $\hat{t}_{yc}$, and $\hat{t}_{y2}$ as linear functions of ratio estimators, there is guidance from the sampling literature about when bias in the estimator itself or its standard error estimate is likely to be large. In an exact result, Hartley and Ross (1954) showed that the ratio of the bias of a ratio estimator to its standard error cannot exceed $CV(\bar{x})$, where $\bar{x}$ denotes the estimator of the mean of the auxiliary variable. The Taylor linearization-based variance approximation is known to underestimate the true variance for

small samples, but by how much depends on the distributions of x and y. A commonly cited rule of thumb (Cochran (2007), p. 163) also relies on $CV(\bar{x})$, which is suggested should be no larger than 0.1 to produce an adequate variance approximation. The settings for our simulations were chosen to challenge Cochran's rule of thumb; i.e., we examined cases for which $CV(\bar{x})$ exceeded 0.1.

The auxiliary variable for the ratio component of $\hat{t}_{yc}$ is $x_i = r_i y_i^*$. Therefore, one can show that when the validation sample is a SRS of size n_2, the relevant CV is

$$CV_c(\bar{x}) = \left[\left\{CV_{1y^*}^2 + (1-p_1)\right\}/p_1 n_2\right]^{\frac{1}{2}}. \tag{15}$$

For both $\hat{t}_{yp}$ and $\hat{t}_{y2}$, the auxiliary variable of the ratio component is $x_i = r_i$. The CV of its sample mean consists of the 2nd term of (15) only. Therefore, we chose simulation settings so that $CV_c(\bar{x})$ in (15) has a range of values, both larger and smaller than 0.1.

First, two finite populations were simulated, each of size $N = 20,000$ with reporters designated randomly, so that reporting is representative. In population 1, the y's were generated from a zero-truncated Poisson distribution with parameter $\lambda = 1.79$ and error-free reporting ($CV_y = CV_{1y^*} \approx 0.55$). In population 2, the y's were generated from a zero-truncated normal distribution with mean 5 and variance 1.59, and contained errors in the reported data generated according to the CME model (13), with normal error and $\alpha = 0.5625$ ($CV_y \approx 0.32, CV_{y^*} \approx 0.40$). Validation samples were repeatedly sampled (20,000 replications) for each design setting and population. The designs were SRS's with six settings for (n_2, p_1): $(80, 0.30)$, $(600, 0.05)$, $(200, 0.90)$, $(600, 0.50)$, $(800, 0.99)$, and $(1000, 0.90)$. Those settings were chosen to produce a range for $CV_c(\bar{x})$ from about 0.20 (for the first pair of settings) to 0.02 (for the last pair of settings) for both populations. From each sample, estimates $\hat{t}_{yp}$, $\hat{t}_{yc}$, $\hat{t}_{y1}$, and $\hat{t}_{y2}$ were calculated, along with each estimator's 95% normal theory-based confidence interval . The confidence intervals were produced by off-the-shelf survey software (R 's package $'Survey'$(Lumley, 2014)), using the Taylor series based variance estimates for

ratio estimators. The variance estimate for $\hat{t}_{y1}$ was that proposed in Olkin (1958), which ignores the variability in the estimate of W, and uses an estimate of $V(\hat{t}_{MR})$ (A.11) . The proportion of the $20,000$ replicates whose confidence intervals covered t_y was computed for each setting/population/estimator.

The results, which are summarized in the supplementary materials, showed that the coverage was near the nominal value (the estimates of coverage rate were all between 93.3% and 95.3%, with a margin of error for these coverage rate estimates of .3%) for all but one of the 12 settings of (n_2, p_1) in the two populations. The one exceptional setting was $(n_2, p_1) = (800, 0.99)$ in population 1, where the coverage for the confidence intervals based on $\hat{t}_{yc}$ and $\hat{t}_{y2}$ was about 90%, even though $CV_c(\bar{x})$ is small (0.02). If the $y's$ are nearly constant, $\hat{B}_c$ is approximately the reciprocal of an estimated binomial proportion. Brown et al. (2001) had a detailed discussion about the problem of interval estimation of a binomial proportion. It is well known that when the proportion gets close to 0 or 1, we would observe erratic behavior of the coverage probability of the standard Wald confidence interval.

A second simulation study was designed to examine the performance of the estimators and confidence intervals when the validation sample has a complex design. The population and sample designs tested were chosen to mimic some of the features of our application's design. We created the finite population structure by replicating each primary sampling unit (PSU) in the Texas validation sample a number of times that was proportional to its weight, to obtain a population of 20,950 trips. The average number of trips per PSU was 12. Then we simulated the "catch" data y for each trip from a zero-truncated Poisson distribution with mean parameter 10. We examined estimation for two forms of "reported" data. For the first, we assumed perfect reporting ($y = y^*$). For the second, erroneous reports were constructed by first computing $y^* = y + \epsilon$, where ϵ was simulated as a mean 0 normal random variable, and then y^* rounded to an integer (or to 0 if negative). The variance of the normal random

variable was set (by trial and error) so that the correlation between y and y^* in the reporting domain was 0.66. In both cases, the reporting units were simulated to be non-representative, by selecting them randomly from among the units in the largest 70% of the y values.

The validation sample was chosen according to a stratified cluster design with PSU's selected with probability proportional to size, where the size measures were those associated with the PSU's in our application data. The strata (weekday and weekend time periods) were defined as in the original data. The fraction of PSU's in the sample that were chosen from the two strata (0.56 from weekday, 0.44 from weekend) match the application sample. Two levels for the number of PSU's sampled (27 and 60) and the reporting rate (0.04, 0.80) were selected for the simulations, and estimators were calculated based on both the perfect and erroneous reports. Sampling was replicated 30,000 times. Then $\hat{t}_{yp}$ and $\hat{t}_{yc}$ were calculated for each sample, along with two hybrid estimators. The first was the complex sample analog of $\hat{t}_{y1}$, which takes the form of $\hat{t}_{MR}$, but with W estimated from (12). The second estimator, which we denote by $\hat{t}_{y2}$, was computed by simply substituting weighted estimates $\hat{n}_1$, $\hat{t}_y$, $\hat{t}_{y^*}$ in (11). This estimator is not necessarily optimal even if there are no reporting errors, since the design effects for the two estimators may differ, but is still approximately unbiased and is simple to compute. For each simulation setting and replicated sample, the estimator variances were estimated using both the Taylor Series and the jackknife standard error options in R's $'Survey'$ package. 95% normal theory based confidence intervals were computed.

A summary of the results are shown in Table 1. For each variance estimation method/estimator/setting, three statistics describing the results of the 30,000 replicates were computed. First is the proportion of confidence intervals that covered t_y, which is reported in the column labeled $Coverage$. Next is the squared average width of the confidence intervals, reported in the column labeled $Width^2$. A comparison of these values is a proxy for relative precision of the estimators. Finally, the variance of each estimator was computed over the replicates of the

simulation, as was the average of its replicate variance estimates. Then the relative bias in the variance estimate was computed as the difference between the estimated and simulated variance divided by the simulated variance. It is reported as a percentage in the table as $RelBias$. A negative relative bias means that the variance estimator is biased downward.

The results show that the Taylor series variance estimates do underestimate the true variance for all estimators when the number of PSU's is small ($n_2 = 27$), resulting in confidence interval coverage that is less than nominal. The jackknife estimate of variance performs better, and provides closer-to-nominal coverage of the confidence intervals. $\hat{t}_{y1}$ has especially low coverage when n_2 is small because it is slightly biased. As predicted from the SRS computations, $\hat{t}_{yp}$ outperforms $\hat{t}_{yc}$ for the small reporting rate, and the reverse is true for the large reporting rate. The presence of reporting errors does degrade the precision of all the estimators except $\hat{t}_{yp}$ (which does not use y^*), but $\hat{t}_{yc}$ still maintains its advantage. The hybrid estimators show mixed results. When the number of matches is very small (small p_1 and n_2), $\hat{t}_{y1}$ does not perform well and $\hat{t}_{y2}$ is virtually identical to $\hat{t}_{yp}$. When the number of matches is large (large p_1 and n_2), they outperform both $\hat{t}_{yp}$ and $\hat{t}_{yc}$.

[Table 1 about here.]

5. Example

Red Snapper is a highly prized species in the Gulf of Mexico, but the management of the species is highly contentious. Due to low red snapper stock estimates in previous seasons, the federal Red Snapper season was only 10 days in 2015, although the Texas season was year round. With several states trying new management strategies, it is an ideal species to test the feasibility of smartphone "app" technology for private recreational anglers to report their catch. The Harte Research Institute (HRI) created a smartphone app, iSnapper, designed to collect catch and effort data from anglers targeting Red Snapper in state and

federal waters off the Texas coast. In this section, we present estimates of total catch and number of recreational anglers fishing for Red Snapper during 2015 from private boats, using self-reported data from iSnapper.

Unlike other Gulf States, self-reporting of catch in Texas was voluntary in 2015. To validate the self-reports, HRI partnered with the state fish and game management agency (Texas Parks and Wildlife Department (TPWD)), who routinely sample anglers during dockside creel surveys according to a probability sample design from a frame of locations crossed with time blocks. The time blocks are stratified by weekday and weekend, while the locations have unequal selection probabilities that are proportional to a "pressure" measure, which is meant to capture the average number of anglers using a particular site in past years. To augment the TPWD sample, HRI also sampled in targeted high use marinas and boat ramps during the first 6 days of the federal Red Snapper recreational season (June 1 – 10, 2015), while TPWD increased the number of random creel surveys throughout the season. Data about catch counts and number of anglers were collected from every vessel intercepted during sampled shifts and locations. Vessel registration numbers were also recorded and used, along with day and time, to identify matches to trips submitted using the app.

The number of intercepted trips in the validation sample was 421, which were clustered into 27 psu's, with 15 and 12 in the weekday and weekend strata, respectively. The proportion of the trips previously self-reported was estimated to be only $\hat{p}_1 = 0.04$. The estimates of mean catch made from the validation sample for the population and for the self-reporters were 9 and 10, respectively. Thus the self-reporters are not representative, but rather have larger than average catch. The CV of catch was estimated to be 0.68. The design effect for the estimate of mean catch from the validation sample alone was about 1.4. The accuracy of reporting was high when measured as a total, with only about a 3.8% higher catch reported than observed in the matched sample. However, the correlation between y and y^* was only

about 0.66 due to the fact that the erroneous self-reports were small in number, but tended to be high outliers.

The estimates of catch from the four estimators, computed as described for the complex design in the previous section, are shown in Table 2. Because of the very small self-reporting rate and imperfect correlation, we would expect to find that $\hat{t}_{y1}$ and $\hat{t}_{y2}$ weight $\hat{t}_{yp}$ more heavily than $\hat{t}_{yc}$, and that is what did occur. The weight of $\hat{t}_{yp}$ is 0.75 for $\hat{t}_{y1}$, and 0.97 for $\hat{t}_{y2}$. The jackknife standard errors are larger than the Taylor standard errors, and based on simulation results, are likely to represent the true uncertainty more accurately. However, unlike the simulation results for the small match case, the (jackknife) standard errors of all similar. This could be because of the the larger-than-average catch of the self-reporters, or some other feature of its distribution that was not captured in the simulated population.

[Table 2 about here.]

6. Discussion

We have examined several estimators that make use of self-reported catch data that can improve on current methods of estimation for recreational fishing, when used along with data from a probability sample of access point intercepts. For the new data collection program to be most beneficial, the management agency should work to increase the reporting rate as much as possible by educational outreach to anglers, with a special emphasis on the most avid anglers, since their participation has the most benefit on precision of catch estimates. When the number of matches is small and estimation is for a fish that is relatively easy for anglers to identify, $\hat{t}_{y2}$ is our recommended estimator, since it is easy to compute with standard survey software, has an intuitively attractive form, and is nearly optimal among the estimators considered. When the number of matches is large, $\hat{t}_{y1}$ would be recommended.

Since all the estimators considered are based on a capture-recapture model, the assump-

tions required for its validity must be considered. The last of the three assumptions listed in the introduction (the "no matching error" assumption) is easily verified for our application. It would mean that matching the self-reports to access point encounters is error-free. This holds reasonably well for our application since Red Snapper angling requires a boat. In addition, catch does not need to be associated with individual anglers, but rather just the boat trip, which can be identified with good accuracy by a registration number and date/time of arrival at shore. For species that may be caught without a boat, or for an access point operation that fails to interview every angler on a boat (such as some head-boats surveys), the accuracy of the matching operation might be more questionable.

The other two assumptions, however, are problematic for our application. The first is that the population is closed, meaning that no members enter or leave during the sampling period. This holds only if no angler trips become inaccessible to selection in the verification sample after self-reporting. But anglers who return from their trip to a private dock, such as one behind a home, are removed from the validation sample frame, since sampling can only occur at publicly accessible locations. The access points in the frame are often referred to as public sites, though some private marinas do allow samplers to conduct creel surveys on their properties. This is a vexing problem for all recreational angler data collection systems. In the estimation system in current use, no measure of catch is available for trips ending at private sites, though counts of these trips are obtained from the effort survey. The unverifiable assumption that catch per trip is identical for trips ending at public and private sites has to be made in order to obtain an estimate of catch. Though the capture-recapture approach does provide some information about catch for the private access point anglers via their self-reports (y^*), we still have no source of data for y for these trips, so an unverifiable assumption that the relationship between y and y^* is the same for public and private trips is necessary. One possible alternative that has been considered is that the verification sample

could add some intercepts that occur before landing, such as at fueling sites or on-the-water encounters. This would add its own problems of assessing probabilities of selection into the verification sample, so that further work is needed on this issue.

The last assumption to be considered is the one stating that all units have an equal probability of being selected into the validation sample. This encompasses both independence of selection in the two capture periods (selection into the 2nd sample does not depend on capture in the first), as well as homogeneity of selection probabilities in the verification sample. We have generalized the estimation method so that it accounts for known differences in selection probabilities due to the probability sample. The problem occurs when those differences are not known. For example, if the probability of reporting is influenced by selection into the validation sample, this altered probability cannot be accounted for in estimation, and thus can bias the estimator. This could occur if a returning angler were more likely to report his catch if he could anticipate that he would be in the validation sample (what capture recapture methodologists would refer to as trap-happy, but with the two sampling periods having reversed labels). Care must be taken to prevent this problem by the way the sampling operation and collection of self-report data is implemented. First, the sampling process should not occur in plain view of anglers returning to the landing site. Next, self-reports made after anglers encounter validation samplers should be removed or at least treated separately from independent reports. This will reduce the reporting rate, but will be necessary to reduce bias from violation of the independence assumption.

Still, despite these problems, this approach has the promise of improving the quality and timeliness of the estimates of catch over those currently available. The decreasing response rates for household surveys nationally have been shared by the effort surveys currently conducted. The access point surveys enjoy a much higher response rate, so this source of non-sampling error is much reduced. Since all data collection is completed at the time that

the trip is made, there is potential for a much faster production of estimates than the current system, since the effort survey is conducted retrospectively. Finally, fisheries management agencies report that some angler advocacy groups are anxious to provide data to improve what they perceive as inadequately precise estimates. This methodology provides a valid way to make use of their shared data.

Acknowledgements

This section is optional...

Supplementary Materials

Supplementary Web Appendices, Web Tables, referenced in Sections 3 and 4 are available with this paper at the Biometrics website on Wiley Online Library.

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Appendix

Variances and Covariances of $\hat{t}_{yp}$ and $\hat{t}_{yc}$

As noted in (2) and (5), $\hat{t}_{yp}$ and $\hat{t}_{yc}$ are ratio estimators, so their variances can be approximated using Taylor linearization. Thus we see (e.g., from (4.11) of Lohr (2009)) that

$$V(\hat{t}_{yp}) = n_1^2 Var(\hat{B}_p) \approx \frac{N^2\left(1-\frac{n_2}{N}\right)}{n_2} S_{dp}^2, \tag{A.1}$$

where $S_{dp}^2 = \sum_{i=1}^{N}(y_i - B_p r_i)^2/(N-1)$.This residual variance can be rewritten as

$$S_{dp}^2 = S_y^2 + \bar{y}^2\left(1+\frac{1}{p_1}\right) - 2\bar{y}\bar{y}_1 \tag{A.2}$$

where $\bar{y} = t_y/N$ and $S_y^2 = \sum_{i=1}^{N}(y_i - \bar{y})^2/(N-1)$ are the mean and variance of y in the entire finite population, $p_1 = n_1/N$ is the fraction of the population in the reporting domain, and $\bar{y}_1 = \sum_{i=1}^{n_1} y_i/n_1$ is the mean of y in this domain. A similar computation yields the variance for $\hat{t}_{yc}$ to have a similar form to (A.1), but with residual variance

$$S_{dc}^2 = S_{dp}^2 + \frac{1}{p_1}\left(\bar{y}/\bar{y}_1^*\right)^2 S_{1y^*}^2 - 2\left(\bar{y}/\bar{y}_1^*\right) S_{1,yy^*}, \tag{A.3}$$

where $\bar{y}_1^* = t_{y^*}/n_1$ is the mean of y^* in the reporting domain. The covariance of the two estimators also has the form shown in (A.1), but with residual covariance

$$S_{dp,dc} = S_{dp}^2 - \left(\bar{y}/\bar{y}_1^*\right) S_{1,yy^*}. \tag{A.4}$$

Next we consider the variance of the optimally weighted average of these two estimators as defined in (6). Its variance is (Cochran (2007) eq (6.100))

$$V(\hat{t}_{MR}) = \frac{V(\hat{t}_{yp})V(\hat{t}_{yc}) - Cov^2(\hat{t}_{yp}, \hat{t}_{yc})}{V(\hat{t}_{yp}) + V(\hat{t}_{yc}) - 2Cov(\hat{t}_{yp}, \hat{t}_{yc})}, \tag{A.5}$$

The covariance of the two ratio estimators is

$$Cov(\hat{t}_{yp}, \hat{t}_{yc}) \approx \frac{N^2\left(1 - \frac{n_2}{N}\right)}{n_2} S_{dp,dc} = \frac{N^2\left(1 - \frac{n_2}{N}\right)}{n_2}\left\{S_{dp}^2 - \left(\bar{y}/\bar{y}_1^*\right) S_{1,yy^*}\right\}, \tag{A.6}$$

where $S_{1,yy^*} = \sum_{i=1}^{n_1}(y_i - \bar{y}_1)(y_i^* - \bar{y}_1^*)/(n_1 - 1)$ is the covariance between y and y^* in the reporting domain. Then from (A.1) - (A.6), we have

$$V(\hat{t}_{MR}) \approx \frac{N^2(1 - \frac{n_2}{N})}{n_2}\left(S_{dp}^2 - p_1 S_{1,yy^*}^2/S_{1y^*}^2\right), \tag{A.7}$$

where $S_{1y^*}^2 = \sum_{i=1}^{n_1}\left(y_i^* - \bar{y}_1^*\right)^2/(n_1 - 1)$ is the variance of y^* in the reporting domain.

Finally, it can be observed from (11) that $\hat{t}_{y2}$ can be written as a constant (t_{y^*}) plus a ratio estimator

$$\hat{t}_{y-ry^*} = n_1 \frac{\sum_{i \in S_2}\left(y_i - r_i y_i^*\right)}{\hat{n}_1}.$$

Therefore the variance of $\hat{t}_{y2}$ can also be approximated using Taylor linearization, yielding

$$V(\hat{t}_{y2}) \approx \frac{N^2\left(1 - \frac{n_2}{N}\right)}{n_2}\left\{S_{dp}^2 + p_1(S_{1y^*}^2 - 2S_{1,yy^*})\right\}. \tag{A.8}$$

In order to facilitate comparison of these variances, it is helpful to rewrite them in canonical form as follows:

$$V(\hat{t}_{yp}) = \frac{t_y^2\left(1-\frac{n_2}{N}\right)}{n_2}\left\{CV_y^2 + \left(1+\frac{1}{p_1}\right) - 2\left(\frac{\bar{y}_1}{\bar{y}}\right)\right\}; \tag{A.9}$$

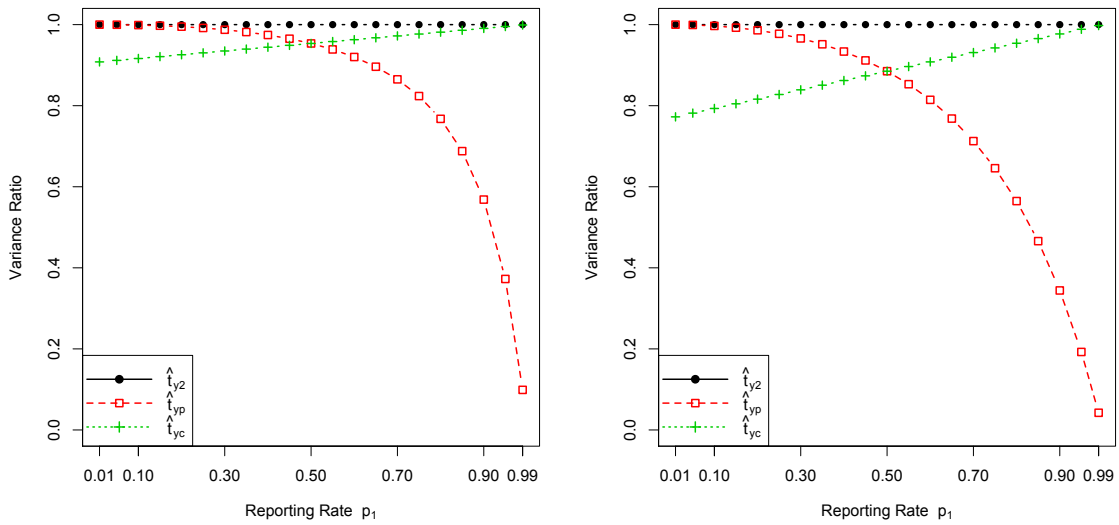
$$V(\hat{t}_{yc}) \approx V(\hat{t}_{yp}) + \frac{t_y^2\left(1-\frac{n_2}{N}\right)}{n_2}\left\{\frac{CV_{1y^*}^2}{p_1} - 2\left(\frac{\bar{y}_1}{\bar{y}}\right)R_{1,yy^*}CV_{1y}CV_{1y^*}\right\}; \tag{A.10}$$

$$V(\hat{t}_{MR}) \approx V(\hat{t}_{yp}) - \frac{t_y^2\left(1-\frac{n_2}{N}\right)}{n_2}\left\{p_1\left(\frac{\bar{y}_1}{\bar{y}}\right)^2 R_{1,yy^*}^2 CV_{1y}^2\right\}; \tag{A.11}$$

$$V(\hat{t}_{y2}) \approx V(\hat{t}_{yp}) + \frac{t_y^2\left(1-\frac{n_2}{N}\right)}{n_2}\left\{p_1\frac{\bar{y}_1^*}{\bar{y}}CV_{1y^*}\left(\frac{\bar{y}_1^*}{\bar{y}}CV_{1y^*} - 2\frac{\bar{y}_1}{\bar{y}}R_{1,yy^*}CV_{1y}\right)\right\}. \tag{A.12}$$

		Validation Sample S_2		
		In	Out	
Report d_1	In	m $\boldsymbol{y}^*, \boldsymbol{y}$	$n_1 - m$ $\boldsymbol{y}^*$	n_1
	Out	$n_2 - m$ $\boldsymbol{y}$		
		n_2		$\hat{N}$

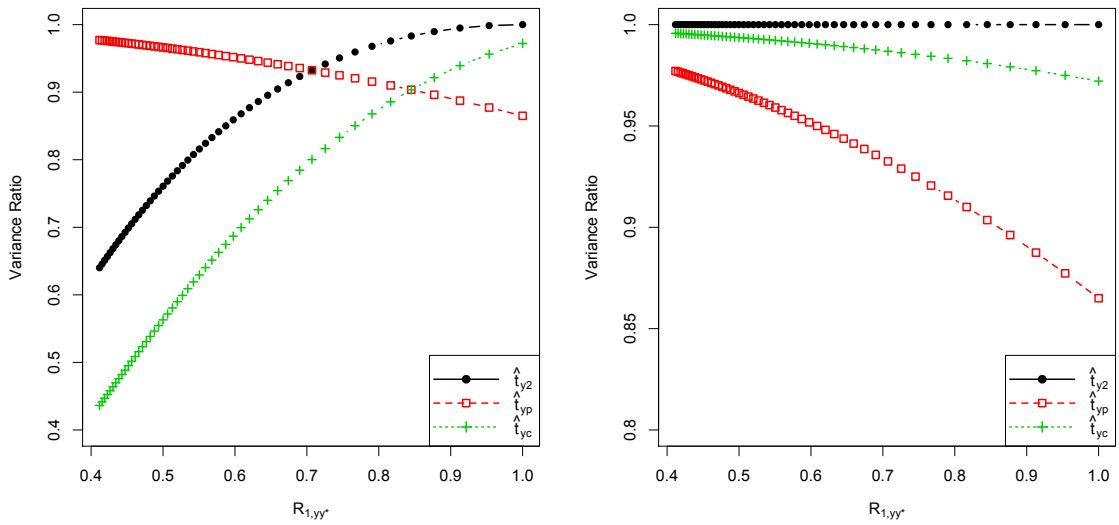
Figure 1. An illustration of the population and sample data.



(a) Variance Ratios when $CV_y = 0.32$.

(b) Variance Ratios when $CV_y = 0.55$.

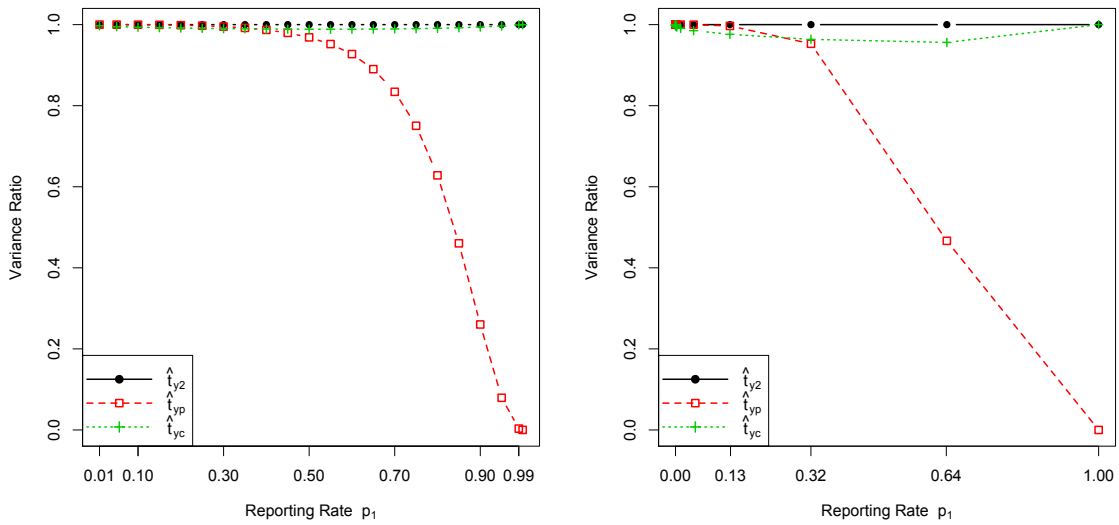
Figure 2. Ratio of variance of $\hat{t}_{MR}$ to the 3 estimators as a function of p_1, when there are no errors, and representative reporting.



(a) Classical measurement error model for y^*.

(b) Berkson measurement model for y^*.

Figure 3. Ratio of variance of $\hat{t}_{MR}$ to the 3 estimators as a function of R_{1,yy^*}, when $p_1 = 0.7$, and reporters are representative.



(a) Zero-truncated Normal distribution with $CV_y = 0.32$. (b) Zero-truncated Poisson distribution with $CV_y = 0.55$.

Figure 4. Ratio of variance of $\hat{t}_{MR}$ to the 3 estimators as a function of p_1, when there are no errors, and max catch reporting.

Table 1

Coverage rate, squared confidence interval width ($*10^9$), and relative bias of variance estimate for each estimator based on 30,000 replicates.

		No errors in report									Errors are present in report with $R_{1,yy^*} = 0.66$					
		$p_1 = 0.04, n_2 = 27$			$p_1 = 0.04, n_2 = 60$			$p_1 = 0.80, n_2 = 60$			$p_1 = 0.04, n_2 = 27$			$p_1 = 0.80, n_2 = 60$		
		Coverage	Width^2	RelBias	Coverage	Width^2	RelBias	Coverage	Width^2	RelBias	Coverage	Width^2	RelBias	Coverage	Width^2	RelBias
$\hat{t}_{yp}$	Taylor	0.936	54.50	-0.17	0.944	20.87	-0.05	0.948	0.168	0.00	0.936	54.50	-0.17	0.948	0.168	0.00
	Jackknife	0.948	76.02	-0.02	0.952	23.40	0.00	0.951	0.173	0.01	0.948	76.02	-0.02	0.951	0.173	0.01
$\hat{t}_{yc}$	Taylor	0.935	58.92	-0.19	0.946	21.68	-0.06	0.945	0.121	0.00	0.934	63.08	-0.19	0.945	0.191	0.00
	Jackknife	0.948	85.67	-0.02	0.955	24.48	0.00	0.948	0.124	0.01	0.948	94.24	-0.01	0.947	0.196	0.02
$\hat{t}_{y1}$	Taylor	0.885	45.82	-0.15	0.924	19.58	-0.07	0.940	0.116	-0.02	0.885	45.91	-0.17	0.940	0.141	-0.02
	Jackknife	0.914	80.46	0.12	0.935	22.22	0.00	0.943	0.119	-0.01	0.910	74.13	0.06	0.938	0.145	-0.01
$\hat{t}_{y2}$	Taylor	0.936	54.46	-0.17	0.947	20.86	-0.05	0.945	0.120	0.00	0.936	54.46	-0.17	0.945	0.172	0.00
	Jackknife	0.948	76.02	-0.02	0.952	23.35	0.00	0.948	0.123	0 .01	0.948	76.11	-0.02	0.948	0.177	0.02

Table 2

Estimated total landings of red snappers using four different estimators.

	$\hat{t}_{yc}$	$\hat{t}_{yp}$	$\hat{t}_{y1}$	$\hat{t}_{y2}$
Estimate	61659	58686	59422	58789
SE(Taylor)	17793	17005	16907	16952
SE(Jackknife)	21723	21646	21462	21573