Evaluating Drivers for Tracking Technology Adoption in Small-scale Fisheries

Photo by Barbara Rose Hoover

Master of Environmental Science & Management

Bren School of Environmental Science & Management
University of California, Santa Barbara

Thomas Butera
Gage Clawson
Corinna Hong
Barbara Rose Hoover
Juan Silva

Faculty Advisor: Christopher Costello

March 2020

Signature Page

Evaluating Drivers for Tracking Technology Adoption in Small-scale Fisheries

As authors of this Group Project report, we archive this report on the Bren School's website such that the results of our research are available for all to read. Our signatures on the document signify our joint responsibility to fulfill the archiving standards set by the Bren School of Environmental Science & Management.

_____

Thomas Butera

_____

Gage Clawson

_____

Corinna Hong

_____

Barbara Rose Hoover

_____

Juan Silva

The Bren School of Environmental Science & Management produces professionals with unrivaled training in environmental science and management who will devote their unique skills to the diagnosis, assessment, mitigation, prevention, and remedy of the environmental problems of today and the future. A guiding principal of the School is that the analysis of environmental problems requires quantitative training in more than one discipline and an awareness of the physical, biological, social, political, and economic consequences that arise from scientific or technological decisions.

The Group Project is required of all students in the Master of Environmental Science and Management (MESM) Program. The project is a year-long activity in which small groups of students conduct focused, interdisciplinary research on the scientific, management, and policy dimensions of a specific environmental issue. This Group Project Final Report is authored by MESM students and has been reviewed and approved by:

_____   _____

Dr. Christopher Costello   Date

Acknowledgements

The authors of this report would like to thank all those who helped support our project.

Abstract

Small-scale fisheries provide livelihoods and food security for millions of people worldwide, while also influencing the health of aquatic ecosystems. Despite their significance, there is a spatiotemporal data gap that limits our knowledge of small-scale fisheries and hinders their sustainable management.

Automatic identification systems and vessel monitoring systems are effective tools for collecting spatiotemporal data on fishing activity. However, the use of vessel tracking technology has seen limited success in small-scale fisheries because there isn't an international body that has mandated its usage with a top-down approach, unlike with industrial fishing. Consequently, there is potential for a bottom-up approach, where fishers participate in a vessel tracking program that is incentive-compatible to their preferences.

For this analysis, we conducted a dual response choice experiment to evaluate fisher preference data from surveys we conducted in Indonesia and Mexico. Additionally, we utilized a contingent valuation to gauge both fishers' willingness to pay for a tracking program and the effects of fishers' characteristics on their willingness to pay.

Our results indicate that fishers are willing to participate and pay for a vessel tracking program that is properly incentivized. Further, individual fisher characteristics are a stronger driver for willingness to pay than tracking technology features.

Executive Summary

Vessel monitoring systems (VMS) and automatic identification system (AIS) equipment have gained popularity as a viable option for fishery monitoring, control, surveillance, and research (Food and Agriculture Organization of the United Nations, 2001). On-board VMS or AIS equipment can provide location data at high spatial and temporal resolution. The use of VMS on fishing vessels has brought transparency to the fishing industry and has allowed for better information on global fishing activity and effort. However, VMS and AIS devices are not installed on all fishing vessels. Current tracking data accounts for 80% of industrial fishing activity, but less than 0.2% of small-scale fishing activity (fishing done by vessels under 12 meters) (Kroodsma et al., 2018). This data gap is problematic due to the current state of global fisheries as well as the large contributions of small-scale fisheries (SSFs) to global catch.

Small-scale fisheries span hundreds of thousands of villages around the world, often with a high presence in developing countries. They provide food security and sustained livelihoods to millions of people, while also contributing an estimated 70% to total global catch which is mainly used for domestic human consumption (Kolding et al., 2014). Vessel monitoring technology usage in small-scale fisheries can help alleviate ecosystem pressure created by problems such as high levels of illegal, unreported, and unregulated (IUU) fishing and incomplete data on fish stocks. These problems can lead to overexploitation of local marine resources that threaten SSF persistence and the worldwide benefits they provide. However, unlike large, commercial fishing vessels, small-scale fishing vessels are not legally mandated to install and use monitoring systems (Shepperson et al., 2018). This means that proposed vessel monitoring programs must be incentive compatible with fisher preferences in order to maximize technology use.

To that end, our project aimed to evaluate drivers to vessel tracking program adoption in small-scale fisheries. We reached this objective by addressing three research questions which were as follows:
1. What are fishers' preferences for different vessel tracking program designs?
2. What are fishers' willingness to pay for a vessel tracking program?
3. What are the effects of fisher characteristics on willingness to pay?

Fisher preferences for vessel tracking program designs were determined with a dual response choice experiment. In a standard choice experiment, each respondent is asked to state their preference for one option over another, usually including an opt out option as a choice. Each option in the choice experiment is composed of a set of attributes that dictate the design of the option. On the other hand, in a dual response choice experiment (DRCE), respondents are first asked to choose among two "packages" (in our case vessel monitoring programs) containing different combinations of attributes for a potential tracking program. The follow-up question then offers the option to accept the program they have chosen or stick with the status quo (no tracking package). This set-up allows surveyors to determine trade-offs and preferences between packages even if respondents would rather not accept one in the end. Our choice experiment was designed to weigh trade-offs between a presence or absence of an SOS button, broadcasted or private vessel identification information, and government, industry, fisher, or publicly owned data.

Willingness to pay was determined through a bidding game. If a fisher decided to accept the package they originally chose, they were then asked about their willingness to pay for it in five increasing monetary monthly payments, until a negative response was given. If a fisher decided to reject the

package they originally chose, they were then asked to indicate their willingness to accept the package if paid over the same increasing monetary amounts, until a positive response was given. The data obtained from this bidding game resulted in ranges, instead of exact monetary values for willingness to pay (e.g. the respondent was willing to pay between $2 and $5 per month for tracking technology). Therefore, willingness to pay was modeled using an interval regression.

The choice experiment and bidding game were followed by a questionnaire to collect data on socioeconomics, fisher perceptions, fishery governance structures, and fishing behavior. These characteristics were then added to an interval regression model to determine how they affect willingness to pay.

A total of 211 surveys were conducted across seven fishing villages in Indonesia and Mexico. Data from the choice experiment was analyzed using a conditional logistic regression and willingness to pay was calculated using an interval regression. Our choice experiment revealed that most respondents preferred a program that contains an SOS function, keeps the fishers' information anonymous, and is owned by the government. Results of our interval regression showed that SOS functionality, exposure to technology (e.g. GPS), perceived problems facing the fishery, and education are highly significant and have large effects on willingness to pay. Additionally, surveyed fishers were willing to pay an average of $2.76 USD/month to participate in the vessel tracking program.

Our conclusions suggest that, given proper design and incentives, fishers are willing to participate and pay for a vessel tracking program. We also found that individual fisher characteristics drive willingness to pay more than tracking technology features. Moving forward, we suggest implementing more surveys in new villages to expand representation in our survey sample and strengthen the external validity of our models. We also recommend conducting Randomized Controlled Trials to test these findings and better hone in on what incentives will be required to motivate widespread adoption of tracking technology in SSFs.

Table of Contents

Project Significance

Increased ability to collect and share data on global fisheries has led to more informed fishery management plans. As fishing effort and illegal, unreported, and unregulated (IUU) catch cause significant declines in marine biodiversity (Dunn et al., 2018), it is critical to provide researchers, policymakers, and fisheries managers with the most accurate and robust data possible. Global Fishing Watch will use insights gained for this research to expand their database on global fishing activity.

A promising and cost-effective contribution to data collection that allows for comprehensive small-scale fisheries (SSFs) management comes from satellite-based monitoring technologies. Spatial and temporal data on the distribution of fishing efforts provided by this technology are currently being collected and analyzed to better understand and manage fisheries. Global Fishing Watch, an independent and international non-profit, successfully uses satellite technology to enable scientific research, tackle IUU fishing, advocate for better marine protection policies, and improve the way fishing is managed (Cabral et al., 2018; Dunn et al., 2018, 2018; Sala et al., 2018). Satellite data can improve several aspects of fishery monitoring and management including quantification of gear-specific fishing effort (Gonzalez-Mirelis et al., 2014; Kroodsma et al., 2018; Lee et al., 2010), assessment of responses to fishing regulation changes (Dinmore et al., 2003), and collection of information on the spatial distribution of fishing pressure patterns to better design marine management plans (Stelzenmüller et al., 2008; Watson & Haynie, 2016). This technology can also be integrated with other management tools to give a holistic picture of the fishery. These tools can include electronic catch reporting (e-logs), integrated catch documentation schemes, and catch share or quota monitoring (Pew Charitable Trusts, 2017). This emerging technology can prove beneficial to marine resource management.

Spatial data from satellite-tracked fishing vessels is a means to effective assessment, monitoring, enforcement, and sustainability of SSFs (Cochrane & Garcia, 2009; Dunn et al., 2018). However, it also has its limitations. The installation and continued use of satellite tracking technology requires voluntary participation by fishers. This is a cooperative action influenced by a myriad of socioeconomic factors and individual characteristics (Kolding et al., 2014; Salas et al., 2007). This project's focus is to glean an understanding of how attributes of a vessel tracking program along with fishers' characteristics predict program desirability, so an informed recommendation can be made to implement a sustainable vessel tracking program.

We expect that the information gathered from this project can be used by our client, Global Fishing Watch, to implement tracking programs in SSFs around the world. These insights will be useful for their conversations with partners about potential sites and design strategies for program implementation.

Background

WHERE VESSEL MONITORING TECHNOLOGY IS NOW

Vessel monitoring systems (VMS) for small-scale fisheries appeared in the early 1990s and have since gained momentum as a viable option for fishery monitoring, control, and surveillance as well as for research (Food and Agriculture Organization of the United Nations, 2001). Vessel Monitoring Systems provide data at high spatial and temporal resolution (Campbell et al., 2014), while remaining more cost effective than independent on-board observers, which have been used to monitor fishing activity and vessel movement (Doherty et al., 2014). Technological innovation has led to additional VMS features that provide benefits to fishers such as catch and effort reporting (electronic logbooks), weather reporting, two-way communication for fleet management and safety at sea, marketing and trade, and internet access (Food and Agriculture Organization of the United Nations, 2001). This growing field of VMS technology lends itself to more research on its benefits and potential for increased use.

A variety of vessel monitoring systems have been implemented in SSFs around the world. Some estimates suggest there are around 1,000 electronic VMS installed on fishing vessels worldwide in a combination of pilots and full-fledged programs (Michelin et al., 2018). However, most of the systems implemented in developing countries have been done only for short term research studies (Metcalfe et al., 2017). Long term use of electronic VMS on small vessels often presents economic and logistic barriers due to the size, power, and maintenance requirements of the technology (Girard & Du Payrat, 2017). As a result, scalability and sustainability of the monitoring technology is seldom considered during the implementation of VMS. Other challenges for scalability for monitoring technology in this context can be associated with minimum viable product, slow regulatory processes, and the lack of business model innovation (Fujita et al., 2018). Although vessel tracking technology has made significant strides, there is still much to be desired when it comes to small-scale fishing vessel tracking.

Regardless of these shortcomings, VMS data is currently used to bring more transparency to the fishing industry. Global Fishing Watch launched in September 2016 as the world's first provider of a global view of commercial fishing activity (Merten et al., 2016). It was originally created by three organizations: Oceana, SkyTruth, and Google to collaborate on ocean conservation with satellite technology and data processing capability (Global Fishing Watch, n.d.). Together, these groups aim to promote ocean sustainability through greater information transparency. Currently, Global Fishing Watch takes satellite data from commercial fishing vessels then compiles, analyzes, and publishes it on their website in near-real time for anyone with an internet connection to access (Merten et al., 2016).

Global Fishing Watch tracks global fishing activity through two different and complementary vessel tracking systems: Automatic Identification System (AIS) devices and VMS (Global Fishing Watch, 2018). AIS equipment is a GPS-like device designed for use as a collision avoidance tool and is used to exchange navigation information in near real-time via ship-to-ship or ship-to-shore communication (Jablonicky et al., n.d.; Shepperson et al., 2018). International law requires boats over a certain size to publicly broadcast their location using AIS devices, making it a standardized, internationally adopted, and non-proprietary communication protocol (Shepperson et al., 2018). Vessel Monitoring Systems are intended for remote monitoring of fishing vessel positions in relation to regulatory areas, maritime boundary lines, and other position-critical enforcement schemes (Shepperson et al., 2018). Compared

to AIS devices, VMS are often more reliable and offer higher resolution data (Shepperson et al., 2018). However, requirements are enforced at the national level and thus, data is proprietary to the national government (Jarke et al., 2014). Despite this, Global Fishing Watch continues to work toward increasing ocean sustainability through greater transparency at sea.

Global Fishing Watch has access to non-proprietary data collected from AIS and VMS devices in countries that have also committed to information transparency including Indonesia, Peru, Chile, Costa Rica, and Panama (Global Fishing Watch, 2018). However, large data gaps still exist. AIS tracking accounts for most of the industrial fishing vessels and as much as 80% of fishing in the high seas, but accounts for only around 0.2% of fishing vessels under 12 meters (Kroodsma et al., 2018). To fill these gaps, Global Fishing Watch hopes to develop strategies to expand the capacity of monitoring small-scale fishing vessels through a better understanding of the key factors affecting technology adoption among fishers.

IMPORTANCE OF AND THREATS TO SMALL-SCALE FISHERIES

Small-scale fisheries are acknowledged for their fundamental contributions to food security, nutrition, and sustained livelihoods globally—especially in the developing world. Small-scale fisheries (including inland) provide 70% of the global catch for domestic human consumption and employ nearly 90% of the world's estimated 120 million fishers (Kolding et al., 2014). Their decentralized distribution also makes them better able to widely share economic and social benefits such as their contribution to the proliferation of cultural heritage and local environmental knowledge (Food and Agriculture Organization of the United Nations, 2005). The large social and economic contribution of small-scale fisheries make them impossible to ignore when accounting for global impacts of fishing activity.

Despite the importance of SSFs, overexploitation severely threatens their persistence and the benefits they provide (Afflerbach et al., 2014). This can have profound and lasting impacts on the individuals and communities that rely on this resource. Resource overexploitation has frequently led to the degradation or failure of fisheries worldwide, which in turn negatively impacts the stakeholders that benefit from them (Cochrane & Garcia, 2009; Worm et al., 2009). While proper management is critical to remedy this issue, there remains a knowledge gap that hinders fishery management from adapting to fit the diversity of SSFs. To overcome this limitation, researchers and managers must rely on more than information analysis alone. Novel spatial data can complement current information on a SSF by providing up-to-date information on an individual vessel's fishing effort (Kolding et al., 2014; Salas et al., 2007). This real-time data can replace the need for on-board observers as well as help combat IUU fishing when coupled with informed management strategies.

COSTS AND BENEFITS OF MONITORING TECHNOLOGY

Vessel tracking technology can provide benefits to both resource managers and fishers. Collecting data on vessel movements has the potential to improve management and compliance with fisheries policies. Real-time observations of fishing vessel positions can help prevent boats from entering marine protected areas or other restricted areas (Girard & Du Payrat, 2017). Location information can also be used by fishers to alert them to protected areas and help them avoid fines and prosecution. In other words, this technology could be used in a proactive monitoring capacity to aid in fisheries management and control IUU fishing (Cabral et al., 2018). This would benefit both fishers and resource managers.

Installing a monitoring system on small-scale vessels can also allow for safety at sea capabilities. An AIS or VMS device onboard can be used to help vessels avoid collisions, which can be beneficial to small vessels. Small fishing vessels, 44 feet in length or less, account for the majority of accidents at sea (Proud et al., 2017). Rough seas, bad weather, or mechanical issues can cause these small boats to tip or sink. Without an AIS or VMS installed onboard, knowing where to search during rescue efforts becomes a huge challenge. However, a vessel tracker equipped with an SOS button can allow fishers on small vessels to call for help and give authorities an exact location. This is arguably the most important benefit an individual fisher can get from using vessel monitoring technology.

Increased data collection on fishing location, species, and effort can help seafood products from SSFs become certified as sustainable. The prominence of eco-labels has increased in recent years along with their ability to influence consumer preference (Kirby et al., 2014). In fisheries, eco-labels are biased toward commercial fisheries. For example, only three developing countries' fisheries have been certified by the Marine Stewardship Council due to certification procedures ill equipped for developing, data-deficient fisheries (Ponte, 2008). Tracking small-scale fisheries can provide them with robust data that can enable them to achieve eco-labeling and minimize the bias. This is important for SSFs because better traced fish results in better satisfaction for customers. It also gives a more complete overview of what is happening in the value chain, providing better market access for fishers. Eco-labeling can also increase public awareness for more sustainable patterns of consumption, which is a benefit in and of itself (Girard & Du Payrat, 2017). As eco-labels rise in consumer popularity, the ability to collect data that can lead to sustainability certifications can present a benefit to small-scale fisheries.

The above benefits exist for current, best available, vessel monitoring technology. However, future technology advancements can provide additional benefits. The integration of vessel tracking and smartphone technology can create a product with great benefits. In particular, owners of fishing vessels can monitor fishing activity without even being aboard (Girard & Du Payrat, 2017). Examples of this include seeing vessel locations and estimated times of arrival back to shore. Additionally, with a smartphone, fishers can sell their catch through apps before returning to port, eliminating a potential "race to port" phenomena (C. Kilgour, personal communication, May 25, 2019). There is also an economic benefit to using smartphones as tracking technology, since many people already own and use smartphones. Although the use of smartphones as tracking devices themselves is limited due to connectivity issues in the open seas, rapid advances could drastically change these conditions and increase potential expansion of tracking technology among millions of fishers worldwide.

Although there are clear benefits to increasing transparency in global fisheries, there are also drawbacks. As with any device that collects location data, privacy is a top concern. The level of apprehension a person might have with position tracking depends on the type of information they are asked to release as well as the usefulness of the product to the consumer (Barkuus & Dey, 2003). This can be a major cost to a fisher when considering proposed vessel monitoring programs. Research has shown that those that hold more privacy concerns may have an increased negative feeling toward the collection of location data (Ketelaar & van Balen, 2018). Fishing can be competitive amongst individuals and fishing groups creating a want for privacy when fishing. Public broadcast of an individual's fishing location could expose some fishers' secret fishing spots and other operational secrets (Michelin et al., 2018). Therefore, fishers might not be so inclined to participate in a vessel tracking program and let others know where they fish.

A second drawback comes with the collection of data itself. All collected data is owned, used, and/or disseminated by an entity or individual as they see fit. Depending on which group(s) own the collected data, data ownership can be a cost associated with vessel monitoring program participation.

In countries where corruption is rampant, fishers might not trust the government or fishing industry enough to allow them to collect data on their movements. Additionally, for those who would like to remain anonymous, they might be uncomfortable with their fishing activity being broadcast to the public. Data ownership in the perceived wrong hands can be a big disincentive for fishers to willingly adopt monitoring technology.

Project Objective

Evaluate drivers for vessel tracking program adoption in small-scale fisheries.

SUB-OBJECTIVES

1. Determine fishers' preferences for different vessel tracking program designs.

   There are several foundational decisions that must be made when creating any new technology. This first sub-objective aims to identify the most important attributes of a newly proposed product and determine what features a user would prefer.

2. Estimate fishers' willingness to pay for a vessel tracking program.

   The second sub-objective aims to determine if fishers would rather pay or get paid for installing and using the technology. From interviews conducted with experts in Indonesia, they believe that monetary incentives have been largely successful and help motivate fishers to both implement and regularly use tracking technology (P. Mous, personal communication, May 8, 2019). However, research also suggests that monetary incentives sometimes are not enough and not the most important aspect determining a program's desirability (Sorice et al., 2018).

3. Evaluate the effects of fisher characteristics on willingness to pay.

   Socioeconomic status, education level, and other external factors can influence an individual's willingness to pay such that we see differences across people for the same vessel tracking program.

Methods

PROJECT APPROACH

At the core of Global Fishing Watch's hope to monitor small-scale fishing vessels around the world is the problem of how to get fishers to voluntarily allow tracking of their vessel. Because humans are social beings, understanding the role of human behavior and society in choice-making helped us develop appropriate sets of incentives. Taking a human centered design approach to our research allowed us to design a project that aimed to figure out motivations behind certain choices people make. Human centered design aims to create useful systems through consideration of users' and stakeholders' needs and preferences at all steps in the development process (Tantia, 2017). Using this idea, we built our research question and methods around uncovering information that would help us create a viable vessel monitoring system for fishers. Applying insights from economics and behavioral science, we designed a choice experiment to implement in our survey to address individuals' desirability of programs with different attributes. Additionally, we included a questionnaire to gather information on fishers' characteristics. Using information from the survey, we estimated an empirical model to predict likelihood of adoption of a vessel tracking program given an individual fishers' characteristics and program attributes. This allowed us to estimate respondents' trade-offs between tracking program attributes. We also estimated a model that predicts individual fishers' willingness to pay for a given tracking program given their characteristics.

DATA COLLECTION

Developing countries are good case studies for exploring the potential for vessel monitoring systems. Small-scale fisheries face many threats that are external to the fishery. For example, new management arrangements and approaches in a fishery, changes in relationships at a regional scale, and the role of the fishery in global trade (Andrew et al., 2007). Introducing a vessel monitoring program has the potential to alleviate some of these external threats.

Surveys were conducted in Indonesia and Mexico with approval from the University of California, Santa Barbara's Human Subjects Committee. Individuals from five locations in Indonesia and two locations in Mexico were surveyed for a total of seven survey sites. These two locations were chosen for the existing connections we had with organizations that would assist with translation and survey administration as well as their importance to small-scale fishing.

Indonesia is the world's largest archipelagic nation located in a hotspot of marine biodiversity (Ferrol-Schulte et al., 2015). This country's surrounding marine ecosystem also experiences a lot of fishing pressure. A 2018 report on the status of Indonesia's marine fisheries showed clear signs of overexploitation in all fishery management units (California Environmental Associates, 2018). An analysis of Indonesia's marine policies revealed that unsustainable resource use has been increasing, posing major threats to the productivity of their coastal ecosystems (Ferrol-Schulte et al., 2015). Because of this, the Indonesian government is looking for ways to promote sustainable fisheries management. The Fishery Resources Directorate of the Ministry of Marine Affairs and Fisheries (MMAF) is leading the charge to implement an Ecosystem Approach to Fisheries (Muawanah et al., 2018). This program has seven principles which are as follows: good governance, an appropriate scale, increased participation, multiple objectives, cooperation and coordination, adaptive management, and a precautionary approach (Muawanah et al., 2018). A small-scale fishing vessel

monitoring program can help the MMAF achieve these seven principles and help Indonesia create sustainable fisheries. Insight from fishers in this country informed our model which can be adapted to other developing nations that suffer from similar threats to their natural resources.

In Mexico, 85% of the country's total fisheries production comes from the 17 states along its coast (C. López-Sagástegui, personal communication, May 13, 2019). However, a lack of effective fisheries governance and catch monitoring has led to unstable fisheries (Cisneros-Montemayor et al., 2013). A survey of Mexican fisheries experts in 2012 found that IUU fishing represented 40% to 60% of reported catches (Cisneros-Montemayor et al., 2013). Because of this, Mexico is a hotspot for fisheries research. For example, the Gulf of California Marine Program works with fishers to analyze their fishing activity using GPS, landing logs, and biological data (Gulf of California Marine Program, 2016). This program has led to more informed management policies in Mexico as well as a strong network of collaborators from all sectors (Gulf of California Marine Program, 2016). Because of fishers' exposure to scientific work in Mexico, having their input on a vessel monitoring program was highly informative. Additionally, because fisheries in Mexico are exposed to similar problems that other small-scale fisheries face, our survey data can be applied to other developing countries.

Our research team worked with community members affiliated with Global Fishing Watch and Rare, an international conservation organization, to administer surveys. These community members have existing connections to fishing communities and were used as enumerators. They were able to interpret and translate if questions about the survey arose. Enumerators were trained by the research team in a "survey bootcamp" before survey administration began. The bootcamp included information on survey administration, bias avoidance, and an explanation of the dual response choice experiment.

The translated surveys were inputted into KoBoToolbox, a data collection tool, and administered on tablets and smartphones. In Indonesia where smartphones were less prevalent, one survey was administered at a time due to only having one tablet. Informal fisher interviews were also conducted by the research team to get acquainted with small-scale fishers.

SURVEY DESIGN

We conducted a literature review that thoroughly examined key factors needed to understand the adoption of new technology in small-scale sectors of developing countries. The review included reading surveys conducted in fisheries and agriculture communities, which used the socio-ecological framework to identify and inform analyses of technology adoption. We also consulted with experts in the field to discuss what they thought the most important questions to ask were. Both the literature review and expert interviews informed our survey questions.

Characteristics of Fisheries and Fishers

Small-scale fisheries are generally characterized by boat size, fleet mobility, production methods, and product distribution (Kolding et al., 2014; Salas et al., 2007). However, we identified several characteristics for SSFs that more adequately inform technology adoption in developing countries:

A. Ecological Threats – The majority of small-scale fishing takes place in areas where stocks are either fully exploited or overexploited and where there is rapid degradation of coastal and riparian ecosystems. The key drivers for this are pollution, climate change, land use change, urban development, coastal erosion, habitat degradation or destruction, ocean acidification, biodiversity reduction, and the alteration of trophic webs (Tietze, 2016).

8

B. Governance Structure – Increased competition amongst small-scale fishers for valuable aquatic resources has led to dwindling catches, while fishers have seen an increase in travel and transaction costs. In order to improve catch levels and secure sustainable livelihoods, it is necessary for fishing communities to actively participate in local, national, and regional governance structures (Kolding et al., 2014; Salas et al., 2007). One example of a governance structure is Territorial Use Rights for Fisheries, which is a traditional system of community ownership of a fishery with a well-defined spatial territory (Cochrane & Garcia, 2009; Dunn et al., 2018).

C. Economic Integration – Unlike industrial fisheries that are driven by market forces, SSFs are primarily based on a subsistence economy, where a large portion of their catch provides for the basic needs of fishers and their families (Basurto & Nenadovic, 2012). Additionally, SSFs have low levels of capital investment, resulting in limited power to influence the fish market (Kolding et al., 2014; Salas et al., 2007).

Small-scale fisher characteristics are important to technology adoption, since it is inevitably up to the fishers themselves if they will adopt or not. Below are the attributes we identified as significant drivers to include in our survey:

A. Fishing Behavior – Small-scale fishers exhibit dynamic fishing behaviors, as their target species, gear types, and fishing locations rotate seasonally throughout the year (Basurto & Nenadovic, 2012).

B. Education Level – Education plays an important role in technology adoption because it increases one's ability to obtain, process, and use information applicable to the adoption of a new technology. Additionally, higher education influences a potential users' attitudes and opinions, making them more open to the idea of adoption because they can analyze the benefits of a novel technology (Mwangi & Kariuki, 2015).

C. Trust Perceptions – Based on the findings in Sorice et al., (2018), trust plays a pivotal role in small-scale fishers' participation in programs designed to benefit them. In the study, researchers measured fisher desirability to take part in a Territorial Use Rights for Fisheries-reserve program. Their results indicated that the likelihood of program adoption increases as: A) fishers show trust that the program will be successfully implemented and B) fishers trust that key institutions will support new programs.

D. Exposure to Technology – Experience with technology, such as electronic monitoring, is a driver of adoption. When fishers have prior exposure to technology, they are more open to the tool's benefits and are more willing to engage in an informed dialogue about its uses (Michelin et al., 2018).

Using this information, we designed a six-part survey to get at information about an individual's fishing practices, fishing community, and marine conservation perspectives. Surveys were translated into the local languages of our study sites, Bahasa and Spanish, and included both words and images.

The survey sections included questions about: general fishing practices, market structure, governance systems, individual perceptions, and demographics. The survey also included a dual response choice experiment with an additional willingness to pay/accept bidding game. Our dual response choice experiment design will be explained below, and our full survey can be read in appendix 3.

Dual response choice experiment

To assess fisher preference for a tracking technology package, we conducted a specific type of discrete choice experiment. A discrete choice experiment elicits individual preferences of survey respondents. These choice experiments provide the richest form of behavioral data for studying the phenomenon of choice, in almost any application (Louviere et al., 2000). In a choice experiment, each survey respondent is asked to state their preference for one option over another, usually including an opt out option as a choice. Each option in the choice experiment is described by a set of attributes.

When designing our choice experiment, we adopted a modified version, called a dual response choice experiment (DRCE) (Figure 1). In this modified design, fishers were asked to choose among two "packages" containing different combinations of design attributes for a potential tracking program. The follow-up question offered the option to accept the package they chose or stick with the status quo (no tracking package). The reason for asking the respondent to make a choice between two packages in the first portion of the DRCE was out of a concern that all fishers may opt out, if initially given the option. Had this happened, we would have been left with little to no information on tracking technology preferences among fishers. Our modified design combats this, and assured us that we would obtain information on trade-offs and preferences among fishers for tracking technologies.

Part 1.

Attribute 1 Attribute 2 Attribute 3 …..	Package A	Package B
	○	○

Part 2.

Participate in Preferred Tracking Package	Opt-out of Preferred Tracking Package
○	○

Figure 1. Dual Response Choice Experiment. Conceptual overview of our dual response choice experiment design.

The choice experiment captured questions regarding attributes of potential tracking programs that, based on our literature review, could drive adoption. Specifically, this survey section explored the trade-offs of three key attributes of a potential vessel tracking program: safety functionality (either the tracking technology contains an SOS function or not), privacy (the identification information of individual vessels is either revealed or not), and information ownership (the collected data is owned by the fishers, the government, the industry, or the public).

The variables of the technology included in our analysis are as follows:

Table 1. Attributes and Levels for the Choice Experiment Task

Attribute[a]	Definition	Levels[a,b]
Safety Feature (sos)	Does the vessel tracking technology have an SOS function?	**Yes** *No*
Level of Privacy (info)	Is individual specific vessel information (name of owner, vessel number etc…) associated with the data?	***Anonymous*** - *Tracking data does not contain individual specific information, vessel remains anonymous.* **Not-Anonymous** - Tracking data is associated with specific vessel and identifying information, vessel is not anonymous.
Data Ownership (own)	Who is the entity or organization that owns the data acquired from the vessel tracking technology?	**Fisher Community** - The fishers from the fishing community where the VMS program is implemented. (fisher) **Industry** - The industry, enterprise, or business that has organized for the implementation of the technology. (industry) **Government** - Local/Regional/Federal fishery governing body. (gov) ***Public Access*** - *Data is publicly accessible. (public)*

a. Abbreviations in parentheses are used to define attributes and levels in supplementary material.
b. Italic typeface indicates the reference levels for the CE model.

Reasoning for chosen attributes and levels

The attributes for the choice experiment were selected among multiple options that could determine the design of a particular tracking program. The attributes considered were not exclusively related to the physical technology, but also to how this technology would be implemented among fishers. Importantly, who would be in charge of implementing the program (and therefore probably owning the data) and by what means would this implementing agent promote the correct use of the technology, so it performs as expected. Based on interviews with people and organizations that have carried out vessel tracking trials in SSFs[1], we created a list of potential attributes and their respective levels (options within an attribute). These included physical characteristics and functions of the technology, hypothetical beneficial outcomes from the use of the technology (e.g. reduction in IUU fishing, long-term increases in biomass), and other aspects not related to the technology itself but to central issues of its implementation, such as how the data will be used and by who.

In making the decision on the final attributes and levels, one of the guidelines was to focus less on the physical characteristics of the hardware; these are often not up for negotiation due to practical requirements. Instead, we focused on selecting attributes that would provide more significant data on fisher preferences regarding broad aspects of an overall tracking program that could inform a general strategy to scale up technology adoption. After careful consideration of several combinations of attributes and levels, we opted for the following:

- **Safety Functionality:** This is the only attribute related to functional capacities of the vessel tracking device. We incorporated this because, according to several sources, tracking devices with a built-in safety function (an SOS button which sends alert messages over a network), is sometimes the only selling point that enables trial programs to move forward. Small-scale fishers are often placed in dangerous fishing situations due to changes in weather or illegal fishing. Providing this feature could give fishers peace of mind while out at sea. Also, an SOS feature is a tangible, easily understood specification that has obvious benefits for fishers. This attribute had two levels in our choice experiment: with SOS, without SOS.

---

[1] Among other places, in Kenya, Seychelles, Myanmar, Honduras, Indonesia, Mexico, Belize and Philippines

- **Level of privacy:** We identified that some fishers have expressed resistance to tracking technology because they do not want people to know where they are. There are several reasons for this such as: engaging in illegal fishing, protecting secret fishing spots, or wanting general privacy. We hypothesized that tracking units that display identification information will be resisted if fishers are not familiar with mapping systems and feel that they are unable to guarantee their privacy. This attribute also had two levels: data collected from the tracker registers and displays their vessel ID and other identifying information, or it does not.

- **Data ownership:** Our literature review and interviews identified that vessel tracking programs have occurred in small scale fisheries through a variety of projects carried out by different levels of institutions. This attribute had four levels, based on the data ownership scenarios we observed in previous projects: Fisher community, industry, government, and public access.

The selection of these attributes implied leaving out many others that also seemed important to consider, a few of which actually proved to be relevant during survey implementation and informal conversations during field work. To mention some examples, we confirmed that tracking technology desirability would increase among fishers if it included the capacity to charge electronic devices (e.g., a cellular phone), or a tool that would allow fishers to pinpoint a particular fishing location, among others that were specified in a follow-up question after the choice experiment.

Bidding game

After the follow-up question including the opt out, survey respondents were moved into a bidding game to assess either their willingness to pay, or their willingness to accept. The bidding game provided an opportunity to assign monetary values to each attribute in the DRCE, as well as individual specific characteristics associated with each survey respondent. This type of experiment is known as contingent valuation. A contingent valuation survey collects information that allows surveyors to place monetary values on environmental or social goods which cannot be bought in stores (Carson, 2000).

If a respondent decided to keep the package they originally chose, they were then asked about their willingness to pay in five increasing monetary monthly payments, until they declined. If a fisher decided to reject the package they originally chose, they were then asked to indicate their willingness to accept in the same increasing monetary amounts, until a positive response was given. The monthly payment values were based on estimated cell phone service monthly costs (Appendix 2).

The possibility of providing payments to fishers for implementation of tracking technology is a particularly interesting one. A monetary incentive seems like it would be of importance to fishers in developing countries and communities. However, relying on monetary incentives raises questions of payment sustainability. With payments, fishers will most likely always accept the program, but after a while, it becomes harder to justify continued payments (C. Kilgour, personal communication, May 25, 2019). Furthermore, existing literature suggests that monetary payments are not the main driver of participation in programs. Studies have shown that payments work only if there is established trust, positive attitudes of participants, and substantial dependence of fishing (Sorice et al., 2018). A key determinant in the adoption of a new technology is a net gain to the participant, which is inclusive of all costs that result from the use of said technology (Mwangi & Kariuki, 2015).

DATA ANALYSIS

Results from the surveys were stored in comma separated values files, and analysis was carried out in R Studio version 3.5.3. We split our analysis into two models, a conditional logistic regression to assess trade-offs and probability of adoption, and an interval regression to address willingness to pay.

Model 1: Conditional logistic regression to assess trade-offs and probability of adoption

A conditional logistic regression model was used to analyze the portion of our choice experiment where fishers were only given the option to choose one or the other offered packages. This is a type of regression analysis which allows us to relate the trade-offs and preferences of choosing one package over another, and compare this to all of the other choice combinations of packages (Hauber et al., 2016). The conditional logit model is as follows:

$$Y_i = \beta_1 \cdot safety_i + \beta_2 \cdot privacy_i + \beta_3 \cdot ownership_i + \varepsilon_i \ (1)$$

Seen in equation 1, the dependent variable, Y_i, represents the predicted level of preference for a specific package i. The safety coefficient represents the presence of an SOS functionality, or not. The privacy coefficient represents our level of privacy attribute. And lastly, the ownership coefficient represents the level of ownership, which was coded as dummy variables since there are four levels associated with the attribute.

By using the dual response choice experiment format, we did not adopt the conventional approach of comparing choice behavior by excluding or including the opt out alternative altogether. In other words, we did not implement two survey treatments in which respondents were either made to see choice scenarios without the opt out alternative (i.e., "forced choices") or scenarios with the opt-out alternative included (i.e., "unforced choices"). This means that during data analysis, we had to test whether it was appropriate to treat our data in a way that assumed we presented the opt out option along with the two proposed packages of the choice experiment simultaneously to respondents. To compare "forced" and "unforced" choices, we separated the sample responses into two sets: responses in which the respondent said "no" to the package in when given the chance to opt-out and responses in which the respondent said "yes" to the package even when given the chance to opt-out. This data segmentation allowed us to test for potential biases associated with including an opt-out using a likelihood ratio test for equality (Louviere et al., 2000). The likelihood ratio test statistic is:

$$-2 \cdot (LL_r - \sum LL_u) \ (2)$$

which is chi-squared distributed with K(M-1) degrees of freedom, where K is the number of restrictions (in our case, 5), and M is the number of treatments (in our case, 2). LL_r represents the log likelihood of the pooled model, while $\sum LL_u$ represents the sums of the log likelihoods for the unforced and forced models. The null hypothesis of the test is that the parameters are not significantly different between treatments. This means that if we do not reject the null hypothesis, we can use the pooled model method with less concern of bias due to the dual response design. If the test statistic exceeds the critical value found in the chi-square table, then evidence suggests that the treatments contribute to explaining the model and the null hypothesis would be rejected. When referring to a "pooled" model, we mean that "unforced" and "forced" choices are not segmented into two datasets, thus, they are "pooled".

Model 2: Interval regression on willingness to pay

To analyze the iterative contingent valuation on willingness to pay, we used an interval regression. Interval regression is used to model outcomes that have interval censoring. In particular, we used a maximum likelihood estimation to model willingness to pay among fishers. Maximum likelihood estimation is specified for nonlinear econometric models (Berndt et al., 1974). This model was chosen because the relationships between our dependent and independent variables are inherently non-linear. Our particular data had researcher supplied bid levels, meaning that the respondent could not choose a narrower or broader interval for which their willingness to pay would fall. Because of this, the category into which each observation falls is known, but the exact value of the observation is not known. This is appropriate for our willingness to pay model, because the data obtained from our bidding game resulted in values that are in ranges, instead of exact values. The exact dollar amount is not known, but it can be narrowed down to be between two values. Thus, willingness to pay (WTP) lies within the interval [X, Y], where $X \leq WTP \leq Y$. Using an interval regression allows us to determine the predicted willingness to pay (or accept) values for any type of tracking technology for a fisher with any characteristics included in the model. The resulting interval regression equation follows this format:

$$WTP_i = \beta_0 + \beta_1 \cdot safety_i + \beta_2 \cdot privacy_i + \beta_3 \cdot ownership_i + \beta_n \cdot X_{n,i} + \varepsilon_i \quad (3)$$

Where our dependent variable, "WTP_i" represents the predicted willingness to pay, "$safety_i$", "$privacy_i$", and "$ownership_i$", represent our technology attributes, and our last coefficient, "$X_{n,i}$" represents individual specific characteristics (such as education level), which will be identified following this explanation.

After calculating and comparing Akaike Information Criterion Statistics (Sakamoto et al., 1986) for 15 different model specifications, we found the best fit model to be:

$$WTP_i = \beta_0 + \beta_1 \cdot safety_i + \beta_2 \cdot privacy_i + \beta_3 \cdot ownership_i + \beta_4 \cdot tech_i + \beta_5 \cdot problem_i + \beta_6 \cdot edu_i + \varepsilon_i \quad (4)$$

As seen in equation 4, variables safety, privacy, and ownership represent the attributes associated with the hypothetical VMS technology. The rest of the variables in equation 4 represent characteristics of the survey respondent. These include exposure to technology used for fishing, "tech" (fishfinder, VHF radio, surveillance camera, catch and data collection app, GPS, or a vessel monitoring technology), their perceived biggest problem facing their fishery, "problem" (IUU fishing, pollution, weather, or corruption), and education level, "edu" (no formal education, formal education, or higher education).

Results

OVERVIEW OF SURVEY RESULTS

211 surveys were completed across seven locations over two months (Figure 2). We surveyed a varied number of people at each fishing community and had different totals for each country (Table 2).

Figure 2. Maps for the Two Countries Surveyed. Map of Indonesia (left) and Mexico (right) with fishing community locations indicated by a red circle with the associated community name next to it.

Table 2. Survey Results: Location Summary

Factor	Response (Total Surveys = 211)		
	n	**%**	**Sample Size**
Country			211
Indonesia	124	58.80%	
Mexico	87	41.20%	
Community			211
Makassar (I)	59	28.00%	
Muncar (I)	27	12.80%	
Raja Ampat (I)	18	8.50%	
Wakatobi (I)	14	6.60%	
Jayapura (I)	6	2.80%	
Puerto San Carlos (M)	46	21.80%	
Altata (M)	41	19.40%	

MODEL 1: CONDITIONAL LOGISTIC REGRESSION

Prior to examining conditional logit model results, we investigated the suitability of pooling forced and unforced responses based on the likelihood ratio test from equation (2).
The test statistic was calculated as follows:

$$-2 \cdot [-74.11 - (-42.90 - 22.25)] = 17.92$$

K(M-1) was used to calculate degrees of freedom for the ratio test. The number of restrictions, K, is equal to 5 since this is the number of parameters in the forced and unforced model, respectively. The number of restrictions, M is equal to 2 since two treatments exist. The test statistic does not exceed the critical value for X^2_5, with a p value < 0.1. The evidence suggests that a pooled model is appropriate for analysis of trade-offs between attributes in determining probability of adoption.

Table 3. Conditional Logistic Results: Pooled Model

	Coefficient	Std. Err. Coefficient
w/ SOS	3.198***	0.3259
Info – Non-anonymous	-0.1317	0.3458
Fisher Ownership	1.2044***	0.4280
Industry Ownership	-0.3134	0.5867
Government Ownership	1.2269*	0.7010
No. of choice sets	211	
No. of obs.	422	

Note: Single, double, and triple (*,**,***) indicated significance at the 10%, 5%, and 1% level respectively

Applying our model equation to our original data and averaging the conditional probabilities per each package gives us preference ranks for each combination of attributes (Table 4). The most preferred technology has an SOS function, keeps the fishers' information anonymous, and is owned by the government. The least preferred technology is one that does not have an SOS function, notates the fisher's information, and is owned by industry. When reviewing these results, keep in mind that the sample these values come from is relatively small (number of respondents = 211 and each were offered two options, resulting in n = 422) and true ranks could be different from what is presented here. However, the results do show us valuable information regarding preferences among fishers for the proposed technologies.

Table 4. Ranks from pooled conditional logistic regression model

Rank	Attributes		
	Safety Feature	**Level of Privacy**	**Ownership**
1	SOS	Anonymous	Government
2	SOS	Anonymous	Fishers
3	SOS	Non-Anonymous	Government
4	SOS	Non-Anonymous	Fishers
5	SOS	Anonymous	Public Access
6	SOS	Non-Anonymous	Public Access
7	SOS	Anonymous	Industry
8	SOS	Non-Anonymous	Industry
9	No SOS	Anonymous	Government
10	No SOS	Anonymous	Fishers
11	No SOS	Non-Anonymous	Government
12	No SOS	Non-Anonymous	Fishers
13	No SOS	Anonymous	Public Access
14	No SOS	Non-Anonymous	Public Access
15	No SOS	Anonymous	Industry
16	No SOS	Non-Anonymous	Industry

MODEL 2: INTERVAL REGRESSION ON WILLINGNESS TO PAY

Results from the interval regression show that SOS, exposure to technology used for fishing, problems facing the fishery, and education are highly significant and have large effects on willingness to pay. On average, respondents were willing to pay $2.76 USD/month to use their chosen vessel tracking program. 67% were willing to pay, 9% were willing to receive a payment to participate in a program, and 11% would not opt-in to a vessel tracking program regardless of the amount paid to them.

The pooled conditional logit model and the interval regression model gave different results regarding ownership of data. Unlike the pooled conditional logit model, the interval regression showed that government ownership of data is the least desirable among the ownership levels, whereas industry ownership is the most desirable (Table 5).

Table 5. Interval regression results for WTP (Model II)

		Coefficient	Std. Err. Coefficient
	Intercept	1.4683	1.2545
Safety Feature	SOS	1.2684**	0.5274
Level of Privacy	Non-anonymous	-0.4140	0.4020
Data Ownership	Fisher Ownership	0.8342	0.5423
	Industry Ownership	1.0889	0.6863
	Government Ownership	-0.3745	0.5493
Individual Characteristics			
	Fishing Tech	1.2040***	0.4541
	IUU Problem	-1.4790**	0.6878
	Pollution Problem	-1.9183***	0.6708
	Weather Problem	-2.9347***	0.6554
	Formal Education	2.3577**	1.0988
	Higher Education	3.2652**	1.3042
P-value	$1.6 \times (10)^{-7}$		
Degrees of freedom	176		

Note: Single, double, and triple (*,**,***) indicated significance at the 10%, 5%, and 1% level respectively

Testing for External Validity

An important step in regression modeling is to test the external validity of the results through predictions. It is especially important to test this when there are hard monetary values associated with the modeling, as policy and management decisions could depend on the accuracy of those predictions. To test our external validity, we used our model to predict willingness to pay values using data collected from Indonesia and Mexico. We then compared our predicted willingness to pay to actual willingness to pay. The results are shown below in figures 3 and 4.
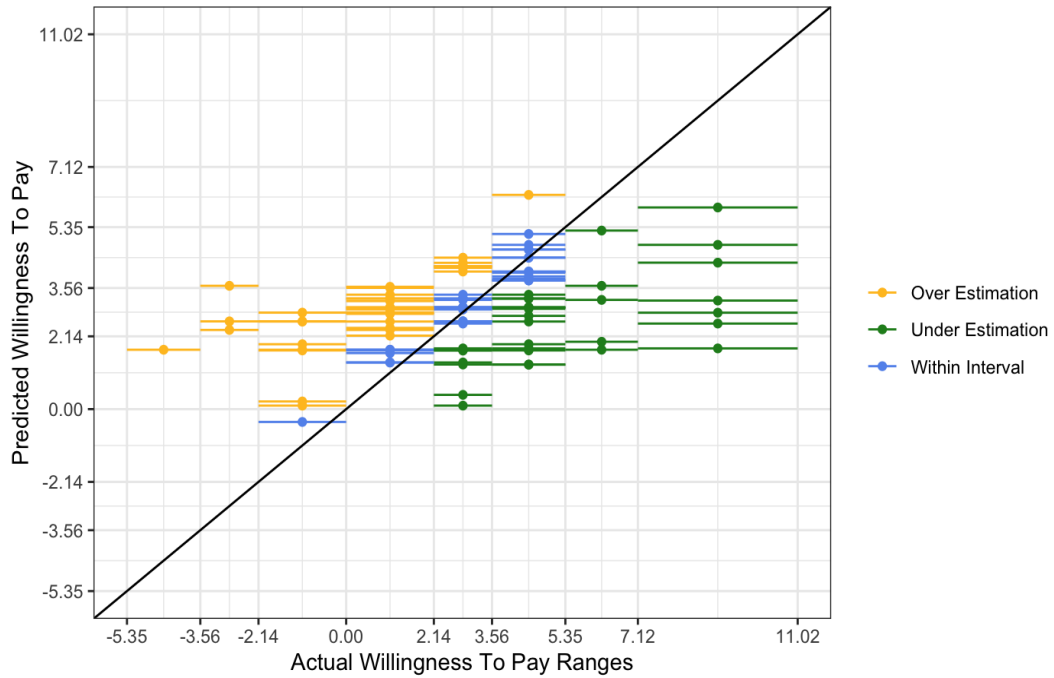
Figure 3: Model 2, Indonesia Predictions. Anything below the diagonal line represents an underestimation (colored in green) from the actual willingness to pay or receive, and everything above the line (colored in yellow) represents an overestimation. Anything that falls on the line represents a correct prediction (colored in blue).
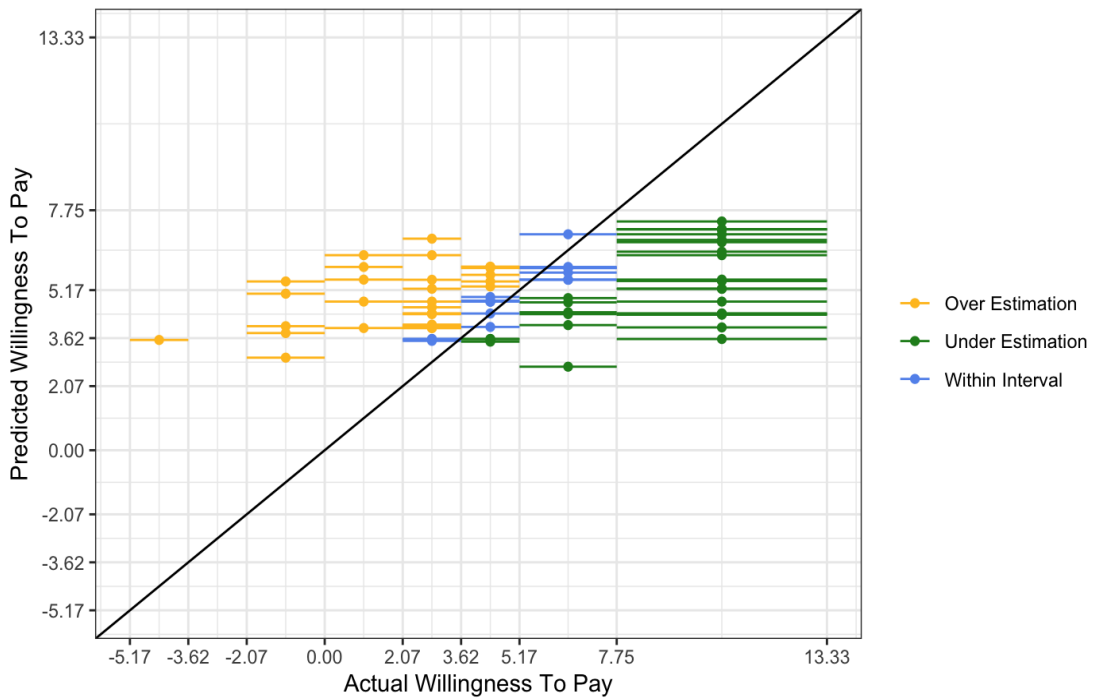

Figure 4: Model 2, Mexico Predictions. Anything below the diagonal line represents an underestimation (colored in green) from the actual willingness to pay or receive, and everything above the line (colored in yellow) represents an overestimation. Anything that falls on the line represents a correct prediction (colored in blue).

After running the predictions depicted in figures 2 and 3, we see that 37.8% of our predictions are over estimations, with an average overestimation of willingness to pay of $1.66. Our model also underestimated willingness to pay 34.6% of the time, with an average underestimation of $1.67. Our model correctly predicted willingness to pay (meaning that the predicted values fall within the indicated willingness to pay of a fisher) 27.7% of the time.

INFLUENCE OF FISHER CHARACTERISTICS

Education
Our model indicated that education was a highly significant predictor of willingness to pay. Specifically, formal education and higher education increased willingness to pay in comparison to no formal education.

Fishing Tech
Technology exposure on a weekly basis was another significant predictor of willingness to pay. Use of any type of technology (e.g. a GPS, fishfinder, or VHF radio) increased willingness to pay by 1.2 times compared to a survey respondent who had no technology exposure.

Perceived problems
Our model shows that the problems of extreme weather events, pollution, and IUU fishing decreased willingness to pay in relation to perceived corruption.

Discussion

MAIN FINDINGS

Our results show that given proper incentives, fishers are willing to participate and pay for a vessel tracking program. Additionally, individual fisher characteristics drive willingness to pay more than tracking technology features.

Model 1: Conditional logistic regression

In most cases, the results match our expectations of preferred technology attributes. Given that the omitted reference variables are no SOS capability, anonymous identification information, and public ownership of the data, we expect the opt in coefficient for SOS to be positive, which it is. Our privacy and information ownership variables, however, tell an interesting story. The results show that while the "privacy - non-anonymous" attribute coefficient is positive—it is small and not significant. This indicates that this attribute had no real effect on the respondent's decision to pick a technology. We can see that compared to public access of data, individual fisher ownership is highly preferred (as expected), government ownership is somewhat preferred, but insignificant, and industry ownership is highly disliked (as expected). Given the significance of the government ownership variable, it is hard to say that government ownership is preferred over public.

Model 2: Interval regression with willingness to pay

89% of fishers were willing to participate in a hypothetical tracking technology program and willing to pay an average of $USD 2.76 per month. The other 11% of respondents indicated that they would not be willing to be paid any amount of money we offered to participate in the tracking program. We labeled these respondents as "protestors", and excluded them from the maximum likelihood interval regression. Because the group of protestors comprised a small portion of the total surveyed population, and we also did not have any ballpark range for what a protestors' willingness to receive would be, we decided to exclude them from the regression model. For the other respondents who reached the maximum bid level for willingness to pay, we assigned them a willingness to pay value of two monthly cell phone payments higher than the maximum value reached for the upper bid limit. Because these respondents were willing to pay the maximum bid level offered, there is a possibility that they hypothetically would have paid more if asked. However, assigning a value of infinity as their upper bid limit could have severely overestimated willingness to pay. Therefore, we chose two monthly cell phone payments higher than the maximum bid to account for this possibility without overestimating willingness to pay. We hypothesized that there is inherently a maximum value for which fishers would pay for this technology, until they reached a limit.

The results of our interval regression generally aligned with our conditional logistic regression. Of note, the inclusion of an SOS functionality had an increased effect on willingness to pay. The level of privacy attribute was insignificant and had a small effect on willingness to pay. However, in contrast to our conditional logistic regression, influence of the ownership variable is different. The interval regression indicates that industry ownership is preferred when considering willingness to pay, whereas it is the least preferred in our conditional logistic regression. Our hypothesis is that those who were offered industry ownership in their tracking technology program must have seen an economic benefit to this option (i.e. possible fishery eco-certification), which influenced the amount

they were willing to pay.

Influence of fisher characteristics

Our results show that education, previous exposure to technology, and perceived fishery problems affected willingness to pay.

Education

Our model indicated that education was a highly significant predictor of willingness to pay. This finding is consistent with literature showing that lower levels of education are obstacles for technology adoption among fishers (Mazuki et al., 2012). In fact, we believe higher education can make fishers more aware of applications of technology to improve fisheries management. It can also shape their ideas around the potential benefits that come from establishing partnerships with organizations that aim to promote healthy fisheries through programs that include the use of such technologies.

Fishing Tech

Technology used during fishing trips by fishers was another significant predictor of willingness to pay with a positive coefficient for willingness to pay. Literature indicates that lower exposure to technology is a predictor for lower technology use rates. Limited previous exposure to technology was one of several factors found that inhibits fishers from using new technologies (Mazuki et al., 2012). This result is consistent with our hypothesis that fishers who were already familiar with the benefits technology provides for fishing can more easily see and understand the potential benefits of a new technology—even if they don't immediately incorporate the full array of specific functions and services it could provide.

Perceived problems

Extreme weather events, IUU fishing, and pollution all decreased willingness to pay compared to perceived corruption. Although it is hard to make causal inferences on our results about the influence of perceived corruption, we do have some speculations. This result could be explained by the fact that corruption likely affects the fishers on a daily basis, or at least more often, than the rest of the perceived problems included in the choice experiment. They might believe that a tracking device could help to combat corruption by providing meaningful data on their fishing efforts.

Our model shows that extreme weather events decreased willingness to pay the most compared to perceived corruption. An interpretation for this result is that fishers who identified this as the biggest threat to their fishery do not experience any other serious problems in their fishery. Therefore, this response could have been an alternative way of indicating that the fishery does not face any major problems. Extreme weather events are in fact something that fishers deal with on a constant basis. If extreme weather was really a problem (as it could be in fisheries increasingly impacted by climate change), we would expect willingness to pay to be higher since the technology could reduce risks associated with such events.

Other demographics

Due to the limited scope of the research, some variables that might be relevant, such as gender and religious beliefs (Mazuki et al., 2012; Wetengere, 2011), were not considered in the survey, and therefore are absent from our analysis. Other demographics that were thought of as important, such as income, livelihood dependence on fishing, and expenses related to fishing showed no significance in the model. Preliminary exploration into other surveyed variables such as trust in fishing association leaders and police, and perception of industrial fishing in fishing grounds were significant, but not included in the final model after calculating Akaike Information Criterion Statistics. More research is

needed to better understand these potential connections, and determine what other variables could also contribute to increased desirability of a vessel tracking technology.

MODEL APPLICATIONS AND LIMITATIONS

Application

The interval regression model can be a tool for Global Fishing Watch or other interested organizations to use to gain knowledge on how to approach a village they are interested in implementing a vessel tracking program in. They could apply the same type of simulation we have to any village in the world, given that descriptive information about the village is available. The information needed to apply our model is: fisher population, education level among the fishers, the biggest problem that the fishery faces (weather, corruption, pollution, or illegal fishing), and the rate of technology use among the fishers. The type of tracking technology should be fixed when applying our model, since every fisher within a village would be given the same vessel tracker.

Shown in figure 5 is a simulation of a fishing village in Indonesia, named Pepela. For this simulation, the technology was fixed to have a non-anonymous privacy level with publicly available data, and the presence of an SOS functionality was toggled on and off. Pepela has a population of 370 fishers; 94% of them have formal education, 4% have no formal education, and 2% have a form of higher education. Weather events are the biggest problem within the fishing village, and 30% of the population do not use fishing technology (such as VHF radio or Fishfinder) while operating. Using all of this information, willingness to pay or accept for every fisher within that village was calculated using the interval regression model.
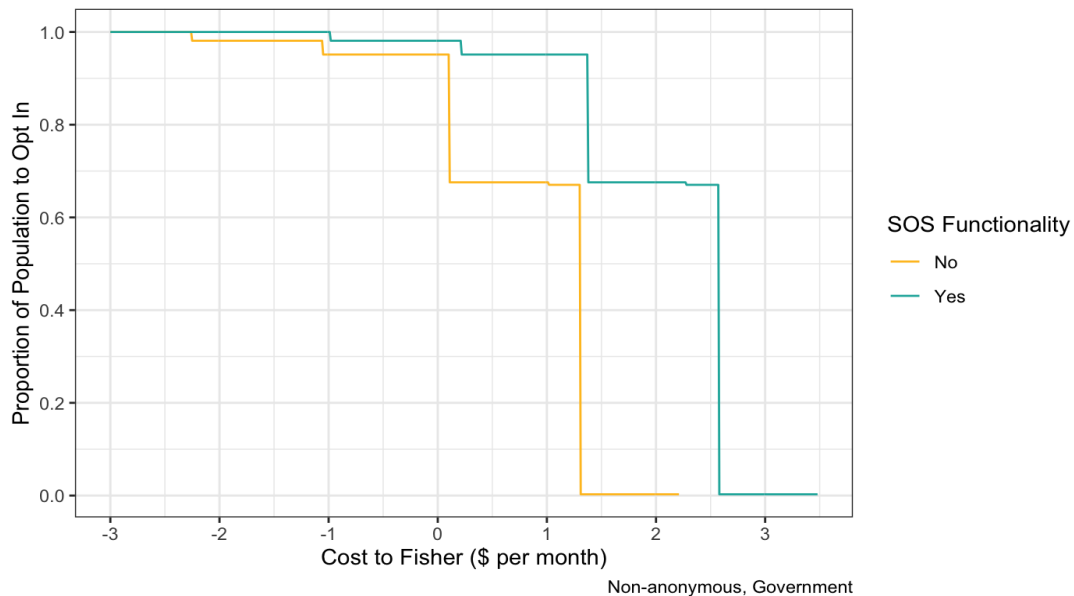

Non-anonymous, Government

Figure 5: Pepela, Indonesia Simulation. The graph shown here has an x axis which represents the cost to the fisher (or how much a fisher would have to pay for a hypothetical tracking technology program). Negative values on the x axis represent fishers getting paid. Our y axis shows the proportion of the fishing village that would opt in to the use of a tracking program. The type of VMS technology was fixed for this simulation, where it was non-anonymous and the data was publicly available.

23

For Pepela, when a tracking technology is priced at $2 per month and doesn't have a SOS functionality, almost nobody in the village would opt-in. Alternatively, if the technology does have an SOS functionality nearly 70% of the population would opt-in for $2 per month. The main take away from this graph is that the presence of an SOS function is something that our client, Global Fishing Watch, can control when attempting to implement this technology, and this shows how important this feature is for adoption. Global Fishing Watch could conduct similar simulations on other fishing villages around the world, to get an understanding of different levels of willingness to use tracking technologies for their fishing activities.

Willingness to pay biases to consider

Our project determined an average willingness to pay for a vessel tracking technology for our survey sites. We also determined an interval of willingness to pay for an individual based on tracking technology features and their personal characteristics. However, our willingness to pay questions were only asked over what a fisher preferred versus having nothing at all. Therefore, our willingness to pay data is conditioned upon being the respondent's preferred package, which creates a bias. There are also studied differences between an individual's stated hypothetical choices and their actual commitments; the extent to which this occurs is known as hypothetical bias (Hensher, 2010). A meta-analysis of 28 contingent valuation studies that reported willingness to pay found that a median ratio of hypothetical to actual willingness to pay of 1.35 exists, but that conjoint choice methods reduce this bias (Murphy et al., 2005). Despite this, our findings can still be used to provide insights into the extent to which small-scale fishers are willing to use a vessel tracking program. Our work shows that fishers are generally willing to pay for a vessel tracking program rather than wanting to be paid, which is important regardless of the dollar amount.

Sampling biases to consider

The countries we selected for surveying presented challenges such as language and cultural barriers, and a general lack of resources to reach the desired level of representation and sample size. Therefore, our approach was centered on using contacts from partner organizations and programs already working in those countries, such as Global Fishing Watch, Rare, Centro para la Biodiversidad Marina y la Conservación, and the Gulf of California Marine Program. Based on their knowledge, contacts and, in some cases, previous collaboration with fishing villages, we were able to use a non-probabilistic convenience sampling, which meant we administered the survey to fisher populations that were closer to hand, both geographically and logistically. Although we tried our best to pick a variety of fishing villages to ensure proper representation, we recognize our sample falls short when compared to the incredible diversity of small-scale fisheries. Our convenience sample could bias what looks like fishers' overall acceptance of a vessel tracking program,

We also recognize the presence of self-selection bias, meaning that fishers who were willing to respond to the survey could have already been willing to collaborate with external organizations or fisheries programs, including those that could involve a vessel tracking component. This convenience sampling was replicated during the fieldwork through the use of the snowball sampling technique, which means that our subject recruitment strategy for the survey was mostly based on recommendations from the previous subject. This could have deepened the self-selection bias by providing a sample that reflects a niche group of fishers who share similar experiences, practices, preferences and beliefs. Another important potential bias comes from the very likely underrepresentation of fishers who participate in illegal fishing behaviors. Although we know for a fact that our sample includes many of them, we weren't able to isolate the respondents and their answers due to the sensitivity of the information, even under the complete guarantee of survey anonymity. Increasing the number of surveys as well as changing the representation of the survey

sample would help reduce this bias.

External Validity

Our external validity tests suggest that extrapolating the results from these limited surveys to the rest of the world should be done with great caution. However, the magnitude and direction of the numbers (i.e. either willing to pay or willing to accept) can help better inform the type of program and price or payment range to implement. Further surveys and a bigger sample would help to improve the external validity and predictions our interval regression model produces.

Conclusions

STUDY RELEVANCE

Results from this study provide useful insights into how to catalyze vessel tracking technology use in SSFs. Our findings have indicated what the value of tracking technology is to fishers and identified incentives that can reduce small-scale fisher's biases toward vessel tracking technology and increase participation in vessel monitoring programs. We explored the application of our models to different fishing villages, which can help other organizations determine the best locations for initial implementation of vessel monitoring programs.

These findings have far-reaching effects beyond data collection for more transparency in fisheries. Vessel tracking technology on small-scale fishing vessels can help remove barriers found in some marketing efforts in certain fishing villages. For example, small-scale fisheries that would like an eco-label certification often run into problems with traceability. Eco-labelling organizations, such as the Marine Stewardship Council, want to know the status of the target fish stock, impact of the fishery on the ecosystem, and the effectiveness of the fishery management system (Ponte, 2008). This requires fisheries managers to have abundant data to determine the health of their target fish stocks as well as create high performing management systems. This is particularly difficult in data poor small-scale fisheries. Implementation of a vessel tracking program can provide these fisheries with the data needed for eco-label certification (Duggan & Kochen, 2016). In turn, this can help local economies bring more seafood to the international market at a higher price. Satellite data on small-scale fishing vessels can also help combat IUU fishing in villages. It can allow for global monitoring from afar and allow for evaluation of impacts of IUU fishing policies (Cabral et al., 2018). Through working out what incentives will allow for adoption of tracking technology, establishing tailored tracking programs can have lasting, positive impacts not just for fishing villages, but for fisheries as a whole.

FUTURE DIRECTIONS AND SUGGESTIONS

Future research should continue to explore preferences for vessel tracking programs among representative samples of small-scale fishers. In subsequent research, we suggest modifications to our survey to simplify data analysis. After completing our surveys, we now know that a standard choice experiment would have sufficed. Instead of using a dual response choice experiment, switching to a standard choice experiment can reduce some bias associated with pooling data from two choice experiment datasets.

The research reported here is limited by the measures used in our study. Further work should attempt to evaluate more measures and implement more surveys in a variety of villages to help create a more representative dataset that can lead to a more refined model. The model can also be expanded to include different variables, such as levels of trust, that were not fully analyzed in our model. We also suggest the creation and implementation of a randomized controlled trial. This type of experiment can reduce sources of bias and hone in on the most important incentives that will be required to motivate widespread adoption of tracking programs in small-scale fisheries.

RECOMMENDATIONS

Based on our results, it seems that designing vessel tracking technology with SOS signal capability would be the most attractive attribute to fishers. Our results also suggest that Global Fishing Watch should consider tailoring payments to the characteristics of each village. This would require Global Fishing Watch to work on conducting surveys in villages they are interested in piloting a program in, or collecting existing information on village characteristics. With information on fisher characteristics, they can use the model we developed to estimate willingness to pay for tracing technology, though recognizing the challenges of external validity discussed above.

References

Afflerbach, J., Lester, S., Dougherty, D., & Poon, S. (2014). A global survey of "TURF-reserves",
Territorial Use Rights for Fisheries coupled with marine reserves. *Global Ecology and
Conservation*, *2*. https://doi.org/10.1016/j.gecco.2014.08.001

Andrew, N. L., Béné, C., Hall, S. J., Allison, E. H., Heck, S., & Ratner, B. D. (2007). Diagnosis and
management of small-scale fisheries in developing countries. *Fish and Fisheries*, *8*(3), 227–
240. https://doi.org/10.1111/j.1467-2679.2007.00252.x

Barkuus, L., & Dey, A. (2003). Location-Based Services for Mobile Telephony: A Study of Users'
Privacy Concerns. *In 9th Ifip Tc13 International Conference on Human-Computer
Interaction, Interact 2003*, 1–4.

Basurto, X., & Nenadovic, M. (2012). A Systematic Approach to Studying Fisheries Governance:
Studying Fisheries Governance. *Global Policy*, *3*(2), 222–230. https://doi.org/10.1111/j.1758-
5899.2011.00094.x

Berndt, E. K., Hall, B. H., & Hall, R. E. (1974). Estimation and Inference in Nonlinear Structural
Models. *Annals of Economic and Social Measurement*, *3*(4), 653–665.
https://www.nber.org/chapters/c10206.pdf

Cabral, R. B., Mayorga, J., Clemence, M., Lynham, J., Koeshendrajana, S., Muawanah, U., Nugroho,
D., Anna, Z., Mira, Ghofar, A., Zulbainarni, N., Gaines, S. D., & Costello, C. (2018). Rapid
and lasting gains from solving illegal fishing. *Nature Ecology & Evolution*, *2*(4), 650–658.
https://doi.org/10.1038/s41559-018-0499-1

California Environmental Associates. (2018). *Trends in Marine Resources and Fisheries
Management in Indonesia* (p. 146). California Environmental Associates.
https://www.packard.org/wp-content/uploads/2018/08/Indonesia-Marine-Full-Report-
08.07.2018.pdf

Campbell, M. S., Stehfest, K. M., Votier, S. C., & Hall-Spencer, J. M. (2014). Mapping fisheries for

marine spatial planning: Gear-specific vessel monitoring system (VMS), marine conservation

and offshore renewable energy. *Marine Policy*, *45*, 293–300.

https://doi.org/10.1016/j.marpol.2013.09.015

Carson, R. T. (2000). Contingent Valuation: A User's Guide [†]. *Environmental Science & Technology*,

34(8), 1413–1418. https://doi.org/10.1021/es990728j

Cisneros-Montemayor, A. M., Cisneros-Mata, M. A., Harper, S., & Pauly, D. (2013). Extent and

implications of IUU catch in Mexico's marine fisheries. *Marine Policy*, *39*, 283–288.

https://doi.org/10.1016/j.marpol.2012.12.003

Cochrane, K. L., & Garcia, S. M. (Eds.). (2009). A fishery manager's guidebook—Second edition.

The Food and Agriculture Organization of the United Nations, 544.

Dinmore, T. A., Duplisea, D. E., Rackham, B. D., Maxwell, D. L., & Jennings, S. (2003). Impact of a

large-scale area closure on patterns of fishing disturbance and the consequences for benthic

communities. *ICES Journal of Marine Science*, *60*(2), 371–380.

https://doi.org/10.1016/S1054-3139(03)00010-9

Doherty, P. D., Alfaro-Shigueto, J., Hodgson, D. J., Mangel, J. C., Witt, M. J., & Godley, B. J.

(2014). Big catch, little sharks: Insight into Peruvian small-scale longline fisheries. *Ecology

and Evolution*, *4*(12), 2375–2383. https://doi.org/10.1002/ece3.1104

Duggan, D. E., & Kochen, M. (2016). Small in scale but big in potential: Opportunities and

challenges for fisheries certification of Indonesian small-scale tuna fisheries. *Marine Policy*,

67, 30–39. https://doi.org/10.1016/j.marpol.2016.01.008

Dunn, D. C., Jablonicky, C., Crespo, G. O., McCauley, D. J., Kroodsma, D. A., Boerder, K., Gjerde,

K. M., & Halpin, P. N. (2018). Empowering high seas governance with satellite vessel

tracking data. *Fish and Fisheries*, *19*(4), 729–739. https://doi.org/10.1111/faf.12285

Ferrol-Schulte, D., Gorris, P., Baitoningsih, W., Adhuri, D. S., & Ferse, S. C. A. (2015). Coastal

livelihood vulnerability to marine resource degradation: A review of the Indonesian national

coastal and marine policy framework. *Marine Policy*, *52*, 163–171.

https://doi.org/10.1016/j.marpol.2014.09.026

Food and Agriculture Organization of the United Nations. (2001). *Fishing operations. 1. Vessel*

monitoring systems (pp. 1–58). Food and Agriculture Organization of the United States.

http://www.fao.org/in-action/globefish/publications/details-publication/en/c/338492/

Food and Agriculture Organization of the United Nations (Ed.). (2005). *Increasing the contribution of*

small-scale fisheries to poverty alleviation and food security. Food and Agriculture

Organization of the United Nations.

Fujita, R., Cusack, C., Karasik, R., Takade-Heumacher, H., & Baker, C. (2018). *Technologies for*

Improving Fisheries Monitoring (p. 71). Environmental Defence Fund.

https://www.edf.org/sites/default/files/oceans/Technologies_for_Improving_Fisheries_Monit

oring.pdf

Girard, P., & Du Payrat, T. (2017). *An inventory of new technologies in fisheries*. 1–28.

https://www.oecd.org/greengrowth/GGSD_2017_Issue%20Paper_New%20technologies%20i

n%20Fisheries_WEB.pdf

Global Fishing Watch. (n.d.). *Global Fishing Watch Factsheet*. Retrieved December 9, 2019, from

https://globalfishingwatch.org/wp-content/uploads/Intro-to-GFW-transparency.pdf

Global Fishing Watch. (2018). *Our Digital Ocean*. https://globalfishingwatch.org/wp-

content/uploads/GFW_FACTSHEET-2_291118_LRES.pdf

Gonzalez-Mirelis, G., Lindegarth, M., & Sköld, M. (2014). Using Vessel Monitoring System Data to

Improve Systematic Conservation Planning of a Multiple-Use Marine Protected Area, the

Kosterhavet National Park (Sweden). *AMBIO*, *43*(2), 162–174.

https://doi.org/10.1007/s13280-013-0413-7

Gulf of California Marine Program. (2016). *Projects*. http://gulfprogram.ucsd.edu/slider-

home/projects/

Hauber, A. B., González, J. M., Groothuis-Oudshoorn, C. G. M., Prior, T., Marshall, D. A.,

Cunningham, C., IJzerman, M. J., & Bridges, J. F. P. (2016). Statistical Methods for the

    Analysis of Discrete Choice Experiments: A Report of the ISPOR Conjoint Analysis Good

    Research Practices Task Force. *Value in Health*, *19*(4), 300–315.

    https://doi.org/10.1016/j.jval.2016.04.004

Hensher, D. A. (2010). Hypothetical bias, choice experiments and willingness to pay. *Transportation*

    Research Part B: Methodological, *44*(6), 735–752. https://doi.org/10.1016/j.trb.2009.12.012

Jablonicky, C., McCauley, D., Kroodsma, D., Boerder, K., & Dunn, D. (n.d.). *Satellite tracking to*

    monitor area-based management tools & identify governance gaps in fisheries beyond

    national jurisdiction (Nereus Scientific & Technical Briefs on ABNJ, p. 4) [Policy Brief].

    International Marine Conservation Congress.

Jarke, M., Mylopoulos, J., Quix, C., Rolland, C., Manololoupos, Y., Mouratidis, H., & Horkoff, J.

    (2014). *Advanced Information Systems Engineering*.

Ketelaar, P. E., & van Balen, M. (2018). The smartphone as your follower: The role of smartphone

    literacy in the relation between privacy concerns, attitude and behaviour towards phone-

    embedded tracking. *Computers in Human Behavior*, *78*, 174–182.

    https://doi.org/10.1016/j.chb.2017.09.034

Kilgour, C. (2019, May 25). *Personal Communication* [Personal communication].

Kirby, D. S., Visser, C., & Hanich, Q. (2014). Assessment of eco-labelling schemes for Pacific tuna

    fisheries. *Marine Policy*, *43*, 132–142. https://doi.org/10.1016/j.marpol.2013.05.004

Kolding, J., Béné, C., & Bavinck, M. (2014). Small-scale fisheries: Importance, vulnerability and

    deficient knowledge. In S. M. Garcia, J. Rice, & A. Charles (Eds.), *Governance of Marine*

    Fisheries and Biodiversity Conservation (pp. 317–331). John Wiley & Sons, Ltd.

    https://doi.org/10.1002/9781118392607.ch22

Kroodsma, D. A., Mayorga, J., Hochberg, T., Miller, N. A., Boerder, K., Ferretti, F., Wilson, A.,

    Bergman, B., White, T. D., Block, B. A., Woods, P., Sullivan, B., Costello, C., & Worm, B.

    (2018). Tracking the global footprint of fisheries. *Science*, *359*(6378), 904–908.

https://doi.org/10.1126/science.aao5646

Lee, J., South, A. B., & Jennings, S. (2010). Developing reliable, repeatable, and accessible methods
to provide high-resolution estimates of fishing-effort distributions from vessel monitoring
system (VMS) data. *ICES Journal of Marine Science*, *67*(6), 1260–1271.
https://doi.org/10.1093/icesjms/fsq010

López-Sagástegui, C. (2019, May 13). [Personal Communication].

Louviere, J. J., Hensher, D. A., Swait, J. D., & Adamowicz, W. (2000). *Stated Choice Methods:
Analysis and Applications* (1st ed.). Cambridge University Press.
https://doi.org/10.1017/CBO9780511753831

Mazuki, R., Man, N., Omar, S. Z., Bolong, J., Shaffril, H. A. M., & Infoport, P. (2012). *Technology
Adoption among Fishermen in Malaysia*.

Merten, W., Amos, J., Reyer, A., Woods, P., Savitz, J., & Sullivan, B. (2016). *Global Fishing Watch:
Bringing Transparency to Global Commercial Fisheries*. 4.

Metcalfe, K., Collins, T., Abernethy, K. E., Boumba, R., Dengui, J.-C., Miyalou, R., Parnell, R. J.,
Plummer, K. E., Russell, D. J. F., Safou, G. K., Tilley, D., Turner, R. A., VanLeeuwe, H.,
Witt, M. J., & Godley, B. J. (2017). Addressing Uncertainty in Marine Resource
Management; Combining Community Engagement and Tracking Technology to Characterize
Human Behavior: Small-scale fisheries. *Conservation Letters*, *10*(4), 460–469.
https://doi.org/10.1111/conl.12293

Michelin, M., Elliott, M., & Bucher, M. (2018). *Catalyzing the Growth of Electronic Monitoring in
Fisheries, Building Greater Transparency and Accountability at Sea*. 64.
https://www.nature.org/content/dam/tnc/nature/en/documents/Catalyzing_Growth_of_Electro
nic_Monitoring_in_Fisheries_9-10-2018.pdf

Mous, P. (2019, May 8). *Personal Communication* [Personal communication].

Muawanah, U., Yusuf, G., Adrianto, L., Kalther, J., Pomeroy, R., Abdullah, H., & Ruchimat, T.
(2018). Review of national laws and regulation in Indonesia in relation to an ecosystem

approach to fisheries management. *Marine Policy*, *91*, 150–160.

https://doi.org/10.1016/j.marpol.2018.01.027

Murphy, J. J., Allen, P. G., Stevens, T. H., & Weatherhead, D. (2005). A Meta-Analysis of

Hypothetical Bias in Stated Preference Valuation. *Environmental and Resource Economics*,

30, 13. https://doi.org/10.1007/s10640-004-3332-z

Mwangi, M., & Kariuki, S. (2015). *Factors Determining Adoption of New Agricultural Technology*

by Smallholder Farmers in Developing Countries. 10.

Pew Charitable Trusts. (2017, April 12). *Tracking Fishing Vessels Around the Globe*.

http://pew.org/2ooIqYm

Ponte, S. (2008). The Marine Stewardship Council and Developing Countries. In T. Ward & B.

Phillips (Eds.), *SEAFOOD Ecolabelling* (pp. 287–306). Wiley-Blackwell.

https://doi.org/10.1002/9781444301380.ch14

Proud, R., Browning, P., Kocak, D. M., Wiafe, G., & Agyekum, K. (2017). Small vessel tracking

using AIS for enhanced maritime domain awareness. *OCEANS 2017*, 1–6.

https://ieeexplore.ieee.org/document/8232293

Sakamoto, Y., Ishiguro, M., & Kitagawa, G. (1986). *Akaike Information Criterion Statistics*. Springer

Netherlands. https://www.springer.com/gp/book/9789027722539

Sala, E., Mayorga, J., Costello, C., Kroodsma, D., Palomares, M. L. D., Pauly, D., Sumaila, U. R., &

Zeller, D. (2018). The economics of fishing the high seas. *Science Advances*, *4*(6), 1–13.

https://doi.org/10.1126/sciadv.aat2504

Salas, S., Chuenpagdee, R., Seijo, J. C., & Charles, A. (2007). Challenges in the assessment and

management of small-scale fisheries in Latin America and the Caribbean. *Fisheries Research*,

87(1), 5–16. https://doi.org/10.1016/j.fishres.2007.06.015

Shepperson, J., Hintzen, N. T., Szostek, C. L., Bell, E., Murray, L. G., & Kaiser, M. J. (2018). *A*

comparison of VMS and AIS data: The effect of data coverage and vessel position recording

frequency on estimates of fishing footprints. https://doi.org/10.1093/icesjms/fsx230

Sorice, M. G., Donlan, C. J., Boyle, K. J., Xu, W., & Gelcich, S. (2018). Scaling participation in payments for ecosystem services programs. *PLOS ONE*, *13*(3), e0192211. https://doi.org/10.1371/journal.pone.0192211

Stelzenmüller, V., Rogers, S. I., & Mills, C. M. (2008). Spatio-temporal patterns of fishing pressure on UK marine landscapes, and their implications for spatial planning and management. *ICES Journal of Marine Science*, *65*(6), 1081–1091. https://doi.org/10.1093/icesjms/fsn073

Tantia, P. (2017, Spring). The New Science of Designing for Humans. *Stanford Social Innovation Review*, 29–33. https://ssir.org/articles/entry/the_new_science_of_designing_for_humans#

Tietze, U. (2016). *Technical and socio-economic characteristics of small-scale coastal fishing communities, and opportunities for poverty alleviation and empowerment*. Food and Agriculture Organization of the United Nations. http://www.fao.org/3/a-i5651e.pdf

Watson, J. T., & Haynie, A. C. (2016). Using Vessel Monitoring System Data to Identify and Characterize Trips Made by Fishing Vessels in the United States North Pacific. *PLOS ONE*, *11*(10), e0165173. https://doi.org/10.1371/journal.pone.0165173

Wetengere, K. (2011). Socio-economic factors critical for intensification of fish farming technology. A case of selected villages in Morogoro and Dar es Salaam regions, Tanzania. *Aquaculture International*, *19*(1), 33–49. https://doi.org/10.1007/s10499-010-9339-2

Worm, B., Hilborn, R., Baum, J. K., Branch, T. A., Collie, J. S., Costello, C., Fogarty, M. J., Fulton, E. A., Hutchings, J. A., Jennings, S., Jensen, O. P., Lotze, H. K., Mace, P. M., McClanahan, T. R., Minto, C., Palumbi, S. R., Parma, A. M., Ricard, D., Rosenberg, A. A., … Zeller, D. (2009). Rebuilding Global Fisheries. *Science*, *325*(5940), 578–585. https://doi.org/10.1126/science.1173146

Appendix

RAW DATA

The translated surveys were inputted into KoBoToolbox, a data collection tool, and administered on tablets and smartphones. Results from the surveys were stored in comma separated values files, and analysis was carried out in R Studio version 3.5.3. Our analysis was split into two models, a conditional logistic regression to assess trade-offs and probability of adoption, and an interval regression to address willingness to pay. For those interested in running our analysis our raw KoBoToolbox data along with the code that transforms it into a usable format for R Studio can be found here: https://github.com/Panga-Watch/raw_data

BIDDING GAME STRUCTURE

Willingness to Pay
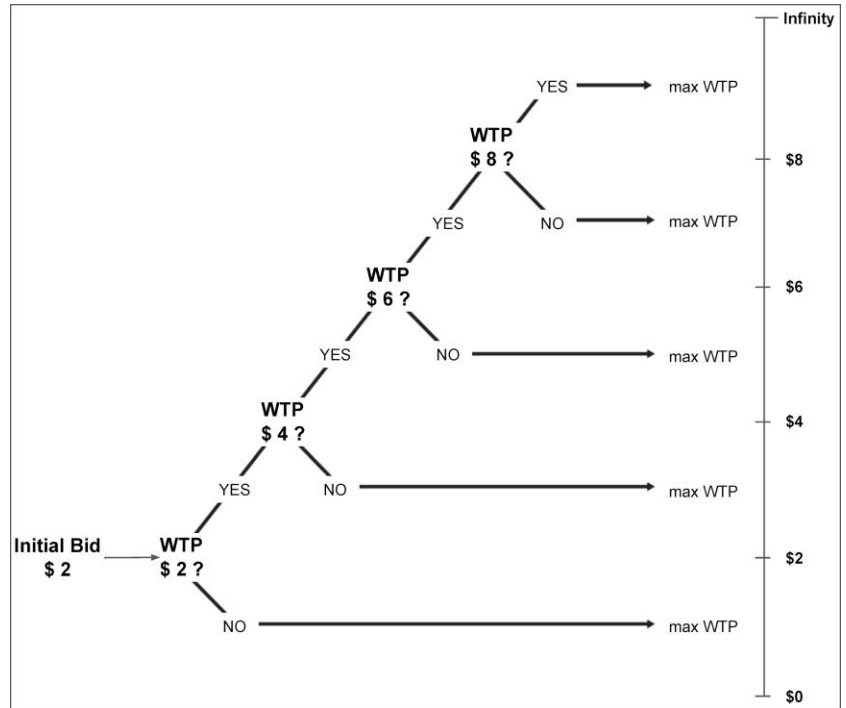
Willingness to Receive
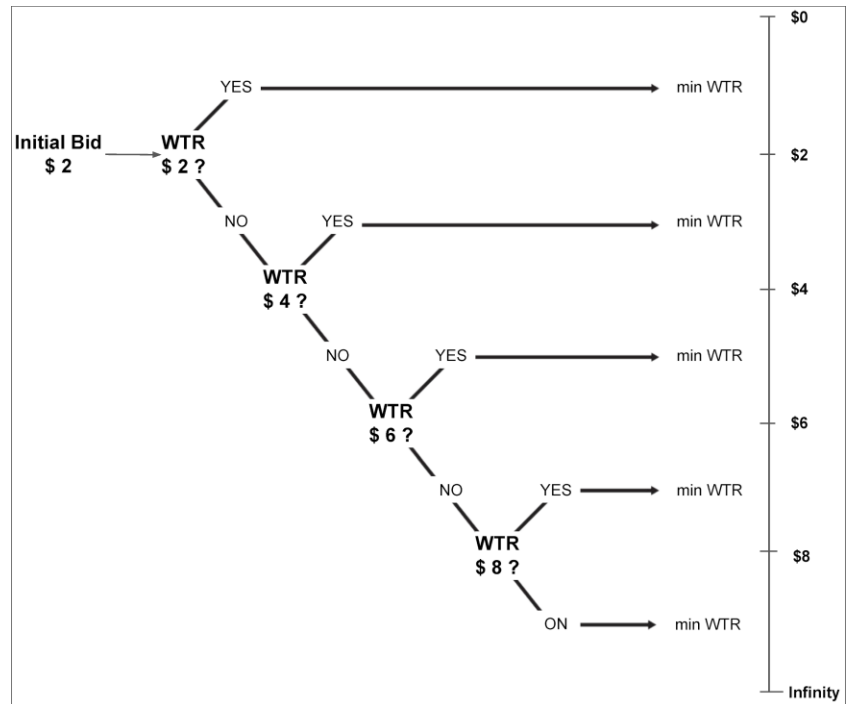
SURVEY

Pre-Survey (To be completed by interviewer)	
Date of Survey (Month/Day/Year)	
Time of Survey	
Purpose of Survey	◯ Data Collection ◯ Training
Survey Version (Number between 1-16)	
Name of interviewer	

◯ I Consent to the terms outlined for this study

Introduction

1. Country
    ◯ Indonesia
    ◯ Mexico

2. Community Name

3. Gender of Respondent
    ◯ Male
    ◯ Female

Gear

4. In the last 12 months, what fishing gear have you used? (Select all that apply)
    ☐ Hand Line
    ☐ Spear
    ☐ Traps
    ☐ Gill Net
    ☐ Mobile Net (e.g., trawl, purse seine, beach seine)
    ☐ Stationary Line (e.g. long line)
    ☐ Other   _____

5. For fishing purposes, do you own a boat, share a boat, or rent a boat from others, or do not use a boat?
    ◯ Own
    ◯ Share with others as part of a collective
    ◯ Share with others as an employee
    ◯ Rent from others
    ◯ Do not use a boat to fish

6. For your primary fishing vessel, please describe the boat in the following aspects:

    i. Length (Rounded to the closest meter)

    ii. Material

    iii. Is the boat motorized?
        ○ Yes
        ○ No

    iv. Is there an on-board power/ electricity source?
        ○ Yes
        ○ No

Technology

7. What types of technology do you use at least once a week? (Select all that apply)
    ☐ Smart-phone with Internet connection
    ☐ Google Maps or other GPS apps
    ☐ Twitter, Facebook, Instagram, or other social media
    ☐ Other _____
    ☐ None

8. What types of technology do you use/ have used at some point for your fishing activity (Select all that apply)
    ☐ VHF radio
    ☐ Fish Finder
    ☐ Surveillance camera
    ☐ Catch and data collection app
    ☐ Vessel tracking technology
    ☐ Other _____
    ☐ None

If you selected Vessel tracking technology in Question 8, please answer Questions 9-11.

9. What type of tracking technology did you use on your vessel?

10. Please list some positive aspects of this technology

11. Please list some negative aspects of this technology

This next question will ask about your preferences for a vessel tracking technology.

Choice Experiment

You are being offered two different options for how tracking technology could be used and affect your life. The options include the presence of an SOS button (or some sort of safety functionality) on the tracker, how private the tracking technology information is, and who actually owns the information gained from the use of the tracking technology.

Package A   Package B

Display Image for Corresponding Survey Version

12. You have to install and use one or the other tracking package for a year. Which would you be more likely to install and use consistently on every fishing trip?

   ○   Package A   ○   Package B

13. Would you prefer the package you chose or no tracking package at all?

   ○   Package Chosen   ○   No Package *(Skip to Question 15)*

14. *Only complete this question if you answered "Package Chosen" in #13*

  i. Would you be willing to pay $5 per month for the package you chose?
    ○   Yes   ○   No *(Skip to Q. 16)*

  ii. Would you be willing to pay $10 per month for the package you chose?
    ○   Yes   ○   No *(Skip to Q. 16)*

  iii. Would you be willing to pay 15 per month for the package you chose?
    ○   Yes   ○   No *(Skip to Q. 16)*

  iv. Would you be willing to pay $20 per month for the package you chose?
    ○   Yes   ○   No

15. Only complete this question if you answered "No Package" in #13

  i. Would you be willing to accept a tracking package for $5 per month?
    ○   Yes *(Skip to Q. 16)*   ○   No

  ii. Would you be willing to accept a tracking package for $10 per month?
    ○   Yes *(Skip to Q. 16)*   ○   No

  iii. Would you be willing to accept a tracking package for $15 per month?
    ○   Yes *(Skip to Q. 16)*   ○   No

  iv. Would you be willing to accept a tracking package for $20 per month?
    ○   Yes *(Skip to Q. 16)*   ○   No

CE Follow Up

16. Please mention any negatives that this technology might bring to you.

17. Please mention any other positives that this technology might bring to you.

18. Please choose 3 benefits you want from the tracking device, if it is installed in your boat (Select three)
    ☐ Data to help obtain a sustainable seafood certification
    ☐ On-board Internet access
    ☐ On-board electrical power for charging cell phones and other electronics
    ☐ Text messaging services
    ☐ Detailed tracking information for your vessel (e.g., drop pin in specific location)
    ☐ Opportunities to acquire new tools and technical capacity (e.g. workshops for computer use)
    ☐ Reduce illegal, unreported, and unregulated fishing in your fishing area
    ☐ Increase in the monitoring capacity of the fishing association
    ☐ Full data reports to show compliance with fishing authorities (e.g. monthly reports with fishing activity information, paired with catch data)

19. Do you think you and your community would adopt this technology? Why or Why Not?

Catch

20. Combining all seasons, what are your top three targeted fisheries?

    1.

    2.

    3.

21. What percent of the total catch (out of 100%) goes to...
    a. Own/household consumption   %
    b. Shared to neighboring household   %
    c. Traded in local market   %
    d. Export   %
    e. Other _____   _____ %

                                          Total = 100 %

Fishing Organization

22. Are you part of a fishing organization?
    ○ Yes
    ○ No   (Skip Questions 23-25)

If you selected Yes in Question 22, please answer Question 23-25

23. What type of organization?
    ○ Cooperative
    ○ Union
    ○ Customary Organization (e.g. indigenous community)
    ○ Other   _____

24. What role do you have in the organization?
    ○ Apprentice
    ○ Partner
    ○ Director
    ○ Other   _____

25. How many members are in your fishing organization?

Regulations and Enforcement

26. Who is allowed to fish for your #1 targeted fishery? (Select all that apply)
    ○ Members of your fishing organization/ community only
    ○ Members from you and neighboring fishing organization/ communities
    ○ Anyone with a fishing permit
    ○ There are no restrictions to access
    ○ Other   _____

27. What regulations exist for your #1 targeted fishery? (Select all that apply)
    ☐ Gear Restrictions
    ☐ Size Restrictions
    ☐ Seasonal Restrictions
    ☐ Spatial Restrictions
    ☐ Quotas
    ☐ Other   _____
    ☐ None

28. Who is responsible for enforcement in your community? (Select all that apply)
    - ☐ Community Members
    - ☐ Village customary leader
    - ☐ Village Government
    - ☐ Provincial Government
    - ☐ National Government
    - ☐ No Enforcement
    - ☐ Other _____

29. On average, how often are these fishing regulations enforced?
    - ○ Every week
    - ○ Once a month
    - ○ A few times per year
    - ○ Once a year
    - ○ Never

30. How severe is the punishment when a person gets caught violating the fishing regulations?
    - ○ No Punishment
    - ○ Weak
    - ○ Moderate
    - ○ Strong
    - ○ Severe

31. Are there any closed areas in your fishing area?
    - ○ Yes
    - ○ No

Fishery Challenges

32. What do you think are the biggest problems your fishery faces?

    1

    2

    3

33. How do you think the problems you mentioned can be solved?

    1

    2

    3

34. Please rank the following problems in regards to your fishing activity

1 = Strongest impact   4 = Least impact

Rank #

_____ Trash polluting the ocean

_____ Illegal Fishing

_____ Extreme Weather

_____ Corruption of fishing authorities

35. In the last few years, the current fish catch has…
   - ○ Declined a lot
   - ○ Declined slightly
   - ○ Stayed the same
   - ○ Improved slightly
   - ○ Improved a lot

Perception

36. How much do you agree with the following statements

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
a. Formal stock assessments help to sustainably manage fisheries	○	○	○	○	○
b. I have many options if I decide to no longer be a fisher	○	○	○	○	○
c. In general, the fisheries in this region are doing well	○	○	○	○	○
d. I am worried about the future of our fishery resources	○	○	○	○	○
e. Outside small-scale fishers are always entering our fishing grounds	○	○	○	○	○
f. Outside industrial fishers are always entering our fishing grounds	○	○	○	○	○
g. Everyone in the fishing community knows where other fishers go (there are no secret spots)	○	○	○	○	○
h. In general, my fishing activity implies severe risks to my life	○	○	○	○	○
i. I feel I have a voice in how my fishing area is managed	○	○	○	○	○

37. Please indicate how much you trust the following groups

	Distrust Entirely	Distrust	Neutral	Trust	Trust Entirely
a. Other members in my fishing community	○	○	○	○	○
b. Other fishing communities in the region	○	○	○	○	○
c. Fishing association leaders	○	○	○	○	○
d. Fisheries officers	○	○	○	○	○
e. Police or security that might enforce poaching events	○	○	○	○	○

37 continued….	Distrust Entirely	Distrust	Neutral	Trust	Trust Entirely
f. Consultants that conduct assessments with fishing associations	○	○	○	○	○
g. Fishery scientists	○	○	○	○	○
h. Local conservation groups	○	○	○	○	○
i. Non-Governmental Organizations	○	○	○	○	○
j. National Government	○	○	○	○	○
k. Local Government	○	○	○	○	○
l. Private Companies	○	○	○	○	○

38. Please indicate how satisfied you were when working with the following organizations

	n/a	Extremely Unsatisfied	Unsatisfied	Neutral	Satisfied	Extremely Satisfied
a. Non-Governmental Organizations	○	○	○	○	○	○
b. Private Companies	○	○	○	○	○	○
c. Government Organizations	○	○	○	○	○	○

Demographics

39. What is your age?

40. How many years have you been fishing?

41. What is your level of education? (Please choose one)
- ○ No Formal Education
- ○ Primary School
- ○ Secondary School / High School
- ○ Vocational Training/ Trade School
- ○ College/ University
- ○ Other _____

42. What is your average monthly income?

43. What percent (out of 100%) of your annual income comes from fishing?

44. What percent (out of 100%) of your income is spent on fishing related expenses?