Integrating a mobile accessible electronic system into dockside monitoring: How can small-scale fisheries data collection programs transition from paper-based to digital data collection?

Gretchen Thuesen

A thesis

submitted in partial fulfillment of the

requirements for the degree of

Master of Marine Affairs

University of Washington

2016

Committee:

Ryan Kelly

Eddie Allison

Program Authorized to Offer Degree:

Marine and Environmental Affairs

University of Washington

Abstract

Integrating a mobile accessible electronic system into dockside monitoring: How can small-scale fisheries data collection programs transition from paper-based to digital data collection?

Gretchen Thuesen

Chair of the Supervisory Committee:
Assistant Professor Ryan Kelly
Marine and Environmental Affairs

Lack of reliable, high quality fishing activity data has undermined efforts to monitor marine fisheries efficiently. Further, there are many barriers to capturing this data including inefficient paper processes, lack of trust or incentives to encourage participation, few sources to verify data, and a landscape of information silos. One way to overcome these barriers is to improve fisheries data capture using technology. This project sought to better understand how small-scale dockside fisheries monitoring programs can transition from paper-based methods to digital data collection using a smartphone app. Market-testing of the app using surveys and interviews revealed that a typical NGO fisheries data collection program operates 7 field sites, is paper-based, collects data using dockside monitors, experiences an average time lag of 5 weeks from data recording to usability, and costs an average of $99,000 annually. These NGOs prioritize ‘sustainable management of local resources’ as their most important organizational goal, rank ‘species type’ as the most valuable type of data collected, and rank ‘building local capacity’ as the most significant issue of concern related to fisheries data collection. Because the success of an

electronic reporting program will hinge on the ability of these technology tools to provide clear and tangible benefits to fisheries, the app was then field-tested in a small-scale Indonesian tuna fishery as part of a pilot study. Specifically, I compared paper-based data collection methods to the app according to predetermined metrics of success (timeliness and availability; data collection cost) at 2 field sites. When using the app, data collectors tended to lose time at one site (34% increase in time) and save time at the other (53% decrease in time). This difference among sites was likely due to variations in patterns of catch landing, internet connectivity, and employee adoption rate. Total cost (including equipment and labor costs) was projected to increase by an average of 20% per field sampling site when using the app. Time and cost metric data were then used to generate a cost-benefit analysis, which revealed that implementing this app at all field sites would result in a 12% increase in total cost during the first year, followed by a 13% cost decrease in subsequent years. Over a 5-year horizon, using the app at all field sites was projected to decrease overall cost of data collection by 8%. Specifically, high initial equipment costs would be balanced by a decrease in labor cost in the medium to long term. Ultimately, the incentive to transition to electronic monitoring in a particular fishery is highly dependent on the data needs of that fishery and the management goals of the organization as well as the strength of time preference (i.e. willingness to wait for future returns), and I hope lessons learned from this case study will provide other organizations with valuable insight as they contemplate similar transitions.

TABLE OF CONTENTS

1.0 INTRODUCTION…………………………………………………………………...7

1.1 Background……………………………………………………………………..7

1.2 Project Outline…………………………………………………………….…8

2.0 METHODS……………………………………………………………………………...9

2.1 Data Collection…………………………………………………………………9

2.1.1 Market-testing Dock……………………………………………...…9

2.1.2 Field-testing Dock………………………………………………….10

2.2 Data Analysis…………………………………………………………………..15

2.2.1 Market-testing Dock…………………………………………………..15

2.2.2 Field-testing Dock……………………………………………………16

3.0 RESULTS……………………………………………………………………….…..20

3.1 Market-testing Dock…………………………………………………………..20

3.2 Field-testing Dock……………………………………………………………..25

4.0 DISCUSSION…………………………………………………………………………33

4.1 Market-testing Dock…………………………………………………….…33

4.2 Field-testing Dock……………………………………………………………..36

4.3 Implications for fisheries monitoring programs……………………………….…43

5.0 REFERENCES……………………………………………………………………...…43

6.0 APPENDICES……………………………………………………………………………46

ACKNOWLEDGEMENTS

This thesis would not have been possible without the help of many people for which I am thankful and grateful. I would like to express a great deal of appreciation to my committee chair, Professor Ryan Kelly. His feedback and advice was immensely helpful in shaping this project into its final form. I would also like to thank my committee member Professor Eddie Allison for providing insight into small-scale fisheries operations and helping me to add context to my results. In addition, I would like to thank Charles Steinback, CEO of Point 97, for providing not only a thesis topic that was of great interest to me, but for continually providing support, information, and new avenues to explore during the course of this project. I would also like to thank Momo Kochen, Program Director of MDPI, and Deirdre Duggan, Communication and Development Manager at MDPI for providing internal information about MDPI's fisheries monitoring program and for supplying crucial contextual information that shed light into the inner workings of fisheries data collection on the ground. Also, I would like to thank Megan Popma, Cheryl Chen, and Stacy Gerritse for their help when collaborating on collecting marketing data about the app. Last, and certainly not least, I would like to thank my fellow thesis advisees for their continuous support and feedback.

1.0 INTRODUCTION

1.1 Background

Marine fisheries provide approximately 4.3 billion people with 15% of their protein intake and 55 million people with jobs; 90% of those jobs are small-scale fishers (FAO 2014). Because of this reliance on fisheries for food and job security, nations worldwide have strived for decades to monitor fisheries more efficiently by advancing towards data-driven adaptive management practices (Caddy and Cochrane 2001). However, lack of reliable, high quality fishing activity data (e.g. catch, gear, location) is a fundamental setback to effective fisheries management (Barkail 2011). Unreliable data leads to a poor basis for stock assessment and management for scientists and a reduction in fishing efficiency for industry, resulting in poor management decisions that often risk fish resources as well as the livelihoods of fishermen (Barkail 2011). While both scientists and fisheries managers alike recognize the importance of collecting fish catch data, there is still confusion about how to best collect and store these data. Further, there are many barriers to capturing this data including inefficient paper processes, lack of trust or incentives to encourage participation, few sources to verify data, and a landscape of information silos[1] (Barkail 2011). For instance, fishermen often record catch data on paper forms, which are then delivered to fisheries managers and transferred to a computer system filled with complex spreadsheets. In other cases, they remain in paper form amongst endless rows of files. The multi-stage process of transcribing from handwritten logbook sheets to paper forms, then to computer databases causes the quality of data to degrade (Barkail 2011). Barriers such as these have stalled efforts to gather the necessary and timely data to properly manage fisheries into the long-term (Steinback et al. 2015).

One way to overcome these barriers is to improve fisheries data capture using technology. However, technological advances in the fishing industry have largely favored improving catchability rather than data collection. Increase in catchability driven by technology developments include rapid advancements in on-board vessel technology (e.g. sonar, gear sensors, navigation systems) as well as gradual improvements to existing vessel technology or gear (e.g. netting materials, deck equipment). This, in turn, has led to overexploitation of many fish stocks worldwide (Eigaard et al. 2014). While technology has been used to increase fleet fishing power, development of technological solutions and their subsequent integration into fisheries monitoring programs has been a much slower process (Caddy & Cochrane 2001).

Even so, there have been notable technological improvements in monitoring over the last two decades, including camera-based electronic monitoring (EM) systems and electronic reporting (ER) tools (Lowman et al. 2013). EM systems have been in use since about 1992, and include closed circuit video cameras, sensors to monitor use of fishing gear, a GPS receiver, and a control center to manage, process and store data. EM tools can also include vessel monitoring systems (VMS), which are becoming increasingly sophisticated in the types and amount of data they can transmit (McElderry 2008; Lowman et al. 2013). ER tools include electronic logbooks,

[1] For the purposes of this report, an information silo refers to a situation in which a data system is incompatible with other platforms, causing data to effectively reach a dead end.

which generally report on fishing activities and catch, and electronic fish tickets, which report on fish landed and sold. E-logbooks track catch data, fishing location, gear used and details of fishing events using a standardized format. Both e-logbooks and e-tickets can be submitted online once an internet connection is available (typically when the vessel returns to port) (Lowman et al. 2013).

However, the use of EM/ER systems is not widespread. A review of EM pilot studies suggested that limited implementation of EM tools was not a result of deficiencies in the tools themselves, but by a recurring failure to identify monitoring objectives and explore how EM data could be combined with or enhance monitoring data from other sources (Lowman et al. 2013). Incorporating new tools or technologies into a monitoring program is often not as simple as trading out one tool for another, but will most likely require careful consideration of how to assimilate these tools into an existing data collection program in order to accomplish fisheries monitoring goals and objectives more efficiently. Integrating these technologies into a fishery monitoring program is therefore a multi-step process that must be tailored to the specific needs of the fishery, fleet and often vessel (Lowman et al. 2013). In other words, a well-crafted tool is meaningless without knowing who would benefit from this innovation, what their incentives and organizational goals are, and how this tool could be plugged into an existing data collection program.

In an effort to resolve inefficiency in data capture, Point 97[2], a marine consulting firm in Portland, OR that specializes in marine resource data capture, management, visualization, and analysis, has created an electronic dockside monitoring solution designed to help organizations transition from error-prone and inefficient paper data collection methods to readily-available mobile technologies. Called Dock, the electronic solution includes a smartphone app that is linked to an online database. Dock is designed to capture the flow of ocean products from harvesters into fisheries monitoring programs and local and export markets, and is intended for use by dockside observers. Expected benefits of this tool include paperless data collection, decreased processing time compared to paper forms, and near real-time availability of catch reports (Steinback et al. 2015).

1.2 Project Outline

This project sought to better understand how small-scale fisheries can transition from paper-based methods to digital data collection, management, and storage, using Point 97's Dock as an example of a digital platform through which to accomplish the transition.

The project entailed two separate but related components (market-testing and field-testing the app), each with a unique set of goals:

(1) **Market-testing Dock:** Efforts to implement new technologies are often unsuccessful because decision makers fail to consider how electronic reporting could be incorporated into an existing fisheries data collection program. In order to avoid making this mistake, I

[2] For more information about Point 97, please visit pointnineseven.com.

analyzed data collected during market-testing of this app to determine who might want to use this kind of technology, and to identify incentives and goals of these organizations. Specifically, the goals were to:

Goal 1: Typify existing fisheries data collection programs and identify current data collection processes.

Goal 2: Identify areas in need of improvement to locate gaps this technology could fill.

Goal 3: Identify and define potential obstacles and adoption barriers to implementation of this technology.

(2) Field-testing Dock: Moving from theoretical exercise to practical application, I analyzed data from a pilot study of Dock in the field. The success of an electronic reporting program will hinge on the ability of this tool to provide clear and tangible benefits to fisheries monitoring programs. Working with MDPI Foundation[3], a non-profit organization headquartered in Bali, Indonesia that focuses on achieving sustainable practices in small-scale Indonesian fisheries, Dock was deployed at two small-scale Indonesian tuna fishery dockside monitoring field sampling sites. Indonesia was selected because of the active and critical role their fisheries play in the Coral Triangle and Point 97's vested interest and previous work in Indonesian fisheries data collection (Steinback pers. comm. 2015). In other words, the objective was to conduct an organization-specific case study with MDPI as the client. Specifically, the goals were to:

Goal 1: Conduct a baseline assessment to outline fisheries management goals and specific monitoring objectives, and to detail MDPI's current process for data entry, management and storage.

Goal 2: Compare current paper-based methods to Dock according to predetermined metrics of success.

Goal 3: Provide recommendations to MDPI regarding implementing an electronic dockside monitoring solution such as Dock.

2.0 METHODS

2.1 Data Collection

2.1.1 Market-testing Dock

In collaboration with Megan Popma, a Packard Environmental Fellow interning with Point 97 during the summer of 2015, and with the oversight and input of Cheryl Chen and Stacy Gerritse of Point 97, I developed questions for both the survey and interviews. Both were intended to assess market potential for Dock.

Surveys

[3] For more information about MDPI, please visit http://mdpi.or.id/.

In developing survey questions, Megan and I used a stratified sampling design containing a few specific demographic categories of interest (age, gender, role in organization) as identifiers (Dillman et al. 2014). We did this to strike a balance between collecting sufficient information to facilitate comparison of survey responses while protecting respondent anonymity. The Institutional Review Board (IRB) determined this project to be exempt from requiring IRB approval. Appendix A contains NGO survey questions.

We then distributed an online survey to NGO respondents using SurveyMonkey in an effort to obtain a representative sample of global NGO fisheries data collection programs.

Interviews

In collaboration with Megan Popma, I used a semi-structured interview design in order to formulate questions that were "sufficiently structured to address specific topics related to the phenomenon of study, while leaving space for participants to offer new meanings to the study focus" (Galletta and Cross 2013). More specifically, the semi-structured approach aims to capture data that can then be codified in order to explain behavior according to predetermined categories (structured) while employing a less rigid framework to establish rapport and focus on understanding (unstructured). Because it is a hybrid method, semi-structured interviews can contain open-ended questions combined with targeted, theoretically-driven questions. Appendix B contains NGO interview questions.

Megan and I interviewed NGO employees to gather contextual information on the following: (1) key characteristics and attitudes, (2) current data collection process, and (3) potential impacts of Dock including possible benefits and obstacles of transitioning to an electronic dockside monitoring solution. Combining results from interviews and surveys, I analyzed the data according to the methods outlined below in 'Data Analysis.'

2.1.2 Field-testing Dock

Before implementing Dock at MDPI's selected field sampling sites, I conducted a baseline assessment to document the current field data collection system by compiling information from a variety of documents obtained from MDPI staff. This baseline served to (1) define fisheries characteristics including target species, selected landing sites, and current management type, (2) outline fisheries management goals and specific monitoring objectives, and (3) detail current monitoring program structure including types and frequency of data collected, data format, data collection process, and current infrastructure for data entry, processing, management and storage. Moreover, this baseline served as a starting point from which progress and implementation success of Dock could be monitored and evaluated over the course of the project, and could be used as a reference point for any continued work beyond the scope of this report.

Baseline assessment

What follows is a description of the handline and pole-and-line Indonesian tuna fisheries monitored by MDPI, including: (1) characteristics of the fishery, (2) management goals and objectives, (3) monitoring program details, and (4) current fisheries data collection process.

(1) *Characteristics of the fishery*

Tuna fisheries monitored by MDPI staff are open-access and do not feature a total allowable catch (TAC) or a vessel/capacity limit. MDPI landing sites include both handline and pole-and-line fisheries, which target mature yellowfin and bigeye tuna and skipjack tuna, respectively. Fish aggregating devices (FADs) are used to locate fish, and catcher vessels are either large (3-15 GT[4]) or small (<3 GT) in size (USAID Indonesia 2015a, b).

Of the 13 total sites, Larantuka and Kupang were selected for field-testing Dock because of their relatively reliable internet connection, English-speaking regional site supervisors, and close proximity to one another. At Larantuka, landed fish are caught using the pole-and-line method only. The fishing season is year-round depending on weather and presence of bait, and 17-43 catcher vessels are sampled per month depending on transient fishers, seasonality, and price of fish. MDPI staff work with a single industry partner on site. Kupang is a busier port; MDPI works with several industry partners on site, dominated by the handline fishery, and there are often at least 100 catcher vessels sampled per month. The fishing season is from February-November and sometimes extends into December (Kochen pers. comm. 2016).

(2) *Management goals and objectives*

Because handline and pole-and-line tuna fisheries management strategies are identical, the following reflects both fisheries. Further, the goals and objectives discussed are only those that may potentially be influenced by the implementation of Dock.

MDPI's tuna fisheries management goals include (1) create data collection networks to increase local government involvement in the data collection process, (2) enhance handline and pole-and-line tuna fisheries competitiveness in the global market by achieving eco-certification status, and (3) maximize profits from tuna fisheries while promoting ecological conservation (USAID Indonesia 2015a, b).

Specific monitoring objectives include (1) uniformity of data collection, (2) data transferability, (3) cost-effective data collection methodology, and (4) granting stakeholder access to high quality tuna catch data (USAID Indonesia 2015a, b).

(3) *Monitoring program details*

There are an average of 3 data collectors per site collecting data 8 hours/day (9am-5pm), 5 days/week (Monday – Friday), 48 weeks/year. Dockside monitor coverage is 20% for daily port sampling data (1 in 5 vessels).

(4) *Current fisheries data collection process*

[4] Gross tonnage (GT) is a measure of a vessel's overall internal volume (Admiralty and Maritime Law Guide 1969).

Flow of data from point of collection to point of use is shown in Figure 1. Enumerators[5], called Sustainability Facilitators at MDPI, use paper forms to record catch data from fishermen and suppliers during individual vessel unloading events (i.e. as they land catches at the dock). Site Supervisors manage operations at a given site. They verify data as they enter it into an Excel spreadsheet on a laptop, then upload this data to the Indonesian Fisheries Information System (I-Fish) database, a transparent tool for data entry, storage and processing. I-Fish provides a platform where stakeholders can access catch data. This final step delivers data into any and all potential pathways, such as into markets (seafood buyers, processors, distributors, restaurants) and into fisheries management (NGOs, government agencies).

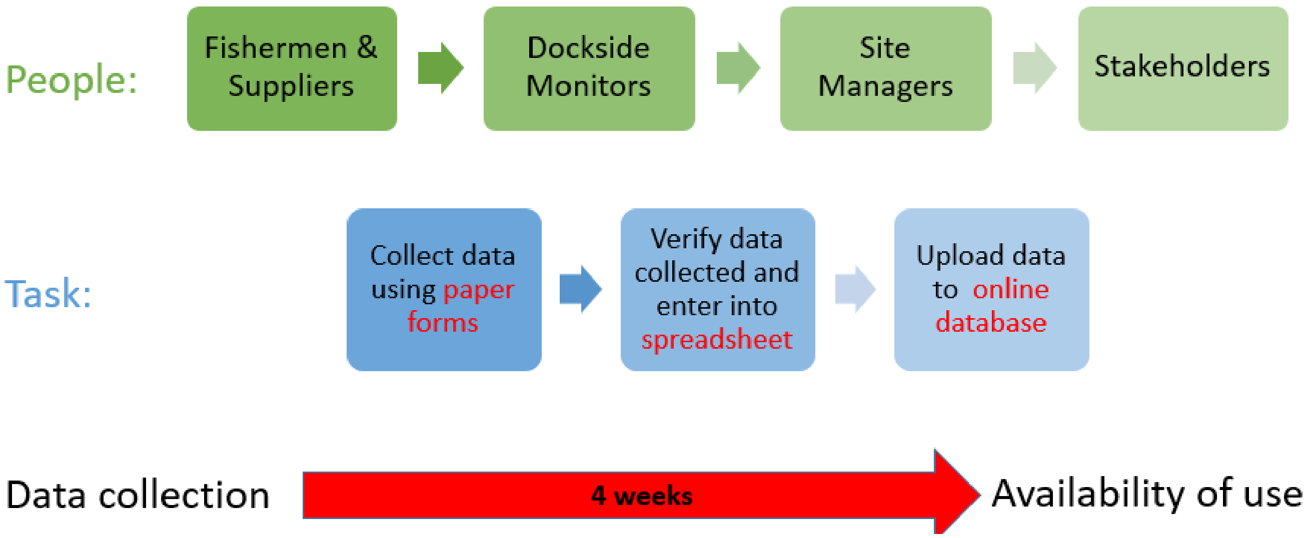


Figure 1. MDPI's current system for data entry, processing, management and storage. The green boxes represents person by job title (to represent the number of hands the data goes through). The blue boxes represents both the task completed and the platform used to complete that task (red).

On average, the process (data collection to availability of use) depicted in Figure 1 (blue boxes) takes 4 weeks. Factors such as internet connectivity, higher workload during peak season, and backlogging of work (e.g. if Regional Supervisors must check data before it can be uploaded to I-Fish) often further delay data submission and processing (Kochen pers. comm. 2016). According to Momo Kochen, MDPI's Program and Research Director, dockside monitors prioritize sampling more vessels over uploading data. "If a vessel lands, staff have to go collect data. The vessels don't wait for our enumerators. Our enumerators have to adjust to what's happening at the landing site, which means that they might start to do 3 or 4 unloadings before they get to data entry or they get to actually uploading something. They'll collect the data, then they will leave it be to come back again later. Only later, when there's no more landings or when

[5] For the purposes of this report, an enumerator is defined as one who is responsible for collecting catch landing data, and is synonymous with 'dockside monitor/observer.'

there's no engagement with any of the stakeholders, then they'll go back to the office and work on data entry or on uploading" (Kochen pers. comm. 2016).

Using this baseline information, I evaluated whether current monitoring tools were meeting monitoring objectives and, if not, I identified areas in need of improvement. When evaluating whether current data collection methods satisfied monitoring objectives, objective 1 was not fully satisfied because catch data must pass through various platforms (paper, Excel) before being uploaded to the I-Fish database. Dock could further unify data collection by requiring entering data into a single platform before being uploaded and available for use. Dock would likely improve data transferability (objective 2) for similar reasons. The impact of Dock on cost-effective data collection methodology (objective 3) was unknown at this time and will be discussed in later sections. Lastly, I expect Dock to facilitate faster completion of objective 4, meaning stakeholders would have access to high quality tuna catch data at a faster rate than it currently becomes available.

I created and defined metrics of success that allowed me to test the potential impact of Dock on objective 3 (data collection cost) and objective 4 (timeliness and availability). Specifically, I used (1) timeliness and availability and (2) data collection cost as metrics of success to document and compare current paper-based data collection methods to Dock.

Dock was implemented at Larantuka and Kupang (see Figure 2) beginning early February 2016 to avoid introducing the app during the height of fishing season. Dockside monitors used Dock alongside existing paper-based data collection techniques (as opposed to temporarily replacing current data collection methods) in order to allow data collection to continue functioning smoothly.

Figure 2. Map of Indonesia. The circled sites (in red) are the 2 sites used for field-testing Dock (map obtained from www.mappery.com).

I collected data on time and cost in order to evaluate the metrics of success defined above. To evaluate the 'timeliness and availability' metric, MDPI enumerators recorded time required to complete individual data collection tasks during a given sampling event[6] when using paper-based methods and when using Dock from February 22 – March 6, 2016. Four enumerators from the 2 test sites recorded time taken to complete individual data collection tasks when using each method. MDPI staff provided itemized lists of equipment costs associated with each method at the 2 test sites. They also provided monthly salaries per enumerator and number of enumerators per site to allow calculation of labor cost. Both equipment and labor cost data were used to evaluate the 'data collection cost' metric.

Interview

I interviewed Momo Kochen, MDPI's Program and Research Director, and Deirdre Duggan, MDPI's Communications and Development Manager at the end of the pilot study on May 15, 2016 to gather contextual information on the following: (1) timeliness and availability metric, (2) data collection cost metric, and (3) challenges and barriers faced during implementation and operation of Dock.

---

[6] For the purposes of this report, a sampling event is defined as collecting catch data from an individual vessel during an unloading event, entering that data into a digital platform, and uploading that data to the online database.

2.2 Data Analysis

2.2.1 Market-testing Dock

Surveys

Survey data was used to typify an average fisheries data collection program. Specifically, I generated descriptive statistics for responses to survey questions for each of the following data types: ranked-choice data (questions 4, 14, 15), other categorical data (questions 8, 16), and numerical data (questions 9, 13) (all questions can be found in Appendix A).

Ranked-choice data

Respondents ranked a series of (1) organizational goals, (2) value of types of data collected, and (3) fisheries data collection issues of concern in order of priority. Ranked-choice data contains categorical ordinal variables, meaning categories can be ranked but distance between categories is unknown (Agresti 2002). To demonstrate these rankings, responses were presented according to percent of respondents that assigned a given ranking within each of those categories.

I then used a Kruskal-Wallis one-way ANOVA to look for significant differences among average rankings within each category. I chose Krusal-Wallis because it allows comparison of 3 or more groups and does not assume normally distributed data (Hollander and Wolfe 1973). In other words, I wanted to compare importance of each goal, value of each data type, and significance of each issue of concern among respondents to determine if differences observed were beyond chance with alpha=0.05 level of significance. If the Kruskal-Wallis test determined there was at least one significant difference among average rankings, I then used a Mann-Whitney test to find these differences. This allowed me to determine which goals, data types, and issues of concern were ranked significantly higher (and lower) than others, thereby suggesting that these rankings were not due to chance and instead represented an actual pattern.

Other categorical data

This data type contains nominal categorical variables, meaning the order of categorical listing is irrelevant (Agresti 2002).

> Types of data collectors: Respondents provided information about who collects and submits the fisheries data they use; categories included at-sea fishermen, enumerators, and other. Responses were presented according to percent of respondents that reported receiving data from one, two or all of these types of data collectors.
>
> Platform for fisheries data capture: Respondents reported their primary method of data capture, and responses were presented according to percent of respondents that reported either using paper or digital (mobile or online tool). I then used the exact test of goodness-of-fit to evaluate the likelihood that the observed differences among methods used arose by chance. I used this test because I had one nominal variable (data capture method) and a small sample size (n=9). I compared the observed paper:digital ratio to an

expected theoretical 1:1 ratio (assuming paper and digital methods are equally used), using the null hypothesis that numbers of the two outcomes are equal and using alpha=0.05 level of significance (Stephens and D'Agostino 1986).

<u>*Numerical data*</u>

Respondents provided numerical values for (1) time lag (in days) between data recording and usability and (2) annual cost (in U.S. dollars) of fisheries data collection. Because these are continuous numerical variables, I generated descriptive statistics for responses to each question, using the median for the time lag category because the data were left-skewed, and using the mean for the annual cost category because the data were not skewed (Agresti 2002).

Interviews

In collaboration with Megan Popma, I organized responses according to predetermined categories to draw out common themes according to the categories discussed above. Interview responses were used as anecdotal evidence to support observed patterns from survey data and provide relevant context.

2.2.2 Field-testing Dock

Time required to collect fisheries data

<u>*Per test site*</u>*:*

For each test site (Larantuka and Kupang), I generated descriptive statistics and ran a series of t-tests to explore differences among data collection methods (paper-based v. Dock). I compared time required to collect data using each method according to 2 different categories: time to complete each individual task and time to complete all data tasks.

(1) <u>Time to complete each individual task</u>:
Using a series of t-tests assuming unequal variances, I compared average time taken to complete each task (in minutes) (see Table 1) across methods (paper v. Dock) per site to determine if data collectors saved or lost time when using the app.
(2) <u>Time to complete all data tasks</u>:
I then calculated total time required to complete data collection by adding minutes required to complete tasks 1-6 when using paper-based methods at both sites and when using Dock at Kupang. I made the same calculation for tasks 3-6 only when using Dock at Larantuka due to missing data for tasks 1-2. I then used a t-test to compare average time required to complete all tasks across methods per site.

<u>*Comparing sites*</u>:

After comparing differences among methods per site, I compared sites (Larantuka v. Kupang) to highlight site characteristics independent of data collection method that may play a role in data collection time.

I first calculated overall time required to collect data for a single sampling event when using paper-based methods by subtracting end time of the last task (task #6 in Table 1) from the start time of the first task (task #1 in Table 1). The same calculation was made when using Dock at Kupang. However, when computing overall time required when using Dock at Larantuka, I subtracted end time of the 6th task from the start time of the 3rd task. This difference was due to limited data available (data missing for tasks 1 and 2 at Larantuka).

I then compared 'overall time' to 'time to complete all data tasks' (calculated in the 'Per test site' subcategory above) to determine the proportion of overall time dedicated to data collection at each site during a given sampling event. The difference between these two time categories is that 'overall time' measures number of minutes from the beginning of task 1 to the completion of task 3 by subtracting end time of task 6 (e.g. 12:28pm) from start time of task 1 (e.g. 6:55am). Conversely, 'time to complete all data tasks' adds minutes required to complete each of tasks 1-6 individually. Values for both time categories should be equal, but they were not, implying there is time unaccounted for during sampling. This is why I compared the 2 time categories separately (see Appendix C for a sample calculation).

I used a t-test to compare average total catch (kg) and total number of fish sampled per sampling event between sites because these are factors independent of data collection method that may impact time necessary to collect data. This was done for paper-based data collection methods only because total catch and total number of fish data were not available for sampling events using Dock.

Table 1. Individual data collection tasks required to complete a single sampling event.

Task #	Data collection task
1	Collecting fisheries data (e.g. length, weight)
2	Interviewing fishermen
3	Checking and completing data
4	Entering data into Excel spreadsheet OR into Dock app
5	Checking and verifying data before uploading to database OR I-Fish
6	Uploading to database OR I-Fish

Cost of fisheries data collection

Using cost information received from MDPI employees, I calculated equipment and labor cost for a single year.

<u>*Equipment Cost*</u>

MDPI staff provided itemized lists of equipment costs associated with paper-based data collection techniques and with Dock methods at the two test sites (Larantuka, Kupang).

Per test site*:* I calculated total annual equipment cost using paper-based data collection methods and using Dock at Larantuka and Kupang (refer to Appendix D for a detailed description of how I calculated annual cost of each item per test site).

All sites: Using Larantuka and Kupang equipment costs provided by MDPI staff, I projected total annual equipment cost using paper-based data collection methods and using Dock at all 13 MDPI field sites (see Appendix E for a description of assumptions made per site when calculating annual equipment cost all 13 field sampling site and Appendix F for a sample calculation). I then calculated total data collection equipment cost per year by adding costs for all 13 sites. I did this for each method in order to compare costs among sites

Labor Cost

Using monthly salaries for site supervisors and enumerators, the number of each type of employee per site, and the fact that MDPI employees collect fisheries data 48 weeks per year, I calculated annual salaries for each employee per site, which I then used to calculate annual labor cost for all 13 sites. I then calculated total data collection labor cost per year by adding costs for all sites.

Total cost

Finally, I combined annual equipment and labor cost to compare total cost per site and total cost of operating all 13 sites when using each data collection method.

Cost-benefit analysis

Using results from these two metrics ('time required to collect catch data' and 'total annual data collection cost') and in an effort to assist MDPI in visualizing the possible outcomes of implementing Dock, I set out to conduct a cost-benefit analysis (CBA). The objectives of the CBA included (1) cataloguing impacts of benefits (pros) and costs (cons), (2) valuing each of these impacts in dollars (assigning weights), and (3) determining net benefits of an alternative relative to the status quo (Boardman et al. 2011). The overarching goal was to test for the "efficiency of a particular intervention relative to alternatives, including the status quo" (Boardman et al. 2011); that is, to see whether the field test suggests that Dock is likely to provide a cost-benefit value to end users.

While the goal was to develop a fully quantitative cost-benefits analysis of the transition to the Dock, this was impossible because 1) Dock is still in the early stages of implementation, meaning there is considerable uncertainty about its actual impacts and benefits, and more generally, 2) limited work has been done to describe and estimate the costs and benefits of electronic reporting systems (Northern Economics, Inc. 2015), meaning looking to prior research for guidance was unfortunately not an option. Finally, 3) while many of the costs of a fishery data reporting system can be quantified in monetary terms, many of the benefits of fishery data reporting system are much more difficult to quantify, particularly when comparing one reporting system to another (e.g assigning a dollar value to higher quality data) (Northern Economics, Inc.

2015). For these reasons, I opted for a more qualitative assessment of the costs and benefits of the transition from paper to digital in MDPI's small-scale tuna fishery. This CBA evaluates data collection costs and benefits only (it excludes office operating cost, overhead, etc. because Dock would not affect these costs).

I used the following steps outlined by Boardman et al. 2011 to conduct the CBA:

(1) **Identified a set of alternatives.** Using findings from the pilot study as a guideline, I identified three potential alternatives. The first alternative was the status quo (i.e. continuing to use paper-based data collection methods at all 13 field sites operated by MDPI), the second alternative was implementing Dock at all 13 sites, and the third alternative was partial implementation of Dock (i.e. continuing to use paper-based methods at some sites while implementing Dock at others).

(2) **Identified impact categories.** Impact categories included inputs (i.e. required resources) and outputs (i.e. expected outcomes) (Boardman et al. 2011). The anticipated cost impact category included high initial implementation and ongoing equipment costs. The anticipated benefit impact category included reduced time lag from data collection to availability of use. Transitioning from hand-written forms to electronic data collection will likely reduce the amount of time enumerators spend entering data. A shift to an interagency electronic reporting system in Alaska commercial fisheries resulted in agency staff spending less than half the time they had spent entering data using legacy paper-based systems (Northern Economics, Inc. 2015). This was largely due to elimination of redundant data entry effort (i.e. one-time data entry of reports), which will likely also occur when using Dock as enumerators would enter data only once, into the app, that would then automatically sync to an online database (as opposed to first recording on paper, then entering into an Excel spreadsheet, then uploading to database). This, in turn, would likely result in reduced labor cost per sampling event.

(3) **Monetized (attached dollar values to) all impacts.**

COSTS:

Implementation and ongoing equipment costs: I used calculations from the equipment cost metric above as initial implementation and ongoing equipment costs (using paper-based methods for alternative 1, using Dock for alternative 2, and using paper-based methods at some sites and Dock at others for alternative 3). Lastly, I calculated percent increase in equipment costs to compare alternatives.

BENEFITS:

Labor cost: I monetized time lag reduction in data collection by converting time saved or time lost (depending on site) to labor cost reduction (or increase) per sampling event. As described earlier, a sampling event is defined as the collection of catch data from an individual vessel during an unloading event, entering that data into a digital platform, and uploading that data to the online database. In other words, a sampling event is the completion of tasks 1-6 defined earlier when outlining the time metric.

For alternative 1, I reported total annual labor cost using paper-based data collection methods at all 13 sites. To calculate labor cost estimates for alternative

2, I calculated labor cost increase (as a proxy for time lost) for the 9 sites deemed comparable to Larantuka (enumerators lost time using Dock): Assilulu (Ambon), Bitung, Bone, Larantuka, Pasar Wajo (Sulawesi), Seram, Sorong, Tolitoli, and Tulehu (Ambon) (see Appendix G for a detailed description of labor cost calculations). I then calculated labor cost decrease (as a proxy for time saved) for the 4 sites deemed comparable to Kupang (enumerators saved time using Dock): Kupang, Lombok, North Buru, and South Buru. Lastly, I added labor cost increase at the 9 sites (time lost) to labor cost decrease at the 4 sites (time saved) to get total labor cost using Dock at all 13 sites. Calculating labor cost estimates for alternative 3 included adding current labor cost using paper-based methods at the 9 sites listed above and estimated labor costs using Dock at the 4 sites projected to be 'time saved' sites. Lastly, I calculated percent decrease in labor cost to compare alternatives.

COMPARING COSTS AND BENEFITS: Finally, I calculated total cost of each alternative by adding costs (implementation and ongoing equipment costs) and benefits (labor cost) to allow comparison over a 5-year time horizon. To compare alternatives, I calculated percent increase/decrease in total cost per year as well as over a 5-year time horizon.

Interviews

Momo Kochen's and Deirdre Duggan's interview responses were used as anecdotal evidence to support observed patterns from pilot study data and provide relevant context.

3.0 RESULTS

3.1 Market-testing Dock

Forty different NGOs participated in the survey, some of which included World Wildlife Fund, The Nature Conservancy, Conservation International, Oceana, Sustainable Fisheries Partnership, and Blue Ventures (see Appendix H for demographic information about survey respondents according to NGO name, age, gender, and organizational role). Together, they operate 99 different fisheries data collection programs worldwide and monitor an average of 7 field sites. Majority of respondents are Program Managers (48%), followed by Project Coordinators (28%) (n=40). Other roles include Executive Director, Data Manager, Science Advisor, and University Professor. Most respondents (72%) reported 'sustainable resource management' as being the primary purpose of their fisheries data collection program. Because some respondents did not answer all survey questions, or only answered certain questions without completing the survey, the results show different sample sizes for each category.

Ranked-choice data

Ranking of organizational goals: Most respondents ranked 'sustainable management of local resources,' 'sustainability of target fish stocks,' and 'marine protection and conservation' as organizational goals of highest importance (69%, 56%, and 48%, respectively) (Figure 3).

Conversely, most respondents ranked ‘addressing IUU fishing,’ ‘establishing the infrastructure for data-rich decision support tools,’ and ‘seafood traceability’ as goals of lowest importance (67%, 61%, and 55%, respectively).

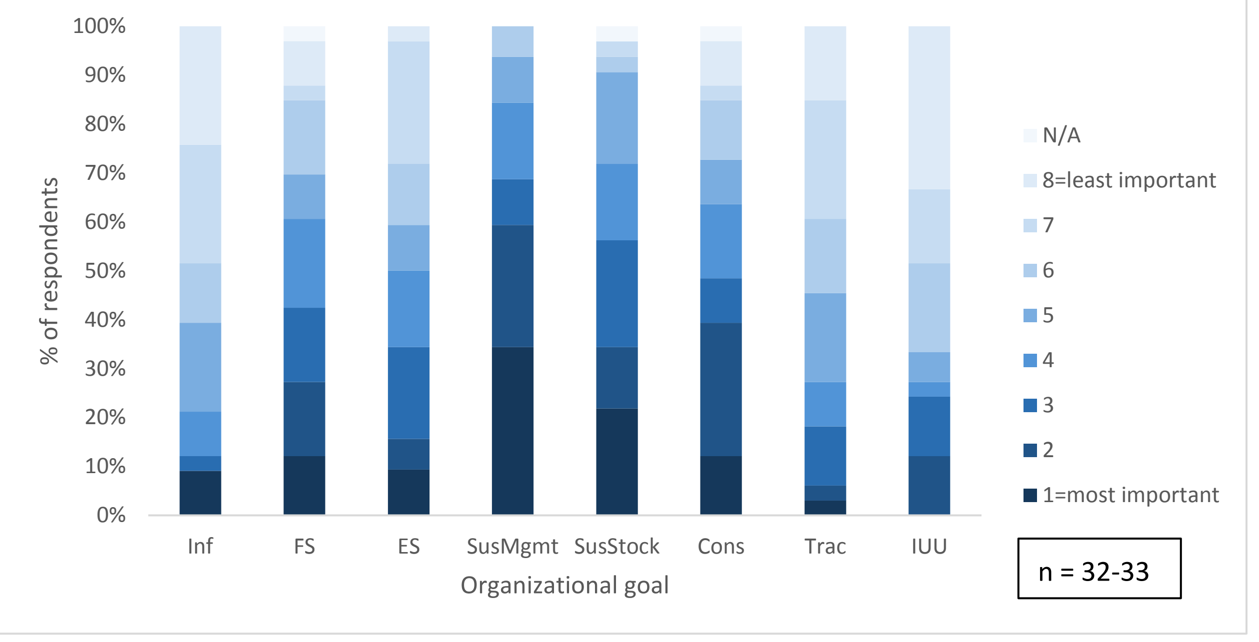


Figure 3. Stated rankings of organizational goals. Refer to Table 2 for description of abbreviated goals on the x-axis. Due to differences in response rate, sample sizes per category ranged from 32-33 (n=33 for 5 of the 8 total categories, n=32 for the remaining 3).

Table 2. Description of organizational goals ranked by respondents in Figure 3.

Abbreviation	**Organizational goal**
Inf	Establishing the infrastructure for data-rich decision support tools
FS	Food security of local community
ES	Economic security of local community
SusMgmt	Sustainable management of local resources
SusStock	Sustainability of target fish stocks
Cons	Marine protection and conservation
Trac	Seafood traceability
IUU	Addressing IUU fishing

According to the Kruskal-Wallis one-way ANOVA, there were significant differences among average rankings of the 8 goals (p-val<10^{-5}). A series of Mann-Whitney U tests revealed that the rankings assigned to ‘sustainable management of local resources’ and ‘sustainability of target fish stocks’ as being the 1st and 2nd most important goals were not due to chance (p-val<10^{-5} and p-val=0.003, respectively), but ranking of 'marine protection and conservation' as being the 3rd most important goal may have been due to chance (p-val=0.129). Looking at lowest-ranked goals, rankings assigned to 'addressing IUU fishing,' 'establishing the infrastructure for data-rich decision support tools,' and 'seafood traceability' as 1st, 2nd, and 3rd goals of lowest importance were not due to chance (p-val<10^{-5}, p-val<10^{-5}, and p-val=.005, respectively).

Ranking of value of types of data collected: Most respondents ranked 'species type,' 'gear type,' 'harvest location,' and 'catch per unit effort (CPUE)' as indicators of high value (86%, 79%, 71%, and 71%, respectively) (Figure 4).

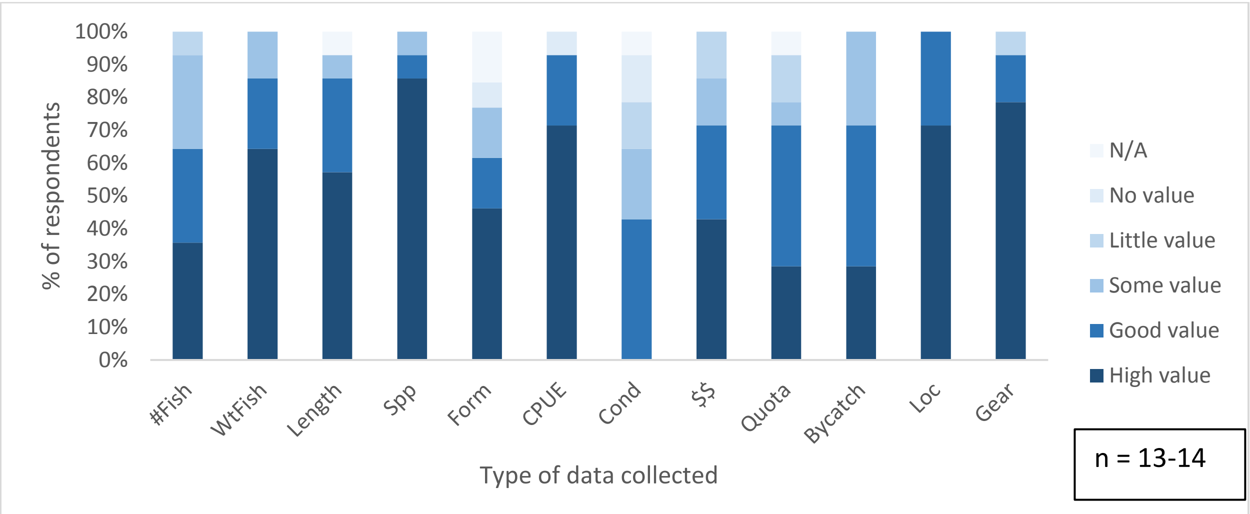


Figure 4. Stated rankings of value of types of data collected. Refer to Table 3 for descriptions of abbreviated types of data on the x-axis. Due to differences in response rate, sample sizes per category ranged from 13-14 (n=14 for 10 of the 12 total categories, n=13 for the remaining 2).

Table 3. Description of types of data collected ranked by respondents in Figure 4.

Abbreviation	Type of data collected
#Fish	Total number of fish caught
WtFish	Total weight of fish caught
Length	Individual fish length
Spp	Species type
Form	Catch form
CPUE	Catch per unit effort
Cond	Catch condition
$$	Market price
Quota	Quota monitoring and tracking
Bycatch	Bycatch
Loc	Harvest location

Gear	Gear type

According to the Kruskal-Wallis one-way ANOVA, there were significant differences among average rankings of the 8 goals (p-val=0.001). A series of Mann-Whitney U tests revealed that the rankings assigned to 'species type' as being the highest value data type was not due to chance (p-val=0.032). Conversely, the ranking of 'gear type' as being the 2nd most valued data type may have been due to chance (p-val=0.099), suggesting that the 3rd and 4th most valued ('harvest location' and 'catch per unit effort (CPUE)') may have also been due to chance.

Ranking of fisheries data collection issues of concern: Most respondents ranked 'data quality assurance and quality control (QA/QC),' 'building local capacity/infrastructure,' and 'incentives to stakeholders for providing data' as issues of concern of highest significance (62%, 57%, and 43%, respectively) (Figure 5). 43% of respondents ranked 'building local capacity/infrastructure' as the utmost significant issue of concern (ranked as #1), implying that this issue is most concerning to NGOs. Further, 43% of respondents ranked 'stakeholder incentives' as #2, implying this the second issue of highest significance. Rankings from 1-3 for QA/QC were more spread out, suggesting less consensus among NGOs regarding its significance. Conversely, 89% of respondents reported 'time required to collect and process data' as an issue of least concern, followed by 'immediacy of data availability' (43%) and 'cost of collecting data' (36%).

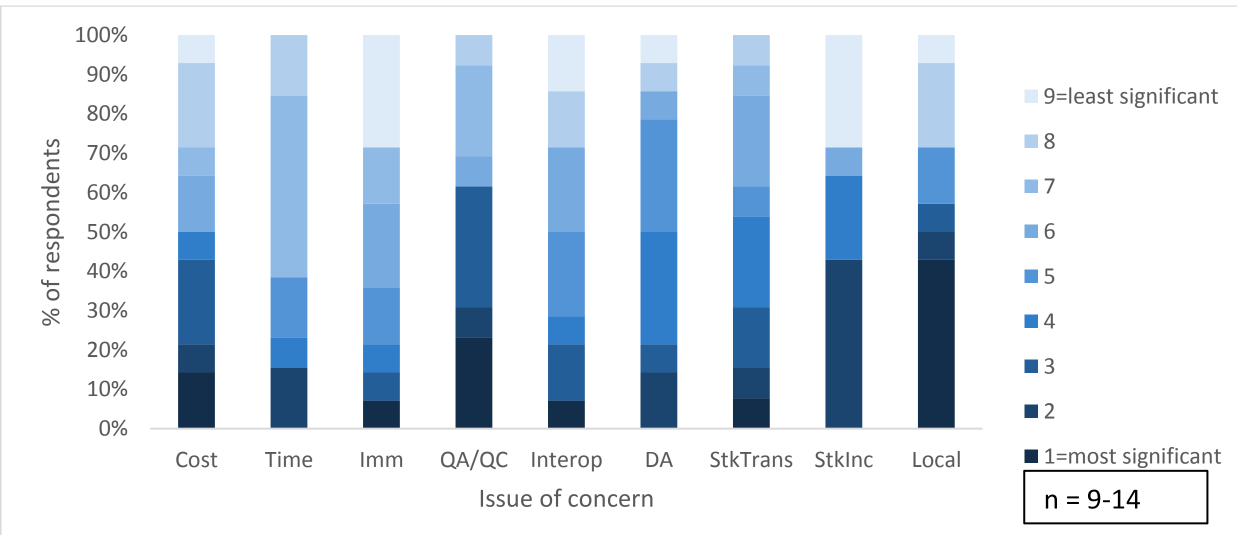


Figure 5. Stated rankings of fisheries data collection issues of concern. Refer to Table 4 for descriptions of abbreviated issues of concern on the x-axis. Due to differences in response rate, sample sizes per category ranged from 13-14 (n=14 for 6 of the 9 total categories, n=13 for 2 of the categories, and n=9 for 1 category).

Table 4. Description of fisheries data collection issues of concern ranked by respondents in Figure 5.

Abbreviation	Issue of concern
Cost	Cost of collecting data
Time	Time required to collect and process data
Imm	Immediacy of data availability
QA/QC	Data quality assurance and quality control (QA/QC)
Interop	Data interoperability across seafood value chain
DA	Data analysis
StkTrans	Stakeholder transparency
StkInc	Incentives to stakeholders for providing data
Local	Building local capacity/infrastructure

The lack of consensus regarding significance of issues of concern demonstrated above was further supported by the results of the Kruskal-Wallis one-way ANOVA as there were no significant differences among average rankings of the 9 issues of concern (p-val=0.239). Although they were not statistically significant, 'building local capacity/infrastructure' and 'data quality assurance and quality control (QA/QC)' were ranked as the 1st and 2nd most significant issues of concern (p-val=0.092 and 0.171, respectively), reflecting the same pattern seen in the figure above. Similarly, despite lack of significant differences, 'immediacy of data availability' and 'time required to collect and process data' were the 1st and 2nd lowest ranking issues of concern (p-val=0.061 and 0.166, respectively).

Other categorical data

Types of data collectors: Respondents reported high variability in types of data collectors. 59% reported collecting data using enumerators, with 32% relying solely on this category of data collector for obtaining fisheries data (Figure 6). 36% reported collecting data from 'Other' sources, with 23% relying solely on these other types of data collectors for obtaining data ('Other' includes processors, fisheries independent scientists, seafood business operators, and suppliers).

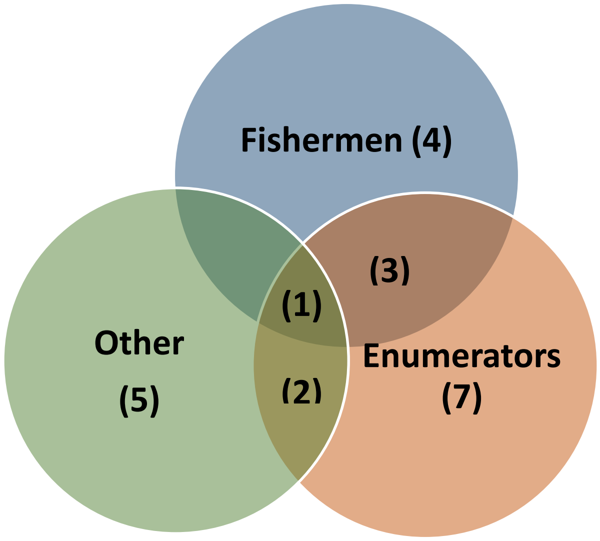


Figure 6. Stated types of data collectors. 'Other' includes processors, fisheries independent scientists, seafood business operators, and suppliers (n=22).

Platform for fisheries data capture: 67% of respondents reported using paper data collection methods as opposed to digital (e.g. online or mobile tool) (n=9). According to the exact test of goodness-of-fit, the number of respondents using paper-based methods was not significantly higher than those using digital methods, meaning I cannot reject the null hypothesis that this result may have occurred due to chance (p-val=0.508, n=9).

Numerical data

Time lag between data recording and usability: Respondents reported high variability in time lag between data collection and availability of use, ranging from 7 to 105 days. 61.5% of respondent reported a time lag of 28 to 70 days (median=35 days, n=13).

Annual cost of fisheries data collection: Respondents reported spending $50,000 to $150,000 annually on fisheries data collection each year (mean=$99,000, n=5).

From market-testing the app, I found that NGOs want to sustainably manage local resources and they value tracking species and gear type. These are items that the app could theoretically aid NGOs in accomplishing more efficiently. In order to transition from a theoretical exercise to practical application, Dock was piloted in the field to get more insight into fisheries data collection programs on the ground.

3.2 Field-testing Dock

Time taken to collect fisheries data

Per test site

Larantuka:

(1) Time to complete each individual task: When comparing time taken to complete tasks 3-6 individually, data collectors took significantly less time to complete task 3 when using Dock and significantly more time to complete task 5 when using Dock than when using paper-based methods (see Table 5 for means and p-values). Conversely, time taken to complete tasks 4 and 6 did not differ significantly among data collection methods.

(2) Time to complete all data tasks: Overall, data collectors at Larantuka tended to lose time using Dock when completing individual data collection tasks (Figure 7). To compare paper to Dock, I ran t-tests to compare average time to complete all tasks (tasks 3-6 only because missing data for tasks 1 and 2). There was no statistically significant difference in time taken to complete tasks 3-6 when using paper or Dock (mean=22 min and 29 min, respectively, p-val=0.095). Despite lack of significant differences, using Dock increased data collection time by 34%, on average.

Table 5. Results from t-tests comparing time taken to complete each individual data collection task using paper-based methods v. Dock at Larantuka. Rows in red indicate significant differences according to significance level alpha=0.05.

Abbreviation	**Data collection task**	**means (in minutes)**	**t-stat**	**p-value**
(1) Measure	Collecting fisheries data (e.g. length, weight)	Missing data	Missing data	Missing data
(2) Interview	Interviewing fishermen	Missing data	Missing data	Missing data
(3) Recap	**Checking and completing data**	**Paper=4, Dock=0**	**6.31**	**$<10^{-5}$**
(4) Data entry	Entering data into Excel spreadsheet OR into Dock app	Paper=11, Dock=18	-2.09	0.059
(5) Verify	**Checking and verifying data before uploading to database OR I-Fish**	**Paper=4, Dock=7**	**-2.37**	**0.028**
(6) Upload	Uploading to database OR I-Fish	Paper=2, Dock=5	-1.75	0.099

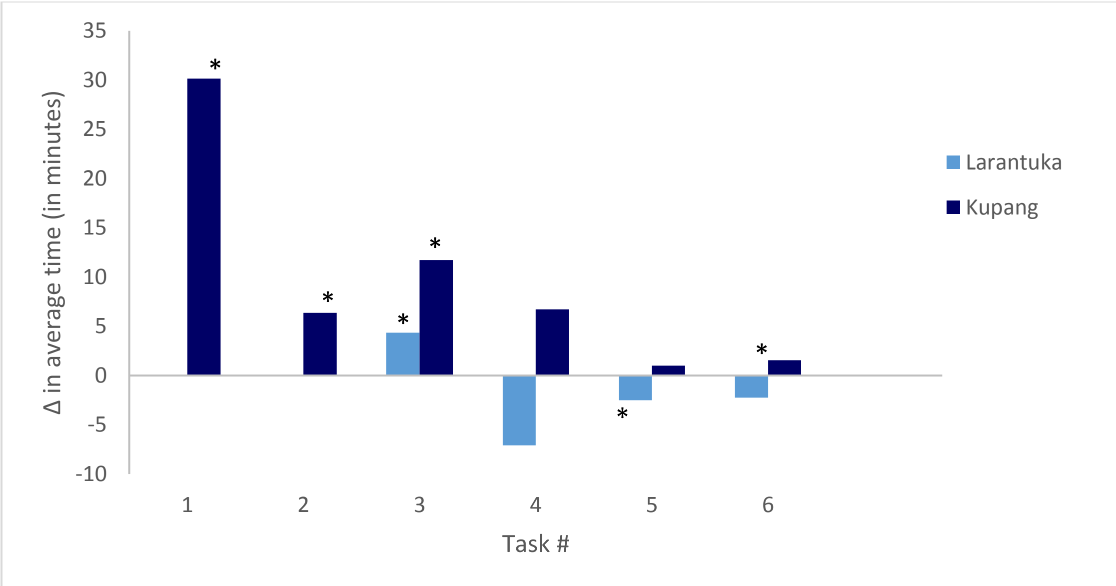


Figure 7. Difference in average time required to complete each individual task when using paper and when using the app. Positive values represent time saved using the app, negative values represent time lost using the app. Asterisks indicate significant differences. The bars missing for tasks 1 and 2 for Larantuka are due to missing data.

Kupang:

(1) Time to complete each individual task: When comparing time taken to complete tasks 1-6 individually, data collectors took significantly less time to complete tasks 1-3 and task 6 when using Dock (see Table 6 for means and p-values). Conversely, time taken to complete tasks 4-5 did not differ significantly among data collection methods.

(2) Time to complete all data tasks: Overall, data collectors at Kupang tended to save time when completing individual data collection tasks using Dock (Figure 7). To compare paper to Dock, I ran t-tests to compare average time to complete all tasks (tasks 1-6) as well as for tasks 3-6 to allow comparison across sites (Larantuka v. Kupang). Completing tasks 1-6 took significantly less time when using Dock than when using paper (mean=55 min and 109 min, respectively, p-val=0.002). Further, using Dock decreased data collection time by 53%, on average. Similarly, data collectors saved a significant amount of time when completing tasks 3-6 using Dock than when using paper (mean=28 min, 49 min, respectively, p-val=0.012). Further, using Dock decreased data collection time by 43%, on average.

Table 6. Results from t-tests comparing time taken to complete each individual data collection task using paper-based methods v. Dock at Kupang. Rows in red indicate significant differences according to significance level alpha=0.05.

Abbreviation	Data collection task	means (in minutes)	t-stat	p-value

(1) Measure	**Collecting fisheries data (e.g. length, weight)**	**Paper=48, Dock=18**	**4.31**	**0.002**
(2) Interview	**Interviewing fishermen**	**Paper=12, Dock=6**	**2.83**	**0.016**
(3) Recap	**Checking and completing data**	**Paper=12, Dock=0**	**4.80**	**0.001**
(4) Data entry	Entering data into Excel spreadsheet OR into Dock app	Paper=25, Dock=18	1.08	0.297
(5) Verify	Checking and verifying data before uploading to database OR I-Fish	Paper=8, Dock=7	0.908	0.376
(6) Upload	**Uploading to database OR I-Fish**	**Paper=4, Dock=2**	**2.65**	**0.024**

Comparing sites

Average overall time taken to collect data using paper-based methods was significantly greater at Larantuka than at Kupang (mean=11.1 hours and 7.3 hours, respectively; p-value=0.045). Interestingly, time spent completing data tasks 1-6 constituted an average of 9% (mean=57 min) of the overall time at Larantuka and 25% of overall data collection time at Kupang (mean=109 min).

Average time required to complete all data collection tasks was significantly greater at Kupang than at Larantuka (mean=109 minutes and 57 minutes, respectively; p-value=0.000). On average, total catch (kg) per sampling event was significantly greater at Kupang than at Larantuka (mean= 2,989 kg and 1,669 kg, respectively; p-value=0.047). Similarly, total number of fish sampled per sampling event was, on average, significantly greater at Kupang than at Larantuka (mean= 218 fish and 106 fish, respectively; p-value= 0.007).

Overall time taken to collect data (tasks 3-6) using Dock was almost identical at both Larantuka and Kupang (mean=32 min and 30 min, respectively).

Cost of fisheries data collection

The following calculations represent static equipment and labor costs (calculated for a single year).

Equipment Cost

Per test site: Each year, equipment for collecting fisheries data using paper-based data collection methods costs IDR 7,185,410 (US $527) at Larantuka and IDR 9,240,410 (US $677) at Kupang (Table 7). Using Dock would increase annual equipment cost to IDR 25,054,680 (US $1,837; 249% increase) at Larantuka and IDR 28,633,064 (US $2,099; 210% increase) at Kupang. Refer to Appendix D for details outlining how I calculated annual equipment costs per site.

Table 7. Itemized annual equipment cost per site using current data collection methods (Paper) and a smartphone app (Dock). Calculations were made according to costs

expended during a trial period beginning February 2016. Total overall cost in Indonesian Rupiah (IDR) was converted to U.S. dollars (US $) using the following exchange rate: US $1 = IDR 13,212.

	LARANTUKA		**KUPANG**	
	Paper	**Dock**	**Paper**	**Dock**
Item	**Total annual cost (IDR)**	**Total annual cost (IDR)**	**Total annual cost (IDR)**	**Total annual cost (IDR)**
Laptop	3,000,000	3,000,000	1,680,000	1,680,000
Handphone (non-Dock phone)	1,116,667	1,116,667	2,666,667	2,666,667
Printer	0	-	350,000	-
Paper clipboard	35,000	-	70,000	-
Pens (1 dozen)	25,000	-	50,000	-
Printed form paper bundle	60,000	-	300,000	-
Calculator	150,000	150,000	300,000	300,000
Modem for uploading data to database	116,667	116,667	116,667	116,667
Monthly internet package for modem	1,657,077	1,657,077	1,657,077	1,657,077
Calipers	500,000	500,000	1,000,000	1,000,000
Measuring board	500,000	500,000	1,000,000	1,000,000
5-6 Ember/bucket	25,000	25,000	50,000	50,000
Android phone	-	2,133,333	-	3,200,000
Sim card (without pulsa)	-	4,000	-	6,000
Pulsa (includes call and data)	-	2,209,436	-	3,314,154
Cost per site to operate Dock	-	13,642,500	-	13,642,500
TOTAL OVERALL COST:	**7,185,410 (US $527)**	**25,054,680 (US $1,837)**	**9,240,410 (US $677)**	**28,633,064 (US $2,099)**

<u>All sites</u>: MDPI currently operates 13 field sites, spending an average of IDR 8,526,692 (US $622) on equipment per site annually using paper-based data collection. Using Dock would increase average equipment cost per site to IDR 25,504,151 (US $1,862); 200% increase).

Total annual equipment cost for operating all 13 sites using paper-based data collection methods is IDR 110,847,001 (US $8,092). Using Dock at all sites would increase total annual cost to IDR 331,553,964 (US $24,203; 199% increase). This does not include the one-time Dock subscription fee of IDR 273,972,603 (US $20,000), which would increase the cost to IDR 605,526,566 (US $44,203) during the first year of operation.

Labor Cost

Labor cost remains unchanged regardless of data collection method (paper v. Dock). Annual labor cost varies by an order of magnitude among the 13 field sites, ranging from IDR 23,141,800 (US $1,689) at Assilulu (Ambon) to IDR 136,293,598 (US $9,949) at Lombok, and averaging IDR 76,162,306 (US $5,560) per site. Total annual labor cost for operating all 13 sites is IDR 990,109,978 (US $72,278).

Total cost

Combining annual equipment and labor cost, MDPI currently spends an average of IDR 84,688,998 (US $6,182) in total cost per site using paper-based methods. Using Dock would increase average total cost per site to IDR 101,666,457 (US $7,422; 20% increase).

Cost-benefit analysis

(1) Alternatives:

Alternative 1: Status quo. This option involves no change from the current system and no implementation of electronic data collection (i.e. continuing to use paper-based data collection methods) and was used as the base case against which I compared alternative options.

Alternative 2: Implementing Dock at all 13 field sites

Alternative 3: Implementing Dock at 4 field sites only. This scenario includes only 4 of the total 13 sites due to site-by-site differences. Specifically, the pilot study revealed dockside monitors saving time at one site (Kupang) but not the other (Larantuka). Thus, the 4 sites included in this scenario are those that are similar to Kupang – namely, they are busier ports (more vessels sampled), have more enumerators on site, a more reliable internet connection, and predictable vessel unloading events. The remaining 9 sites not included in this scenario are similar to Larantuka – namely, they are less busy (less vessels sampled), have fewer enumerators on site, an unreliable internet connection, and random vessel unloading events.

(2) Monetizing impact categories:

COSTS:

Implementation and ongoing equipment costs: Cost estimates (see Table 8) are the same as those reported above for total annual equipment cost for operating all 13 sites. Alternative 1 includes equipment costs using paper-based data collection methods at all 13 sites, alternative 2 includes equipment costs using Dock at all 13 sites, and alternative 3 includes projected equipment costs using Dock at 4 sites (Kupang, Lombok, North Buru, and South Buru) and current equipment costs of using paper-based methods at the remaining 9 sites (Assilulu (Ambon), Bitung, Bone, Larantuka, Pasar Wajo (Sulawesi), Seram, Sorong, Tolitoli, and Tulehu (Ambon)). The increased cost observed during the first year for alternatives 2 and 3 is due to the one-time Dock subscription fee.

Implementation of alternative 2 would result in a 446% increase in implementation and ongoing equipment costs during the first year, followed by a 199% cost increase in subsequent years. Alternative 3 would cause equipment costs to increase by 315% during the first year, followed by a 68% increase in ongoing costs in subsequent years.

BENEFITS:

Labor cost: Alternative 1 includes total annual labor cost using paper-based data collection methods at all 13 sites (reported above when discussing cost metric) (see Table 8). Alternative 2 includes labor cost using Dock at all 13 sites, which includes a cost increase for the 9 sites deemed comparable to Larantuka (enumerators lost time using Dock: Assilulu (Ambon), Bitung, Bone, Pasar Wajo (Sulawesi), Seram, Sorong, Tolitoli, and Tulehu (Ambon)) and cost decrease for the 4 sites deemed comparable to Kupang (enumerators saved time using Dock: Lombok, North Buru, and South Buru).

Alternative 3 includes labor cost using Dock at the 4 sites listed in the previous sentence and using paper-based methods at the remaining 9 sites.

Implementation of alternatives 2 or 3 would cause an almost identical decrease in labor cost (37% and 38%, respectively).

Table 8. Comparing costs and benefits of 3 different alternatives.

	ALTERNATIVE 1: STATUS QUO		
	COSTS	**BENEFITS**	
Year	**Implementation & ongoing costs**	**Labor cost**	**Total cost**
2017	IDR 110,847,001 (US $8,092)	IDR 990,109,978 (US $72,278)	IDR 1,100,956,979 (US $80,370)
2018	IDR 110,847,001 (US $8,092)	IDR 990,109,978 (US $72,278)	IDR 1,100,956,979 (US $80,370)
2019	IDR 110,847,001 (US $8,092)	IDR 990,109,978 (US $72,278)	IDR 1,100,956,979 (US $80,370)
2020	IDR 110,847,001 (US $8,092)	IDR 990,109,978 (US $72,278)	IDR 1,100,956,979 (US $80,370)
2021	IDR 110,847,001 (US $8,092)	IDR 990,109,978 (US $72,278)	IDR 1,100,956,979 (US $80,370)
Total:			**IDR 5,504,784,893 (US $401,849)**
	ALTERNATIVE 2: DOCK AT ALL 13 SITES		
	COSTS	**BENEFITS**	
Year	**Implementation & ongoing costs**	**Labor cost**	**Total cost**
2017	IDR 605,526,566 (US $44,203)*	IDR 623,097,744 (US $45,486)	IDR 1,228,624,310 (US $89,689)
2018	IDR 331,553,964 (US $24,203)	IDR 623,097,744 (US $45,486)	IDR 954,651,708 (US $69,689)

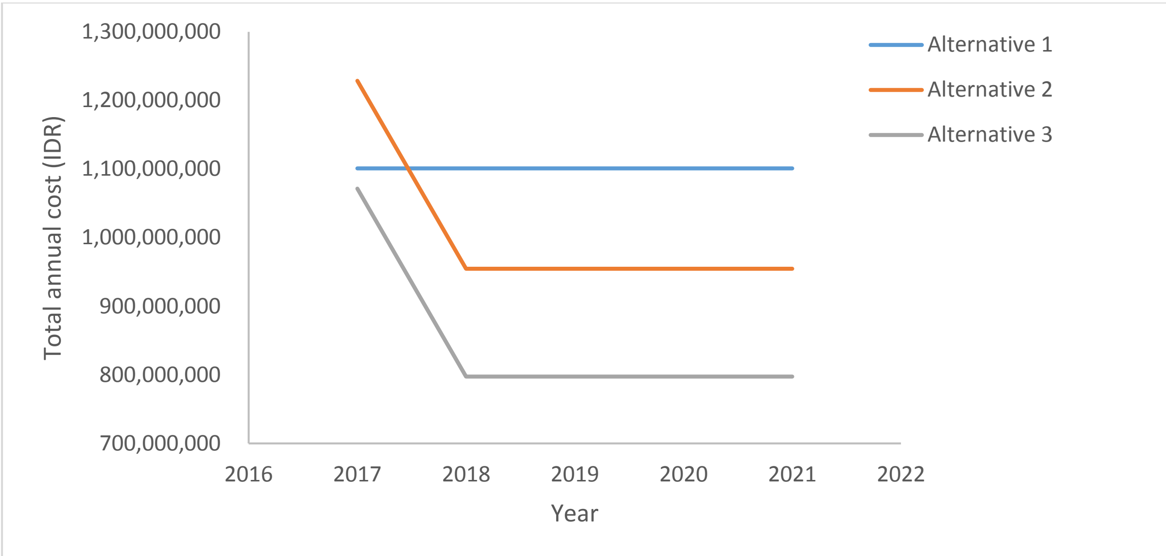
2019	IDR 331,553,964 (US $24,203)	IDR 623,097,744 (US $45,486)	IDR 954,651,708 (US $69,689)
2020	IDR 331,553,964 (US $24,203)	IDR 623,097,744 (US $45,486)	IDR 954,651,708 (US $69,689)
2021	IDR 331,553,964 (US $24,203)	IDR 623,097,744 (US $45,486)	IDR 954,651,708 (US $69,689)
Total:			**IDR 5,047,231,141 (US $368,447)**
	ALTERNATIVE 3: DOCK AT 4 SITES ONLY		
	COSTS	**BENEFITS**	
Year	**Implementation & ongoing costs**	**Labor cost**	**Total cost**
2017	IDR 460,036,835 (US $33,582)*	IDR 611,394,006 (US $44,632)	IDR 1,071,430,841 (US $78,214)
2018	IDR 186,064,232 (US $13,583)	IDR 611,394,006 (US $44,632)	IDR 797,458,238 (US $58,215)
2019	IDR 186,064,232 (US $13,583)	IDR 611,394,006 (US $44,632)	IDR 797,458,238 (US $58,215)
2020	IDR 186,064,232 (US $13,583)	IDR 611,394,006 (US $44,632)	IDR 797,458,238 (US $58,215)
2021	IDR 186,064,232 (US $13,583)	IDR 611,394,006 (US $44,632)	IDR 797,458,238 (US $58,215)
Total:			**IDR 4,261,263,794 (US $311,073)**

*Increased cost due to one-time Dock subscription fee

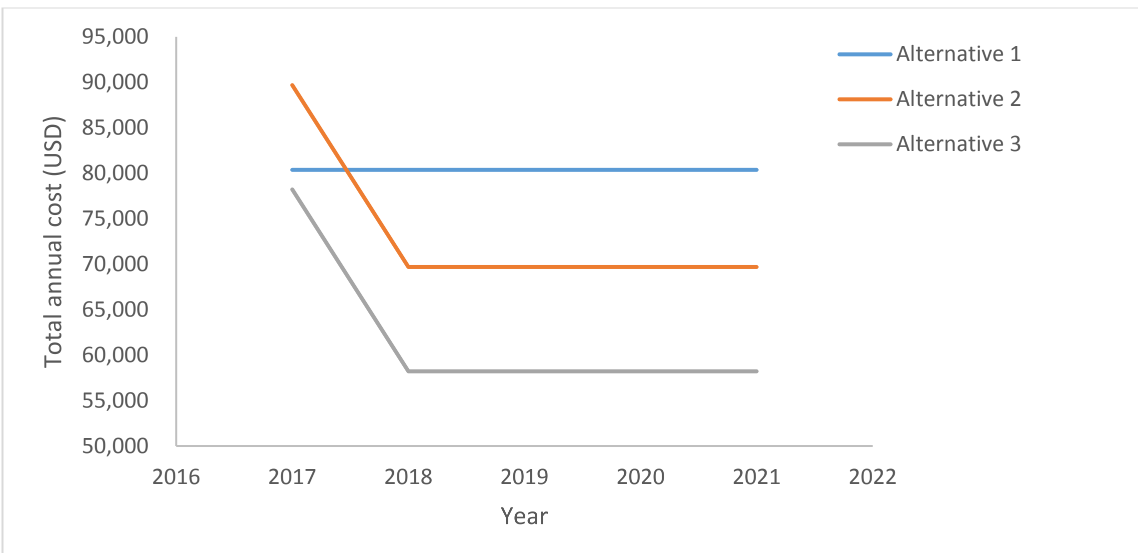
COMPARING COSTS AND BENEFITS:

Combining costs (high implementation and ongoing equipment costs) and benefits (decreased labor cost), comparison of total cost among the three alternatives showed that implementation of alternative 2 would result in a 12% increase in total costs during the first year, followed by a 13% cost decrease in subsequent years. Alternative 3 would cause total costs to decrease by 3% during the first year, followed by a 28% decrease in subsequent years (Table 8).

Over a 5-year horizon, alternatives 2 and 3 are projected to decrease overall cost (Figure 8). Specifically, alternative 2 would decrease total cost from IDR 5,504,784,893 (US $401,849) to IDR 5,047,231,141 (US $368,447) (8% decrease) and alternative 3 would decrease cost from IDR 5,504,784,893 (US $401,849) to IDR 4,261,263,794 (US $311,073) (23% decrease).



(a) Total cost of each alternative (in Indonesian Rupiah)



(b) Total cost of each alternative (in U.S. dollars)

Figure 8. Comparison of total cost in (a) IDR and (b) USD of the 3 alternatives over a 5-year horizon.

4.0 DISCUSSION

4.1 Market-testing Dock

Ranked-choice data

Ranking of organizational goals: Survey responses demonstrated that NGOs pursue sustainable resource management so long as it does not negatively impact local stakeholders. Human-centered objectives (food and economic security of the local community) were consistently ranked just below this top goal, suggesting that surveyed NGOs are first concerned with the health of the local ecosystem, and second with the communities themselves. NGO representatives see themselves as advocates of local community empowerment, a theme that surfaced repeatedly in interviews. As Momo Kochen of MDPI stated, “MDPI is trying to empower the stakeholders from fishermen and up through the supply chain.” This implies that both environmental and social elements must be considered when contemplating changes to existing fisheries data collection programs.

The low-ranking of traceability as an important organizational goal is likely due not to lack of interest, but instead due to lack of funds. NGOs are highly cost sensitive, and funding is limited and specific. Although NGOs are unlikely to fund end-to-end traceability, the frequency with which interviewees mentioned its importance implies its value to NGOs.

Ranking of fisheries data collection issues of concern: Organizations demonstrated less unanimity around concerns specific to fisheries data collection programs. Despite this, building local capacity emerged as the top issue of concern. NGO representatives work with many different stakeholders in the fisheries space: partner NGOs, USAID, governments, foundations, importers, exporters, processors, local communities, and local fishermen. Coordinating the efforts of these different actors requires substantial capacity and infrastructure to support and nurture collaborations.

Incentivizing stakeholders to provide data, a related concern, has proven a major challenge for NGOs. Oftentimes this is because stakeholders, particularly fishermen, fail to see the value of collecting these data. According to Matt Fox of CI Indonesia, “It’s not a culture of science. They don’t understand what this data is used for and think this data is useless. [Sometimes it’s just about] handing in a piece of paper to make sure they get paid.” As Momo Kochen of MDPI put it, “going to a community and getting buy-in isn’t an easy process; the incentive is still not really there, but the goal is making the data they do collect of tangible interest to them.” While it is true that properly incentivizing stakeholders will likely improve data quality, demonstrating how this data can benefit stakeholders, especially fishermen, is key to stakeholder support and will likely improve long-term success of the data collection program.

Because NGO representatives feel their efforts are closely linked to the communities in which they work, data QA/QC was ranked as a concern of lower significance. This further demonstrates the intimate relationship NGOs have with the local communities they serve, again reiterating the importance of considering social elements in addition to environmental conservation concerns.

Interestingly, most NGO respondents were least concerned with ‘time required to collect and process data’, followed by ‘immediacy of data availability’. Additionally, ‘cost of collecting data’ was the third least important concern. This implies that, among NGOs, the importance of time lag between data collection and availability of use as well as cost pales in comparison to other concerns. However, these lower-ranked concerns are intimately linked with the highest-ranked concerns. Monitoring of fisheries catch data in near-real time would likely allow more flexibility to collaborate with fishermen in managing the fishery (e.g. allocating quotas, responding to in-season closures), thereby allowing organizations to better address concerns regarding incentivizing stakeholders and building local capacity. Secondly, timely reporting of catch data could potentially reduce negative impacts to local stocks (e.g. stock overexploitation events), which could aid organizations in better achieving sustainable management of local resources.

Other categorical data

Types of data collectors: Most NGOs collect data from enumerators, or dockside monitors, who collect fisheries catch information from fishermen during vessel unloading events. Enumerators are employed by the NGOs themselves, meaning they can more directly influence the data collection process (as opposed to attempting to convince and subsequently train external stakeholders such as fishermen or seafood buyers). However, NGO representatives must consider employee adoption rate when implementing a tool such as Dock. Many fisheries data collection programs are located in remote fishing villages where literacy levels might be low. Additionally, exposure to mobile technology may be limited, meaning training would require significant time investment for familiarization (Popma 2015). Issues surrounding employee adoption rate and potential solutions are discussed later in the 'Field-testing Dock' section.

Platform for fisheries data capture: Although most respondents reported collecting data using paper-based methods, the number of NGOs using paper was not significantly higher than those using digital methods. This is encouraging because it implies that a noticeable proportion of NGOs are familiar with digital data collection, suggesting that the movement away from paper has already begun. A survey of 62 government agency employees asked participants to prioritize a series of science-and-technology (S&T) innovations according to their potential to improve regional fisheries management of Associated of Southeast Asian Nation (ASEAN) and Coral Triangle countries. Participants ranked electronic monitoring (EM), video monitoring systems (VMS), and electronic reporting (ER) as 1st, 2nd, and 3rd most promising, respectively. Smartphone and crowd-sourcing apps ranked as the 4th most promising for improving fisheries-dependent data collection (PIFSC 2015).

Prior exposure to other technologies (EM, VMS, ER) may facilitate higher levels of acceptance of a smartphone app like Dock which, in turn, may increase willingness to consider integrating digital tools into fisheries data collection programs as it is not a completely foreign concept. However, smartphone apps are still not widely used or popular, suggesting there is opportunity to demonstrate the potential benefits of using a smartphone app for data collection in small-scale fisheries.

Numerical data

Time lag between data recording and usability: The wide-ranging answers for length of time between data collection and usability implies high variability in data collection processes among NGOs, and may even reflect the disorganized nature of current data collection methods in these programs.

Annual cost of fisheries data collection: Similarly, the range in program cost estimations implies that the amount of funding allocated to fisheries data collection varies considerably among NGOs. For these reasons, it is important for NGOs to first assign a level of priority to their data collection program in relation to other programs requiring funding before deciding if implementing a tool like Dock is worthwhile.

Potential impacts of Dock

Internet connectivity appears to be the most prevalent potential obstacle to transitioning to an electronic dockside monitoring solution. Poor connectivity is due to the remoteness of these field sites, riddled with logistical complications. According to Mariana Velez of TNC, "connectivity is the biggest concern in the developing world." In places like Indonesia, which contains the seventh largest population of smartphone users in the world (eMarketer 2014), familiarity with mobile technology is not the issue: "fishermen do have phones, but they need a system that can work with limited connectivity" – Momo Kochen, MDPI. For instance, Momo claimed that even very remote villages have a sporadic Wi-Fi connection, but oftentimes it only works during inconvenient hours such as 3am. With this in mind, Dock must work with limited internet connectivity, making offline data collection and storage a necessity (Popma 2015). For instance, Dock could include a sync-activation feature that automatically updates stored data when an active internet connection is detected. This would eliminate much of the headache around data submission.

Because most NGOs collect data from enumerators, who are employed by the organization, placing Dock in the hands of these employees seems like the ideal approach. Further, NGOs prioritize empowering local communities in addition to conservation of the natural resource. This means they will need to know how a tool such as Dock might impact these local communities before integrating it into an existing fisheries data collection program. To accomplish goals of building local capacity and incentivizing stakeholders, NGOs would likely benefit from a socialization process to support Dock integration. This would include enumerators explaining the benefits of this tool while providing continuous support and encouragement to fishermen and suppliers in order to ensure gradual adoption and acceptance of Dock by all stakeholders.

Time lag between data collection and availability of use appeared to pale in comparison to other concerns reported by NGO survey participants. Despite this, the real potential impact lies in the ability of Dock to make the data collection process more efficient by doing away with slow, inefficient paper-based methods in favor of an electronic tool that will, theoretically, deliver high value data in a more timely manner. These data would then be available to stakeholders quicker, and could then be used to make fishery management decisions on a significantly shorter time scale. This, in turn, would allow for improved management of the local resource, which would likely have positive environmental and social repercussions.

4.2 Field-testing Dock

The following section outlines the observed differences among sites according to the predetermined metrics of success: (1) timeliness and availability and (2) data collection cost. These differences are further explained by contextual information provided by Momo Kochen (MDPI Program and Research Director) and Dierdre Duggan (MDPI Communications and Development Manager).

Time required to collect fisheries data

Per test site:

(1) Time to complete each individual task: When using Dock, data collectors took significantly less time to complete task 3 at both Larantuka and Kupang. Task 3 includes checking and completing data on a paper form before entering it into an Excel spreadsheet. This step is not needed when using Dock because the enumerator enters data directly into the app. In other words, Dock eliminates the need to transfer data from paper to an electronic format, thereby removing task 3 from the data collection process.

At Larantuka, data collectors took significantly more time to check and verify data before uploading to the database (task 5) when using Dock. This could be because when using the app at this site, enumerators were first recording on paper before entering data into Dock (as opposed to entering directly into Dock). Due to hardware complications (phones overheating, batteries dying after a few hours) and unfamiliarity with the app, data collectors had trouble using Dock and were thus recorded data on paper before entering into Dock (Deirdre Duggan pers. comm. 2016).

On the other hand, at Kupang, Dock saved data collectors a significant amount of time when collecting fisheries data (e.g. length, weight) (task 1), interviewing fishermen (task 2), checking and completing data (task 3), and uploading data to the database (task 6).

At both sites, entering data into an Excel spreadsheet or into the Dock app (task 4) did not appear to be impacted by Dock. This could be due not to a lack of effect but instead that when using the app, this task is combined with task 1 (enumerators simultaneously collect fisheries data and enter into the app) rather than these being separate tasks as with paper-based methods (enumerators first record fisheries data on paper (task 1), then transfer to an Excel spreadsheet (task 4)).

(2) Time to complete all data tasks:

In general, data collectors tended to lose time at Larantuka and save time at Kupang when using the app. Due to missing data, I was only able to compare time required to complete tasks 3-6 among the two different methods (paper-based v. the app) at Larantuka, which revealed no significant time differences. In fact, using Dock took 34% more time per sampling event, on average. However, one of the projected benefits (which was apparent at Kupang) was reduction in time needed to collect fisheries data (task 1). Because data was missing for this task at Larantuka, I was unable to measure the potential effect of Dock on this portion of the data collection process.

Conversely, at Kupang, using Dock cut data collection time per sampling event (completion of tasks 1-6) in half, on average.

Comparing sites:

Differences in methods (paper v. Dock) at each test site were discussed above according to each time category. Below I highlight differences among sites when using paper-based methods only to allow comparison of site-specific characteristics that, while independent of data collection method, may contribute to observed differences among sites.

Time spent completing tasks constituted 17% of overall time at all sites, on average, implying that a relatively small proportion of overall time is dedicated to data collection. What is taking place during the remaining 83% of time that appears to be unaccounted for? According to Momo, a likely reason is that data collectors must also attend to everyday office maintenance tasks. For example, "they might have a deadline for submitting a specific report, so they will prioritize other work before they will prioritize uploading or data entry" (Kochen pers. comm. 2016).

At Larantuka, time dedicated to data collection appears to be noticeably smaller (9%) than at Kupang (25%). In fact, enumerators took 1.5 times longer (in terms of overall time when using paper) when collecting data at Larantuka than at Kupang. This may be because Larantuka was recently added as a field sampling site to MDPI's fisheries monitoring program (January of this year), meaning MDPI employees are still figuring out how to collect data from vessel unloading events in the most efficient manner. Further while the flow of data collection at all sites is at the mercy of vessel behavior, this dynamic is accentuated at Larantuka. In fact, enumerators at this site recently had to alter their data collection shift from 9am-5pm to 4pm-12am because vessels were unloading at nighttime. "They're very much at the beck and call of the vessels, whereas in Kupang, they just have to wait until the tide is at the right level, and that's when they collect the data because that's when the vessels can actually land" (Kochen pers. comm. 2016). Also, because of the high level of uncertainty regarding when vessels will land, Momo says enumerators have much more downtime included – another factor likely contributing to higher overall data collection time when compared to Kupang.

Despite enumerators at Larantuka clocking significantly longer overall time, enumerators at Kupang took twice as long to complete all data tasks. This is because Kupang is a busier port, where enumerators sample approximately 5 times more vessels per month unloading almost 2 times more fish per sampling event by total weight and total number when compared to Larantuka. At Kupang, "we have a lot more partners that we work with, it's a lot busier, whereas in Larantuka we just work with one company" (Kochen pers. comm. 2016).

Cost of fisheries data collection

<u>Equipment Cost</u>

Based on information from the pilot study, implementing Dock would increase equipment cost by 200% per site, on average, resulting in a 199% increase in total annual equipment cost for operating all 13 sites. Because enumerators had problems with hardware at the field sites, MDPI may need to purchase higher quality smartphones, which would increase equipment costs associated with Dock. "I think it was a really big mistake that we bought bad phones. It slowed us down, it made it really difficult for the staff to work with them, the phones were overheating, the batteries were dying within an hour. It was really causing them to have a hard time working with the system" (Kochen pers. comm. 2016). The phones "were freezing up and then we'd have to find paper and start recording on paper and then have to try and match it up later" (Duggan pers. comm. 2016). According to Deirdre, these problems with hardware were mainly happening in Larantuka, but not in Kupang.

Because many small-scale fisheries operate in hot, humid climates and on or near the ocean, it is essential that a technology tool be extremely robust and able to withstand moisture, heat, and other external factors. “It’s a little complicated with technology when related to fisheries. These sites are not pretty places, and equipment isn’t going to last very long – it’s either really hot or really wet, or it’s humid. So technology has to be robust, and that’s not something that we factored in to this pilot” (Kochen pers. comm. 2016). More robust technology, while essential for successful prolonged use of this tool in this environment, is often more expensive. This would mean higher equipment costs, which would in turn require more funding – which can also be a barrier depending on an organization’s willingness to pay and availability of funds.

Total cost

When combining equipment and labor cost, implementing Dock would increase total cost by 20% per site, on average, resulting in a 20% increase in total annual cost for operating all 13 sites. Adding labor cost (which I assumed to be constant based on information from the pilot study) to equipment cost decreases percent increase in cost by an order of magnitude when compared to equipment costs alone (decrease from 200% increase in equipment cost to 20% increase in total cost after adding labor cost). Because labor cost constitutes a larger proportion of the total cost (90% of total cost when using paper-based methods, 75% of total cost when using Dock), it acts as an apparent buffer when combined with the high equipment cost increase.

The relationship between equipment and labor cost is discussed in more detail in the next section when introducing time (high implementation and ongoing equipment cost balanced by decrease in labor cost over time).

Cost-benefit analysis

In general, cost will be high in the short term due to initial investment while benefits will be high in the medium to longer term, highlighting the importance of considering a time horizon. Full implementation of Dock (alternative 2) would substantially increase implementation and ongoing equipment costs (year 1: 446% increase, all successive years: 199% increase/year). Because partial implementation of Dock (alternative 3) includes placing Dock at 4 sites only, these costs would be noticeably less, particularly after the first year (year 1: 315% increase, all successive years: 68% increase/year). However, due to problems MDPI employees experienced with phone hardware during the pilot, it would be wise to purchase more robust phones capable of withstanding hot, humid, and wet climates for extended periods of time. This means that implementation and ongoing equipment cost will likely increase, thus requiring repeated calculation of these costs.

Over time, high initial equipment costs would be balanced by approximately equal decreases in labor costs among alternatives (alternative 2: 37% decrease/year, alternative 3: 38% decrease/year). Keeping in mind that labor cost constitutes a relatively large proportion of the overall cost in data collection (90% when using paper-based methods, 75% when using Dock), adding percent decrease in labor cost to equipment cost magnifies when computing total data collection cost, resulting in a 12% increase in total costs during the first year, followed by a 13% cost decrease in subsequent years when implementing alternative 2. Conversely, partial implementation of Dock (alternative 3) would cause immediate decrease in total cost (3% decrease during the first year, 28% decrease in subsequent years). However, it is important to consider that integration of a new technology into a current data collection system may cause a temporary decrease in productivity. This occurred when transitioning from paper documents to electronic filing (more commonly known as e-filing) in the legal sector which, as with fisheries monitoring, requires intensive record-keeping.

Legal professionals have complained about the burden of learning an entirely new operational system, stating that “switching gears is always a challenge” (Lash 2015). However, many recognize that "it's not going to be perfect from the get-go," and that although it’s a learning experience for most involved, and "there's growing pains or system pains, but as time goes by there's going to be a benefit" (Lash 2015). In fact, the legal sector has already enjoyed the benefits of going digital, including ease of management and access to documents as well as reduction of court costs. A return on investment (ROI) study in Manatee County, Florida, revealed a cost saving of almost $1,000,000 based on e-filing of 2,321,252 documents per year (Shore et al. 2009). Medical professionals have experienced similar benefits by transitioning to Electronic Health Records (EHRs), recognizing that electronic systems could facilitate surveillance of infectious diseases, disease outbreaks, and chronic illnesses thanks to reporting of timely data to public health authorities (Hoffman and Podgurski 2013).

Similar benefits and drawbacks will likely be realized in the fishing sector with the application of electronic monitoring to fisheries management. Potential drawbacks, as with the legal sector, may include temporary decrease in productivity, likely due to variability in employee adoption rate. This was observed when piloting Dock at MDPI’s field sites. “For our staff, using Dock was slowing them down. We all realize that it’s a transition phase – once you get used to something, you speed up. For example, we have an enumerator in Kupang who is extremely fast at measuring fish. The person writing was better able to keep up with him writing than they were by entering the data into the phones, which means that the process was being slowed down to such a point that we potentially were aggravating our partners. The reason this enumerator has become so fast at measuring fish is so that we’re not a burden on the industry partners that we work with” (Kochen pers. comm. 2016).

As Momo Kochen alluded to in the previous paragraph, her concerns are not only a temporary decrease in productivity among MDPI employees, but also, and perhaps even more so, she is concerned with disrupting the work flow of MDPI’s partners during vessel offloading events. “It’s better to ensure that we’re not disrupting the work flow of our partners rather than having data be uploaded every time” (Kochen pers. comm. 2016). This highlights the importance of communicating very clearly, and from early on, with any and all stakeholders that may be impacted by implementation of a technology system such as Dock. This includes stakeholders such as MDPI’s fishing industry partners, who are not using the app directly but may be indirectly affected by temporary interruption or slowing down of the work flow on site. The key is to communicate to these stakeholders that the drop in productivity is only temporary: “If you are making a transition it's always going to be the case that you'll have this dip in productivity, which in the long run will increase efficiency" (Kochen pers. comm. 2016).

Despite this temporary decrease in productivity in the early stages of Dock implementation, this technology would likely cause a notable decrease in total cost due to labor cost reduction – a trend that was observed at one field site (Kupang) during the pilot. Transitioning from hand-written forms to electronic data collection will likely reduce the amount of time enumerators spend entering data (as it did at Kupang) due to elimination of redundant data entry effort (i.e. one-time data entry of reports) and a decrease in the number of steps in the data entry process, meaning reduced labor cost per sampling event. This, in turn, would reduce time lag from data collection to availability of use.

While many of the costs of a fishery data reporting system can be quantified in monetary terms, many of the benefits of fishery data reporting system are much more difficult to quantify, particularly when comparing one reporting system to another. For instance, how can one assign a dollar value to higher quality data, or to data reported in near-real time as opposed to a lag time of one month? Oftentimes intuitively important impacts are difficult to value in monetary terms (Boardman et al. 2011). Nonetheless, they are worth discussing. Electronic reporting can provide near real-time reporting of fisheries catch, effort, and location of fishing activities, and timely catch accounting is important for managing fishing effort (Lowman et al. 2013). Near real-time data collection is especially important for fisheries reliant on allocation of seasonal or vessel-specific quotas as well as fisheries managed using in-season closures. Moreover, electronic reporting allow data to be submitted in a format that allows for integration with other data sources to monitor fleet catches in close to real-time (Lowman et al. 2013). The more timely that data, the more flexibility the organization may have to collaborate with fishermen in managing the fishery (NOAA 2015). Much like the management of disease outbreaks in the medical sector, timely reporting of catch data could potentially reduce stock overexploitation events by monitoring of in-season fishing activity more closely. This, in turn, could aid organizations in better accomplishing management goals and objectives centered around sustainable management of local resources, which may contribute to increasing the effectiveness of catch accounting and reduce monitoring costs. According to the pilot, implementing a technology like Dock in MDPI's fisheries data collection program is projected to decrease cost of data collection activity over a five-year span/horizon by 8% using alternative 2 and 23% using alternative 3.

Recommendations for MDPI

Ultimately, the choice between implementing the app and continuing to use paper depends on the strength of time preference (i.e. willingness to wait for future returns). Despite Dock being in the early stages of implementation, meaning there is considerable uncertainty about its actual impacts and potential benefits, information obtained during the pilot and the subsequent CBA suggest that replacing paper with Dock would, over time, be beneficial to MDPI's fisheries data collection program. Based on this overarching finding, I recommended (per Momo Kochen's request) next steps:

(1) Immediate implementation of alternative 3

The field tests suggest that Dock is likely to provide a cost-benefit value to MDPI. Based on the net benefits of alternative 3 to the status quo, I recommend immediate implementation of alternative 3 by implanting Dock at the following 4 sites: Kupang, Lombok, North Buru, and South Buru. Due to similar site characteristics (busier ports (more vessels sampled), have more enumerators on site, a more reliable internet connection, and predictable vessel unloading events), these were deemed comparable to Kupang (enumerators saved time using Dock). The remaining 9 sites, or those deemed comparable to Larantuka (enumerators lost time using Dock; less busy (less vessels sampled), have fewer enumerators on site, an unreliable internet connection, and random vessel unloading events), would continue collecting data using paper-based methods: Assilulu (Ambon), Bitung, Bone, Larantuka, Pasar Wajo (Sulawesi), Seram, Sorong, Tolitoli, and Tulehu (Ambon).

(2) Conduct socialization process with partners

Conducting a socialization process with local fishermen and suppliers while implementing Dock is crucial to increasing the likelihood of partner acceptance (i.e. maintaining relationships that have taken years to build) and thus increasing the likelihood of successful introduction of Dock.

Specifically, I recommend MDPI staff explain the uses and expected benefits of Dock as well as highlight the potential disruption of the work flow during vessel unloading events (enumerator sampling rates may decrease temporarily and thus may indirectly impact fishermen and suppliers). Continuous support and encouragement to these stakeholders will hopefully ensure gradual adoption and acceptance of Dock at sampling sites.

(3) Program evaluation at the end of year 1

With Dock, it is highly likely that increased net benefits would come at a later stage in the project's life. In order to monitor this, I recommend that MDPI staff conduct another cost-benefit analysis at the end of the first year of implementation to determine (1) status of Dock program and (2) if Dock can and should be implemented at the remaining 9 sites. This decision should be made on a site-by-site basis by evaluating the following factors: (1) busyness of the port (i.e. number of vessels sampled per month), (2) number of enumerators on site, (3) reliability of internet connection, and (4) predictability of vessel unloading events. I recommend evaluating these characteristics on a site-by-site basis because during the pilot, these factors appeared to influence the success (Kupang) or failure (Larantuka) of Dock at a given site.

(4) Consider using Dock to scale up from 13 to 25 total field sites in operation

Technology tools such as Dock can open up the possibility of increasing output and thus potentially allowing for scalability, such as increasing number of sampled sites or sampling rate per site. Based on the findings from the pilot study, over time it appears that Dock would reduce overall program cost by reducing field data collection costs, thereby potentially allowing MDPI to scale up. In other words, MDPI could collect more data per site or collect data for a greater number of sites. Momo Kochen expressed interest in eventually increasing number of field sampling sites from 13 to 25, and Dock may allow for this type of scalability.

(5) Integrate Dock with other technologies and efforts

Synching Dock to I-Fish (MDPI's online database) would allow interoperability of data platforms and further decrease time lag from data collection to availability of use by stakeholders. Similarly, implementation of Dock in Indonesian tuna fishery supply chains would support and further progress development of a traceability-based technology platform – an endeavor MDPI is currently undertaking as part of their Netherlands Organisation for Scientific Research (NWO) and Improving Fisheries Information and Traceability for Tuna (IFITT) projects[7]. Full traceability requires technology for capturing, receiving, and transmitting information between every step in the supply chain, from pre-catch to point-of-catch to point-of-processing/packaging and, finally, to point-of-purchase/consumption (FoF 2014; PIFSC 2015). Dock contributes to this end-to-end traceability by connecting 'point of data collection' steps at the base of the supply chain.

4.3 Implications for fisheries monitoring programs

This project serves as a specific case-study example of what it might look like for an organization to transition from paper to electronic data collection. A 'case study' is typically associated with exploratory research but, as Yin (1984) pointed out, it can also "be used as a research design for theory development and testing via analytical generalization. Critics typically state that single cases offer a poor basis for generalizing. This is because survey research relies on *statistical* generalization, whereas case studies (as with experiments) rely on *analytical* generalization. In analytical generalization, the investigator is striving to generalize a particular set of results to some broader theory" (Yin 1984, p.39, original emphasis). Thus, organizations operating fisheries monitoring programs could use findings from this case study of market- and field-testing the Dock app as guiding lessons when considering implementing a tool such as this. Additional considerations include determining adoption barriers into organizational (particularly NGO and agency) frameworks and outlining strategies to overcome these thresholds (e.g. via optimal placement and scale of proposed technology). This could be used as a roadmap for navigating these frameworks and their associated obstacles (e.g. funding, structural and political frameworks, regulatory frameworks) and to determine strategies for overcoming these barriers (e.g. organizational incentives, de-risking of technology via pilot studies) in order to increase the likelihood of successful and persistent adoption of electronic monitoring tools.

Ultimately, the incentive to transition to electronic monitoring in a particular fishery is highly dependent on the data needs of that fishery and the management goals of the organization, and I hope lessons learned from this case study will provide other organizations with valuable insight as they contemplate similar transitions.

5.0 REFERENCES

[7] For more information about these projects, refer to the MDPI Annual Report 2015.

Admiralty and Maritime Law Guide. 1969. *International Convention on Tonnage Measurement of Ships*. London, UK. < http://www.admiraltylawguide.com/conven/tonnage1969.html>.

Agresti, A. 2002. *Categorical Data Analysis*. 2nd ed. Wiley Series in Probability and Statistics, Vol. 482. John Wiley: Hoboken, NJ.

Barkail, A. 2011. *The Development and Implementation of eLog Technology for the Local and International Fishing Industry*. IST-Africa 2011 Conference Proceedings.

Boardman, A.E., Greenberg, D.H., Vining, A.R., and D.L. Weimer. 2011. *Cost-Benefit Analysis: Concepts and Practice*. 4th ed. Pearson Education, Inc.: Upper Saddle River, New Jersey.

Caddy, J.F. and K.L. Cochrane. 2001. *A review of fisheries management past and present and some future perspectives for the third millennium*. Ocean and Coastal Management **44**: 653-682.

Dillman, D.A., Smyth, J.D., and L.M. Christian. 2014. *Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method*. 4th ed. John Wiley: Hoboken, NJ.

Duggan, D. May 15, 2016. Telephone interview.

Eigaard, O.R., Marchal, P., Gislason, H., and A.D. Rijnsdorp. 2014. *Technological Development and Fisheries Management*. Reviews in Fisheries Science & Aquaculture **22**(2): 156-174.

eMarketer. 2014. *2 Billion Consumers Worldwide to Get Smart(phones) by 2016*. eMarketer. < http://www.emarketer.com/Article/2-Billion-Consumers-Worldwide-Smartphones-by-2016/1011694>.

Food and Agriculture Organization (FAO). 2014. *The State of World Fisheries and Aquaculture*. <http://www.fao.org/fishery/sofia/en>.

Future of Fish (FoF). 2014. *Getting There from Here: A Guide for Seafood Traceability*. < http://futureoffish.org/sites/default/files/docs/resources/fof-traceability_report-final_0.pdf >.

Galletta, A. and W.E. Cross. 2013. *Mastering the Semi-Structured Interview and Beyond: From Research Design to Analysis and Publication*. NYU Press: New York, NY.

Hoffman, S., A. Podgurski. 2013. *Big Bad Data: Law, Public Health, and Biomedical Databases*. Journal of Law, Medicine & Ethics **41**: 56-60.

Hollander, M. and D.A. Wolfe. 1973. *Nonparametric Statistical Methods.* John Wiley & Sons: New York, NY.

Kochen, M. 2016. Email interviews.

Kochen, M. May 15, 2016. Telephone interview.

Lash, S. 2015. *County courts moving from paper to digital filing system*. Capital Gazette. < http://www.capitalgazette.com/news/for_the_record/ph-ac-cn-court-efiling-0105-20150105-story.html>.

Lowman, D.M., Fisher, R., Holliday, M.C., McTee, S.A., and S. Stebbins. 2013. *Fishery Monitoring Roadmap. Environmental Defense Fund*. < https://www.edf.org/sites/default/files/FisheryMonitoringRoadmap_FINAL.pdf >.

McElderry, H. 2008. *At-Sea Observing Using Video-Based Electronic Monitoring*. Electronic Monitoring Workshop, Archipelago Marine Research Ltd.

NOAA. 2015. *NMFS Pacific Islands Region Electronic Reporting and Electronic Monitoring Implementation Plan*. NOAA.

Northern Economics, Inc. 2015. *A Review of the Alaska Interagency Electronic Reporting System (IERS) with an Emphasis on Costs and Benefits to Stakeholders*. Prepared for NMFS Alaska Regional Office and Alaska Department of Fish and Game.

Pacific Islands Fisheries Science Center (PIFSC). 2015. *Science and technology to promote sustainable fisheries in Southeast Asia and the Coral Triangle*. NOAA Fisheries Pacific Science Center, PIFSC Special Publication, SP-15-002, 66p.

Popma, M. 2015. *PEF Market Assessment Final Report*. Internal document for Point 97.

Shore, R. B., M. Singer, and C. Pettijohn (2009). *The ROI of Emerging Technologies*. Presented at the National Court Technology Conference, Denver. <http://contentdm.ncsconline.org/cgibin/showfile.exe?CISOROOT=/tech&CISOPTR=745>.

Steinback, C., Chen, C., and S. Gerritse. 2015. Point 97 Product Business Plan. Point 97 Internal Document.

Steinback, C. 2015. Email interviews.

Stephens, A. and R.B. D'Agostino. 1986. *Goodness-of-fit techniques*. Marcel Dekker, Inc.: New York, NY.

USAID Indonesia. 2015(a). *Data collection protocol for small-scale pole and line tuna fisheries of Indonesia*. Indonesia Marine and Climate Support (IMACS) Project.

USAID Indonesia. 2015(b). *Data collection protocol for small-scale handline tuna fisheries of Indonesia*. Indonesia Marine and Climate Support (IMACS) Project.

Yin, R.K. 1984. *Case Study Research: Design and Methods*. 2nd ed. Sage: Beverly Hills, CA.

6.0 APPENDICES

6.1 Appendix A – NGO Survey Questions

(1) General information

1. What is your age?
   - 18-24
   - 25-34
   - 35-44
   - 45-54
   - 55-64
   - 65-74
   - 75 or older
2. What is your gender?
   - Male
   - Femail
3. Which of the following best describes your role in your organization?
   - Executive Director
   - Program Manager
   - Project Coordinator
   - Data Manager
   - Other (please specify)

(2) Information about your organization

4. Please rank the following goals in terms of their importance to your organization (1 = most important, 8 = least important).

Goal	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Establishing the infrastructure for data-rich decision support tools	○	○	○	○	○	○	○	○
Food security of local community	○	○	○	○	○	○	○	○
Economic security of local community	○	○	○	○	○	○	○	○
Sustainable management	○	○	○	○	○	○	○	○

of local resources								
Sustainability of target fish stocks	○	○	○	○	○	○	○	○
Marine protection and conservation	○	○	○	○	○	○	○	○
Seafood traceability	○	○	○	○	○	○	○	○
Addressing IUU fishing	○	○	○	○	○	○	○	○

5. Does your organization currently fund or operate a fisheries data collection program?
   - Yes
   - No, but we would like to in the future
   - No, and it's not something we would consider doing

(3) Information about your fisheries data collection program

6. Please indicate the country or countries where your fisheries data collection program(s) take place.
7. What is the primary purpose of your fisheries data collection program?
   - Sustainable resource management
   - Stock assessment
   - Traceability
   - Quota monitoring
   - Regulatory information/enforcement
   - Other (please specify)
8. Who collects and submits that data? Check all that apply.
   - Fishermen at sea
   - Enumerators
   - Other (please specify)
9. On average, how many weeks pass between collection of data and availability of use? Please enter your best estimate.
10. Is your fisheries data collection program site-based?
    - Yes
    - No
11. How many total sites are in operation? Please enter your best estimate.
12. If resource constraints were of no concern, approximately how many additional sites would you like to see in operation?

13. As an organization, approximately how much money is spent on fisheries data collection each year? Please enter your best estimate.
14. How valuable are the following indicators that you monitor?

Indicator	**High value**	**Good value**	**Some value**	**Little value**	**No value**	**N/A**
Total number of fish caught	○	○	○	○	○	○
Total weight of fish caught	○	○	○	○	○	○
Individual fish length	○	○	○	○	○	○
Species type	○	○	○	○	○	○
Catch form	○	○	○	○	○	○
Catch per unit effort (CPUE)	○	○	○	○	○	○
Catch condition	○	○	○	○	○	○
Market price	○	○	○	○	○	○
Quota monitoring and tracking	○	○	○	○	○	○
Bycatch	○	○	○	○	○	○
Harvest location	○	○	○	○	○	○
Gear type	○	○	○	○	○	○

15. Which of the following are of the highest concern for your organization when it comes to fisheries data collection? Please rank as 1 = most significant and 9 = least significant.

Concern	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Cost of collecting data	○	○	○	○	○	○	○	○	○
Time required to collect and process data	○	○	○	○	○	○	○	○	○
Immediacy of data availability	○	○	○	○	○	○	○	○	○
Data quality assurance and quality control (QA/QC)	○	○	○	○	○	○	○	○	○

Data interoperability across seafood value chain	○	○	○	○	○	○	○	○	○
Data analysis	○	○	○	○	○	○	○	○	○
Stakeholder transparency	○	○	○	○	○	○	○	○	○
Incentives to stakeholders for providing data	○	○	○	○	○	○	○	○	○
Building local capacity/infrastructure	○	○	○	○	○	○	○	○	○

16. Which of the following best describes the primary method of data capture for your fisheries data collection program?

    Paper and pen
    Online tool
    Mobile tool
    Other (please specify)

6.2 Appendix B – NGO Interview Questions

(1) Key characteristics and attitudes:

1. How do you best describe what you do?
2. What kinds of trends do you see going on in your field (ex: inefficiency of logging catches, traceability/sustainability issues, consumer preferences)?
3. Could you tell me a little bit about what comes to mind when you think of seafood sustainability? Is this an important issue for you? Why or why not?

(2) Current data collection process:

1. Walk me through your process for collecting fisheries catch data. What are the steps you take to collect this data?
2. Do you use or have you used software to help collect data (e.g. Excel, online database)?
3. What are your biggest challenges (specifically those related to fisheries data collection)?
4. Could this data collection process be improved? How?

(3) Potential impacts of Dock:

1. Do you think NGOs like yours would benefit from a tool such as this? How?
2. If you could add any features or capabilities to this tool, what would they be?
3. What potential obstacles and/or adoption barriers do you foresee if your NGO were to transition to an electronic dockside monitoring solution such as this?

6.3 Appendix C. Sample calculation from a single sampling event at Larantuka on February 22, 2016 demonstrating difference in ‘overall time’ and ‘time to complete all data

tasks'. I subtracted end time of task 6 (12:28PM) from start time of task 1 (6:55AM) to get an 'overall time' of 333 minutes. I added number of minutes to complete each individual task to get a 'time to complete all data tasks' of 104 minutes. The difference between these two (229 minutes) represents time unaccounted for during a given sampling event.

Task	Start/End time	Time to complete (min)
1	6:55AM	12
2		66
3		10
4		10
5		4
6	12:28PM	2
Overall time:	**333**	
Time to complete all tasks:		**104**
Difference:		**229**

6.4 Appendix D: Detailed explanation of techniques used and assumptions made when calculating total annual equipment cost per data collection method at (a) Larantuka and (b) Kupang. Calculations were made according to costs expended during trial period beginning February 2016. Note: Equipment purchase costs were amortized over the number of years seen in the 'Explanations and assumptions' column. These numbers were obtained by asking Momo Kochen about the lifetime of these items when collecting data at MDPIs field sites. Cost in Indonesian Rupiah (IDR) was converted to U.S. dollar (USD) using the following exchange rate: US $1 = IDR 13,212.

(a) Larantuka

Item	Price per item (IDR)	Number of items per site	Total annual cost (IDR)	Explanations and assumptions
Laptop	7,500,000	1	3,000,000	Lasts 2.5 years. Assumed 1 per site
Handphone (non-Dock phone)	1,675,000	1	1,116,667	Lasts 1.5 years. Assumed 1 per team
Printer	-	0	0	Lasts 2 years. Assumed 1 per site
Paper clipboard	35,000	1	35,000	Assumed 1 per team per year
Pens (1 dozen)	25,000	1	25,000	Assumed 1 per team per year
Printed form paper bundle	30,000		60,000	Assumed use roughly 2 bundles per year based on # vessels sampled per year

Calculator	150,000	1	150,000	Assumed 1 per team per year
Modem for uploading data to database	350,000	1	116,667	Lasts 3 years. Assumed 1 per site
Monthly internet package for modem	150,000/month	1	1,657,077	Collect data 48 weeks/year
Calipers	500,000	1	500,000	Assumed 1 per team per year
Measuring board	500,000	1	500,000	Assumed 1 per team per year
5-6 Ember/bucket	25,000	1	25,000	Assumed 1 set per team per year
Android phone	1,600,000	2	2,133,333	Lasts 1.5 years. Assumed 1 per team
Sim card (without pulsa)	10,000	2	4,000	Lasts 5 years. Assumed 1 per team
Pulsa (includes call and data)	100,000/month	2	2,209,436	Collect data 48 weeks/year
Cost per site to operate Dock	13,642,500	1	13,642,500	Cost per site per year

(b) Kupang

Item	Price per item (IDR)	Number of items per site	Total annual cost (IDR)	Comments
Laptop	4,200,000	1	1,680,000	Lasts 2.5 years. Assumed 1 per site
Handphone (non-Dock phone)	2,000,000	2	2,666,667	Lasts 1.5 years. Assumed 1 per team
Printer	700,000	1	350,000	Lasts 2 years. Assumed 1 per site
Paper clipboard	35,000	2	70,000	Assumed 1 per team per year
Pens (1 dozen)	25,000	2	50,000	Assumed 1 per team per year
Printed form paper bundle	30,000		300,000	Assumed use roughly 10 bundles per year based on # vessels sampled per year
Calculator	150,000	2	300,000	Assumed 1 per team per year
Modem for uploading data to database	350,000	1	116,667	Lasts 3 years. Assumed 1 per site
Monthly internet package for modem	150,000/month	1	1,657,077	Collect data 48 weeks/year
Calipers	500,000	2	1,000,000	Assumed 1 per team per year
Measuring board	500,000	2	1,000,000	Assumed 1 per team per year
5-6 Ember/bucket	25,000	2	50,000	Assumed 1 set per team per year
Android phone	1,600,000	3	3,200,000	Lasts 1.5 years. Assumed 1 per team
Sim card (without pulsa)	10,000	3	6,000	Lasts 5 years. Assumed 1 per team
Pulsa (includes call and data)	100,000/month	3	3,314,154	Collect data 48 weeks/year
Cost per site to operate Dock	13,642,500	1	13,642,500	Cost per site per year

6.5 Appendix E: Description of assumptions made per site when calculating annual equipment cost all 13 field sampling sites. Equipment costs were estimated for each data collection method (Paper, Dock) using costs expended at the test site (Larantuka, Kupang) during trial period beginning February 2016 as a baseline. These costs where then projected both temporally (per year) and spatially (per site) based on site-specific characteristics (number of employees per site, data collected individually or in teams) and using the specific assumptions.

Site name	Total # employees	Data collection	Assumptions
Assilulu (Ambon)	1	Individual	Laptop: Kupang and Larantuka cost averaged; assumed 1 per site Handphone: Kupang and Larantuka cost averaged; assumed 1 per individual Printer: None* Paper clipboard, pens, calculator, calipers, measuring board, buckets: Assumed 1 per individual Paper: Used Larantuka cost** Modem + monthly internet package: Assumed 1 per site Android phone + sim card + pulsa: Assumed 1 per individual
Bitung	2	Team	Laptop: Kupang and Larantuka cost averaged; assumed 1 per site Handphone: Kupang and Larantuka cost averaged; assumed 1 per team Printer: None* Paper clipboard, pens, calculator, calipers, measuring board, buckets: Assumed 1 per team Paper: Used Larantuka cost** Modem + monthly internet package: Assumed 1 per site Android phone + sim card + pulsa: Assumed 1 per team
Bone	2	Team	Laptop: Kupang and Larantuka cost averaged; assumed 1 per site Handphone: Kupang and Larantuka cost averaged; assumed 1 per team Printer: None* Paper clipboard, pens, calculator, calipers, measuring board, buckets: Assumed 1 per team Paper: Used Larantuka cost** Modem + monthly internet package: Assumed 1 per site Android phone + sim card + pulsa: Assumed 1 per team
Kupang	4	Team	Laptop: cost provided; assumed 1 per site Handphone: cost provided; assumed 1 per team Printer: Used Kupang cost* Paper clipboard, pens, calculator, calipers, measuring board, buckets: Assumed 1 per team Paper: Used Kupang cost** Modem + monthly internet package: Assumed 1 per site Android phone + sim card + pulsa: Assumed 1 per team
Larantuka	2	Team	Laptop: cost provided; assumed 1 per site

			Handphone: cost provided; assumed 1 per team Printer: None* Paper clipboard, pens, calculator, calipers, measuring board, buckets: Assumed 1 per team Paper: Used Larantuka cost** Modem + monthly internet package: Assumed 1 per site Android phone + sim card + pulsa: Assumed 1 per team
Lombok	5	Team	Laptop: Kupang and Larantuka cost averaged; assumed 1 per site Handphone: Kupang and Larantuka cost averaged; assumed 1 per team Printer: Used Kupang cost* Paper clipboard, pens, calculator, calipers, measuring board, buckets: Assumed 1 per team Paper: Used Kupang cost** Modem + monthly internet package: Assumed 1 per site Android phone + sim card + pulsa: Assumed 1 per team
North Buru	4	Individual	Laptop: Kupang and Larantuka cost averaged; assumed 1 per site Handphone: Kupang and Larantuka cost averaged; assumed 1 per individual Printer: Used Kupang cost* Paper clipboard, pens, calculator, calipers, measuring board, buckets: Assumed 1 per individual Paper: Used Kupang cost** Modem + monthly internet package: Assumed 1 per site Android phone + sim card + pulsa: Assumed 1 per individual
Pasar Wajo (Sulawesi)	2	Team	Laptop: Kupang and Larantuka cost averaged; assumed 1 per site Handphone: Kupang and Larantuka cost averaged; assumed 1 per team Printer: None* Paper clipboard, pens, calculator, calipers, measuring board, buckets: Assumed 1 per team Paper: Used Larantuka cost** Modem + monthly internet package: Assumed 1 per site Android phone + sim card + pulsa: Assumed 1 per team
Seram	2	Individual	Laptop: Kupang and Larantuka cost averaged; assumed 1 per site Handphone: Kupang and Larantuka cost averaged; assumed 1 per individual Printer: None* Paper clipboard, pens, calculator, calipers, measuring board, buckets: Assumed 1 per individual Paper: Used Larantuka cost** Modem + monthly internet package: Assumed 1 per site Android phone + sim card + pulsa: Assumed 1 per individual
Sorong	2	Team	Laptop: Kupang and Larantuka cost averaged; assumed 1 per site Handphone: Kupang and Larantuka cost averaged; assumed 1 per team

			Printer: None* Paper clipboard, pens, calculator, calipers, measuring board, buckets: Assumed 1 per team Paper: Used Larantuka cost** Modem + monthly internet package: Assumed 1 per site Android phone + sim card + pulsa: Assumed 1 per team
South Buru	3	Individual	Laptop: Kupang and Larantuka cost averaged; assumed 1 per site Handphone: Kupang and Larantuka cost averaged; assumed 1 per individual Printer: Used Kupang cost* Paper clipboard, pens, calculator, calipers, measuring board, buckets: Assumed 1 per individual Paper: Used Kupang cost** Modem + monthly internet package: Assumed 1 per site Android phone + sim card + pulsa: Assumed 1 per individual
Tolitoli	2	Individual	Laptop: Kupang and Larantuka cost averaged; assumed 1 per site Handphone: Kupang and Larantuka cost averaged; assumed 1 per individual Printer: None* Paper clipboard, pens, calculator, calipers, measuring board, buckets: Assumed 1 per individual Paper: Used Larantuka cost** Modem + monthly internet package: Assumed 1 per site Android phone + sim card + pulsa: Assumed 1 per individual
Tulehu (Ambon)	2	Team	Laptop: Kupang and Larantuka cost averaged; assumed 1 per site Handphone: Kupang and Larantuka cost averaged; assumed 1 per team Printer: None* Paper clipboard, pens, calculator, calipers, measuring board, buckets: Assumed 1 per team Paper: Used Larantuka cost** Modem + monthly internet package: Assumed 1 per site Android phone + sim card + pulsa: Assumed 1 per team

**Printer cost: I assumed sites with 2 or less employees do not have a printer (because a printer cost for Larantuka was not provided), and those with 3 or more employees do have a printer (because a printer cost for Kupang was provided).*

***Paper cost: I assumed that the number of vessels sampled at sites with 2 or less employees were the same as Larantuka (average=30 vessels sampled per month), meaning ~2 bundles per year. Conversely, I assumed that the number of vessels sampled at sites with 3 or more employees were the same as Kupang (average=150 vessels sampled per month), meaning ~10 bundles per year.*

6.6 Appendix F: Itemized list of annual equipment cost for Lombok as sample of calculations made for all 13 field sampling sites. Cost in Indonesian Rupiah (IDR) was converted to U.S. dollar (USD) using the following exchange rate: US $1 = IDR 13,212.

Item	Price per item (IDR)	Number of items per site	Total annual cost (IDR)	Comments
Laptop	5,850,000	1	2,340,000	Lasts 2.5 years. Assumed 1 per site. Averaged laptop cost for Larantuka and Kupang
Handphone (non-Dock phone)	1,837,500	2	2,450,000	Lasts 1.5 years. Assumed 1 per team. Averaged handphone cost for Larantuka and Kupang
Printer	700,000	1	350,000	Lasts 2 years. Assumed 1 per site
Paper clipboard	35,000	2	70,000	Assumed 1 per team per year
Pens (1 dozen)	25,000	2	50,000	Assumed 1 per team per year
Printed form paper bundle	30,000		300,000	Assumed use roughly 10 bundles per year based on # vessels sampled per year
Calculator	150,000	2	300,000	Assumed 1 per team per year
Modem for uploading data to database	350,000	1	116,667	Lasts 3 years. Assumed 1 per site
Monthly internet package for modem	150,000/month	1	1,657,077	Collect data 48 weeks/year
Calipers	500,000	2	1,000,000	Assumed 1 per team per year
Measuring board	500,000	2	1,000,000	Assumed 1 per team per year
5-6 Ember/bucket	25,000	2	50,000	Assumed 1 set per team per year
Android phone	1,600,000	2	2,133,333	Lasts 1.5 years. Assumed 1 per team
Sim card (without pulsa)	10,000	2	4,000	Lasts 5 years. Assumed 1 per team
Pulsa (includes call and data)	100,000/month	2	2,209,436	Collect data 48 weeks/year
Cost per site to operate Dock	13,642,500	1	13,642,500	Cost per site per year

6.7 Appendix G: Description of labor cost calculations for all 3 alternatives in cost-benefit analysis. Cost in Indonesian Rupiah (IDR) was converted to U.S. dollar (USD) using the following exchange rate: US $1 = IDR 13,212.

Calculation for 9 sites projected to experience labor cost increase ('time lost' sites):

For Larantuka, I first calculated average time lost per sampling event by adding average differences in time taken to complete tasks 1-6 using paper and using Dock (column 2). Knowing that enumerators sample an average of 30 vessels per month (one sampling event represents data from a single vessel), and knowing that enumerators sample 48 weeks of the year, I calculated average time lost (in hours) on data collection per year at Larantuka (column 3). I then calculated an hourly labor cost using total monthly salary provided by MDPI and knowing that employees collect data for 48 weeks, 5 days/week, 8 hours/day (column 4). I calculated average cost increase per year by multiplying columns 3 and 4, then added this increase to current labor cost when using paper-based methods to determine projected annual labor cost when using Dock (column 5).

Task	**Δ t (tP-tD) (min)**	**Avg time lost/year (hrs)**	**Total hourly labor cost (IDR)**	**Avg cost increase/yr (IDR)**	**Dock annual labor cost**
1	-	41	IDR 35,232 (US $2.57)	IDR 1,456,007 (US $106)	IDR 68,324,205 (US $4,988)
2	-				
3	4				
4	-7				
5	-3				
6	-2				
Total time lost per vessel	**-7**				

This represents a 2% increase in annual labor cost when compared to current labor cost using paper-based methods. Using this 2% increase, I project annual labor cost when using Dock for the remaining 8 sites deemed similar to Larantuka by multiplying current labor cost by 1.02 to account for a 2% increase in cost per site. I then added together these costs to get total projected annual labor cost when using Dock at these 9 sites.

Calculation for 4 sites projected to experience labor cost decrease ('time saved' sites):

For Kupang, I first calculated average time saved per sampling event by adding average differences in time taken to complete tasks 1-6 using paper and using Dock (column 2). Knowing that enumerators sample an average of 150 vessels per month (one sampling event represents data from a single vessel), and knowing that enumerators sample 48 weeks of the year, I calculated average time saved (in hours) on data collection per year at Kupang (column 3). I then calculated an hourly labor cost using total monthly salary provided by MDPI and knowing that employees collect data for 48 weeks, 5 days/week, 8 hours/day (column 4). I calculated average cost decrease per year by multiplying columns 3 and 4, then subtracted this decrease from current labor cost when using paper-based methods to determine projected labor cost when using Dock (column 5).

Task	**Δ t (tP-tD) (min)**	**Avg time saved/year (hrs)**	**Tot hourly labor cost (IDR)**	**Avg cost decrease/yr (IDR)**	**Dock annual labor cost**
1	30	1,589	IDR 59,587 (US $4.35)	IDR 94,678,993 (US $6,912)	IDR 18,472,805 (US $1,349)
2	6				
3	12				
4	7				
5	1				
6	2				
Total time saved per vessel	**58**				

This represents an 84% decrease in annual labor cost when compared to current labor cost using paper-based methods. Using this 84% decrease, I project annual labor cost when using Dock for the remaining 3 sites deemed similar to Kupang by multiplying current labor cost by 0.16 (1-0.84) to account for an 84% decrease in cost per site. I then added together these costs to get total projected annual labor cost when using Dock at these 4 sites.

6.8 Appendix H: Demographic information about survey respondents, including number of responses received according to (a) NGO name (50% of respondents choose to remain anonymous), (b) age, (c) gender, and (d) organizational role.

(a) NGO

NGO name	**# respondents**
The Sustainable Grenadines, Inc.	1
Gulf and Caribbean Fisheries Institute	1
Conservation International	4
Northwest Atlantic Marine Alliance	1
FishChoice	1
The Nature Conservancy	2
World Wildlife Fund South Africa	1
Fauna & Floral International	1
Sustainable Fisheries Partnership	2
Oceana	1

FishWise	1
MDPI	1
Blue Ventures	1
Humanity United	1
Wageningen University (Netherlands)	1
Chose to remain anonymous	20
TOTAL NUMBER OF RESPONDENTS:	**40**

(b) Age

Age (in years)	**# respondents**
25 to 34	21
35 to 44	10
45 to 54	2
55 to 64	5
65 to 74	1
75 or older	1
TOTAL NUMBER OF RESPONDENTS:	**40**

(c) Gender

Gender	**# respondents**
F	28
M	12
TOTAL NUMBER OF RESPONDENTS:	**40**

(d) Organizational role

Organizational role	**# respondents**
Consultant	1
Data Manager	3
Division Director	1
Executive Director	3
Other (Science Advisor)	1
Program Manager	19

Project Coordinator	11
University Professor	1
TOTAL NUMBER OF RESPONDENTS:	**40**