Assessing the Effectiveness of Citizen Science: A Case Study of Publications Produced by Earthwatch Projects

Assessing the Effectiveness of Citizen Science: A Case Study of Publications Produced by Earthwatch Projects

Kyle Hutton

A Thesis in the Field of Sustainability

for the Degree of Master of Liberal Arts in Extension Studies

Harvard University

November 2017

Abstract

Worldwide, decision makers and non-governmental organizations are increasing their use of citizen science-based projects to improve how they manage natural resources, track species at risk, and conserve protected areas (Conrad & Hilchery, 2009). Engaging the public provides access to a large labor force, enabling scientists to collect data on unprecedented spatial and temporal scales (Cohn, 2008). Despite its benefits, citizen science (CS) is frequently stigmatized, and many in the scientific community believe that data collected by volunteers are of lower quality than those collected by experts. There is a strong need to assess citizen science on the merits of its research outcomes, as well as to explore the variables that may be associated with the production of quality data.

This thesis built upon the findings of a 2016 publication (Chandler et al., 2016) that used Earthwatch— an environmental non-profit that has been running field-based citizen science research expeditions since 1971— as a case study. This study evaluated the quality of Earthwatch-supported citizen-science data based on each project's ability to produce peer-reviewed publications. This assessment measured publications for 62 research projects that were partnered with Earthwatch between 2008 and 2014. The analysis looked at seven independent variables, but did not evaluate the sustainability of funding, which is essential for a project to continue its operations on the ground. The analysis also did not consider the implementation of quality assessment and quality control (QAQC) measures, which are important for mitigating volunteer error with data collection.

This thesis addressed the gaps in this initial publication by augmenting the dataset that spanned from 2008-2014 and added project outputs with respect to the number of peer-reviewed publications produced from an expanded 2000-2016 window. It also considered two new independent variables: 1) a measure to quantify whether projects were meeting their required annual budgets to cover core costs, and 2) a scoring system that quantified the different QAQC measures in place for each project.

Overall, the results of this study found a negative correlation between assurance of data quality score and the total peer-reviewed publications produced by the principal investigators supported by Earthwatch. Contrary to my expectations, there was also a negative relationship between the project QAQC Score and the mean number of publications produced annually. A stepwise Akaike Information Criterion test (AIC) was also performed to select the regression model of best fit. Results indicated that the ratio between funds provided and the project's approved budget best described the pattern of the mean publications produced annually. The AIC results also indicated that the affiliation of the PI best described the pattern of projects' mean MoS score (a scaled metric of publication outputs).

The results of this study can be used to inform Earthwatch's decision-making for project selection, as well as bolster research outputs for existing projects. More importantly, the results can also inform other organizations that support research through citizen science, and provide insight on whether funding and QAQC measures play a significant role in helping citizen science projects produce contributions to science.

Acknowledgments

Thank you to my wife and family for carrying me these past 5 years. Special thanks to Stan Rullman who served as my thesis advisor. Without his direction, statistical assistance with R and SPSS, and many brainstorming sessions, this paper would not be possible. Thank you to Professor Mark Leighton, who reviewed my initial thesis proposal and helped me hone in on a worthwhile topic. I would also like to thank the Harvard Extension School for a fruitful journey. This process has been incredibly rewarding. Lastly, I would like to thank Earthwatch and its project scientists for providing research proposals, annual budgets and field reports, and the Earthwatch volunteers that fuel the projects and make data collection possible.

Table of Contents

List of Tables

List of Figures

Chapter I

Introduction

Citizen science (CS) projects have been successful in advancing scientific knowledge— particularly with regard to environmental and ecological field research— and contributions now provide a large quantity of data about species occurrence and distributions around the world (Bonney et al., 2009; Chandler et al., 2016a; Kosmala, Wiggins, Swanson, & Simmons, 2016; Theobold, Ettinger, Burgess, & Debey, 2014). Yet the adoption of citizen-science datasets has been hindered by the belief that data generated by volunteers contains greater levels of variability and bias compared to those collected by experts or instruments (Bird et al., 2013, Foster-Smith & Evans, 2003). There is an emerging need to evaluate citizen science based on the merits of its research outputs and impacts, and not presumptions about its practice.

Research Significance and Objectives

This thesis used the field research projects funded by Earthwatch Institute as a case study to evaluate the effectiveness of citizen science. Earthwatch is an environmental non-profit organization that has run CS-based research expeditions since its founding in1971. Earthwatch expeditions connect members of the general public, who serve as citizen science volunteers, with scientists around the world. These volunteers are trained as temporary field assistants to collect environmental/ conservation data and other field research tasks over spans of one to two weeks. The volunteers pay for their experience in the field, and their contribution directly funds project research. In this sense, Earthwatch volunteers serve as both the project's workforce and its financial backbone.

The primary objective of this thesis was to evaluate the effectiveness of Earthwatch-supported projects based on each project's ability to produce peer-reviewed publications. For this analysis, I used the successful publication of peer-reviewed journal articles as a readily verifiable metric of project success.

The second objective of this research was to look at Earthwatch's funding model and evaluate whether a group of projects supported from 2000-2016 successfully met their annual financial targets. This objective is significant for Earthwatch as it will show how project's meeting their core financial requirements not only makes good business sense, but ultimately highlights the need for a stable funding model that allows for sufficient data collection to occur.

The third objective was to create and implement a scoring rubric that measures the quality assessment and quality control (QAQC) measures in place for data collection for each Earthwatch project. This rubric was customized to measure the QAQC metrics for the assessed Earthwatch projects running from 2000-2016, but a similar model could be used by other organizations to score their own CS projects.

Ultimately, the results of this research could help Earthwatch create more informed project standards, leading to better business decisions when selecting new projects, and stronger organizational sustainability. While the results are contextual and built around CS projects that are specific to Earthwatch, in a broader sense, the methods from this thesis can be applied to other organizations and agencies that support citizen science, providing insight on possible funding models, the need for sustained financial support, and the relationship between QAQC measures and meaningful research outputs.

Background

Citizen science engages non-professionals in authentic scientific research, from long-term, large-scale projects, to personalized backyard research experiences. The European Commission Green Paper defines citizen science as “general public engagement in scientific research activities where citizens actively contribute to science either with their intellectual effort, or surrounding knowledge, or their tools and resources” (Follett & Strezov, 2015). CS in ecological and conservation topics engages interested volunteers in a wide variety of projects including monitoring wildlife, vegetation, phenological shifts in plant phases, and other biotic and abiotic environmental metrics, as well as classifying images, transcribing old records and annotating images from past biodiversity collections (Kullenberg & Kasperowski, 2016).

CS project objectives range from supporting scientific investigations within academic institutions, government agencies, and non-governmental organizations, contributing to the body of scientific knowledge through publications, providing data and analytics that help inform management plans and policies (at a wide variety of spatial and temporal scales), to increasing scientific literacy and generating interest in science among the public (Crall et al., 2010; Follett & Strezov, 2015). Ultimately, the most important features of citizen science are the authentic engagement of public researchers in the research and a genuine intention to use data to address questions of value with results that stand up to peer review (Dickinson & Bonney, 2012).

Two centuries ago, nearly all scientists made their living in another profession. Benjamin Franklin was a printer, diplomat and politician. Charles Darwin sailed on the *Beagle* as an unpaid companion to the captain, and though described as a naturalist, his most formal schooling—at the time— was in theology and medicine. The rise of science as a paid profession didn't come about until the end of the 19th century (Silvertown, 2009). Citizen science returns to these roots as a way for non-experts to work alongside professionals on projects that were designed to give amateurs a role. Early examples of CS projects include the Christmas Bird Count, which has been run annually since 1900 by the National Audubon Society (www.audubon.org). Bird counts engage observers and are based on monitoring select species (Silvertown, 2009). Other large-scale monitoring occurs for fungi, amphibians, reptiles and coral reef taxa (Chandler et al., 2016a). With large monitoring projects, citizen scientists report observations and produce datasets on a scale that experts couldn't have achieved on their own.

Current Uses and Status of Citizen Science

Today, citizen science exists in a variety of different forms, and volunteers now participate in projects on climate change, invasive species, conservation biology, ecological restoration, water quality monitoring, population ecology and many other research areas (Theobold et al., 2014; Dickinson & Bonney, 2012; Wiggins, Newman, Stevenson, & Crowston, 2011). The advance of technology, including the internet and smart phones and specific apps designed for data collection (Teacher, Griffiths, Hodgson, & Inger, 2013), has made disseminating information about projects and gathering data from the public more streamlined. In addition, the development of data collection tools that function to improve the accuracy and validity of data and reduce bias (Silvertown, 2009) has improved the quality of CS data.

Follett and Strezov (2015) have categorized modern citizen science projects into three major types, based on the degree that volunteers are involved in various stages of the project:

- Contributory, where participants contribute to data collection, and sometimes help analyze the data and disseminate results
- Collaborative, where citizens also analyze samples, data, and sometimes help design the study, interpret the data, draw conclusions and disseminate the results
- Co-created, where citizens participate at all stages of the project, including defining the questions, developing the hypotheses, to discussion of the results and answering new questions

Whether contributory, collaborative or co-created, citizen science projects hold great potential for gathering data and building collaborative networks. Not only can the public be used to collect data on unprecedented scales, but citizen science projects also educate and engage non-experts and makes important scientific subjects more accessible.

Significance of Citizen Science

The urgent environmental problems we face today, whether it be the acidification of oceans, climate driven changes in temperature and precipitation, or the widespread extinction of species, are so large that scientists alone, working within academia, can't solve them (Eisenberg, 2015). Professional scientists are realizing that the public represents an important source of labor, skills, and computational power. Citizen science enables researchers to answer questions that entail collecting large amounts of data over a wide geographical area over long periods of time (Silvertown, 2009; Tulloch, Possingham, Joseph, Szabo, & Martin, 2013).

In addition to their scientific impact, CS projects can also contribute to significant social outcomes. In one study, the sea turtle monitoring network, Grupo Tortugeuro, in northwestern Mexico, helped to establish marine protected areas and sustainable fishing practices that were sensitive to the livelihoods of locals. If projects are designed with scientific objectives as well as planned investments in infrastructure and partnerships, then CS can not only be used to collect quality data, but can also inform conservation policy while yielding a stronger science-society relationship (Dickinson & Bonney, 2012).

Citizen science-based projects also have implications for public policy because they can engage the public from the start. Participation in scientific research creates deep learning experiences, and CS is a powerful option to generate ecological knowledge, and place-based learning (Crall et al., 2010; Dickinson, Zuckerberg, & Bonter, 2010; Newman et al., 2016). Most CS projects also help participants learn about the species they are observing and experience firsthand the process by which scientific investigations are conducted (Bonney et al., 2009). This is especially relevant today as many global scientific issues have become increasingly politicized. The scientific community questions whether the public understands the value, nature and importance of science. More specifically, there is unease about whether people understand evidence and facts or want to distinguish between opinion and scientific evidence (Durani, 2017). Citizen science could play an important role in bridging this gap by helping the public understand the scientific process and by directly engaging them in research.

In addition to its social benefits, CS projects also have the potential to use the public as a source of funding. This is especially relevant in the United States, as funding for environmental research has been restricted, and in 2017, an estimated $54 billion in cuts are planned for federal programs (Earth Island Journal, 2017). These cuts may reduce the EPA's annual spending by 31 percent and potentially cut $250 million from the National Oceanic and Atmospheric Administration for grants and programs that support coastal and marine management, research, and education. The cuts also impact payments to the United Nations' climate change programs such as the Green Climate Fund and Climate Investment Fund (Earth Island Journal, 2017).

Theobold et al. (2014) found that for 388 sampled citizen science projects, volunteers contributed up to $2.5 billion in-kind annually. These funds exceeded most federally-funded studies both in spatial and temporal extent. It is clear that the general public can prove invaluable as a funding source. With organizations like Earthwatch, the public is not only used to help scientists collect data in the field, but also to pay for their field experience, which supports research projects directly.

Criticisms of Citizen Science

Despite its benefits, citizen science is not universally accepted as a valid method of scientific investigation. Scientific papers presenting volunteer-collected data sometimes have trouble getting reviewed and are placed in the outreach sections of journals or education tracks of scientific meetings (Bonney et al., 2009). The categories below highlight some of the common citizen science criticisms.

Issues of project design: monitoring vs. hypothesis-driven research. It has been suggested that citizen science is best viewed as complementary to more localized, hypothesis-driven research. This is because CS generally doesn't always seek to uncover mechanisms underlying ecological patterns (Dickinson et al., 2010). CS projects that focus on monitoring species will generate datasets that can later be used by experts to create testable hypotheses. The primary issue here is the perception of volunteer error and bias and how non-experts should be utilized. It is assumed that volunteers are better suited for projects that are monitoring-based with simple tasks.

Issues of volunteer error and bias. Data quality issues are not unique to citizen science, but CS criticisms commonly center on issues of bias and the skill of participants to collect data, as volunteers vary in ability, experience, and training (Dickinson et al., 2010). One study demonstrated that trained volunteers were not as good as professionals at detecting low densities of wooly adelgids (Hemiptera), an invasive insect that feeds on Eastern hemlock (*Tsuga canadensis*) (Dickinson et al., 2010). Volunteers only performed better when accompanied by professionals. It should be noted that this study didn't distinguish the importance of training from experience. In another study, the North American Amphibian Monitoring Program found that observer skill and inter-observer reliability varied widely with species identification and had to be controlled for either in sampling design or data analysis (Dickinson et al., 2010).

With sampling bias, variation might appear with sampling effort. When projects allow for any amount of error, samples may be split, with rarer species over-reported and common species under-reported (Dickinson et al., 2010). In these cases, the more "interesting" species are favored. A similar analysis found that students over reported relatively rare pines and larger oaks relative to professionals (Galloway, Tudor, & Haegen, 2006). Volunteers may also stop observing when there are no interesting species in sight (Dickinson et al., 2010). Additionally, if volunteer groups follow different monitoring protocols, their data may be heterogeneous (Bonardi, Manenti, & Corbetta, 2011).

Sampling effort can also be geographically biased. If volunteers sample from sites that are not representative of the larger landscape, then differences in abundance reflect spatial sampling bias and not geographic differences in sampling size (Dickinson et al., 2010). Volunteers may also only sample from areas that are easily accessible, and uninhabited areas might be avoided (Dickinson et al., 2010). Similarly, data may be less accurate in areas that are physically more difficult to reach. In a study of topographic, bathymetric and biological data for reefs in Belize, the accuracy of volunteer data declined in deeper and drop-off reef zones due to physical, physiological and psychological phenomena (Mumby, Harborne, Raines, & Ridley, 1995).

Volunteer error can also be a function of education and aptitude. The determination of the gender of crabs was more challenging for seventh graders and accuracy was only 80% for this age group (Delaney, Sperling, Adams, & Leung, 2007). By comparison, students with at least 2 years of university education were able to predict the sex with 95% accuracy. In another study that monitored deer populations, scientists similarly found that volunteers' ability to find and identify droppings was correlated with their willingness and aptitude (Buesching, Newman, & Macdonald, 2013).

Issues of sustained funding. On a fundamental level, sustained funding is a critical issue with most CS projects. Not unlike other forms of scientific research, CS projects must contend with securing funds for cyber infrastructure, databases, and project leadership (Dickinson & Bonney, 2012). CS is limited by the availability of resources (Chandler et al., 2016a and b; Crall et al., 2010) and while citizen scientists are frequently more efficient than paying professionals, issues that may be specific to CS include procuring funding for the marketing, recruitment and retention of volunteers. Without sustainable finances, CS projects fail to cover basic operational costs like staff salaries or stipends and field equipment. Data cannot be obtained, managed and ultimately analyzed without secure funding sources.

Addressing Citizen Science Criticisms

While the above criticisms are certainly well-founded, each issue can be addressed and mitigated.

Addressing project design assumptions: monitoring vs hypothesis driven research. Some studies suggest that long, arduous, or repetitive tasks, complex methods, or difficult taxonomic identification are not suited for citizen scientists. In particular, ecologists working with long term projects have to consider whether cognitive biases lead to systemic data biases, whether certain attributes or species are particularly difficult to measure or tell apart, and how much experience or training is required before data are reliable (Dickinson et al., 2010; Tulloch et al., 2013).

While monitoring studies designed to detect patterns of species occurrence over time or space are well suited for citizen science, it is also possible to involve volunteers in more complex designs and even experiments (Tulloch et al., 2013). For example, the Cornell Lab of Ornithology's Seed Preference Test involved thousands of participants who examined the food preferences of birds by providing different seeds in a continent-wide experiment (Bonney et al., 2009). Participants in the Birds in Forested Landscapes project were required to select survey sites, describe site habitats in detail, and use playbacks of recorded songs and calls to locate and map breeding birds (Bonney et al., 2009). These examples indicate that citizen scientists, with appropriate training, research design protocols and oversight, are capable of contributing directly to hypothesis-driven projects (Newman, Buesching, & Macdonald, 2002).

Addressing volunteer error and bias. Analysts are discovering ways to filter large data sets, using mechanisms to eliminate error and bias, such as excluding data from first-year participants, people who submit erratically, and participants who submit erroneous reports (Cohn, 2008; Dickinson et al., 2010). Statistical and high-performance computing tools have addressed data-quality issues like sampling bias, detection, measurement error, identification and spatial clustering (Bonney et al., 2009; Hochachka et al., 2012).

It should be noted that the issues of error and bias that are present in CS data are not unique to these types of data. The same problems exist in datasets across a wide variety of disciplines and can be addressed with analytical approaches. Volunteer training, data standardization, validation and filtering procedures, can all reduce sources of error and bias (Brandon, Spyreas, Molano-Flores, Carroll, & Ellis, 2003; Buesching et al., 2013; Crall et al., 2010; Crall et al., 2011; Foster-Smith and Evans, 2003; Newman et al., 2003; Wiggins et al., 2011). These controls can be applied before, during, and after data are collected (Bird et al., 2013). As an example, hierarchical models can be used when the sampling design has some element of systematic bias, specifically for spatially or temporally clustered data. Other ways to deal with systematic bias include models for imperfect detection, false-positives, and species misidentification (Bird et al., 2013).

It should be noted that scalability of data validation methods must be taken into account during the project design phase. In many cases, the chosen validation mechanism hinges on the human and financial resources available for each project. For larger datasets, many CS projects lack the resources to engage computer science researchers and statisticians for data mining algorithms and models (Wiggins et al., 2011)

In some cases, CS projects have an advantage over standard research projects where the data is collected by only a few experts in the field. As mentioned previously, data quality issues are not unique to citizen science, but using the public to generate a larger sample size is beneficial because more measurements lessens sampling error (and tightens associated confidence intervals) by increasing overall precision (Brandon et al., 2003; Dickinson et al., 2010).

Issues of volunteer error and bias can also be addressed with what Shirk et al. (2012) describe as “deliberate project design”. This is effectively a framework for CS project developers to use concerning decisions about whose interests can and should be addressed, and how end goals, or desired outcomes should be defined (Shirk et al., 2012).

The framework helps researchers think deliberately about research design choices, and how the interactions between scientific interests and public interest can influence potential outcomes. Initially, projects should consider the desires, goals and expectations of both the public volunteers and the scientists to determine the focus of the project; i.e., will a project be primarily a learning experience or is the primary objective simply to collect data? Project design should also consider the specific activities or tasks that the scientists and participants will be performing.

Sampling strategies and protocols, training materials, and data submission/entry should all be considered in this phase, and research tasks should not only be built around the expectations of the scientists and the public volunteers, but also around the desired outputs of the research (Shirk et al., 2012). For example, if the goal is to expose and engage volunteers in standard field methods, then the tasks might be more complex and require a higher level of training and supervision by the researchers.

At the end of the design phase, the outputs are the results of the activities and include observations, recorded data, along with the experiences of making, facilitating, and/or analyzing measurements. In conjunction with outputs, impacts must also be considered, which are the projected changes the project will yield to support human well-being or conservation efforts (Shirk et al., 2012).

The level of involvement by volunteers and the extent to which they are trained and engaged will largely depend on the desired outputs and long term desired impacts of the project. If a project is built with the knowledge of its desired impacts and outputs, along with the expectations of the researchers and public volunteers, this will make it easier to select appropriate research tasks and training protocols based on the level of input required by the project. Projects will more successfully incorporate volunteers to collect meaningful and accurate data if the design correctly reflects each of these aspects.

Addressing issues of sustained funding. Inconsistent funding leads to data fragmentation, where data is broken up and not collected at consistent intervals across time. Suitable funding and commitment must be secured before data collection occurs. Funding should be pursued from the government, foundations, and the private sector (Dickinson, 2012). Strategic collaborations and partnerships are necessary to secure resources and build the volunteer base needed to sustain projects long-term. Sufficient funding is critical for project marketing, and projects must consider the volunteers they are recruiting for, and craft messages that are designed to appeal to these audiences directly (Dickinson & Bonney, 2012). Many citizen-science projects have actually received funding because of their ability to connect scientific research with science education. This requires projects to create materials that engage volunteers and describe how their participation ties into the overarching research questions (Bonney et al., 2009). Background information is critical to understanding the theory and ideas behind the research (Dickinson & Bonney, 2012). Groulx, Brisbois, Lemieux, Winegardner, & Fishback, (2017) and Bonney et al. (2009) have similarly found that CS can promote individual changes in environmental attitudes through experiential learning and connecting the public to the natural world. In Earthwatch's case, funding can come from the volunteers directly, and members of the general public pay for the experience to learn from and help research experts collect data in the field.

Ultimately, concerns for error and bias can be accounted for, and citizen science projects, just like any ecologically based project, should be evaluated based on the quality of the research and not presumptions about its practice.

The Citizen Science Model at Earthwatch

Earthwatch Institute is an environmental non-profit that has been fielding citizen science based research projects since 1971. Earthwatch's mission is to connect the public with scientists and provide people with educational opportunities to promote the understanding and action necessary for a more sustainable environment (www.earthwatch.org).

What distinguishes Earthwatch from other CS models is that the organization involves volunteers in research directly using practices similar to an ecologist engaging undergraduate field assistants (Dickinson, 2010). In this sense, Earthwatch projects don't fall into the category of large-scale, crowd-sourced citizen monitoring efforts. Instead, CS at Earthwatch can be categorized as "contributory" in nature (following Follett and Strezov, 2015), where volunteers join research teams for an average of 12 days and are trained by scientists in the field to perform specific research tasks and collect data. On these expeditions, the scientists themselves do the initial research design and are ultimately responsible for the analysis of data, drawing conclusions, and using the results to produce publications and/or inform policies to conserve taxa.

Earthwatch projects are also "deliberately designed" (following Shirk et al., 2012), with clear expectations for the specific roles of volunteers and scientists. The scientists are expected to engage volunteers in tasks that are simple enough to be learned within a few days, and the volunteers are essentially "temporary field staff" and are trained, and in most cases supervised, until they are proficient with data collection. Volunteers can also expect supplementary lectures and trainings explaining the significance of the research and how their efforts fit into the project's larger goals. Earthwatch also outlines clear expectations for research outputs and requires researchers to report on their outcomes each year in a standard field report. These annual reports highlight research achievements at the end of each field season, and detail scientific results in relation to each project's research objectives. The report also discusses positive impacts in areas like conservation, publications, contributions to management plans and policies, local community engagement and education. The report not only allows Earthwatch to track annual progress, but is posted publically so volunteers have the ability to see the results of their efforts.

How Earthwatch Projects are Selected

When scientists first apply to partner with Earthwatch, they are required to submit a research proposal. The research proposal is a tool to assess project suitability, and is based on a variety of criteria, including marketability and appeal of the project to the public, the alignment of the research with the Earthwatch mission and current priorities for support, and the overall project risk as it relates to the country of operation and the project's research tasks. Earthwatch also considers the ease of logistics on the ground to reach the field site, along with the ease of travelling to and from the country of operation. Scientists must also create a draft budget to assess financial viability based on projected costs, overall team size, and the total number of research teams. This budget leads to a per capita field grant value, with the amount of funding provided based directly on the number of volunteers who sign up for and participate in the research expedition.

For research quality, projects are evaluated based on the scientist's proposed objectives, research design, methods, and the engagement of volunteers in research tasks. Research tasks are evaluated both in terms of their accessibility to non-professionals, as well as their overall usefulness to the scientists for collecting data. The volunteer tasks must be additive, and not redundant to existing research protocols. Prospective scientists are also evaluated based on their qualifications (academic credentials and existing partnerships with universities and NGOs) and their projected impacts in terms of publications and/or policies they plan to produce. Lastly, projects are considered for their ability to engage the local community, as well as their capacity for disseminating project outcomes to wider audiences.

Projects are vetted based on the above criteria to help predict their longevity and success. More importantly, the application process sets clear expectations, and projects must be designed with volunteers in mind so research tasks are not only engaging, but also useful to the scientists' overall research goals. The application process also sets the expectation for projects to generate outputs in the form of publications and/or contributions to management plans or conservation/environmental policies from the start.

Earthwatch represents a unique niche in the field of citizen science. Projects are team- based, researcher-facilitated, and the research is conducted in field sites across the globe (in over 130 countries, collectively, to date). Projects are brought on with clear expectations for scientists and volunteers, and they are reported on annually to track their progress on objectives.

Earthwatch as a Case Study for Quality Citizen Science Data Outputs

Chandler et al. (2016b) compiled a dataset for 62 individual Earthwatch projects that were partnered with the organization and actively running teams between 2008 and 2014. Collectively, these 62 projects represented 237 individual years of partnership with the organization (the range a project was supported within this analysis was between 1 and 38 years). Within this 2008-2014 timeframe, 8,872 volunteers contributed 465,830 hours of support. 333 peer-reviewed scientific publications were produced (an average of 1.6 per project/ year) and 264 conservation plans/policies were informed (an average of 1.3 per project/year). A subset of 51 of these projects had sufficient metrics for a more detailed analysis on predictors of project impact and success.

In their paper (Chandler et al., 2016b), a number of independent variables were tested against the publications and policies produced by each project to determine their influence on these project impacts. The independent variables tested were: 1) total years of support per project; 2) number of volunteers that fielded per project; 3) number of volunteer hours contributed per project; 4) sources of funding for volunteers (self-paying versus primarily sponsored or underwritten by an external funding source); 5) PI affiliation with either a university, NGO or other agency; 6) scientist nationality (whether the project was locally based or the principal investigator was working as an expat/foreigner); and 7) research team size in terms of the number of professional researchers working on or leading the research project.

In addition, the paper assessed the efficacy of an Earthwatch project evaluation tool developed in 2005 and ultimately implemented in 2008 called *Measures of Success,* hereafter referred to as “MoS”. This tool evaluated 12 MoS criteria that could be tracked against project outcomes, outputs, and impacts. For each MoS criterion, a scoring rubric was developed along a 1-5 weighted scale (with “0” indicating no metric provided), resulting in easily comparable metrics to assess project impacts. For their analysis, the authors focused on two areas of project outputs and impacts, direct counts of 1) peer-reviewed publications, and 2) contributions to management plans or policies, and their associated MoS metrics (MoS 1.2 and MoS 4.1, respectively).

For their analysis, the authors recognized that projects are not expected to produce strong impacts until sufficient data had been collected. As such, the first two years of support were eliminated from the full analysis, reducing the total years of project support from 237 to 207 for analysis. Critically, as several projects were in their first two years of support within the 2008-2014 window, this process eliminated eleven projects from the final analysis, leaving 51 projects for consideration within the associated analyses.

The authors found a significant positive relationship between years of support and publication rates with the “Years of support” variable strongly contributing to the overall model of project publication rate. The “Years of support” on “Contributions to management plans” was significant for the associated MoS driven by differences in project outputs supported for three to four years (Med-low) with those supported between five and nine years (Med-high). What this means is that projects produced more publications when they were partnered with Earthwatch for longer periods of time, certainly not a surprising finding for assessing project outputs.

The authors also found that the annual contributions to management plans and policies appeared to peak earlier than publications at 5–9 years of support (“Med-high”) for both counts of contributions to plans (mean annual contribution to plans = 1.63), and the weighted management plans MoS score (mean score=2.90).

PI affiliation also had a significant model effect on contributions to publications, with scientists having an exclusive university affiliation producing 5.7 times the publications produced by government-affiliated scientists. The strength of the PI affiliation held true for MoS scoring as well, significantly contributing to the model.

Both the “number of volunteers per year”, and the covariate “number of participant hours per year” provided significant support for MoS 1.2 scores, but not in the model of actual counts of publications. Importantly however, while this finding was statistically significant, low beta values for each indicated these independent variables were not strongly influencing project “success” (Rullman, pers. com.).

For sources of funding, projects supported solely by philanthropic funding sources contributed to 38% of the plans and policies of those funded through a combination of public participation in the research and philanthropic resources, whereas projects supported solely through public participation contributed to just over half of the plans and policies as the combined funding approach. The other variables did not yield significant results.

Next Steps for Analysis

The results of the Chandler et al. (2016b) publication provided some insight into which independent variables helped define “project success” with the production of publications and conservation policies. As a way to build upon and bolster their study, and in response to several brainstorming sessions, Earthwatch staff (myself included) determined that it would be useful to account for the criticisms of CS related to sustainable funding and volunteer error and bias. More specifically, it was important to determine how these variables independently influenced project success, and most importantly, when combined with the previous overall model, if these variables served to provide a stronger assessment of project impact.

Chandler et al. (2016b) initially found a statistically significant (though functionally weak) correlation between volunteer hours and publications produced. While recruiting volunteers provides the effort needed to gather data in the field, it is likely that the money volunteers contribute to support the full research effort may also be significant as it accounts for the operational costs to actually run the projects. This thesis therefore also evaluated each project's ability to meet its annual budget targets through recruiting sufficient volunteers as a metric of project sustainability and thus, able to fully conduct their planned research and data collection.

Similarly, the number of volunteers recruited doesn't necessarily reflect the quality of data being collected, so each project's quality assessment and quality control measures was quantified using a scoring rubric. This addressed common criticisms of volunteer error and bias and determined whether there is a correlation between the number of QAQC measures in place for each project and their production of research outputs.

Before discussing the specific methods used to evaluate project budget targets and QAQC measures, it is first necessary to explain Earthwatch's budget model as well as Earthwatch's existing requirements for data quality. These will both provide the necessary context to understand the methods section.

Earthwatch's Financial Model

When scientists initially apply to partner with Earthwatch, they are required to submit a draft budget with their proposal. When building their budgets, researchers must consider several variables including team duration, the number of teams they would like to run each year, and all of the relevant costs associated with running the project.

Earthwatch participants typically assist researchers in the field for set blocks of time in groups called "teams". A typical project engages a minimum of four to 12 participants per team on a minimum of three teams and up to 10 teams per fielding season. Each team typically spends one to two weeks in the field. The average project grant was approximately $70,000 USD for one full field season (Earthwatch 2016 budget instructions to PIs).

Grants cover the cost of maintaining participants and principal research staff in the field. Specifically, the budget covers the per team cost of living expenses including food, accommodations and infield transportation. Funds cover scientist travel to and from the research site, and stipends can be provided for employing local research staff. Camp staff members, including cooks, drivers, etc. are also covered. Other costs include first aid training for the scientists, communication costs (cell phone or satellite phone service), and basic field research equipment purchases or equipment rentals. By comparison, if scientists were to hire their own full crew of field technicians, they would be responsible for these amenities and the associated costs of their crew on their own. The Earthwatch model outsources both the research labor and the operational costs to willing participants. It should be noted that the funding does not cover principal scientist salaries, capital equipment for items over $2,000 USD (in most cases), or the costs of post-expedition data analysis. The budget also excludes the costs associated with conferences and workshops, and overhead for any associated universities or institutions.

Each project budget is based on a per capita field grant model, where the total annual budgeted costs are divided by the total number of expected Earthwatch volunteers. The budget is formatted to calculate the number of volunteers needed to cover the project's core costs, which Earthwatch refers to as the "financial minimum". Any field grants sent beyond this minimum are used to pay for variable costs. The purpose of this set up is to frontload project payments, so the scientists receive larger field grants at the beginning of their season to insure they meet their core costs. Once the financial minimum of volunteers has been achieved, the subsequent field grants are smaller as operational costs have been met. The rationale for this payment structure is that Earthwatch grants are incremental and contingent on the number of volunteers that sign up, and it is difficult to predict the total number of volunteers that will be recruited and what the total grant amount will be each year.

In summary, the minimum number of volunteers is based on the number of people physically needed to complete the fieldwork successfully while covering essential project costs. The number of volunteers beyond minimum is based on the greatest number of participants that the project can safely accommodate to occupy the vehicles, living quarters, and be meaningfully engaged in the research tasks.

While field costs are primarily funded using per capita grants, Earthwatch also pursues a variety of other funding sources including foundations and corporations/ organizations to help cover and supplement the agreed project budgets. If fundraising efforts are successful, the money is applied directly to the budget by adjusting the per capita field grant paid per volunteer. This application of funds effectively underwrites the project budget.

It should be noted that all Earthwatch budgets are reviewed on an annual basis and renewal funding is not guaranteed. Renewal of each project is contingent on an evaluation of the reported accomplishments against the goals outlined in the research proposal, the quality of the participant experience, and the financial viability of the project.

An example of Earthwatch's current budget template is in Table 4 of Appendix 1. The colored cells represent the different budget sections (food, accommodations, equipment, support staff, students, scientists transport to the field, infield transportation, and other). All of the sections, with the exception of "other" are broken down into costs at min and costs at max. These costs feed into the total expedition budget cell, which in the example is $6,600 USD at minimum and $11,885 USD beyond minimum. These totals are then divided by the number of volunteers at min and max, which in this case are 20 volunteers and 40 volunteers respectively. This yields the field grant at min ($330) and the field grant beyond min ($264), which are the funds sent to the scientist per volunteer. In this mock budget, the scientists need 20 volunteers to meet their core costs. They would receive $330 per person for the first 20 volunteers that signed up, and then for each subsequent volunteer, they would receive $264 per person to cover variable project costs.

It should be noted that the field grants Earthwatch sends to the scientists are different than the price the organization charges to each volunteer. When a volunteer signs up on a project, approximately 50% of their funds go to the scientist directly in the form of the field grant, about 34% of the volunteer's contribution goes to advance planning, risk management, site reconnaissance, team recruitment, and logistical support, and about 16% is used for administrative backup, communications, and post-expedition follow-up (Earthwatch financial terms and conditions- www.earthwatch.org).

The description of Earthwatch's financial model is important because it is necessary to understand the methods section that describes which projects have met their financial minimum targets. It is also relevant because other organizations and agencies that support or employ citizen science can use the described budget as a reference for them to recruit their own volunteers for funding.

Evaluation of QAQC Measures in Citizen Science

Freitag et al. (2016) define data credibility as the quality of being believable or trustworthy. They suggest that citizen science credibility standards vary from project to project, largely because CS projects are diverse and come in a variety of formats. Therefore, standard methods of peer review and quality assurance are not sufficient for building trust in citizen science data (Freitag, Meyer, & Whiteman, 2016).

Freitag et al. (2016) suggest three ways to break down CS credibility strategies. The first stage is defined as "early actions" and includes the steps taken to increase credibility before any data are collected. This includes working with volunteers to train them to complete the required tasks, and setting expectations that the volunteers have a specific skillset so they have a standard that must be met before joining. It also includes whether the project is scientifically advised by a university or advisory team during the development stage to ensure standard practices in the field.

The second stage occurs "in the field" when volunteers are in the process of collecting data. This includes in-person oversight where an expert researcher directly oversees the volunteers to ensure field tasks are completed correctly and accurately. In the field strategies also include retraining opportunities for volunteers either through readings, online trainings, or in-field sessions. The last in field strategy is to employ technological aids to help streamline challenging forms of data (Freitag et al., 2016).

The third stage occurs "in the office" to review project data after it has been submitted by the volunteers. This includes validating volunteer observations, either by checking data sheets to ensure observations are legible or flagging incorrect data. Another post-fielding strategy is to compare data collected by volunteers with data collected by experts. This confirms the credibility of the methods and also demonstrates that volunteers can collect data accurately. Another post-fielding option is to submit the resulting research through academic peer review for publication. This subjects the research to the same criticisms as research conducted by expert scientists. Table 7 in Appendix 3 provides an example spreadsheet that captures the strategies used by various citizen science programs to increase data credibility.

In addition to the stages described by Freitag et al. (2016), Kosmala et al. (2016) also review different methods for assessing citizen science data quality. They note that variation in volunteer accuracy is largely attributed to experience and task difficulty. They suggest making tasks as simple and as accessible as possible without compromising data quality. They highlight the importance of training, and in one study where volunteers monitored tropical resources, training over two to three days, coupled with shorter, refresher training, produced data of similar quality to professional scientists.

In a second example from Kosmala et al. (2016) publication, BeeWatch volunteers were provided with feedback continuously on their ability to identify different bee species based on responses from professionals validating their photographs. Expert validation is also highlighted as its own category, where data collected by volunteers is double checked by experts for errors and accuracy. Kosmala et al. (2016) also note the importance of replication and calibration across volunteers. They use the example of Mountain Watch, where volunteers collect data at fixed locations as well as self-selected locations with trained staff present to report on data from the fixed plots. This allows the staff members to verify observations from volunteers, but also allows for statistical normalization across the volunteers, and provides covariate data for analysis.

Current Quality Assessment and Quality Controls at Earthwatch

When scientists apply to Earthwatch, they are asked to detail their research objectives, methods, and projected outcomes in their initial research proposal. The Earthwatch research proposal is broken down into seven sections which include the project design, impacts, project overview for lay audiences, field logistics, draft budget, scientist and staff information, and acknowledgements/appendices. For the purpose of this thesis, only the project design and field logistics sections were considered as they specifically provided information on the implemented quality assessment and quality control measures for each project.

The project design section asks the scientists to identify their research problem and summarize the project's overall goal. The goal should be measurable and address the problem that has been identified (and will also need to align with Earthwatch's current priorities for research support). The project's objectives must also be described in this section, and should detail the desired accomplishments, milestones, or outcomes of the project. The methods for the objectives must also be provided with detailed descriptions for how the data will be collected and analyzed. Scientists are encouraged to provide sample data sheets and interview questionnaires as appendices. The methods section of the proposal is important because scientists describe the detailed sampling scheme for each research task and the specific plans for data analysis.

The project design section also asks for information on the project's need for volunteer participation. The proposal specifies that projects must authentically involve participation by non-specialists and include a range of tasks that can be conducted under the scientist's supervision. The proposal also asks how the scientists plan to ensure that data collected by volunteers are scientifically sound. This last point is important, because it sets the expectation that every project should have controls in place to account for volunteer error and bias. It should be noted that this specific question hasn't always been present in past years' proposals, and only for any project that applied to Earthwatch after 2005, Earthwatch has consistently required scientists to describe measures that ensured quality data from volunteers.

The "need for volunteers" section is also useful because it can be compared with the proposals methods section to establish which tasks the volunteers will be conducting, and which ones they are being excluded from. This comparison makes it possible to determine how involved the volunteers will be in the data collection and data entry process. It is also useful to see if projects are withholding the more technical or challenging tasks from the volunteers, and to some degree, how trusting the scientists are of using non-experts.

The logistics section of the proposal asks for the projected number of teams and the number of volunteers each team can recruit. It also asks for a date range that these teams will field, along with projected team length. For this thesis, the most important component of this section is the proposed daily itinerary, where the scientists are asked to outline a typical research day from rising to retiring. Earthwatch asks scientists to approximate times for field work, meals, data input, and daily briefings/facilitated discussions. If the need for volunteers section was missing important information, the proposed itinerary often fills in these gaps by providing insight on time allotted to volunteer training and data collection/data entry.

Research Question, Hypotheses and Specific Aims

The questions put forward by this thesis largely build off the findings of Chandler et al. (2016). In their publication, the authors focused on variables that were related to functional components of Earthwatch projects (years of project support, number of volunteers, PI nationality, etc.) to assess which were most significantly contributing to the production of peer reviewed publications. Their overall goal was to determine which factors were driving CS project outputs. This thesis expanded on these findings by exploring two new variables that stem from the following research questions:

Does sustained financial support play a role in a project's ability to collect consistent data and produce peer reviewed publications? While issues of sustained funding aren't specific to CS, it might seem obvious that projects that are sustainably funded are better positioned to collect good data. The assumption is that steady financial support makes it possible to purchase research equipment, pay staff salaries, and cover basic operational costs from year to year. In practice at Earthwatch, I have seen on an individual project level that this isn't always the case. Factors like scientist motivations and experience play a role in their ability to produce publications, as does the competiveness of the specific field they work in. All things being equal, however, it is worthwhile to look at Earthwatch projects collectively and assess whether funding plays a role in producing research outputs.

Another variable worth exploring is the role of quality assessment and quality controls in the production of research outputs. If the stigma associated with citizen science stems from the assumption that lay audiences collect less accurate data, then this begs the question of whether sufficient QAQC measures can be used to mitigate volunteer error. More specifically, if projects are designed from the onset to account for error and bias in data collection, will this lead to better data and more publications?

Hypotheses

Stemming from the questions above, I hypothesized that that there is a positive relationship between projects that are meeting (or exceeding) their annual financial targets and the number of peer-reviewed publications they produce. The assumption is that sustained funding leads to sustained data collection and a more consistent production of publications.

I also hypothesized that there is a positive relationship between the number of QAQC measures implemented per project and the number of peer-reviewed publications they produce. The assumption is that projects with more controls in place will collect more accurate datasets, in turn making it easier to perform analyses and produce publications.

Specific Aims

To address the questions and hypotheses above, I followed the specific aims below:

1. Selected a sample of Earthwatch projects that expands upon the dataset used by Chandler et al. Specifically, increased their sample size to include projects that ran between 2000 and 2016.
2. Using this expanded dataset, I counted the total number of publications produced for each added project.
3. I gathered budget information for all Earthwatch projects in the expanded dataset and created a ratio of the money the projects were receiving against their core budget targets.
4. To assess QAQC measures, I created a scoring rubric so the projects in the expanded dataset could be compared against one another.
5. I performed statistical analyses to determine if a project's ability to meet its financial targets were correlated with the number of peer reviewed publications it

produced. I performed a similar analysis to see if the number of QAQC measures implemented was correlated with the number of publications produced.

6. I performed a larger statistical analysis comparing my two new variables with the explanatory variables already established by Chandler et al. to see which was the best predictor for generating publications.

Chapter II

Methods

This thesis used the same initial 62 projects evaluated by the Chandler et al. publication, but expanded on the 2008 - 2014 timeframe to include project data from 2000 – 2007, and 2015 – 2016. This timeframe was selected due to the availability of budget data. Gaps in the availability of both budgetary and data quality assurances resulted in a final dataset of 55 projects to be included in this analysis, representing a total of 464 project years of support. Newer projects that began after 2008 had their budgets stored in Earthwatch's Microsoft Dynamics CRM database. These were readily accessible to download and review. For projects that began before 2008, budgets were usually stored in one of three shared organizational drives. A quick search within these drives for the project scientist's last name would usually yield the annual confirmed budgets. If an annual budget for one of the older projects was not found in these three electronic data repositories, it was possible to review the project archives for any non-digitized, paper-based copies of the resources as part of the original research proposal submission.

The year 2000 was selected as the cut-off date for this study because the process of finding budgets, collating them, and then transferring relevant data to a consolidated spreadsheet took many months to complete, and more time could not be allocated to extract data for earlier projects; 2015 and 2016 data were added because the analysis for the Chandler et al. publication was completed in 2014 and these data weren't available when their publication was released.

Publications were measured both per year while they were supported by Earthwatch, as well as by the total publications that were produced after the partnership with Earthwatch concluded. The combination of these values was used to calculate the metric "Mean publications per year of support" also referred to as "mean publications produced annually". While the "sum of total publications" measures the overall outputs for each project, this variable is obviously influenced by the number of years a project is supported. Logically, it makes sense for projects with more years of support to produce more publications. By comparison, assessing the mean publications produced annually is perhaps a better measure of success because it controls for project duration, and gauges the annual productivity of each project.

Organization of Budget Sections for Analysis

Data from Earthwatch's budgets and database were collated into a single Excel spreadsheet with the following columns: Resource ID, Contract ID, Resource Name, Underwriting, True FG Total, Original Currency, Paid Bookings, Days, Sessions, Minimum Food, Minimum Accommodations, Minimum Equipment, Minimum Support Staff, Minimum Students, Minimum Scientist Transportation, Minimum in Field Transportation, Minimum Other, and Minimum Total. Full descriptions of these categories can be found in the Ancillary Appendix.

Once the annual budget totals were collated, the data were manipulated to create metrics more appropriate for a robust analysis. Primary among these was dividing the research budget based on the minimum volunteer recruitment (named “Minimum Total” in the dataset and which are the core funds that the project needs to cover its basic costs) by the amount of the field grant provided to the scientist (“True FG Total”).

This provided a way to assess how well projects met their core costs each year. In instances where projects are recruiting sufficient volunteers, the resulting value will be “1” or higher. In instances where projects are under-recruiting and not meeting their minimum budget requirements, this total will be below “1”. This column allows comparison of each project against each other to see which expeditions are meeting their financial targets and which are falling short. This data can then be compared to project research outputs to establish if there is a correlation between projects meeting their core operational costs and the number of publications they produce.

Statistical Analyses of Budget Data in R

After compiling the budget data in the master Excel sheet, the free software platform, R, was used for statistical computing and graphics; R version 3.4.1 (Single Candle) was used in conjunction with R Studio and R Commander.

Before performing analyses, the response data were checked for conformance to a normal distribution. The response variables considered were the “Total Sum of Publications”, the “Mean Publications Produced per Project per Year”, and the “Mean Measures of Success Score”. Shapiro-Wilk normality tests showed that that three variables failed to conform to the expectations of a normal distribution ($p<.05$). The descriptive statistics indicated substantially positive (>2) skewness for the “Sum of Publications”. The response data also included zero values, so a log 10(X + 1) transformation was applied. A Shapiro-Wilk normality test confirmed that the transformed data was normally distributed (p = 0.107). The original and transformed data can be seen in the histograms below (Figure 1).

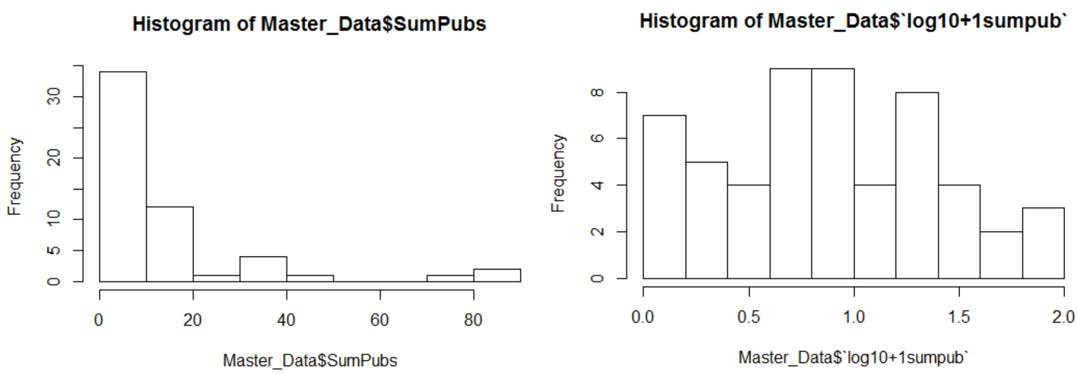


Figure. 1. Normalized sum of publications. Original sum of publications histogram indicating non-normal distribution (left) and transformed Log10(X+1) of sum of publications (right).

For the "Mean Publications Produced Annually" data, the descriptive statistics also indicated significantly positive (>2) skewness. In this case, a square root transformation yielded normal distribution (p = 0.092). Histograms of the original and transformed data can be found in Figure 2 below.

For "Mean MoS", the descriptive statistics indicated a moderately positive skewness (between 0.5 and 1). Logarithmic and square root transformations were unsuccessful, so a non-parametric Spearman rank-order correlation analysis was used.

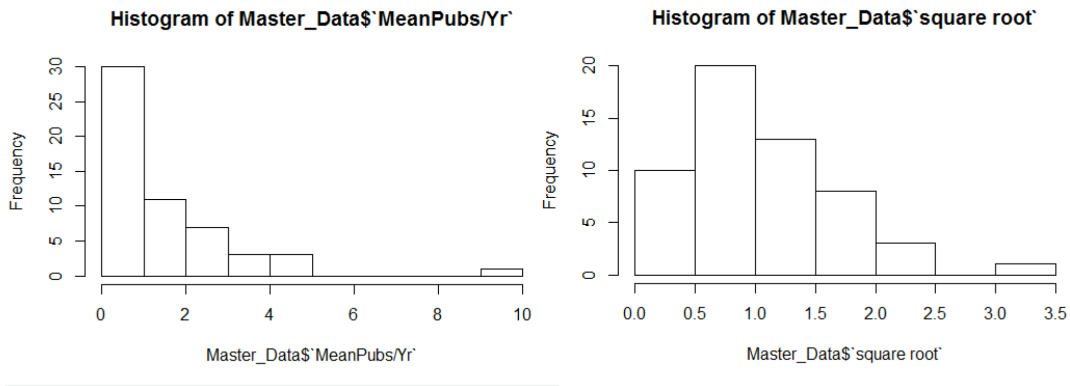


Figure. 2. Normalization of mean publications. Original mean publications histogram indicating non-normal distribution (left) and transformed normalized Square Root Mean Publications Produced Annually Histogram (right)

For statistical analyses, the first independent variable tested was the "True Field Grant/ Min Total". Since this variable is continuous, a Pearson's product-moment correlation test was conducted against the transformed "Sum of Publications" and against the transformed square root of the mean annual publications produced. To test the "True Field Grant/Min Total" against the "Projects' Mean MoS scores", a non-parametric Spearman rank-order test was used. In all three cases, the tests were used to test whether there was a relationship between a project's ability to meet its financial targets and the number/quality of publications it produces, with the expectation of a positive correlation.

Using the Existing Literature to Develop a QAQC Scoring Rubric

The strategies suggested by Freitag et al. (2016) and Kosmala et al. (2016) were used to examine which methods were being implemented by projects in the Earthwatch research proposals. In the "early action" stage, Earthwatch scientists consistently described the number of days required to train volunteers. For the "in field" stage, scientists would describe overseeing the volunteers to either validate data or ensure that the research tasks were being performed correctly. In some instances, the researchers would incorporate additional time for volunteers to practice the research task beyond the initial training sessions. Performing quick searches in the research proposal for keywords like "training" and "practice" were useful for finding these strategies. For the final "in office" stage, the scientists consistently mentioned who would be responsible for recording and entering data. If the scientists didn't specify that the volunteers were performing these tasks, it was assumed that the scientists were. The scientists also would describe whether data collected by volunteers were compared to a control or to data collected by researchers. Performing a quick search in the proposals for "data", "entry" and "record" was useful for finding these strategies.

In addition to the categories listed above from the existing literature, this thesis also used other categories to assess QAQC measures. For example, many Earthwatch scientists described new research designs and developed novel sampling methods for their project, noting this in the language of their research proposal. It was assumed that these projects would collect less accurate data because they were using methods that weren't tried and tested by other peer-reviewed publications. This could be determined by reading the methods section of the research proposal and noting whether the scientists were citing other researchers for standard sampling protocols.

Another category used was the scientists' prior experience working with groups or students in field research. It was assumed that scientists with prior experience would already be familiar with the common pitfalls of CS data quality and were more likely to have measures in place to reduce error. Performing a quick search for “prior” or “experience” was useful for finding this strategy in the research proposal.

In addition to the strategies above, it was important to note whether a specific project research proposal template included language specifying that the scientist account for quality data collection by their volunteers. The research proposal template has evolved over the years, always improving the guidance to ensure scientifically robust research. The request in the proposal for scientists to ensure data quality first appeared in 2005. It was a concern that this would skew data, and projects that joined after 2005 might provide more complete information on their QAQC measure because the proposal specifically asked them to. To address this potential source of bias, statistical analyses were run that considered the complete dataset for QAQC scores, as well as a subset of these data for projects that fielded before and after 2005.

Another category added to the rubric was the total number of tasks that the volunteers would be responsible for on each project. This is not part of the QAQC score, but is useful to report on in the descriptive data. A screenshot of the scoring rubric and its respective categories can be found in Table 5 of Appendix 4. Columns B through I were summed to give the project its overall score from 0-8. The score was broken down into three categories which included “low” for a score of 0-2, “medium” for 3-5 and “high” for 6-8.

Statistical Analyses Performed for Project QAQC Scores

To assess the impact of data quality assurances on project “success”, a linear regression analysis was performed of the “QAQC Score” versus the transformed “Total

Sum of Publications" and against the transformed "Mean Annual Publications Produced," with the assumption that the "QAQC Score" variable can either be considered ordinal or categorical. As with the financial metrics, a non-parametric Spearman rank-order test was used for the "QAQC Score" against the projects' "Mean MoS Score" as the MoS Score data did not meet assumptions of normality.

Other Statistical Analyses Performed

In addition to the budget and QAQC analyses described above, this thesis considered independent variables from the Chandler et al. publication that were significantly correlated with the production of research outputs and which could be obtained for the earlier range of years of support (2000-2007). These variables were tested against the bolstered datasets for the response variables. A summary of all the response and explanatory variables used in this thesis with definitions and descriptions of the units can be found in Table 1.

To assess (or technically, confirm) that increased "Years of Project Support" led to increased publications, a Pearson's product-moment correlation test was employed against both the transformed "Sum of Publications" and the transformed "Mean Annual Publications Produced". Lastly, a one-way ANOVA was conducted of "PI Affiliation" versus the transformed "Mean Annual Publications Produced" to assess the professional position held by the PI.

The final tests performed were non-parametric as the "Mean MoS Score" response variable was not normally distributed. The Kruskal-Wallis rank sum test was used for the "Mean MoS Score" against the "PI Affiliation", and a non-parametric

Spearman's rank correlation test was used for the "Mean MoS Score" against the "Years of Support".

Table 1. Response and explanatory variables assessed for Earthwatch-supported research projects.

Response Variable (Impacts)	**Type**	**Units/Categories**	**Definition**
Total Peer-Reviewed Publications	Counts (continuous)	Number of peer-reviewed publications	Peer-reviewed publications from projects that are both based on or acknowledge Earthwatch Support.
Mean Publications Produced per Year	Average (continuous)	Average number of publications produced annually per project	Publications were measured both per year while they were supported by Earthwatch, as well as by the total publications that were produced after the partnership with Earthwatch concluded. The combination of these values was used to create the mean.
Mean MoS Score	Average (continuous)	Average policy impact score for each project	Policy impacts are measured as low, medium or high. Low scores (1) occur when scientists have published 1-2 articles over the past 3 years in low impact factor journals. Medium (3) scores are for scientists who have published 2-3 articles in the past 3 years in medium impact factor journals. High (5) scores are for scientists who have published at least 1 article in the past 3 years in a high impact factor journal.
Explanatory Variables	**Type**	**Units/Categories**	**Definition**
Total Years of Support	Counts (continuous)	Number of years	Total number of years a project was supported by Earthwatch
PI Affiliation	Categorical	University, NGO, Univeristy+NGO, Government	Type of institution or organization for which the lead scientist is affiliated
Mean True Field Grant/Min Total	Continuous	Ratio of money sent to a project versus the core costs required to operate	Average of total field grants sent to project over its history with Earthwatch (between 2000 and 2016) divided by the average minimum budget needed to meet core costs.
QAQC Score	Continuous	Score counting the number of QAQC measures per project	Project's score between 1-7 based on QAQC scoring rubric

Once the individual models were complete, an Akaike Information Criterion (AIC) test was performed to estimate the quality of each model relative to one other. The purpose of this test was to determine which individual model was the best predictor of projects' production of peer-reviewed publications, and as such, which model (or single variable) might Earthwatch focus on to increase project success. While a stepwise function is possible in R Project, I had access to SPSS, which is a simpler program to model this type of function. In SPSS, a multinomial logistical regression was selected with covariate patterns defined by factors and covariates. The specific model selected was stepwise. Two tests were performed. The first test modeled the transformed "Mean Publications Produced per Year" (response variable) with "PI Affiliation", "Years of Support", "Mean True FG/ Min Total", "Volunteer Tasks", and "QAQC Score" (predictor variables). The second stepwise model used the "Mean MoS Score" against the same predictor variables. The stepwise functions are useful because they select the model of best fit and shed light on which individual predictor variable best fits the pattern for the response variables.

Chapter III

Results

For the financial analyses, the relationship between True Field Grant/Min Total ratio and Sum of Publications was not significant (r=0.13; t = 0.963, df = 53, p = 0.34 n=55; with 95 percent confidence intervals: -0.139 - 0.383). The scatterplot with the line of best fit indicates the relationship is non-linear with many outliers for publications produced with for the Mean True FG/ Min total ratio between 1 and 1.5 (Figure 3).

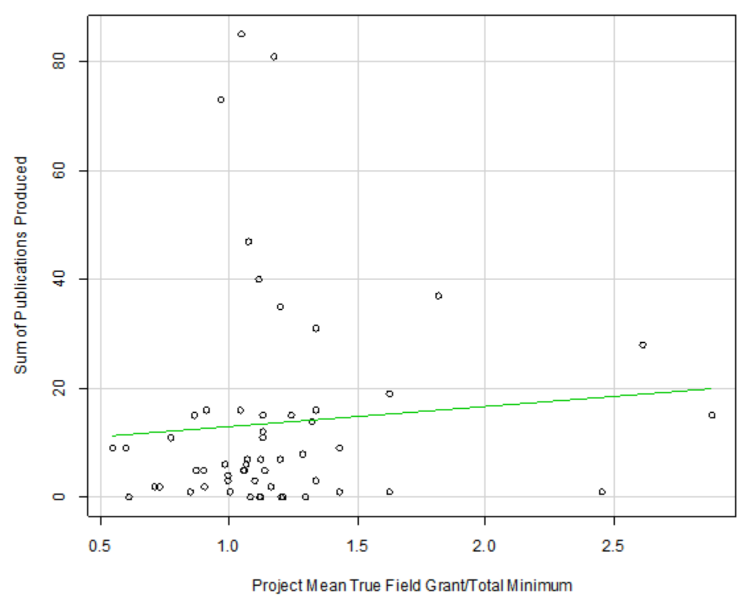


Figure 3. Earthwatch project true field grant/ min total vs. sum of publications produced.

In a second test, the correlation between the True Field Grant/Min Total ratio and the transformed square root of Mean Annual Publications, was also not significant (r=0.039; t = 0.286, df = 53, p = 0.78, n=55). The scatterplot (Figure 4) shows many outliers between 1 and 1.5 for the Mean True FG/ Min Total and doesn't appear to follow a linear or quadratic distribution pattern

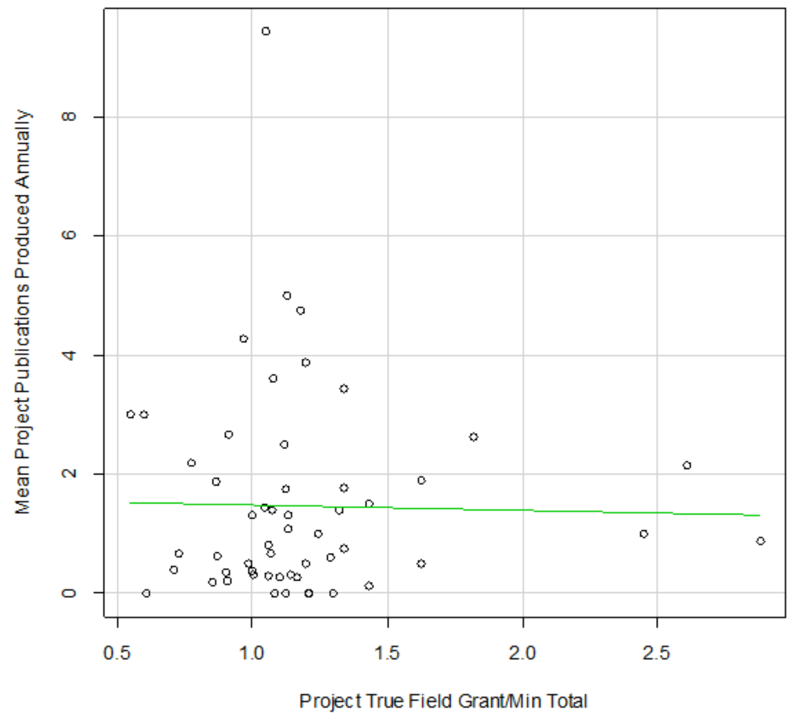


Figure 4. Project true field grant/min total vs. mean publications produced annually.

The final analysis performed for the financial data was a non-parametric Spearman rank-order test for the relationship between True Field Grant/Min Total ratio against the Mean MoS Score; these variables were also uncorrelated (Spearman's rho= 0.12; p=0.193, n=55; one-tailed test). The scatter plot (Figure 5) indicates the variance in the data.

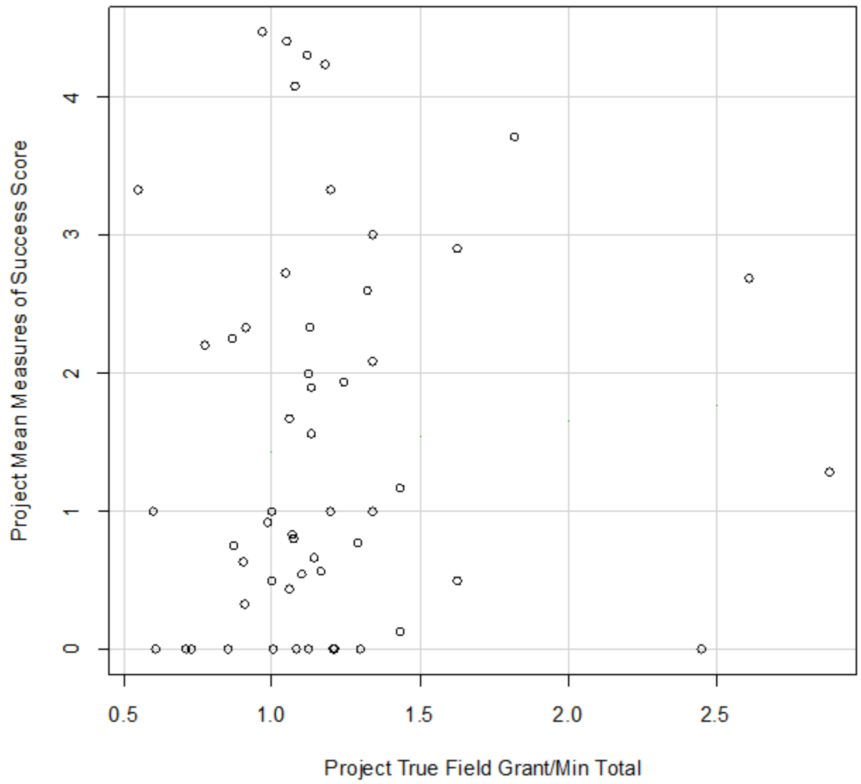


Figure 5. Project mean true field grant/ min total vs. mean MoS score.

Results of QAQC Score Analyses

The influence of the “QAQC Score” on the transformed “Sum of Publications” was assessed through linear regression, yielding a significant result ($F=13.905$, $r^2 = 0.225$, $p = 0.0005$, $df=1, 49$; $n=50$). However, the scatterplot of the non-transformed data and best-fit line indicates a negative relationship between an increasing QAQC score and the Sum of the Publications (Figure. 6). Therefore, contrary to my prediction, projects with a higher QAQC score tend to yield fewer total publications.

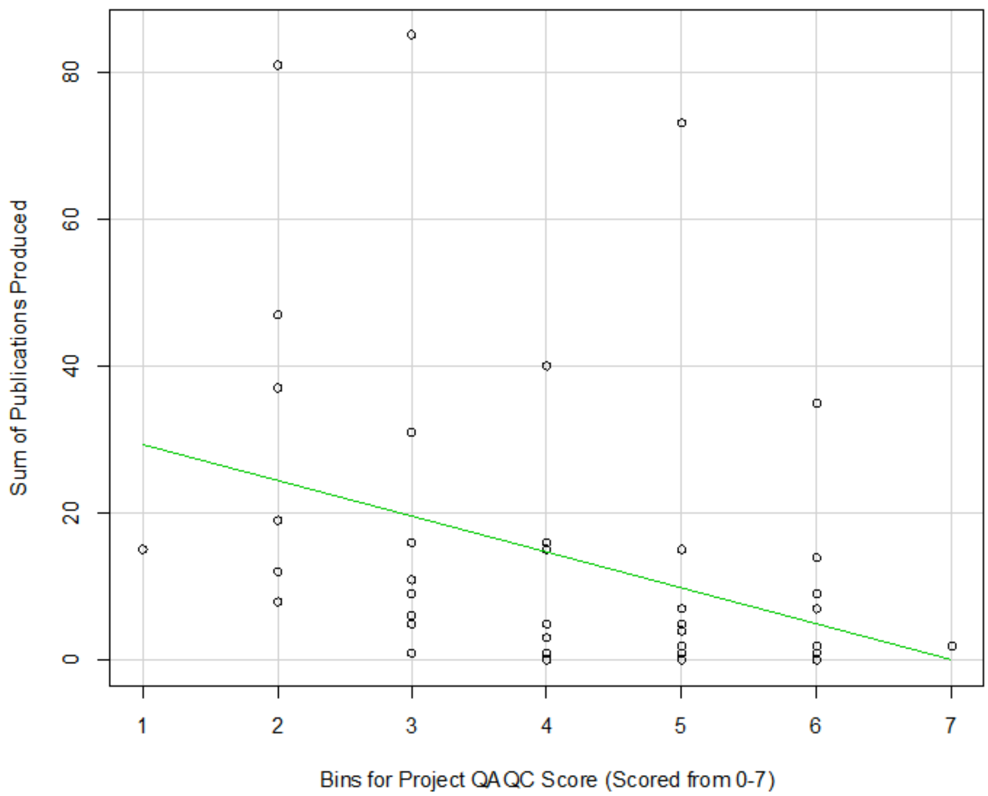


Figure 6. Earthwatch project QAQC scores vs. sum of publications produced.

To assess the influence of the same "QAQC Score" on the transformed "Mean Publications Produced Annually", a linear regression was again used, which yielded the following results: ($F=5.337$, $r= -0.316$; $r^2 = 0.100$, $p = 0.013$, $df=1, 49$; $n=50$). Again, the negative r value (and scatterplot of the non-transformed data, Figure 7) indicate a negative relationship between an increasing QAQC score and the Sum of the Publications.

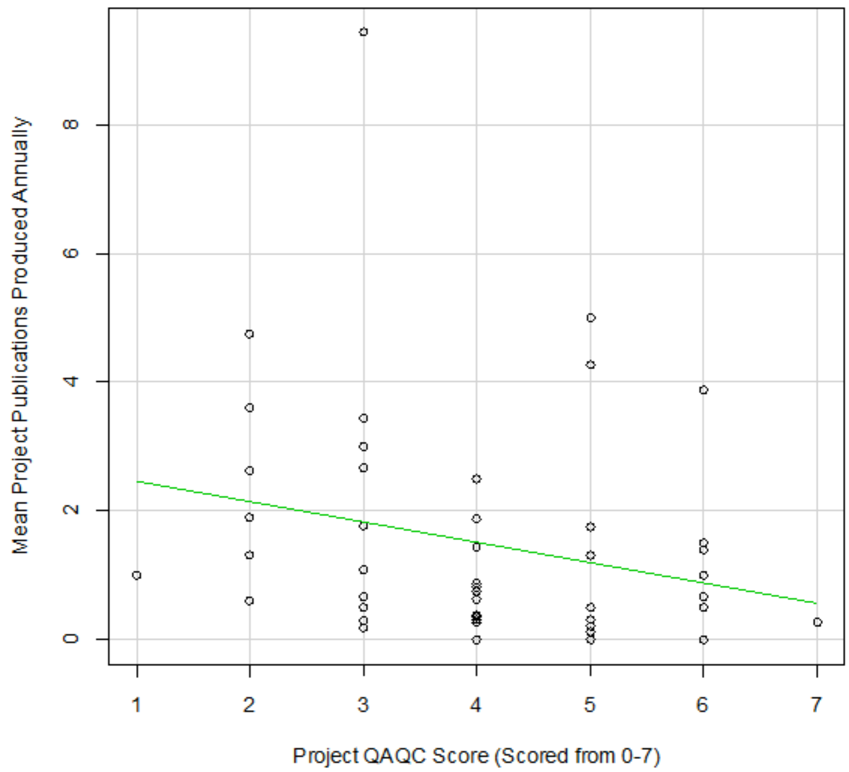


Figure 7. Project QAQC score vs. mean publications produced annually.

These results are interesting because they suggest that projects with a higher "QAQC Score" are more likely to produce fewer mean publications. As an added level of analysis, it was known that the "QAQC Scores" may have been skewed by the research proposal language. For projects brought on before 2005, the proposals didn't ask the scientists to account for methods to mitigate volunteer error/bias. By comparison, the research proposals for projects that applied to Earthwatch on or after 2005 did include language asking the scientists to account for volunteer error.

To account for this discrepancy, the data was broken down into two parts for projects pre- 2005 and post- 2005. In both cases, linear regressions were used to compare the slope of the lines of best fit. The slope for the best-fit line for the scatterplot of the pre- 2005 data is negative, indicating that projects with higher QAQC scores actually produced fewer publications (see Figure. 8).

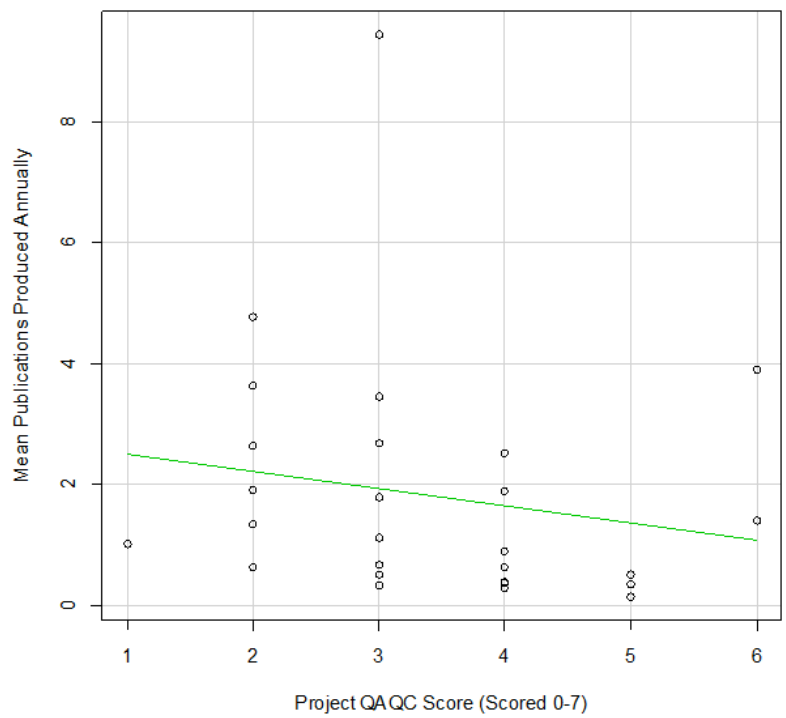


Figure 8. Project QAQC score vs. mean publications produced for pre 2005 projects.

The slope of the regression line for scatterplot of the post- 2005 data is also negative (Figure 9); however, for both periods, the QAQC score is significantly correlated, but not in the way that was expected, as projects with more measures in place to mitigate volunteer error end up producing fewer publications, both in terms of total publications and mean publications produced each year.

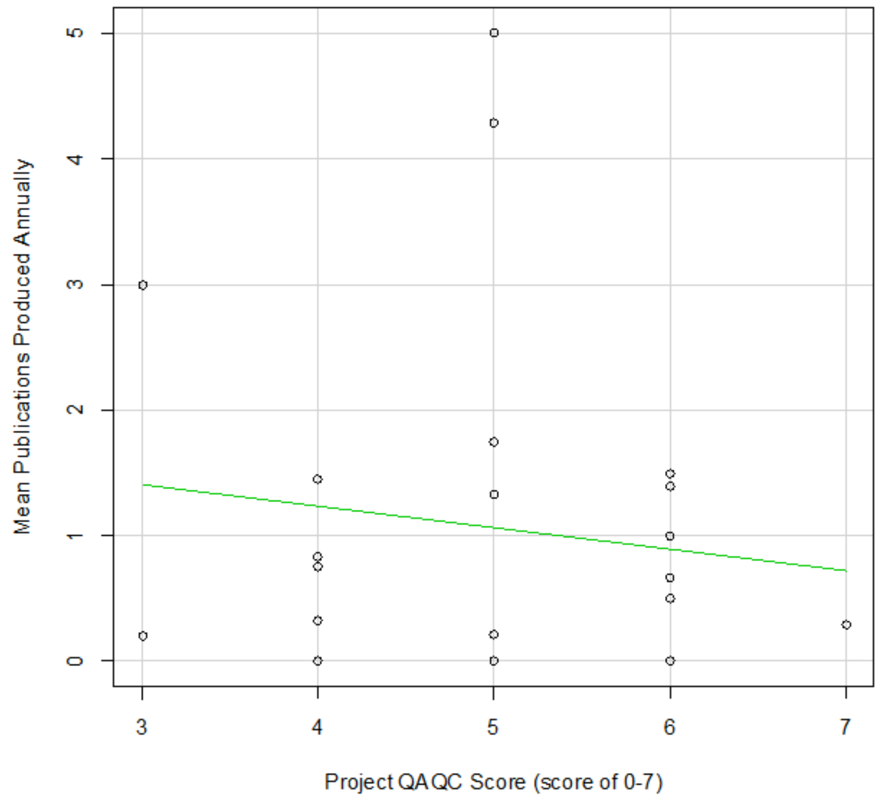


Figure 9. QAQC score vs. mean publications for post 2005 projects.

The last analysis performed was a non-parametric Spearman rank-order test for the “QAQC Score” versus the “Mean MoS Score”. There was no relationship between the variables (rho = -0.418, p=0.998, n=55; one-tailed test) (Figure 10).

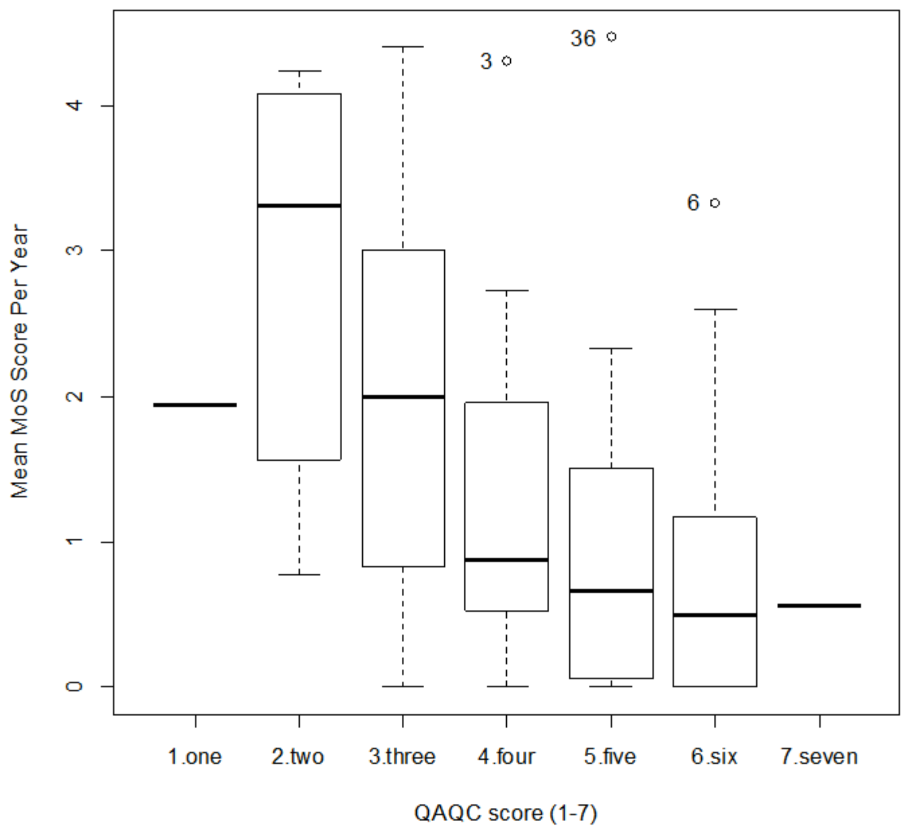


Figure. 10. QAQC score vs. mean MoS score. The bar graph features the mean measures of success score per year by QAQC Score for 50 Earthwatch projects with 95% confidence intervals.

Results of Other Analyses Performed

The "Years of Project Support" was significantly correlated with the transformed "Sum of Total Publications" ($r = 0.48$, $t = 3.929$, $df = 53$, $p < 0.0001$, $n=55$). Projects produce more publications with more years of support, confirming the finding by Chandler et al. (2016b).

The influence of "PI Affiliation" on the (transformed) "Sum of Publications" was also assessed with the larger dataset using a one-way ANOVA. The results were not significant (F-ratio=0.724, $p = 0.40$ (Figure 11).

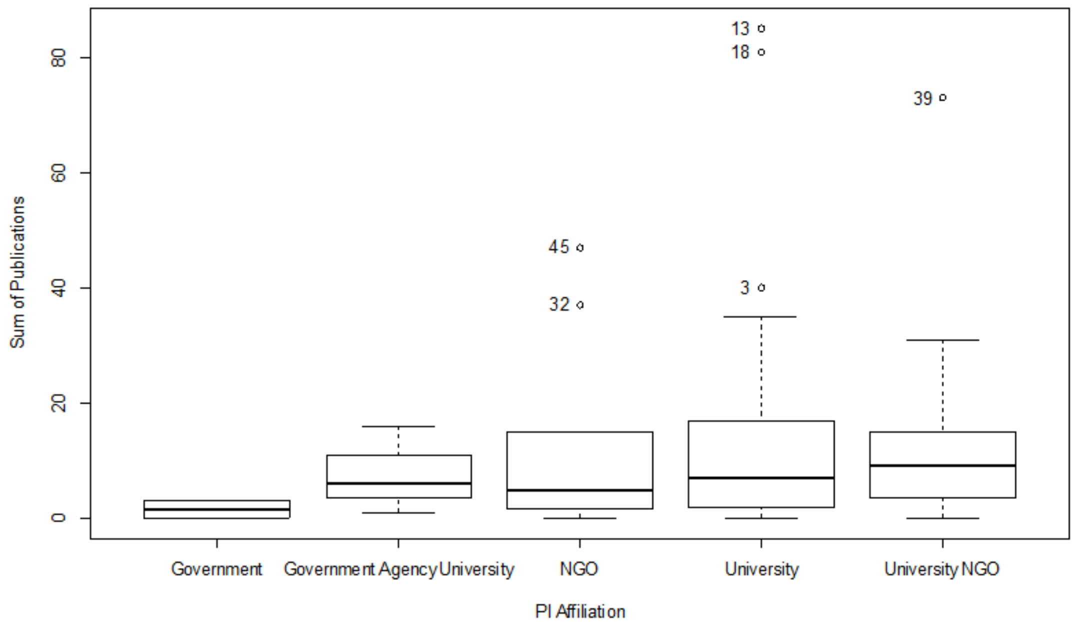


Figure 11. PI affiliation vs. sum of publications. This bar graph features the sum of publications for 55 projects versus PI affiliation with 95% confidence intervals. Affiliation in this case was categorized as working with a university, NGO, university+NGO or government.

The "Years of Project Support" was nearly significantly related to "Mean Project Publications Produced per Year" ($r = 0.179$, $t = 1.33$, $df = 53$, $p = 0.095$, ($n=55$) (Figure 12).

To assess the influence of "PI Affiliation" on mean publications per year, a one-way ANOVA test against the transformed "Mean Project Publications per Year" was used. The results indicated PI affiliation did not influence publication rate ($F=0.69$, $p=0.41$, $df=51$) (Figure. 13).

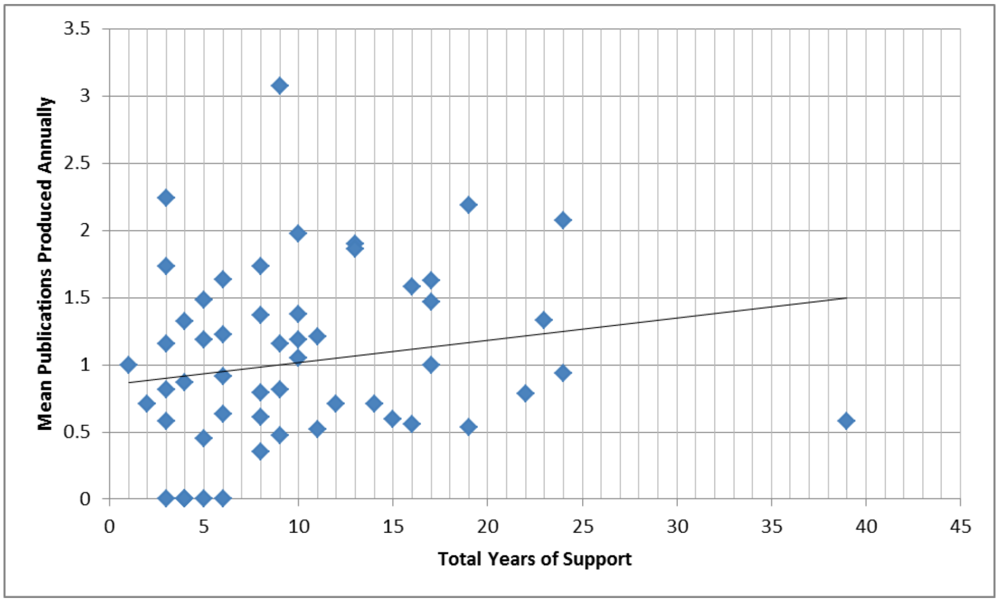


Figure 12. Project total years of support vs. mean publications produced annually. This scatterplot features the mean publications produced annually for 55 projects versus total years these projects were supported by Earthwatch.

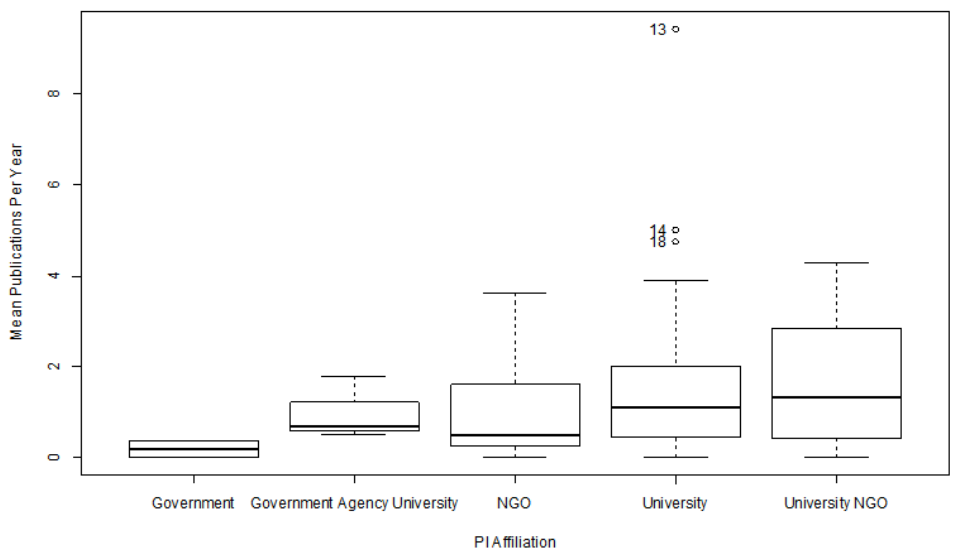


Figure 13. PI affiliation vs. mean publications produced per year. The bar graph features the mean publications produced with 95% confidence intervals.

The years of support was significantly related to the “Mean MoS Score” (Spearman’s rho = 0.497, p = 0.00006, n=55). The scatterplot and best fit line indicate that a project's MoS score increased the longer it was supported (Figure 14).

Figure 14. Total years of project support vs. mean MoS score.

Lastly in this single-independent variable analyses, there was no significant effect of “PI Affiliation” on the “Mean Measure of Success (MoS)” (Kruskal-Wallis rank sum test: chi-squared = 37.9, df = 35, p = 0.34, n=55) (Figure 15).

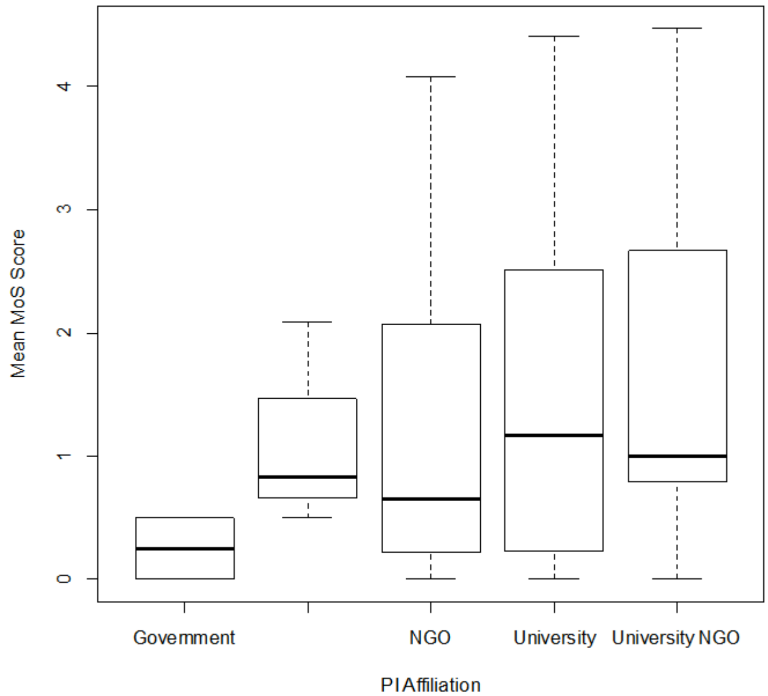


Figure 15. PI affiliation vs. mean MoS score. Note: The government box actually has large confidence intervals that are not displayed in the figure. The second box label also doesn't appear, but should be listed as "Government Agency University".

Lastly, the AIC analysis to determine the best overall model that fit the various publication response metrics suggested that of the five predictor variables, the "Mean True FG/ Min Total" best fit the pattern of mean publications produced each year (Table 2). For the second stepwise function ("Mean MoS Score" versus the predictor variables), the PI affiliation best fit the pattern of the projects' "Mean MoS Score" (Table 3).

Table 2. Summary of AIC results for the mean publications produced per year. (square root transformed).

Effect	AIC of Reduced Model	-2 Log Likelihood of Reduced Model	Delta AIC	Chi-Square	Df
Mean FG/Min Total	1.107E3	144.097	-	13.530	37
Years Support Analysis	1.109E3	147.498	3.401	16.932	37
PI Affiliation	889.242	149.242	5.145	18.676	148
Volunteer tasks	1.116E3	154.435	10.338	23.868	37
QAQC Score	797.497	205.497	61.4	74.930	222

Table 3. Summary of AIC results for the mean MoS score.

Effect	AIC of Reduced Model	-2 Log Likelihood of Reduced Model	Delta AIC	Chi-Square	Df
PI Affiliation	838.805	138.805	-	7.049	140
MeanTrueFG/MinTotal	1.053E3	142.627	3.822	10.871	35
VolTasks	1.065E3	154.706	15.901	22.950	35
YrsSupportAnalysis	1.073E3	162.521	23.716	30.765	35
QAQC Score	744.863	184.863	46.058	53.107	210

Chapter IV

Discussion

Ultimately the analyses rejected most of the proposed hypotheses. In assessing the financial effects of project support by itself, there was not a significant correlation between projects that were hitting their annual budget targets and the number of publications that were produced. To exemplify this point, the *Costa Rican Sea Turtles* expedition has produced a total of 73 peer-reviewed publications between 2000-2016, with a mean of 4.3 publications per year. Yet its mean “True Field Grant/ Min Total” ratio is just below 1 (0.967), indicating that on average, the project was on the threshold of meeting its core annual budget targets. By comparison, the *Archeology in Britain* expedition has a True Field Grant/ Min total ratio that is almost three times that of the Costa Rican Sea Turtles project, but only produced 15 total publications with a mean of 0.94 publications per year over that same window of time.

It should be noted that for project outputs, only publications were considered as a measure of project success. Policy contributions were excluded because an effective project impact tracking tool wasn’t developed by Earthwatch until the 2008 *Measure of Success* tool. Policy contributions were also excluded because Earthwatch’s language of asking for project outputs and outcomes before 2008 primarily emphasized publications. Lastly, while peer-reviewed publication counts are easily verified through tools like Web of Science, HOLLIS+, and Google Scholar, contributions to typical management plans and policies (at all scales) are not so readily accounted for and verifiable.

Interestingly, while the individual model tests proved non-significant for the Mean True Field Grant/ Minimum total, the Akaike Information Criterion indicated that when all the models were compared simultaneously, the function ranked the “True Field Grant/ Minimum Total” ratio (i.e. the money actually sent to a project versus the money needed to cover core budget costs) as the best fit against the mean number of publications produced per year. It should be noted that the first time the AIC test was conducted there were two projects that were skewing the data significantly to a point that the models were not describing the actual trend seen for the other projects. More specifically, these two projects were generating much more money in their first two years of operation than any of the other research expeditions. These outliers are likely attributed to the actual project locations, Costa Rica and the Galapagos respectively, as these are both popular travel destinations that initially attracted more volunteers. When these two projects were removed, the “True FG/Min Total” ratio emerged as the best fit model.

On the one hand, the “True Field Grant/Min Total” ratio was not significantly correlated with the total or mean publications produced. However, the AIC tells us that of all the predictor variables, it is ultimately the model that has the most parsimonious fit to those response variables. Moving forward, Earthwatch and other citizen science-based organizations can interpret this to mean that project funding, and more specifically, the ability of projects to meet their core budget requirements, is currently the best predictor of research outputs when held against the other potential predictor variables included in this analysis. Even though it is a rather poor predictor, it should be given some priority when considering desired publication outputs.

Though a diverse matrix of independent predictor variables was included that could potentially affect citizen science project "success" based on the production of peer-reviewed publications, and that were somewhat consistently tracked by Earthwatch, it is certainly possible that there are other key factors not considered which play a more significant role in the production of these scientific contributions. Future studies might want to consider how established the PIs are in their respective fields and whether they are already producing publications (in general, and specifically within the context of the focus of the Earthwatch-supported research) before they partner with Earthwatch. Parallel to this, another variable to consider might be whether new scientists are partnering with Earthwatch with an established research project in place, or if their proposed project is new and needs to be developed from scratch. There might be two ways to measure this: 1) determine the exact number of years a project has been running before it partners with Earthwatch, and 2) create a metric to evaluate where the PI is in their career. Other variables that should also be considered are the project's research focus. After reviewing the data, there were certain project types that were producing fewer publications than others. Specifically, archeology-based projects yielded fewer mean publications than other fields of study. It might prove useful to categorize Earthwatch projects by discipline/research focus to see if some fields inherently produce more or less publications than others. Lay publications (e.g., *National Geographic, Smithsonian*, other smaller-distribution magazines) were also excluded. Many of these have an enormous circulation (*National Geographic* produces between 6.5-12 million monthly issues around the globe over the past 40 years). As with contributions to management plans and policies, tracking authentic Earthwatch-supported PI contributions to stories in these magazines is much more difficult than assessing peer-reviewed outputs.

For the QAQC analyses, there were significant correlations between the QAQC Score and the Sum of Publications and Mean Annual Publications Produced, but the slope of the lines were negative, which implies that projects with more QAQC measures actually produce fewer publications. Perhaps this is more a testament to the quality of publications being produced and not the quantity, and projects with more QAQC measures in place are producing fewer but higher quality articles. If this were true however, we would expect to see a more positive correlation between the number of QAQC measures in place and the Mean MoS Score, which takes the publications' impact factor into account. Since there was no positive correlation, this is likely not the case.

It is possible that the QAQC scoring rubric that was developed for this analysis is inherently biased as the criteria were constructed based on the questions that Earthwatch asked the scientists in their initial research proposal, and is not necessarily indicative of what they eventually did in the field. For example, it's possible that what the scientists list in the methods section of their application differs from what they actually practice in the field. The research proposal also doesn't take experience or infield learning into account. A project could have a low QAQC score based on its initial proposal, but after 1-2 years (or even 1-2 teams) of fieldwork and working with volunteers, the scientists are likely learning how to better assess and control for volunteer error. Theobold et al. (2014) reached a similar result --- the probability of publication for CS projects was largely unaffected by the data quality assurance measures they assessed. They concluded that this result suggests that most projects have sufficient data quality measures in place, and that data collected by the public can be comparable to data collected by experts. As a follow up study for Earthwatch, it would be useful to compare the QAQC scores from the initial research proposals against scores from Earthwatch research renewals, which are project tracking tools that evaluate the research direction of the project every three years.

Lastly, the final Akaike Information Criterion test performed evaluated which predictor variable best fit the pattern for the Mean MoS Score. The results indicated that the PI Affiliation was the best overall predictor, which confirmed the individual model tests performed in the Chandler et al. (2016b) publication. To reiterate, Chandler et al. (2016b) found scientists having an exclusive university affiliation produced 5.7 times more publications than government-affiliated scientists. The strength of the PI affiliation held true for MoS scoring (Multinomial logistic regression-Likelihood Ratio Test; Chi-Square = 50.90, df = 9; $p < 0.001$). Overall, PI affiliation should be given priority over the other variables when considering research outputs for Mean MoS Score, though this rubric is, as constructed, rather Earthwatch-centric. As mentioned before, future tests should focus more on PI characteristics, both in terms of where they are in their career, their specific field of study, and the institutional or organizational affiliations that may be pressuring or driving them to produce more outputs. Identification of stellar potential PIs for recruitment or upon receiving proposals for research early in the process could have strong benefits to the supporting organization, the success of the citizen science project, and ultimately, on the science itself.

Conclusions

CS organizations should seek sustainable funding models for their research projects. With Earthwatch, the projects that met their core annual budget costs best predicted the mean number of publications produced annually. Organizations should also consider PI affiliation, especially scientists who are exclusively affiliated with universities, as this relationship best described the pattern of projects' mean MoS score (a scaled metric of publication outputs).

While this thesis highlights the above variables as possible drivers of citizen science research outputs, there is ultimately a need to strengthen the capacity of citizen-science research efforts to produce robust impacts that benefit science and society on a global scale. While Earthwatch is actively working towards the intersection of meaningful public engagement and quality research outputs, there is a need to engage volunteers on a much larger scale to reshape how the public views science and, more importantly, work collectively towards solving the critical environmental issues of our time.

Appendix 1

Example Budget

Table 4. Example Earthwatch budget template.

EXPEDITION BUDGET		Currency used in calculating budget:				USD
See "How to Complete your Budget" tab for instructions.				**FY 20XX**		
Insert title here				**Insert name here**		
Project Title				PI		
		Minimum Approved		**Beyond Minimum Approved**		**Notes**
Number of Research & Volunteer Staff						
• Principal Investigators		1		2		
• Professional Staff		1		2		
• Teen/Family team Facilitators		1		2		
• EW Volunteers		5		10		
Total team size		8		16		
Number of teams	4					
Number of days per team	12					
Total EW Volunteers for Expec		20		40		
Field Expenses			*% of total*		*% of total*	
• Food		$1,540	23%	$3,080	26%	
• Accommodations		$3,080	47%	$6,160	52%	
• Equipment, tools, supplies		$300	5%	$725	6%	
• Support Staff		$0	0%	$0	0%	
• Students		$0	0%	$0	0%	
Transport						
• Scientist transport to the field		$0	0%	$0	0%	
• Research team transport while in the field		$1,680	25%	$1,920	16%	
Other						
• Communications		$0	0%	$0	0%	
• Land use fees		$0	0%	$0	0%	
• 1st Aid/CPR/dive safety training		$0	0%	$0	0%	
• Contingencies		$0	0%	$0	0%	usually 1-2% of the total budget
Total Expedition Budget		**$6,600**		**$11,885**		
Standard Team Total Per Capita Grant Request						
AT MINIMUM:		**$330**				
BEYOND MINIMUM:				**$264**		

Team duration	12	days	
Food & Accomd	11	days	(generally, team duration minus 1 day)

Food	cost/day	# days	#vol/team	# teams	subtotal		
volunteers at min	$5	11	5	4	$1,100		
staff/PI at min	$5	11	2	4	$440	**$1,540**	min
volunteers beyond min	$5	11	10	4	$2,200		
staff/PI beyond min	$5	11	4	4	$880	**$3,080**	max

Accomodations	cost/day	# days	#vol/team	# teams	subtotal		
volunteers at min	$10	11	5	4	$2,200		
staff/PI at min	$10	11	2	4	$880	**$3,080**	min
volunteers beyond min	$10	11	10	4	$4,400		
staff/PI beyond min	$10	11	4	4	$1,760	**$6,160**	max

Equipment, Tools, Supplies	cost/team	amt @ min	min subtotal	amt @ max	max subtotal
Item 1 (please describe)	$50	1	$50	5	$250
Item 2	$200	1	$200	2	$400
Item 3	$25	2	$50	3	$75
Item 4	$0	3	$0	4	$0
Item 5	$0	4	$0	5	$0
Item 6	$0	5	$0	6	$0
Item 7	$0	6	$0	7	$0
Item 8	$0	7	$0	8	$0
		min	**$300**	max	**$725**

Support Staff	cost	# staff	# teams	subtotal		
Staff at min	$0	1	4	$0	**$0**	min
Staff beyond min	$0	2	4	$0	**$0**	max

Students	stipend	# students	#teams	subtotal		
Students at min	$0	0	4	$0	**$0**	min
Students beyond min	$0	0	4	$0	**$0**	max

Scientist transport to the field	cost/trip	# trips	subtotal		
Flights at min	$0	0	0		
Other (taxi, visa, etc)	$0	0	0	**$0**	min
Flights beyond min	$0	0	0		
Other (taxi, visa, etc)	$0	0	0	**$0**	max

Field Transport for Standard Tea	cost/day	# days	#teams	Sub-Total		
Transport 1 at min	$30	12	4	$1,440		
Transport 2 at min	$5	12	4	$240	**$1,680**	min
Transport 1 beyond min	$30	12	4	$1,440		
Transport 2 beyond min	$10	12	4	$480	**$1,920**	max

Appendix 2

Example of Financial Summary Pages from Earthwatch Databases

Table 5. Scientist summary page from Earthwatch's CRM database. This collates the field grants sent per team in a given year along with the total number of volunteers fielded per project. Highlighted fields were used in this thesis.

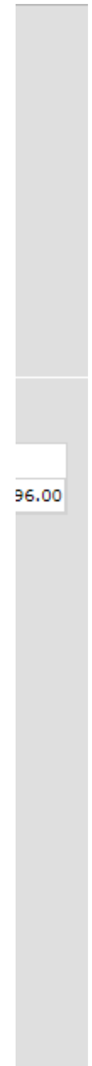
Date:
PI:
Fiscal Year:
Contract ID:
Currency:
Project Title:

Dates	Min	Max	Current	Paid For
May 22, 2016 - May 28, 2016	4	8	6	6
May 28, 2016 - Jun 03, 2016	4	8	6	6
Jun 05, 2016 - Jun 11, 2016	4	8	1	1
Jun 11, 2016 - Jun 17, 2016	4	8	5	5
Jul 02, 2016 - Jul 08, 2016	1	2	2	2
Jul 02, 2016 - Jul 09, 2016	6	12	9	9
Aug 28, 2016 - Sep 03, 2016	4	8	4	4
Sep 03, 2016 - Sep 09, 2016	4	8	6	6
Sep 17, 2016 - Sep 23, 2016	4	8	3	4
Oct 01, 2016 - Oct 07, 2016	4	8	3	4
		Total	45	48

Field Grant Paid to Date:

Date	Wire/Check#	Type	Team	Vols	Base FG		Per Cap	Adv.	Add'l	Cncl's	Total
27 Apr, 2016	**801511**						**€12,972.00**	**€0.00**	**€0.00**	**€0.00**	**€12,972.00**
		Standard	2a	3	€1,081.00		€3,243.00			€0.00	
		Standard	2a 2b	3	€2,162.00		€6,486.00			€0.00	
		Standard	2b	3	€1,081.00		€3,243.00			€0.00	
In Progress	**801521**						**€5,405.00**	**€0.00**	**€0.00**	**€0.00**	**€5,405.00**
		Standard	3a 3b	1	€2,162.00		€2,162.00			€0.00	
		Standard	3b	3	€1,081.00		€3,243.00			€0.00	
26 May, 2016	**801552**						**€1,081.00**	**€0.00**	**€0.00**	**€0.00**	**€1,081.00**
		Standard	3b	1	€1,081.00		€1,081.00			€0.00	
13 Jun, 2016	**801579**						**€0.00**	**€0.00**	**€800.00**	**€0.00**	**€800.00**
			2a						€800.00		
13 Jun, 2016	**801576**						**€8,157.00**	**€0.00**	**€0.00**	**€0.00**	**€8,157.00**
		Visitor/Facilitator	4f	2	€0.00		€0.00			€0.00	
		Teen	4	6	€979.00		€5,874.00			€0.00	
		Teen	4	3	€761.00	*	€2,283.00			€0.00	
02 Aug, 2016	**9000056**						**€7,567.00**	**€0.00**	**€0.00**	**€0.00**	**€7,567.00**
		Standard	5a 5b	2	€2,162.00		€4,324.00			€0.00	
		Standard	5a	1	€1,081.00		€1,081.00			€0.00	
		Standard	5b	2	€1,081.00		€2,162.00			€0.00	
01 Sep, 2016	**90000112**						**€10,810.00**	**€0.00**	**€0.00**	**€0.00**	**€10,810.00**
		Standard	5a	1	€1,081.00		€1,081.00			€0.00	
		Standard	5b	2	€1,081.00		€2,162.00			€0.00	
		Standard	6a 6b	1	€2,162.00		€2,162.00			€0.00	
		Standard	6b	2	€1,081.00		€2,162.00			€0.00	
		Standard	7b	3	€1,081.00		€3,243.00			€0.00	
In Progress							**€2,162.00**	**€0.00**	**€0.00**	**€-2,162.00**	**€0.00**
		Standard	6b	1	€1,081.00		€1,081.00			€1,081.00	
		Standard	7b	1	€1,081.00		€1,081.00			€1,081.00	
07 Oct, 2016	**9000127**						**€0.00**	**€0.00**	**€400.00**	**€0.00**	**€400.00**
			6b						€400.00		
					GRAND TOTAL		**€48,154.00**	**€0.00**	**€1,200.00**	**€-2,162.00**	**€47,192.00**

Table 6. Example financial summary page from Earthwatch's EXPED database. Highlighted lines were used in this thesis



.

Appendix 3

QAQC Scoring Strategies

Table 7. Summary of data credibility strategies before, during and after fielding.

	Credibility-building Strategies												**total**	**Context for Strategies**				
	early actions			**in the field**				**in the office**										
	prior expertise	**training**	**science advising**	**ranking system**	**in-person oversight**	**re-training**	**technological aids**	**Validation of observations**	**cross comparison**	**publication**	**management use**	**Quality assurance**		**sole source of data?**	**institutional affiliation**	**size of volunteer pool**	**group vs. individual**	**time commitment**
Beach Watch	N	H	Y	N	N	optional	N	Y	N	N	Y	N	**5**	Y	Y	L	G	M
BeachCOMBERS	N	H	Y	N	N	optional	N	Y	Y	Y	Y	N	**6**	Y	Y	M	G	M
Beachkeepers	N	N	N	N	N	N	N	N	N	N	Y	N	**1**	Y	N	L	G	L
Black Oystercatcher Monitoring	Y	N	Y	N	N	N	N	N	N	Y	Y	N	**4**	Y	N	M	G	M
Blue Water Task Force	N	L	Y	N	Y	N	N	N	Y	Y	Y	Y	**7**	N	N	L	G	M
CA King Tides	N	N	N	N	N	N	Y	N	N	N	N	N	**1**	Y	N	L	I	L
CCFRP	N	L	Y	N	Y	N	N	Y	N	Y	Y	N	**6**	N	Y	L	G	M
CWC (First Flush)	N	M	Y	N	N	N	Y	N	N	N	Y	Y	**5**	N	N	M	G	L
CWC (Urban Watch)	N	M	Y	N	maybe	optional	Y	N	N	N	Y	Y	**7**	N	N	S	G	L
Elkhorn Slough (otters)	Y	L	Y	N	N	N	Y	N	Y	Y	Y	N	**7**	N	Y	S	G	M
Elkhorn Slough (algae)	Y	L	Y	N	Y	N	N	N	N	Y	N	N	**5**	N	Y	S	G	M
Elkhorn Slough (nestboxes)	N	M	Y	N	N	N	N	N	N	Y	Y	N	**3**	N	Y	S	I	H
Elkhorn Slough (shorebirds)	Y	L	Y	N	Y	N	N	N	Y	Y	Y	N	**6**	N	Y	M	G	L
Grunion Greeters	N	M	Y	N	maybe	N	N	N	Y	Y	Y	N	**5**	N	Y	L	G	M

Table 8. Screenshot of the QAQC Scoring Rubric and Metric Categories

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	PI Name	Do methods follow established protocols	Scientists provide initial volunteer training(possibly field staff)	Scientists provide time for volunteers to practice tasks beyond initial training	Scientists provide continual oversight/supervision of volunteers to ensure accurate data collection	Scientists responsible for recording data(assume vols entering data are less accurate than experts)	Scientists responsible for entering data	Lead scientists have prior experience working with groups or students in the field	Data collected by volunteers compared to a control and/or data collected by the scientis	Does the Proposal include language requesting how the Scientist will ensure quality data from volunteer and account for volunteer error	Proposal Ye	Total Proposal	Number of volunteer tasks (count of individual methods used to capture distinct dat
15		1	1	0	0	0	1	0	0	0	2011	3	17
16		1	1	1	1	0	0	1	1	0	2010	6	18
17		1	1	0	1	0	0	0	0	0	2010	3	13
18		1	0	1	1	0	0	1	0	0	2002	4	17
19		0	1	0	1	0	0	0	0	0	1990	2	17
20		1	1	1	1	0	0	1	1	1	2014	6	8
21		1	1	0	1	0	0	1	0	1	2013	4	14
22		0	1	0	1	0	0	0	0	0	1996	2	14
23		1	1	0	0	0	0	1	0	1	2005	3	15
24		1	1	1	0	0	1	1	0	0	2000	5	9
25		1	1	0	0	0	0	0	0	0	2003	2	13
26		1	1	0	1	0	0	0	0	0	2001	3	7
27		1	1	0	0	0	0	0	0	1	2005	2	8
28		1	1	0	1	0	0	1	0	1	2013	4	12
29		1	1	0	1	0	0	1	1	1	2012	5	10
30		0	1	0	1	0	0	1	1	0	2001	4	9
31		1	1	1	1	0	0	1	1	1	2008	6	17
32		1	1	0	1	0	0	1	1	1	2010	5	14
33		1	1	1	1	0	1	1	1	1	2005	7	26
34		0	1	0	0	0	0	0	0	0	1999	1	11
35		1	1	1	1	0	0	0	1	1	2003	5	5

References

Bird, T., Bates, A., Lefcheck, J., Hill, N., Thomson, R., Edgar, G. & Frusher, S. (2013). Statistical solutions for error and bias in global citizen science datasets. *Biological Conservation, 173,* 144-154.

Bonardi, A., Manenti, R. & Corbetta, A. (2011). Usefulness of Volunteer Data to Measure the Large Scale Decline of "Common" Toad Populations. *Biological Conservation*, *144*, 2328-2334.

Bonney, R., Cooper, C., Dickinson, J., Kelling, S., Phillips, T., Rosenberg, K. & Shirk, J., (2009). Citizen Science: A Developing Tool for Expanding Science Knowledge and Scientific Literacy. *Bioscience*, *59*, 977-984.

Brandon, A., Spyreas, G., Molano-Flores, B., Carroll, C. & Ellis, J. (2003). Can Volunteers Provide Reliable Data for Forest Vegetation Surveys? *Natural Areas Journal*, *23*, 254-262.

Buesching, C., Newman, C. & Macdonald, D. (2013). How Dear are Deer Volunteers: The Efficiency of Monitoring Deer Using Teams of Volunteers to Conduct Pellet Group Counts. *Oryx*, *48*, 593-601.

Chandler, M., See, L., Copas, K., Bonde, A., Claramunt-Lopez, B., Danielsen, F. & Legind, J. Masinde, S. Miller-Rushing, A. Newman, G. Rosemartin, A. Turak, E. (2016a). Contribution of Citizen Science Towards International Biodiversity Monitoring. *Biological Conservation*, *213*, 280-294.

Chandler, M., Rullman, S., Cousins, J., Esmail, N., Begin, E., Venicx, G., Eisenberg, E. & Studer, M. (2016b). Ecological and social outcomes from 7 years of citizen science evaluation: an Earthwatch case-study.

Cohn, J. (2008). Citizen Science: Can Volunteers do Real Research? *Bioscience*. *58*, 192-197.

Conrad, C. & Hilchey, K. (2010). A review of citizen science and community -based environmental monitoring: Issues and opportunities. *Environmental Monitoring and Assessment*, *176*, 273-291.

Crall, A., Newman, G., Jarnevich, C., Stohlgren, T., Waller, D. & Graham, J. (2010). Improving and Integrating Data on Invasive Species Collected by Citizen Scientists. *Biological Invasions*, *12*, 3419-3428

Crall, A., Newman, G.J., Stohlgren, T.J., Holfelder, K.A., Graham, J. & Waller, D.M. (2011). Assessing citizen science data quality: an invasive species case study. *Conservation Letters, 4*, 1-10.

Delaney, D., Sperling, C., Adams, C. & Leung, B. (2007). Marine invasive species: validation of citizen science and implications for national monitoring Networks. *Biological Invasions, 10*, 117-128.

Dickinson, J. & Bonney, R. (2012). *Citizen Science: Public Participation in EnvironmentalResearch*. Comstock Publishing Associates, A Division of Cornell University Press. Ithaca and London.

Dickinson, J., Zuckerberg, B. & Bonter, D. (2010). Citizen Science as an Ecological Research Tool: Challenges and Benefits. *Annu. Rev. Ecol. Evol. Syst. Annual Review of Ecology, Evolution, and Systematics*, *41,* 149-172.

Earth Island Institute Journal Staff. (2017). Environment takes the biggest hit in Trump's budget blueprint. Retrieved from www.earthisland.org/journal/index.php/elist/eListRead/environment _takes_the_biggest_hit_in_trumps_budget_blueprint/?gclid=CjwKEAjwpdnJB RC4hcTFtc6fwEkSJABwupNiNYHRS69_onXs664NHzI8yBkoTuDTeTdScrPX Lo-d1BoCwDnw_wcB. Accessed 20 Aug. 2017.

Earthwatch Budget Template With PI Instructions. Retrieved from https://earthwatch.org/Portals/0/Downloads/Research/scientist -materials/earthwatch-field-grant-budget -template.xls

Earthwatch Mission and Values. Retrieved from http://earthwatch.org/About/Earthwatch-Mission-and-Values.

Earthwatch's Financial Terms and Conditions. Retrieved from http://earthwatch.org/images/Pdfs/Expeditions/FinancialTerms.pdf .

Eisenberg, C. (2014). Citizen Science Comes of Age: Everyday People Doing Extraordinary Science. *Huffington Post*.

Follett, R. & Strezov, V. (2015). An Analysis of Citizen Science Based Research: Usage and Publication Patterns. PLoS ONE PLOS ONE, *10*.

Foster-Smith, J. & Evans, S. (2003). The Value of Marine Ecological Data Collected by Volunteers. *Biological Conservation*, *113*, 199-213.

Freitag, A., Meyer, A. & Whiteman, L. (2016). Strategies Employed by Citizen Science Programs to Increase the Credibility of Their Data. *Ubiquity Press*.

Galloway, A., Tudor, M. & Haegen, W. (2006). The Reliability of Citizen Science: A Case Study of Oregon White Oak Stand Surveys. *Wildlife Society Bulletin*, *34*, 1425-1429.

Groulx, M., Brisbois, M., Lemieux, C., Winegardner, A. & Fishback, L. (2017). A Role For Nature-Based Citizen Science in Promoting Individual and Collective Climate Change Action? A Systematic Review of Learning Outcomes. *Science Communication*, *39*, 45-76.

Hochachka, W.M., Fink, D., Hutchinson, R.A., Sheldon, D., Wong, W-K. & Kelling, S. (2012). Data-intensive science applied to broad-scale citizen science. *Trends in Ecology and Evolution*, *27*, 130-137.

Kosmala, M., Wiggins, A., Swanson, A. & Simmons, B. (2016). Assessing Data Quality in Citizen Science. *Front Ecol Environ*, *14*, 551-560.

Kullenberg, C. & Kasperowski, D. (2016) What Is Citizen Science? – A Scientometric Meta-Analysis. PLoS ONE, *1*.

Mumby, P., Harborne, A., Raines, P. & Ridley, J. (1995). A Critical Assessment of Data Derived From Coral Cay Conservation Volunteers. *Bulletin of Marine Science*, *56*, 737-751.

National Audubon Society. Retrieved from http://www.audubon.org/conservation/science/christmas-bird-count.

Newman, C., Chandler, M., Clyde, M., McGreavy, B., Haklay, M., Ballard, H., Gray, S., Scarpino, R., Hauptfeld, R., Mellor, D. & Gallo, J. (2016). Leveraging the Power of Place in Citizen Science for Effective Conservation Decision Making. *Biological Conservation*, *208*, 55-64.

Newman, C., Buesching, C. & Macdonald, D. (2002). Validating Mammal Monitoring Methods and Assessing the Performance of Volunteers in Wildlife Conservation. *Biological Conservation*, *113*, 189-197.

Silvertown, J. (2009). A new dawn for citizen science. *Trends in Ecology & Evolution*, *24*, 467-471.

Teacher, AGF., Griffiths, DJ., Hodgson, DJ. & Inger, R. (2013). Smartphones in ecology and evolution: a guide for the app-rehensive. *Ecology and Evolution*, *3*, 5268 -5278.

Theobold, E., Ettinger, A., Burgess, H. & Debey, L. (2014). Global Change and Local Solutions: Tapping the Unrealized Potential of Citizen Science for Biodiversity Research. *Biological Conservation*, *181*, 236-244.

Tulloch, A., Possingham, H., Joseph, L., Szabo, J. & Martin, T. (2013). Realising the Full Potential of Citizen Science Monitoring Programs. *Biological Conservation*, *165*, 128-138.

Wiggins, A., Newman, G., Stevenson, R. & Crowston, K. (2011). Mechanisms for Data Quality and Validation in Citizen Science. IEEE Seventh International Conference on e-Science Workshops, 14-19

Ancillary Appendix

Description of Fields Included in the Master Excel Sheet

The Contract ID field refers to the identification number given to each individual project and its respective year. More specifically, the first part of the ID is the identification number for the project and the second number denotes the specific fielding year for the project. For example, the 2009 Contract ID for Earthwatch's Archeology in Tuscany project is 7894-1. In this case the project ID is 7894 and the 1 stands for the first year of the project as the expedition began in 2009. The Contract ID was obtained by searching for the scientist's name and the year the project fielded in Earthwatch's CRM database.

The Resource ID is an extension of the Contract ID. It includes the project identification number, the contract year of the project, and then the final number represents the associated budget. This is important because in a given year, a single Earthwatch project may have several budgets depending on the team types they run. The "resource" refers to the individual budgets a project has in a given year. For example, a project could run 3 standard teams and then a special corporate group that has twice as many volunteers. In this case, the standard teams would fall under one resource, and the corporate team would have its own budget and require a separate resource. Using the Tuscany example above, the resource ID could be 7894-1-1 for its standard teams, then if there was a corporate team, its resource ID could be 7894-1-2. Each resource ID was obtained by opening up the project's contract year in Earthwatch's CRM database.

The Contract ID and Resource IDs are important to capture because they help prevent duplication of data. For example, Earthwatch will sometimes have Scientists with the same last name, or in other instances, a scientist will partner with Earthwatch for a number of years, part ways, and then return years later to start a completely new project. Since Earthwatch uses the last names of scientists to identify individual projects, the contract ID ensures that each project is unique and distinct. The resource ID is similarly useful because it is a record for how many budgets a project has in a given year. When looking for project budgets in the Earthwatch database or organizational drives, the resource ID is a useful way to ground truth the total number of functional budgets used by a project in a given year.

The Resource Name is simply the last name(s) of the Earthwatch scientist(s) and the year the project fielded. The Resource Name will also often include the team type in its title as well, for example, "teen" will stand for Earthwatch teams that only field teenagers and "standard" refers to a standard team filled with adult volunteers. The Resource Name is readily accessible by searching for the scientists name and the project year in Earthwatch's CRM database.

The True Field Grant Total represents the sum of the field grants sent out by Earthwatch to a project. It is the money that Earthwatch sends based on the number of volunteers that have signed up for a specific team type in a given year. Using the Tuscanny project as an example, the true field grant was 14,887 Euros in 2010 for all of the teen volunteers that fielded on the project. In that same year, the true field grant was 93,991 Euros for all of the standard adult volunteers that fielded on the project. The sum of these true field grants represent the total amount of money sent to the scientist for that year. The True Field Grant totals were located using several methods. The first was to use the Earthwatch CRM database, locate the contract year for a given project, and then open the financial tracking page called the "scientist confirmation page". This page tracks all of the payments sent to a project in a given year, and can be converted into an Excel or PDF file for scientists to use at the end of the field season for their final accounting. There is an example of the scientist confirmation page in table 5 of appendix 2. This confirmation page breaks down the number of volunteers that fielded, the number of cancelled volunteers, the individual payments that were sent per team, any underwriting provided, and the financial totals which are captured at the bottom of the page. In table 5, the specific fields used for this thesis are highlighted in yellow.

It is worth noting that the Earthwatch CRM database came online in 2008, so the scientist confirmation page was only useful for projects that ran teams on or after this date. Before CRM, Earthwatch used a different database called EXPED. This database similarly tracked annual payments sent to the scientists. Table 5 below in appendix 2 provides an example page from EXPED capturing a project's financial summary. The highlighted cells capture the minimum number of volunteers needed to cover the project's core costs (36), the actual number of volunteers recruited (69) and the total amount sent to the field for the season (65294.49 pounds).

In some instances, the project financial summaries were missing from both CRM and EXPED. In these cases, the True Field Grant totals could be extrapolated using other project data. For example, if the True Field Grant totals were missing, both databases would still track the total number of volunteers that fielded. If the project budgets were available for a given year, then it was possible to know the field grant at min, the field grant beyond min, and the number of volunteers needed to reach the financial minimum. As a hypothetical example, let's say the Archeology in Tuscanny expedition was missing its True Field Grant data for 2011 in the CRM database, but it was known that 35 standard volunteers fielded that year. Using the standard project budget, if the field grant was 800 euros at min and 600 euros beyond min, and it was known that project needed 24 volunteers to reach its financial minimum, then the true field grant would be calculated by multiplying 24 volunteer * 800 euros and then adding this to the remaining 11 volunteers * 600 euros.

The Underwriting field represents money that was provided to the project that wasn't originally part of the per capita budget. For example, an individual donor, corporation, or separate organization might have given money to the project, and Earthwatch would take these funds and offset line items in the existing project budget, which effectively lowers the per capita field grants. The benefit of lowering the field grant is that the scientist receives the additional funds much earlier to purchase equipment and prepare for the field season. It also allows Earthwatch to reduce the price charged to volunteers which helps to attract and recruit more participants. Direct underwriting can be found in the project budget directly, which lists the total being used to offset other line items. Underwriting also appears in the CRM database and is listed as an additional payment in the scientist confirmation pages.

The Original Currency field represents the currency used by Earthwatch to send fund to the scientist. Occasionally, the project budgets are built in a different currency then the funds sent by Earthwatch, so noting project currency is a way to account for and rectify this discrepancy using historical exchange rates.

The Paid Bookings field represents the number of volunteers that fielded on a specific project team type in a given year. This is labeled as “paid” project bookings because occasionally Earthwatch sends unpaid volunteers into the field either as visitors to the project or as chaperones on teen teams. We are only interested in the money actually sent to the field, so unpaid volunteers were excluded from this thesis. Paid bookings data were found in the CRM database under the Scientist Confirmation Page, or in EXPED under the financial summary page.

The Day field refers to the number of days each project fields per team. For example, the duration of an Archeology in Tuscanny standard team in 2017 is seven days. This information is located in the project budgets, as well as in the CRM database.

The Sessions column refers to the total number of teams that fielded for a project team type in a given year. As a hypothetical example, there could be 6 standard Tuscanny teams in 2016 and 3 teen teams. The number of sessions for each project was obtained from CRM or the project budgets.

The Minimum Food column data was pulled directly from each project’s respective budget. We are interested in the project’s food costs at minimum because this is a core cost required for the project to run. Food costs beyond min are variable and not essential. The minimum food includes the cost to feed the volunteers and the field staff on a given project.

The Minimum Accommodations column data was pulled directly from each project’s respective budget. Accommodation costs beyond min are variable and not essential. The minimum accommodation includes the cost to house the volunteers and the field staff on a given project. Accommodations typically range from hotels to field stations to camping. In some instances, the food costs and accommodations costs at min were combined.

The Minimum Equipment column data is also pulled from each annual budget. Like the food and accommodations at min, we are only interested in the minimum costs and not the costs beyond minimum. Equipment line items include any items needed to conduct the research tasks, but do not include capital equipment over $2,000 (in most cases).

The Minimum Support Staff column is pulled directly from the project budget and represents the stipends needed to pay for support staff while teams are in the field. The Minimum Support staff does not cover lead scientist salaries.

The Minimum Students column is pulled directly from the project budget and represents the core costs needed to bring students into the field as additional staff to conduct the research. This does not include food or transport costs, and is essentially a stipend.

The Minimum Scientist Transportation is also pulled from the project budget and represents the core costs needed for scientists to travel to and from the research site. For scientists that are not from the country where their project operates, these costs usually include airfare.

The Minimum in Field Transportation column is pulled from the project budget and represents the costs of running project vehicles to get the staff members and volunteers to the necessary research sites. For example, this could include van or car rental costs, fuel costs, or costs associated with running a boat for water based projects.

The Minimum Other costs are from the project budget and represent items like first aid costs, communication fees for local cell phones or satellite phones, along with a contingency for funds used for emergencies (usually 1-2% of the total budget). In older budgets before 2004, the Minimum Other costs sometimes included funds for PIs to travel to a gathering called the Earthwatch Summit. This summit used to be held annually as a chance for scientists to convene and exchange information about their projects and to attend trainings to improve the volunteer fielding experience.

The last budget category used in this thesis is the Minimum Total. This cost is effectively the sum of all the fields listed above. It represents the sum of the core costs needed for each project to operate.

In some instances, projects were missing budgets for an entire year. This would lead to gaps in data where the Minimum Food, Minimum Accommodations, Minimum Equipment, Min Support Staff, Minimum Students, Minimum Scientist Transportation, Minimum in Field Transportation, Minimum Other fields were all missing. This occurred 27 times, and the solution was to extrapolate the data using the budgets from either previous or subsequent project years. In most instances where the budget was missing, the CRM or EXPED databases still tracked the individual per volunteer field grants sent to the scientists each year. As an example, if the Archeology in Tuscanny project was missing a budget from 2009, the solution would be look up the field grant at min and compare this to the field grants sent from previous or subsequent years. Whether the previous or subsequent annual budget was selected would depend on how closely the field grants matched. For example, if the 2009 field grant at min was 1300 euros, and then the field grant for 2008 was 1200 euros and field grant for 2010 was 1350 euros, then 2010 budget would be chosen as the closest match.

In order to extrapolate the 2009 budget fields, we would take the 1300 euro per person field grant from 2009 and the 1350 euro field grant from 2010, and use the ratio of these field grants to extrapolate the missing budget fields. For example, 1300/1350 equals .9629. If we take this value and multiply it by the other fields in the known budget, we can estimate the unknown fields in the 2009 budget. If the minimum equipment cost in the 2010 budget is 6000 euros, we can multiply this by the ratio value of .9629 to get an estimate of 5777 euros for the minimum equipment cost in the 2009 budget.

This method is useful for filling data gaps, but is subject to error as project costs vary from year to year and each budget field doesn't necessarily increase by a standard increment. Using the example just described, it's possible that the 2009 Tuscany project spent more on equipment in 2009 because they needed to replace wheelbarrows, trowels, etc. and as a result cut back on staff salaries in 2010. These nuances aren't captured when we extrapolate the missing fields.

The fields for these columns were populated for all 62 Earthwatch projects in the master excel document for projects fielding from 2000 to 2016. Once complete, the data were manipulated by taking the financial fields from each project's respective budget and summing them so the resulting field represented the *total* for the project in a given contract year. For example, if the Archeology in Tuscany project had three different team types in 2009 (adult teams, short duration teams, and corporate teams), these would show up as three distinct lines in the summary excel document. Summing these lines, specifically the financial data (Underwriting, True FG Total, Paid Bookings, Minimum

Food, Minimum Accommodations, Minimum Equipment, Min Support Staff, Minimum Students, Minimum Scientist Transportation, Minimum in Field Transportation, Minimum Other, Minimum Total) and collating them into one line gives us the budget totals of the project for that specific year.