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Collaboration and engagement produce more actionable science: quantitatively analyzing uptake of fish tracking studies

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Abstract. Aquatic telemetry technology generates new knowledge about the underwater world that can inform decision-making processes and thus can improve conservation and natural resource management. Still, there is lack of evidence on how telemetry-derived knowledge can or has informed management, and what factors facilitate or deter its use. We present one of the first quantitative studies related to the science-action gap and evaluate factors that influence the uptake of fish telemetry findings into policies and practices, as well as social acceptance of these findings. We globally surveyed 212 fish telemetry researchers regarding the knowledge uptake of an applied fish telemetry research project of their choice. Respondents' personal and professional attributes, as well as the attributes of their chosen projects, were analyzed using machine learning algorithms to identify important factors that influenced the uptake (i.e., use, trust, and/or acceptance) of their findings. Researchers with extensive collaborations and who spent more time engaging in public outreach experienced greater uptake of their findings. Respondents with greater telemetry experience and commitment (e.g., more telemetry publications, higher proportion of research on fish telemetry) tended to achieve more social acceptance of their findings. Projects led by researchers who were highly involved and familiar with the fisheries management processes, and those where greater effort was devoted to research dissemination, also tended to experience greater uptake. Last, the levels of complexity and controversy of the issue addressed by the research project had a positive influence on the uptake of findings. The empirical results of this study support recent messages in the science practitioner literature for greater collaboration, knowledge co-production with partners, and public engagement to enable the transfer of knowledge and the use of evidence in decision-making and policies. Scientific organizations should consider shifting reward incentives to promote engagement and collaboration with non-scientific actors, and perhaps even rethinking hiring practices to consider personal and professional characteristics or attitudes such as altruism and networking skills given the influence of these factors in our model. Last, networks composed of both research and practice potentially have a key role in brokering and facilitating knowledge exchange and actions.

Key words: environmental management; fish biotelemetry; fisheries; knowledge co-production; knowledge exchange; knowledge mobilization; public outreach; quantitative evaluation; research impact; science communication; science policy; stakeholder engagement.

Introduction

It is axiomatic in the environmental governance literature that sound scientific evidence and up-to-date knowledge should inform environmental policy, management, and decision-making (Pullin and Knight 2003, Sutherland et al. 2004). Yet research has consistently found that these processes rely heavily on the experiential or tacit knowledge grounded in the social networks of environmental managers and other decision-makers (Pullin et al. 2004, Cook et al. 2012, Young et al. 2013). Because of this, the question of how to better integrate science into decision-making practices has become an important topic in the conservation, environmental, and natural resource management literature (Fazey et al. 2012, Cook et al. 2013, Cvitanovic et al. 2015, 2016). To date, however, much of the research on the science–action gap in conservation and resource management is qualitative (Raymond et al. 2010, Young et al. 2016*a*,*b*), case-study based (Thakadu et al. 2013, Saarela and Rinne 2016), context specific (Bayliss et al. 2012, Young et al. 2016*a*), or conceptual (Gibbons et al. 2008, Reed

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et al. 2014, Nguyen et al. 2017*b*). Quantitative and comparative work is now needed to round out the field, particularly research that involves the evaluation of multiple case studies to empirically identify common factors that influence the movement of science into action (Posner et al. 2016). This approach offers a more comprehensive understanding of the science–action gap, and how to effectively use new knowledge for the benefit of the environment and society. We present a quantitative study that compares multiple case studies from around the globe related to the use of fish telemetry science to inform fisheries management and conservation practices.

Context: Telemetry science and fisheries management

Telemetry is the tracking of animals using electronic devices attached to an individual that autonomously emit a signal to a receiver (Cooke et al. 2004). Telemetry has greatly enhanced our understanding of animal movement, spatial ecology, habitat usage, and other animal–environment interactions, providing such an unprecedented level of information that it could be considered to be a "disruptive" technological innovation (Young et al. 2018). In the aquatic world, telemetry has opened a window to underwater wonders and has informed conservation and management decisions such as delineation of marine protected areas, identifying critical habitats, understanding post-release survival of bycatch species, informing stock assessments, and more (Hussey et al. 2015, Cooke et al. 2016, Crossin et al. 2017). The growing catalogue of telemetry-derived data throughout the oceans and inland waters has led to novel insights into the ecology of many aquatic species, and their interaction with the environment and response to environmental changes. A recent review (Hussey et al. 2015) indicated that aquatic telemetry research has grown exponentially over the last decade, with thousands of published studies using acoustic and satellite telemetry from all regions of the globe. Effectively using this information is thus critical for improving conservation and sustainable practices in a complex and rapidly changing world (Cooke 2008, Hussey et al. 2015, Mcgowan et al. 2016, Lennox et al. 2017). Such an endeavor, however, has not proven to be an easy task.

Even with great investments in telemetry science, there is still a lack of documentation and assessment of the conservation impact of telemetry research (Jeffers and Godley 2016, Mcgowan et al. 2016). Hesitation and delay in applying telemetry-derived data to fisheries management have also been reported for reasons such as uncertainties associated with telemetry studies, limitations of the technology, unknown effects on tagged animals, distrust of telemetry (reliability and credibility issues), mismatches between management needs and design of telemetry studies (e.g., compatibility, representativeness, timeliness), or lack of awareness and access to new findings (Cooke et al. 2013, Young et al. 2013, 2018, Crossin et al. 2017; Nguyen et al., 2018*a*,*b*). It has also been suggested that publications are too focused on research results rather than on conservation and management implications, and that the recommendations put forth lack context and are not readily useable by decision makers (Roux et al. 2006). Furthermore, Mcgowan et al. (2016) went so far as to suggest that the value of information derived from telemetry studies that "promised" management-relevant knowledge was wanting. As such, understanding the integration of telemetry findings into fisheries management practices is important for identifying conditions and factors that better link science to conservation actions.

Conceptual framework

Research on understanding the movement of knowledge is scattered across several disciplines and fields of study, and the development of a knowledge–action framework was needed to synthesize the growing research on the knowledge–action gap (Nguyen et al. 2017*b*). The framework is based on the theories of knowledge mobilization and knowledge exchange, which both emphasize the social dimension of knowledge movement, particularly the nonlinear, iterative, and dynamic way that knowledge moves and is interpreted within and across social groups (van Kerkhoff and Lebel 2006, Fazey et al. 2012, Gainforth et al. 2014). According to the knowledge–action framework, factors that mediate knowledge flow take place in a "knowledge mediation sphere," which is composed of (1) the knowledge network (made up of knowledge actors, characteristics of the actors, relationships among actors, and characteristics of the knowledge), and (2) the environmental and contextual dimension. Factors involved in the knowledge production (such as engaging with knowledge users) and the desired outcomes are also considered to influence knowledge movement (Nguyen et al. 2017*b*). Our study investigates the components of the knowledge–action framework—the knowledge transfer, knowledge characteristics, knowledge actors and characteristics, relational dimension, and environmental and contextual dimension—to assess their influence on the successful uptake of knowledge or desired outcome (Fig. 1).

We apply this framework by building exploratory models that examine various factors suggested in the literature to influence knowledge outcomes, including Cash et al. (2003) framework on the salience, credibility and legitimacy of knowledge as important preconditions for linking knowledge to sustainability action. We seek to identify factors that are important for achieving a "successful knowledge outcome," which, in this study, is defined as the perceived success of knowledge utilization and acceptance from two standpoints: (1) formal uptake of telemetry study findings (e.g., knowledge transfer, integration into policy), and (2) social uptake of telemetry study findings (e.g., stakeholder acceptance, trust, and media interest). We use fish telemetry science and

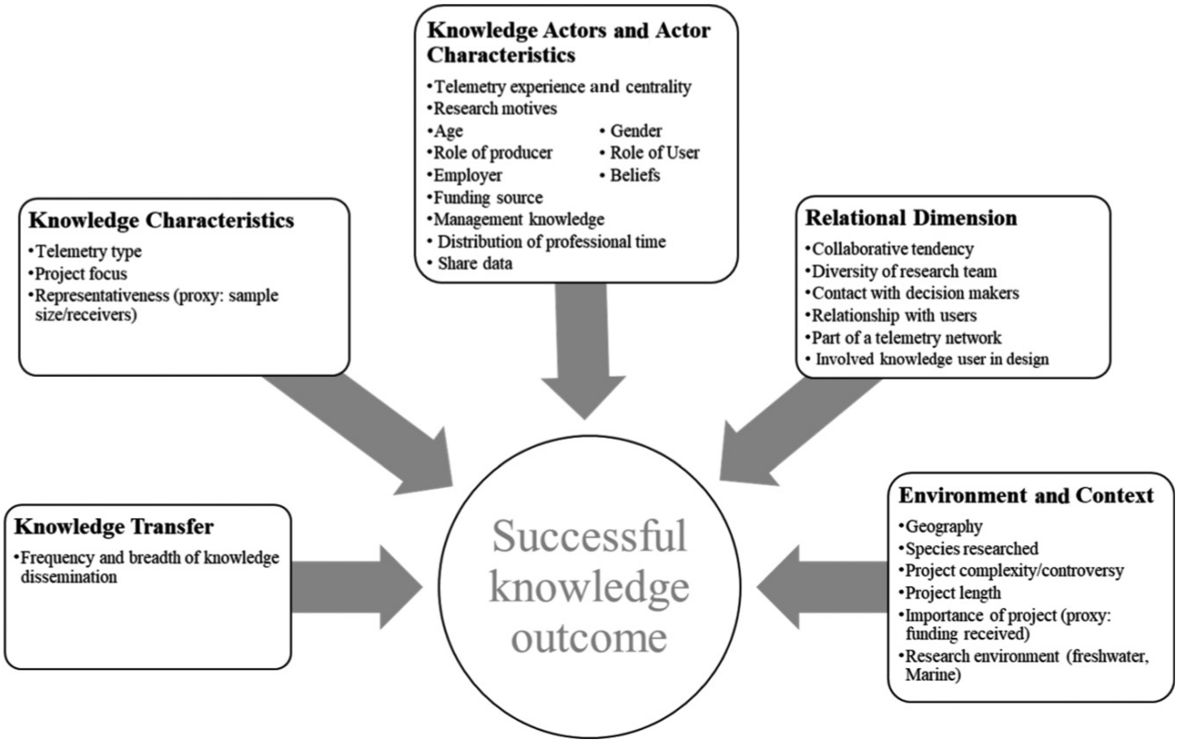

FIG. 1. Conceptual model of a knowledge–action framework that guides the development of the quantitative models built to test the predictions (Appendix S2) from hypotheses that suggest areas of knowledge transfer, knowledge characteristics, knowledge actors and actor characteristics, relational dimension, and environmental and contextual dimension have an influence on the uptake of knowledge (i.e., successful knowledge outcome). Descriptions of variables can be found in Appendix S3: Table S1.

management as a model for exploration, recognizing that such studies are also common in the terrestrial sphere (Kays et al. 2015). In doing so, we address the question, "What explains the formal and/or social uptake of fish telemetry findings?" The study identifies important mechanisms of successful knowledge outcomes, use, and uptake, and is one of the first attempts to quantitatively compare multiple case studies to empirically test knowledge–action hypotheses that have been suggested in the literature (Posner et al. 2016).

METHODS

Instrument development and data collection

We surveyed fish telemetry researchers working around the globe in marine and inland waters as part of a broader study on mobilization of fish telemetry-based knowledge, which included both online questionnaires and semi-structured interviews (see Appendix S1 for questions and Data S1). The interviews provided opportunities to capture in-depth responses and pursue follow-up queries, while the online questionnaire allowed us to reach a broader population, to access international respondents, and increase the sample size. The survey questions were developed based on hypotheses synthesized in the knowledge–action framework described above (Nguyen et al. 2017*b*), as well as the authors' collective experience in the field of knowledge mobilization and fisheries.

The survey instrument consisted of three parts: (1) measurements of the researchers' attributes, which included fish telemetry experience, sociodemographics, underlying constructs measuring beliefs, values and motivations, as well as assessment of their professional network and sharing/collaborative tendencies; (2) attributes and characteristics of a chosen "fish telemetry project" of their choice (i.e., case study) in order to assess factors that may influence the "successful" use of telemetry findings, and (3) assessment of researchers' behavior and attitudes toward data sharing (which was not analyzed in this study).

In this study, we restricted "telemetry" to acoustic, radio, or satellite tracking only, as these telemetry techniques are used to address similar research questions and management issues (Cooke et al. 2012). The online questionnaire was pre-tested with 11 individuals who have worked with fish telemetry. The interview was pretested with the first five interviewees and minor adjustments were made. The Carleton University Ethics Board approved the study with anonymity of respondents being maintained (permit number: 102887).

Data collection

The initial sample population was built in consultation with two telemetry experts who were also included in the sample. This initial population was further supplemented by snowball sampling when participants voluntarily referred us to others. We restricted the sample population to researchers who studied fish using telemetry and focused on applied conservation and management objectives. We conducted 25 face-to-face interviews with fish telemetry experts at the International Conference on Fish Telemetry (Halifax, Nova Scotia, Canada), 13-17 July 2015. The sample was supplemented with 12 interviews at the meeting of the American Fisheries Society (Portland, Oregon, USA), 16–20 August 2015. Nine phone/Skype interviews were also conducted, totaling 46 interviews (including responses from the pre-tests).

The population for the online questionnaire was determined by extracting the e-mail addresses of authors who have published about fish telemetry as determined by citation records from the Web of Science online database. A search was conducted for articles between 2011 and 2015 using the following string, (*telemetry OR track* OR tag*) AND (*sonic OR VHF OR radio OR acoustic OR satellite OR pop-up OR tag*) AND (lake OR river OR aquatic OR freshwater OR marine OR fisher*OR reef OR estuary* OR bay OR fish), to identify relevant authors in fish telemetry research. The search was undertaken on 29 September 2015 using Web of Science (consisting of Web of Science Core collections, Biosis Previews [subscription up to 2008], MEDLINE < SciELo and Zoological Record), which resulted in a set of records that contained 2,605 valid e-mail addresses. We identified 1,908 unique e-mail addresses after removing duplicate e-mails and irrelevant records.

Invitations were sent via email on 7 October 2015. There were 112 bounce-backs and 110 respondents notified us that they did not meet the criteria of a "fish telemetry researcher," resulting in a final population of 1,686. This number likely includes non-target populations, as we were aiming to reach the whole population of fish telemetry researchers and used broader search strings. Reminders were sent on the 4 and 14 November 2015. We gathered contact information for an additional 155 individuals using a snowball approach, and sent invitations and reminders on 4 and 14 February 2016, for a total sample pool of 1,841. The survey closed on 19 February 2016.

Data analysis

We used several statistical tests and analyses in this study, as we consider the research to be exploratory. First, we used a principal component analysis to reduce the number of dependent variables for analysis. We then selected important independent (or predictor) variables using a random forest classifier for input into multiple regression models. Last, we supplemented the results using simple test of associations (*t* test, chi-square, simple regression) to provide further insights and strength to the findings of the regression (Fig. 2). We conducted additional logistic regression analyses on the dependent variable "findings used" to assess the reliability of responses for the focal dependent variables and is not the focus of this study (Appendix S5: Table S1).

Dependent variables.—The dependent variables were developed from six three-item Likert-type questions that measured various aspects of what could be considered as a *successful knowledge outcome*. Respondents were asked to rank on a three-point scale whether the knowledge outcome was "not at all successful" (received a score of zero for construct purposes), "somewhat successful" (score of 1), and "very successful" (score of 2). A "not applicable" option was provided to capture the reality that not all projects have the same objectives. We asked respondents, "In your opinion, how successful were your telemetry findings with respect to the following?": (a) making scientific advancements; (b) knowledge transfer (i.e., findings being used by knowledge users such as stakeholders, managers, etc.); (c) changing, developing, or affirming a policy/practice, integration into policy or management framework; (d) adoption/buy-in/uptake by stakeholders; (e) trusted by stakeholders; and (f) generating media interest. We dropped the "making scientific advancements" statement from the analyses because it was highly biased toward "very successful" and suspected to have high confirmatory bias. A factor analysis with principal component analysis (PCA) was conducted to reduce the number of items to create constructs using the mean scores and verified with Cronbach's alpha test (Appendix S3: Table S1).

In addition to using a Likert-type question to assess the *successful knowledge outcome*, we also directly asked the question, "Have findings from this particular telemetry project been used in management practices or policy decisions?" to obtain a binary response (yes/no). This binary response makes up the third dependent variable (herein called "findings used") assessed in this study. This third dependent variable provides additional information about the reliability and validity for the focal dependent variable described above but is not the focus of the study (Appendix S5: Table S1).

Explanatory variables.—A total of 27 variables were measured to explore and understand factors that may influence the uptake of knowledge (i.e., fish telemetry findings). The variables measured were based on literature review and factors suggested by the knowledge–action framework (Nguyen et al. 2017*b*; Fig. 1; Appendix S2 and S3: Table S1). Some variables are constructs that were measured by combining several items summed into a scale or index (Appendix S4: Table S1). For example, a construct was created for the

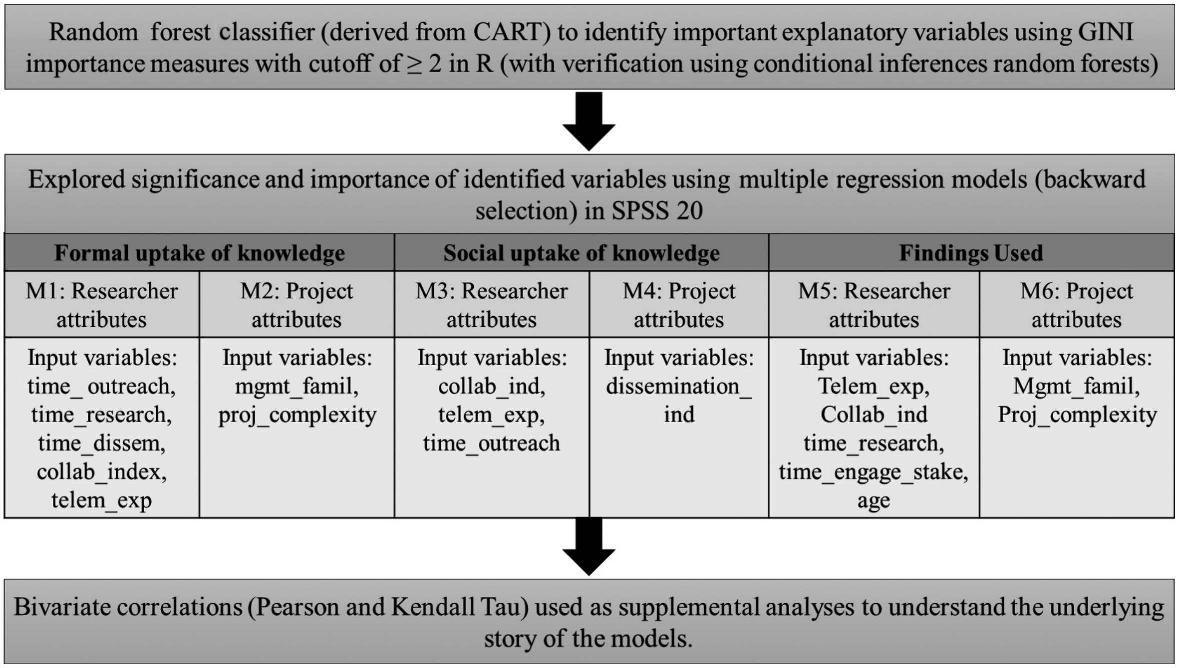

FIG. 2. Flowchart of statistical analyses undertaken using R and SPSS (IBM Corp. Released 2017. IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY) statistical packages. First, a random forest (RF) classifier derived from classification and regression tree analyses was used to identify important explanatory variables from 27 variables. The Gini Index was used to select independent variables for model input (cutoff at ≥2). Second, both general linear model fitting and multiple linear regression models were used to explore the significance of variables grouped under researcher attributes and project attributes against dependent variables "formal uptake" (of telemetry study findings) and "social uptake" (of telemetry study findings). "Findings used" was used a reliability and validity measure. A total of six models (M) were fitted. Bivariate correlations using both Pearson and Kendal Tau correlation coefficients were conducted to further understand the relationships of independent.

respondent's *telemetry experience and centrality* (centrality defined as how central telemetry is to a respondent's research program) to their research by summing the numerical responses from six questions into an index. Another example of a construct includes our assessment of the *collaborative extent* of an individual by summing scores based on their coauthored publications, breadth and frequency of collaborations with different types of organizations such as universities, government, industry, non-profit organizations, etc. (see Appendix S4: Table S1 for full list of constructs).

The explanatory variables were subsequently grouped into "researcher attributes" and "project attributes" for the purpose of model input. Categorical variables were dummy coded, and scales for underlying constructs (e.g., motivation, collaborative tendencies, etc.) were developed. Cronbach's alpha and assessment of correlation matrices with additional bivariate correlation analyses were examined for internal consistency and reliability of the scales (Appendix S4: Table S1).

Factor selection.—Because of the large number of potential predictors of knowledge uptake in this exploratory study, we used random forests (RF) machine learning algorithms to identify important variables for input into multiple regression models (Grömping 2009). RF have been widely applied in ecological studies (Gislason et al. 2006, Prasad et al. 2006), life sciences (Touw et al. 2013), bioinformatics (Wu et al. 2009), and remote sensing (Chan and Paelinckx 2008). RF is a nonparametric technique that utilizes classification and regression trees (CART), which are modern statistical techniques ideally suited for both exploring and modeling complex data that may contain missing values, and handling large numbers of variables with relatively small sample size (Breiman 2001, Grömping 2009). A tree is constructed by recursive partitioning using a randomized subset of predictors to repeatedly split the data into to mutually exclusive groups (De'ath and Fabricius 2000). RF fits a combination of many trees (n = 1,000 used here), where each tree is generated by bootstrap samples, leaving about one-third of the overall sample for validation (the out-of-bag predictions, OOB). The Gini Index (i.e., the node purity resulting from data partitions; Breiman et al. 1984) was used as a measure of variable importance; higher Gini Index values indicated greater importance (Breiman 2001). Variables were selected for further analysis with regression models using a Gini index of 2 or higher because of how the data visually aggregated (Fig. 3). Although the RF Gini Index can be biased in variable selection in some cases compared to permutation importance via conditional inference trees (Strobl et al. 2007), similar results were found with the two methods and RF were more stable in variable importance outputs, potentially due to the large number of missing values and/or large number of predictors relative to sample size. RF was implemented using the randomForests package (Liaw and Wiener 2002) in R (R Core Team 2018) via Rstudio (RStudio Team 2016).

Models.—We applied Multiple Linear Regressions using the most important predictors identified with RF for each dependent variable to identify predictor significance (Fig. 2). The models were fitted to three dependent variables with groups of explanatory variables that related to researcher attributes and project attributes, resulting in six regression models (Fig. 2). We used a stepwise backward model selection to select the final model. Multicollinearity was assessed using correlation matrices and variance inflation factor scores. Linearity, homoscedasticity, and normality were assessed visually. Durbin-Watson tests were used to assess autocorrelations in the residuals of the regression models. Similar analyses were repeated for the dependent variable *findings used*, for reliability and validity evaluations (Fig. 2). In addition, we conducted exploratory analysis by performing bivariate correlations, *t* tests, chi-square, and simple regressions between the explanatory variables and each dependent variable. This was done to explore and understand the significant associations that exist between the explanatory and dependent variables.

Results

For this study, 212 (166 online + 46 interviews) responses were used in our analysis. Although we received 348 responses from a sample pool of 1,841 potentially relevant participants to the questionnaire, only 212 completed the questionnaire in its entirety. The overall response rate for the online survey was 19%, which falls within the typical range for expected responses rates for online surveys (Deutskens et al. 2004).

Characteristics of the sample

The sample was confirmed to be "experts" in fish telemetry with 74% of the respondents identified as principal investigator of at least one fish telemetry project. The average researcher in the sample spent 49% of their research time on fish telemetry with 10.4 ± 7.8 (mean ± SD) years of fish telemetry experience, and 56% of respondents were members of a telemetry network. Most of the respondents fell between the ages of 30–49 yr. The majority of the respondents were from North America (66%) and 83% were male. The sample was largely comprised of those

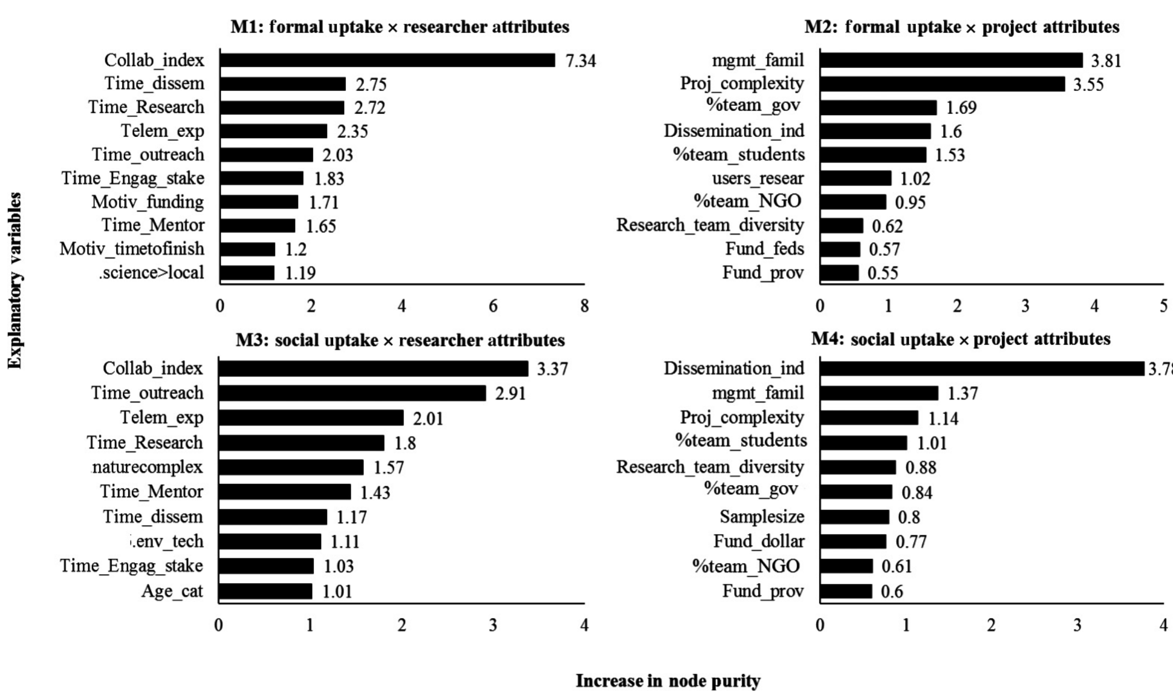

Fig. 3. Top 10 variables based on Gini measure of importance (shown as increase in node purity) in the random forest analyses. More important variables achieve higher increase in node purities, that is, to find a split in the classification trees that has a high internode variance and small intranode variance. Numbers to right of bars indicate increase in node purity score. Descriptions of variables can be found in Appendix S3: Table S1.

Table 1. (a–c) Demographics and other relevant covariates describing the sample population of fish telemetry researchers.

Variable	Frequency	%
(a) Demographics and covariates		
Age (N = 213)		
20–29 yr	16	8
30–39 yr	79	37
40–49 yr	61	29
50–59 yr	38	18
60+ yr	19	9
Gender (N = 213)		
Male	175	82
Female	38	18
Geographic location (N = 219)		
North America	140	64
Europe	39	18
Other	40	18
Employer†		
Academia	106	44
National government	57	24
Regional government	43	18
Industry	3	1
NGO	16	7
Private	15	6
(b) Telemetry research characteristics		
Refereed articles published (N = 206)		
None	13	6
1–4 articles	105	51
5–9 articles	39	19
10–14 articles	16	8
15–20 articles	12	6
>20 articles	21	10
Non-refereed articles published (N = 207)		
None	38	18
1–4 articles	85	41
5–9 articles	39	19
10–14 articles	16	8
15–20 articles	12	6
>20 articles	17	8
Number of telemetry projects involved in (N = 194)		
None	34	18
1–4 projects	92	47
5–9 projects	39	20
10–14 projects	10	5
15+ projects	19	10
Telemetry technology used†		
Radio	103	28
Acoustic	191	52
Satellite	72	20
(c) Engagement behaviors and activities		
Professional time (%) spent on		
Research	47 ± 20	
Engaging stakeholders	13 ± 12	
Disseminating research	17 ± 13	
Outreach	6 ± 5	
Mentoring students	12 ± 11	
Project dissemination activities score (scale 0 = none to 4 = 10+ times)		
Presented at a conference	2 ± 1.1	
Published a refereed article	1.3 ± 0.9	
Published a non-refereed article	1.3 ± 1.1	
Attended a stakeholder workshop/consultation meeting	1.6 ± 1.3	
Organized a stakeholder workshop/consultation meeting	0.7 ± 1.1	
Attended a manager's meeting	1.3 ± 1.2	
Made media appearances or comments	1.4 ± 1.3	
Wrote a press release	0.7 ± 0.9	
Engaged in new media/social media	0.85 ± 1.2	
Engaged in public outreach activities	1.4 ± 1.4	

Note: Values with error measurements are mean ± SD.
† Categories that are not mutually exclusive.

affiliated with academic institutions (50%) or government science staff (47%). There was a relatively even number of researchers conducting research in inland and marine systems.

Principal component analysis

We reduced the number of dependent variables measuring the *successful uptake of knowledge* (from each case study reported by each respondent) with a PCA. The suitability of PCA was assessed prior to analysis. Inspection of the correlation matrix determined that all variables had at least one correlation coefficient >0.3. The overall Kaiser-Meyer-Olkin was 0.8 with individual KMO measures all greater than 0.7, classifications according to Kaiser (1974). Bartlett's test of sphericity was statistically significant ($P < 0.01$), indicating that the data was likely factorizable. Visual inspection of the scree plot, however, indicated that potentially two components should be retained, which would explain 74% of total variance. A forced factor of 2 PCA was rerun, and we used a varimax orthogonal rotation to help with interpretation of each component. Component 1 described "formal" uptake of telemetry study findings (knowledge transfer; change, affirmation, or development of policy; and integration into policy), while Component 2 described more "social" uptake of telemetry findings (Appendix S6: Table S1). As such, we use these two dependent variables for all the analyses.

Random forest classifier

Random forests analyses identified the most important variables in explaining the dependent variables to be used in regression analyses: formal and social uptake of knowledge (Fig. 3). Based on the Gini index (≥2), We identified a total of five researcher attributes and four project attributes for input into the six regression models (shown in Fig. 2): proportion of researcher's *time spent on public outreach* (time_outreach), proportion of researcher's *time spent on research* (time_research), proportion of researcher's *time spent on dissemination activities* (time_dissem), *researcher's collaborative extent and tendency* (collab_index), *researcher's telemetry experience/centrality* (telem_exp), *researcher's age* (age_cat), *researcher's familiarity with fisheries management process relevant to project* (mgmt_famil), the *complexity/controversy of the issue the project addresses* (proj_complexity), and the *frequency of dissemination* of the project (dissemination_ind; Figs. 2, 3).

Researcher attributes explaining formal and social uptake of telemetry study findings

Backward stepwise regression models and GLMs indicated that the *collaborative extent* (collab_ind), *telemetry experience/centrality* (telem_exp), and *proportion of researchers' time spent on public outreach* (time_outreach) were significant predictors of both formal and social uptake of knowledge, respectively, $F_{3, 199} = 12.483$, $P < 0.001$ and $F_{2, 190} = 16.990$, $P < 0.001$ (Table 2). The reliability and validity assessment using the variable "findings used," show similar results to the other models, but indicate that a researcher' *time spent on stakeholder engagement* (time_engag) was more important than public outreach (Table 2). Here, stakeholder engagement is focused on user groups and groups who have interest in the telemetry project, whereas outreach activities are broader and often targeted to the general public. Descriptive statistics of significant variables are found in Table 3a, b.

Project attributes explaining formal and social uptake of telemetry study findings

The final backward stepwise regression model and GLMs indicated that the researcher's *familiarity with fisheries management processes* relevant to the project (mgmt_famil), and *complexity/controversy of the issue the project addresses* (proj_complexity) were significant positive predictors of formal uptake of telemetry study findings, $F_{1, 168} = 16.161$, $P < 0.001$ and $F_{3, 191} = 17.963$, $P < 0.001$, respectively (Table 2). These findings were confirmed with the reliability and validity evaluations against the outcome variable "findings used" (Appendix S7: Table S1). Furthermore, the *familiarity with fisheries management processes* of the project (mgmt_famil) and frequency of *dissemination activities related to the project* (dissemination_ind) were found to be significant positive predictors of social uptake of telemetry findings, $F_{2, 189}$, $P < 0.001$ (Table 2). Descriptive statistics of significant variables are found in Table 3a, b.

Insights from bivariate associations and correlation analyses

Simple bivariate analyses were conducted as supplement analyses to explore and gain further insights into the results from the regression models (Table 4a, b; Appendix S8: Table S1). Similar trends to the regression models emerged indicating that the collaborative extent and engagement tendencies of researchers show positive associations with both formal and social uptake of telemetry study findings. The negative association between the uptake of telemetry findings and researchers who spent more *time on research activities* strengthen the finding that collaboration and engagement are strong influences on uptake of knowledge. It also appears that projects with *freshwater research* and use of *radio telemetry* (only compatible in freshwater) have positive associations with the uptake of telemetry findings, while *saltwater or marine research* appear to be negatively associated with uptake telemetry findings. Furthermore, the associations test confirmed that researcher *familiarity and involvement with fisheries management*, as well as the *complexity/controversy of issues addressed by the project*, were important variables. So too was the *diversity of the research team,* which can be considered an indicator of the collaborative scope of the project.

Discussion

This study presents one of the first attempts in the conservation and environmental literature to quantitatively examine the conditions and factors under which scientific findings have influenced institutional practices or achieved social acceptance. We have focused on fish telemetry studies to examine the extent to which those researchers who conducted the research perceived that their findings influenced management practices, as well as the perceived influence on stakeholder acceptance of the findings. In addition, we designed the first study that attempts to quantitatively apply the knowledge–action framework for conservation and natural resource management (Nguyen et al. 2017*b*). Our results have important implications for fish telemetrists looking to impact policies and/or stakeholder behaviors, as well as implications for the broader scientific community and science programs for improving the link between scientific outputs and desired outcomes.

Getting one's hands dirty: engagement, collaboration, and co-production

The results of this study show that altruistic, collaborative, and pro-engagement behaviors and activities are significant factors that positively influence the successful uptake of telemetry study findings. Posner et al. (2016) also quantitatively demonstrated that the legitimacy of ecosystem services knowledge (i.e., production of information and technology was fair, unbiased, and respectful of stakeholders' values) is a strong predictor of

Table 2. Correlation coefficients from the final four multiple linear regression models (researcher attributes × formal uptake; researcher attributes × social uptake; project attributes × formal uptake; project attributes × social uptake).

	Formal uptake				Social uptake					
Independent variables	B_s	SE	B_u	P	IV	B_s	SE	B_u	t	P
Researcher attributes										
Intercept	0.28	0.159		0.022	Intercept	0.322	0.141		1.812	0.072
Collab_index	0.04	0.008	0.322	<0.001	Collab_index	0.03	0.008	0.272	3.927	<0.001
Time_outreach	0.196	0.088	0.148	0.028	Telem_exp	0.026	0.008	0.177	3.190	0.002
Time_outreach					Time_outreach	0.218	0.081	0.217	2.701	0.008
Project attributes										
Intercept	0.337		0.184	0.069	Intercept	0.633	0.094		6.739	0
Mgmt_famil	0.186	0.275	0.048	0	Dissemination_ind	0.028	0.005	0.404	5.888	0
Proj_complexity	0.041	0.255	0.011	0	Mgmt_famil	0.136	0.040	0.231	3.363	0.001

Notes: B_s, standardized coefficient, alpha < 0.01; SE, standard error; B_u, unstandardized coefficient; IV, independent variables. Significant variables explaining formal and social uptake of fish telemetry study findings include collaborative extent and tendency (collab_index); professional time spent on outreach (time_outreach); telemetry experience and commitment (telem_exp), fisheries management familiarity and involvement (mgmt_famil); complexity and controversy of issue addressed by project (proj_complexity); breadth and frequency of dissemination activities for project (dissemination_ind). For researcher attributes, formal uptake $R^2 = 0.142$ and Durbin-Watson = 1.888; social uptake $R^2 = 0.212$ and Durbin-Watson = 1.913. For project attributes, formal uptake $R^2 = 0.162$ and Durbin-Watson = 1.786; social uptake $R^2 = 0.339$ and Durbin-Watson = 2.034.

impact, which creates an incentive for researchers to participate in greater stakeholder engagement and collaboration with decision-makers. The authors of that study also suggested that the processes for bridging science–policy or knowledge–action gaps are doubly important because they influence the perceptions of knowledge as legitimate. Regular interactions between scientists and knowledge users are essential for building support and trust. These iterative exchanges help build perceptions and beliefs that the study findings are salient because the knowledge users helped frame and inspire the research (Cash et al. 2003, Posner et al. 2016). Although in a different context, Zardo et al. (2018) also quantitatively demonstrated that increased engagement can support increased research impact from a knowledge consumer's perspective of a communication platform called *The Conversation*. The authors also found that different types of engagement activities predicted different types of knowledge use, which means greater nuanced understanding of *engagement* should be considered.

Scientists often shy away from public outreach to either maintain their autonomy and objectivity, or because there is a lack of reward or incentives to engage and participate with the public or mass media (Pace et al. 2010, Lalor and Hickey 2013). However, with human societies facing major environmental crises and human-accelerated environmental changes, there is a need for evidence-based information to guide policy (Sutherland et al. 2004). Scientists are now expected to be more proactive in communicating and engaging with the public and with policy (Gibbons 1999, Samarasekera 2009, Likens 2010). Our results provide empirical support for the growing calls for collaboration and engagement found throughout the literature (Pohl 2005, Pita et al. 2010, Schuttenberg and Guth 2015). The literature is replete with examples of how and why researchers should collaborate, engage, co-produce, and co-create knowledge and research agendas with knowledge users (Bousquet 2008, Eden 2011, Reed et al. 2014, Cvitanovic et al. 2016, Jeffers and Godley 2016, Nel et al. 2016); as such, we do not go into further detail on this topic.

Our analysis also reveals that researchers who tend to engage in outreach and in stakeholder interactions were more successful in achieving a desired outcome. However, our survey results show that fish telemetrists only spend, on average, 6% of their professional time on public outreach activities, and only 12% on engaging and consulting with managers and stakeholders (Table 2). While there is no consensus in the literature on what is an appropriate amount of time one should spend on engagement and outreach, this evidence supports calls for greater incentives and reward structures to encourage researchers to focus efforts on engagement, knowledge exchange and sharing, and relationship building. These incentives should include career evaluation mechanisms that recognize these time-intensive efforts as productive activities metrics, much as publications are today (Samarasekera 2009, Lam 2011). Furthermore, researchers who dedicated time to understanding and becoming involved in fisheries management processes experienced more successful knowledge outcomes. An excellent example of "getting one's hands dirty" from the literature is from conservation scientists who helped implement the corrective measure they proposed, and witnessed a rapid recovery of an endangered hoopoe (*Upupa epops*) population in the Swiss Alps (Arlettaz et al. 2010). Furthermore, Brooks et al. (2008) describe three case successful case studies of biotelemetry informing fisheries management and highlight that although co-production is useful, other factors such as sociopolitical and economic impact of management change can dictate the strength of evidence required to influence

Table 3. (a) Descriptive statistics for significant explanatory variables for regression models describing (a) formal uptake and (b) social uptake for research attributes and project attributes.

Model and variable	Score < 1	Score ≥ 1
(a) Formal uptake		
Researcher attributes × formal uptake		
Collaborative extent and tendency	15.2 ± 5.0	18.4 ± 4.9
Telemetry experience and commitment	9.3 ± 4.0	10.8 ± 4.9
Professional time spent on outreach		
0%	10 (5%)	17 (8%)
1–20%	36 (17%)	124 (59%)
21–30%	16 (8%)	7 (3%)
Mean outreach	4.60%	6.90%
Project attributes × formal uptake		
Researcher's familiarity and involvement with management		
Not familiar	4	10
Somewhat familiar	21	25
Familiar	8	47
Very familiar	9	54
Level of complexity and controversy of issue surrounding project	12.7 ± 4.3	15.0 ± 4.0
(b) Social uptake		
Researcher attributes × social uptake		
Collaborative extent and tendency	14.1 ± 4.1	18.7 ± 4.9
Telemetry experience and commitment	8.7 ± 3.8	11.1 ± 4.9
Professional time spent on outreach		
0%	8 (4%)	17 (9%)
1–20%	32 (16%)	122 (63%)
21–30%	2 (1%)	14 (7%)
Mean	5.4% ± 4.8%	6.8% ± 5.3%
Project attributes × social uptake		
Researcher's familiarity and involvement with management		
Not familiar	6	7
Somewhat familiar	15	30
Familiar	8	44
Very familiar	8	54
Breadth of dissemination activities of project (mean index)	7.7 ± 4.3	14.7 ± 8.6

Notes: Scores were binned into scores <1 and ≥1 to facilitate interpretation of descriptive statistics. Continuous explanatory variables are presented as the mean ± SD, while categorical variables are presented as frequencies and % of total number of respondents in brackets.

decisions. Nonetheless, the willingness, commitment, and motivation to embark on a path of continuous, honest, and transparent engagement among researchers and managers/stakeholders are key and has been a common theme in the literature (Nguyen et al. 2017*b*, Zardo et al. 2018; Brooks et al. 2008). Maintaining positive and active relationships with relevant stakeholders groups is important to ensure that data is relevant and accessible for informing decisions (Brooks et al. 2008).

Experienced and committed fish telemetrists have greater social uptake of telemetry study findings

Respondents who were highly involved and experienced in fish telemetry research (e.g., fish telemetry is central to respondent's research program including involvement in telemetry committees and networks) may display characteristics of collaborators. Our results show that these researchers had high success in the social uptake and use of their study findings. There are several possible explanations for this observation. First, it is possible that the core fish telemetry community is composed of highly collaborative individuals because telemetry science demands it (Campbell et al. 2015, Hussey et al. 2015). For example, the high cost of acoustic telemetry infrastructure may encourage collaborations among telemetry scientists and telemetry networks to leverage their return on investments. Tagged fish can be found on other researchers' receiver arrays, and therefore cooperation and collaboration have a direct impact on data quality (Nguyen et al. 2017*a*). Second, it is possible that individuals engaged in telemetry have been unusually successful in extending their connections and influence into policy realms. Telemetry technology is currently viewed by some as unjustifiably expensive (Young et al. 2018), and without demonstrating the benefits of tracking, or investing effort into linking telemetry-derived information to management actions, the use

Table 4. Statistically significant ($P < 0.05$) bivariate associations and correlations between (a) formal uptake or (b) social uptake and independent variables and using simple t tests, chi square, and regression analyses.

Model and significant predictor variable	Coefficient	P
(a) Formal uptake		
Researcher attributes correlating with formal uptake:		
Collaborative extent	0.275	<0.01
Telemetry experience and centrality to research	0.171	<0.01
Radio telemetry	0.167	<0.01
Freshwater research	0.166	0.008
Research priority: importance to society	0.163	<0.01
North America	0.144	0.023
Role: Government scientist	0.138	0.027
Time spent on stakeholder engagement	0.135	0.014
Dissemination frequency and extent	0.133	0.01
Research priority: policy implications	0.123	0.044
Time spent on research	−0.115	0.029
Project attributes correlating with formal uptake:		
Researcher familiarity with fisheries management	0.285	<0.01
Complexity and controversy of issue addressed by project	0.239	<0.01
Location: coastal	−0.143	0.024
Study species: saltwater	−0.145	0.021
(b) Social uptake		
Researcher attributes correlating with social uptake:		
Collaborative extent	0.267	<0.01
Telemetry experience and centrality to research	0.212	<0.01
Freshwater research	0.186	0.003
Telemetry network member	0.179	<0.01
Time spent on outreach	0.169	0.003
Radio telemetry	0.162	0.01
Age	0.161	0.006
Gender	0.154	0.015
Time spent on mentoring students	0.132	0.016
Time spent on research	−0.112	0.035
Project attributes correlating with social uptake:		
Team with high percentage of local, industry, user groups	0.185	0.003
Complexity and controversy of issue addressed by project	0.162	0.002
Diversity of research team	0.152	0.009
Team with high percentage of NGO	0.152	0.009
Study focus: catch and release	0.127	0.045
Study species: saltwater	−0.136	0.033
Location: coastal	−0.152	0.017
Knowledge users of project: other researchers	−0.154	0.016

Notes: Results are grouped into researcher and project attributes. These bivariate tests were examined to complement the exploratory analysis and strengthen the understanding of the underlying story of the data.

of telemetry for conservation is not justified. It is therefore important for these researchers, who have been successful in making impact, to share their lessons learned and experiences so that the telemetry community can improve the conservation return on investment highlighted by Mcgowan et al. (2016) as a major barrier to further development of the field.

Context matters: complexity and controversy surrounding the issue addressed by projects

We expected that the greater the complexity and controversy that surrounded a particular project, the less likely it would be used or integrated into practice, due in part to the difficulty in translating complex science into actionable tools, and in part because greater conflict or disagreement may be associated with such projects. Surprisingly, complexity and controversy of the project issue was shown to be a positive significant factor in explaining successful integration of telemetry study findings. It is possible that a higher score on project issue complexity and controversy reflects higher societal importance of the project, greater funding, or enhanced public attention (as described by Mcgowan et al. 2016). As such, the context of particular research projects matter, and considerations of these external or contextual factors may help researchers navigate the science-policy nexus, as observed by Brooks et al. (2008) who assessed three successful case studies of biotelemetry informing fisheries management.

The origin of the science doesn't matter

We expected that science generated in the public and private sectors would have a higher rate of successful formal knowledge outcomes than science generated in academia. Private scientists (i.e., environmental consultants) are often hired to answer specific questions, and government scientists often conduct "mandated science" in service of management and policy development (Young et al. 2013). The observed lack of difference in the application of telemetry findings among all groups was therefore surprising. First, it may be an indication that fish telemetry technology is still novel and has not penetrated traditional fisheries management frameworks. Second, research studies in fish telemetry may still lack explicit links between the research and actions (as stated by Mcgowan et al. 2016). Last, this finding may show that even some work of government scientists (even though employed in mission-oriented agencies), or that of private sectors whose client is often government, is not directly embraced by managers and stakeholders. This may mean that the type of data (i.e., new telemetry findings) is as important as who generates it. However, Young et al. (2016*a*) report that government employees involved in Canadian Pacific salmon management have a more positive view of the reliability of knowledge produced by government scientists, as they are viewed as "peers." This does not necessarily mean that the science and policy in government are interacting, leaving more unknowns about the science–policy interface.

Evaluating the application of the knowledge–action framework

The knowledge–action framework was useful in assisting with generation of hypotheses and determining what predictor variables to measure. The framework was helpful to place the findings in a broader context (Fig. 1) and was flexible enough to adapt to our fish telemetry model. However, the flexibility of the framework comes at a cost, in which the framework does not offer clear pathways to measure spatial temporal scales at which some of the processes of knowledge movement occur. In this study, we used "funding received" as a proxy for assessing the economic value and scale of the project, as well as "project complexity" to capture the importance of the cases. As for time, we measured length of the project from beginning to completion, but found recall bias and interpretation of "beginning" and "ending" to be inconsistent. Therefore, this study did not include time as a factor, due to the inconsistencies of the data, but we acknowledge that it may be important. Improvements on how to measure these attributes should be considered in future research.

Furthermore, grouping and distinguishing variables between researcher and project attributes was helpful with the application of the framework. This is because one cannot assume that a researcher is consistent with their behavior and attitudes/beliefs through time. For example, a researcher who is highly collaborative, may not have been collaborative for the particular case study; as such, it was imperative to measure both the researcher attribute (e.g., general collaborative tendency) and the project attributes (collaborative extent of the project). Overall, the framework potentially lacks methods to evaluate interactions among the different components of the framework, which we believe is an important area for future research.

Study limitations

This study is exploratory, and therefore, we cannot claim the findings to be predictive of successful knowledge outcomes, and certain caveats should be recognized. First, the use of a survey approach introduces respondent bias with regards to self-reporting and confirmation bias. The outcome variables are not "true" measures of success but rather "perceived" success by the researcher respondent. Second, the study population is also biased toward North American and male fish telemetry scientists. Nonetheless, we surveyed people from 31 countries and 20% of respondents were female. Third, there is also potential for recall bias when respondents were asked to discuss "a completed fish telemetry project with applied objectives." It is likely that respondents chose the most recent project for which they have the most recollection, leading to a sample of case studies that may or may not have fit the criteria. Last, we do not have information on respondents who did not participate in the study; therefore, there are potentially nonresponse biases. Despite these caveats, our findings revealed strong correlations and associations among similar themes, and reveal theoretically significant trends that we believe have broader implications for future research directions.

Application of findings and future research

Fish telemetry is an advancement in technology that offers novel insights on fish ecology and animal–environment interactions that is invaluable to understanding the natural world (Hussey et al. 2015). This kind of new information is critical for creating and refining policies and management actions. The world is rapidly changing, and the rate at which it is changing makes it difficult for traditional fisheries management practices to keep up (Stephenson and Lane 1995, Caddy and Cochrane 2001). Fisheries management needs to change and evolve to reflect these realities. If collaboration and engagement are strong indications of successful use of telemetry findings, we, as the conservation community (academia, public, private, non-governmental), need to foster these behaviors and competencies. One approach may be to reassess criteria for hiring and/or assigning the right people for projects and programs that require high return on conservation investments and bridging the scientific outputs to desired outcomes, or to hire outside experts who specialize in bridging science and action (i.e., knowledge brokers, boundary spanning organizations). Another way would be for academic institutions, government, and funding agencies to offer incentives for individuals to engage in collaborations and get their hands dirty with management and policy (Baas and Hjelm 2015, Dick et al. 2016). The "publish or perish" system (Campos-Arceiz et al. 2013) is arcane, and greater emphasis needs to be put on research that has societal and conservation impact, which, from the present findings, should be measured through engagement, co-production of knowledge, and collaborative activities. Meaningful collaboration, knowledge co-production, and stakeholder engagement can be costly in both time and financial resources. Long-term investments in face-to-face time and knowledge exchange should be encouraged and budgeted in research proposals. Public/governmental agencies should look at formally building multi-sector partnerships and leverage the limited human and financial resources (Sorensen and Torfing 2011, Torfing et al. 2016). Collaboration with other sectors has the potential to leverage the return-on-investments and telemetry is a unique tool that thrives off of collaborative research and designs for it to reach its potential.

An essential next step is to capture and compare the perspectives of managers and policy-makers on these questions. To date, only a handful of case studies have been completed that compare managers' and researchers' perspectives (Posner et al. 2016; Brooks et al. 2008). A recent study by Zardo et al. (2018) found that the position and status of a knowledge user (politician, policy officer or government employee) predicted use of articles from an Australian open access research communication platform, indicating that policy officers and politicians are seeking readily available and accessible advice. Research networks offer an opportunity to expand this research, given that they often include both scientists and practitioners. For example, the Great Lakes Fishery Commission and its associated Great Lakes Acoustic Telemetry Observation System (network of telemetry researchers) make up a community of both science and practice (Krueger et al. 2018). Evaluating the various cases that have derived from Great Lakes fisheries research using telemetry could be a viable method to get to a truer measure of "successful" knowledge outcomes. Telemetry networks, such as Ocean Tracking Network (OTN) and Australian Animal Tracking and Monitoring System (AATAMS), will play key roles in brokering and facilitating knowledge exchanges and linking telemetry findings into actions and public policy (Nguyen et al. 2017*a*).

Conclusion

In conclusion, findings from this research support the increasing calls in the literature for more transdisciplinary, collaborative, and solution-oriented research agendas to ensure that science is informing resource management and conservation practice. Researchers looking to impact real-world management or policy decisions need to step outside of the traditional scientific framework, and familiarize and engage themselves with fisheries management processes, as well as collaborate beyond the scientific boundaries to include non-scientists, particularly policy makers and officers, and stakeholders. Institutions need to be innovative and create collaborative arenas to build support for evidence-informed decision making, to leverage resources and avoid reinventing the wheel. The context for the research also matters. Building support, and investments of stakeholders into the project will help ensure that the findings do not sit on the shelf. Processes of building relationships, trust, and engaging end users have been shown to have positive impacts on linking telemetry science to action, which is needed now more than ever with the increasing complexity of environmental problems and conservation crises.

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